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Evaluating Alternative Measures of Bicycling Level of Traffic Stress Using Crowdsourced Route Satisfaction Data

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MINETA TRANSPORTATION INSTITUTE

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REPORT 19-20

EVALUATING ALTERNATIVE MEASURES OF BICYCLING LEVEL OF TRAFFIC STRESS USING CROWDSOURCED ROUTE SATISFACTION DATA

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16. Abstract

Approaches for evaluating the quality of bicycling have become increasingly important for planning bicycle infrastructure improvements. Mekuria, Furth, and Nixon's (2012) "Level of Traffic Stress" (LTS) approach, which requires minimal data inputs and produces a simple and intuitive output, has emerged as a widely-used framework for identifying streets that are "low-stress" for cyclists. The LTS framework is based on a hierarchy of characteristics, largely related to traffic speed and roadway layout, that are presumed to cause higher or lower levels of stress. Despite the apparent simplicity of LTS, several key challenges emerge from its application. Firstly, multiple LTS classification methods have been developed, and it is difficult to know whether they represent stress in equivalent ways. Secondly, LTS is intended only to define an ordinal scale of stressfulness, but has often been misinterpreted as defining a continuous scale; there is no intended implication that the stress levels are spaced equally. Third, while LTS provides a useful summary of diverse infrastructural variables, it is poorly understood which of these variables are most strongly associated with cyclist satisfaction and may, therefore, be most important to capture in an LTS framework.

These challenges were examined in the contexts of two U.S. cities: Portland, Oregon, which has a very well-developed bicycling infrastructure, and Austin, Texas, which has more moderately-developed bicycling infrastructure. In both cities, LTS outcomes differed depending on the LTS classification method used. In addition, even when classified using the same method, LTS outcomes differed depending on the source of the data used. This suggests that LTS analyses based on different methods or data sources are unlikely to be comparable. Associations between LTS classifications and continuously-scaled user satisfaction data from the crowdsourcing mobile app Ride Report suggested that LTS levels represented a fairly linear scale, though differences in average Ride Report scores between successive LTS levels were rarely large. Ride Report user satisfaction data were most strongly and consistently associated with variables related to bicycling-specific infrastructure, such as bike lanes and boulevards, and indicators of street size. These variables may be most useful for developing LTS classification methods with minimal data inputs. Unsurprisingly, our analysis also supports the addition of bicycle-specific infrastructure and reduction of roadway size and traffic volume as among the most effective approaches for reducing LTS levels and maximizing user satisfaction along cycling networks.

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EXECUTIVE SUMMARY

The “Level of Traffic Stress” (LTS) framework is an increasingly popular approach to evaluating the quality of roadways for bicycling. First described by Mekuria, Furth, and Nixon,[1] the framework provides a straightforward ordinal system for classifying the overall stress level of street segments based on variables related to bicycle infrastructure, roadway size and layout, and intersection characteristics. LTS levels typically range from 1 to 4. Segments that are are assumed to be comfortable for inexperienced cyclists and children are classified as LTS 1. Segments that are comfortable only for the most experienced cyclists are classified as LTS 4. Intermediate levels are considered appropriate for cyclists with moderate experience.

OBJECTIVE 1: AGREEMENT OF LTS RESULTS ACROSS DIFFERENT CLASSIFICATION METHODS AND DATA SOURCES

One of the greatest assets of the LTS system is its simplicity. When used appropriately, it aggregates many variables into an intuitive scale that enables comparison acoss diverse street segments. Despite its apparent simplicity, however, LTS can be difficult to implement and interpret. The challenge of collecting numerous segment-level variables to fuel LTS analysis has prompted the development of alternative simplified LTS classification methods that require fewer and more commonly-available inputs (Table 1). Most of these methods also produce outputs on a four-level scale; however it is not yet well-understood whether different methods typically yield the same outcomes. This study’s first objective was to examine the equivalency of outputs from different LTS methods, for the same street segments, using different sources of input data. Python scripts were used to calculate LTS classifications according to the seven methods listed in Table 1 across large samples of street segments in Portland, Oregon and in Austin, Texas, the two cities in which crowdsourced cyclist satisfaction data were most readily available for later stages of the analysis (see Objectives 2 and 3, below). Parallel classifications were conducted with manually-audited data, which were assumed to be most reliable, and with data from OpenStreetMap (OSM) and local agencies, which depended on numerous assumptions to fill in missing values. Visual comparisons of histograms and Cohen’s kappa coefficients were used to assess agreement between classifications derived from the different methods and data sources.

Table 1. LTS Methods Evaluated in This Study

Author(s)	Abbreviated Name	Year	Input Variables
Conveyal[2]	Conveyal	2015	4
Furth[3]	Furth	2017	6
Lowry, Furth, and Hadden-Loh[4]	Lowry	2016	4
Mekuria, Furth, and Nixon[5]	Mekuria	2012	18
Montgomery County, Maryland[6]	Montgomery	2017	12
Oregon Department of Transportation[7]	ODoT	2017	15
People For Bikes[8]	PFB	2017	6

Different LTS methods were found to produce substantially different results. Figure 1 shows histograms of street segments for each of the methods, all calculated using the same, audit-derived data. If the methods had produced similar results, all of the histograms within each city (Portland, top row; Austin, bottom row) would have been shaped similarly. Instead, the histograms had substantially inconsistent shapes, favouring different LTS levels. Classifications were somewhat more consistent in Austin than in Portland, potentially due to greater design consistency among Austin streets. Linearly weighted kappa coefficients comparing LTS methods based on audit data also tended to be slightly higher, indicating greater agreement, in Austin (0.59 on average between all pairs of methods except for those with PFB) than in Portland (0.54). Nonetheless, these weighted kappa coefficients represent only moderate levels of agreement.[9]

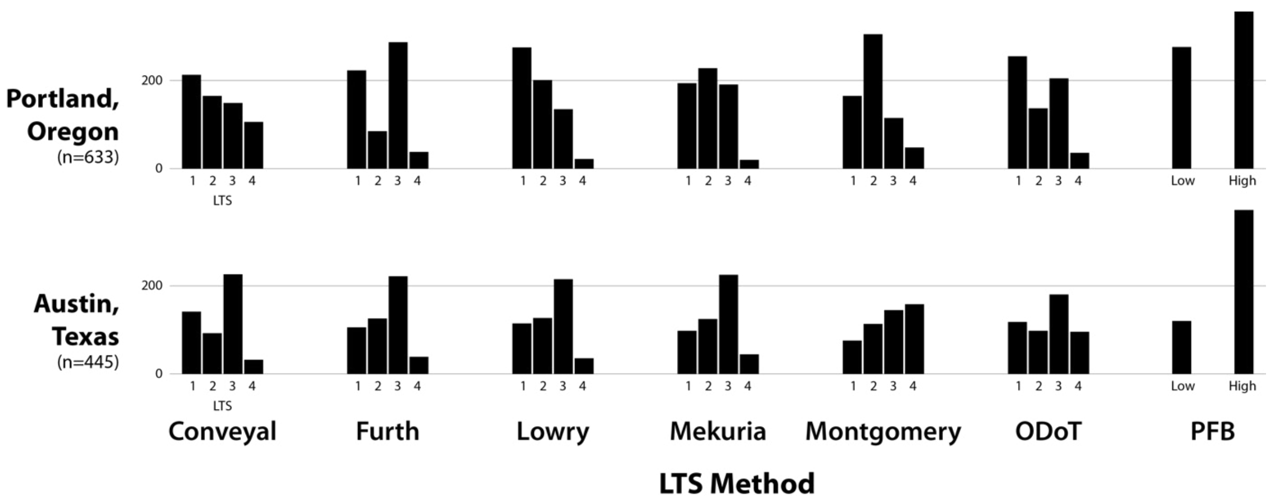

Figure 1. Histograms of Street Segment Count by LTS Level

Note: All classifications are based on audited data.

OBJECTIVE 2: ASSOCIATIONS BETWEEN LTS AND CROWDSOURCED BICYCLE USER SATISFACTION

Although LTS levels were intended to be defined on an ordinal scale, they have often been misinterpreted as a continuous scale. This study's second objective was to evaluate whether there is any merit to this interpretation. Is there a linear association between LTS levels and a continuous measure of cyclist satisfaction? If so, what is the approximate interval between successive LTS levels? To address these questions, the authors compared cyclist satisfaction scores derived from a crowdsourcing smartphone application called Ride Report, to LTS classifications throughout Portland and Austin, the two cities where the app had the most extensive user base. Ride Report asked users to rate their bicycle rides on a "thumbs up-thumbs down" scale. Ratings were then aggregated in to a score representing the proportion of positive ratings along each street segment. Spearman rank correlations (r_S) were used to evaluate associations between LTS and Ride Report score, and Ride Report score means were used to examine the linearity and degree of difference between successive LTS levels. Ride Report scores derived from subsets of cyclists and cycling conditions, such as cyclist age and trip length, were used to investigate the ways in which relationships between LTS and cyclist satisfaction were influenced by personal and trip-related factors.

In line with expectations, correlations between LTS and Ride Report scores were generally negative, suggesting that lower LTS levels were associated with greater cyclist satisfaction (Figure 2). Trends between LTS and Ride Report scores were also reasonably linear, with each decrease in LTS level corresponding to an approximately 2–3% increase in Ride Report score. Given the narrow distribution of Ride Report scores across all street segments, this corresponded to an increase from each city's median segment to between 65th and 75th percentile of segments within that that, a substantial improvement.

Nonetheless, rank correlations between LTS and Ride Report scores were not strong (r_S=0.26 on average between all LTS methods in Portland; r_S=0.13 in Austin; both statistics based on audit data). The weakness of these correlations may be been driven by the imprecision of both LTS classification methods and crowdsourced cycling quality data. Interestingly, rank correlations between LTS and cycling quality were higher when Ride Report scores were based only on responses from cyclists who rode relatively slowly and made shorter trips, which were presumed to be indicators of less cycling experience. This suggests that LTS may have been most representative of less experienced cyclists.

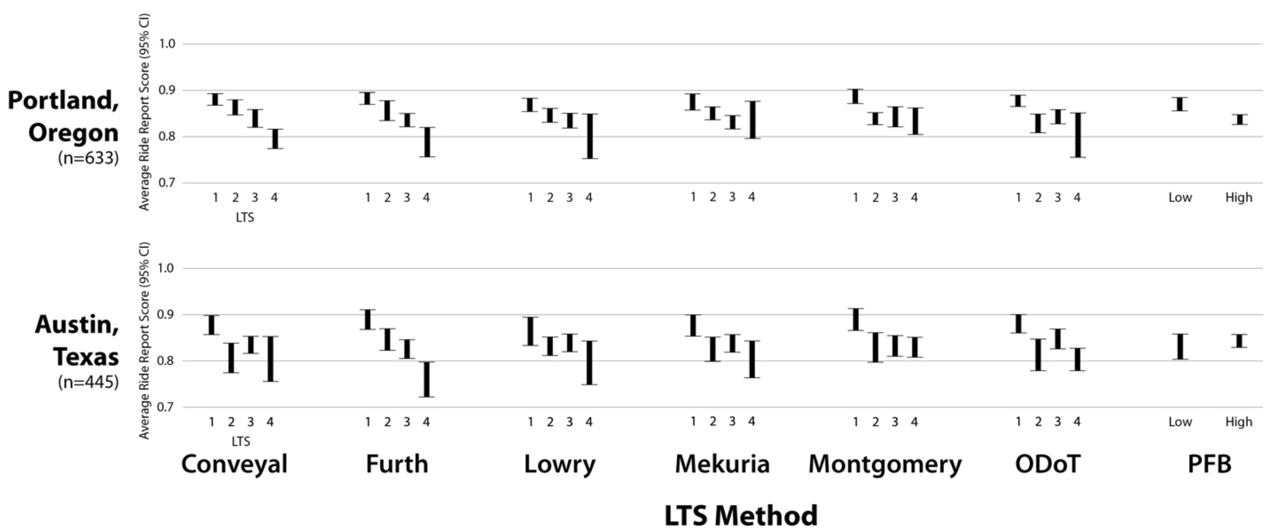

Figure 2. 95% Confidence Intervals for Average Ride Report Scores by LTS Level

Note: All classifications are based on audited data.

OBJECTIVE 3: ASSOCIATIONS BETWEEN CYCLING ENVIRONMENT VARIABLES AND USER SATISFACTION

Consideration of which variables have the strongest influence on cycling satisfaction is important for the development of improved LTS methods. The third objective of this study was to examine associations between individual street environment variables and Ride Report scores. Regression models were used to predict Ride Report scores based on variables from each of the three data sources (audit, OSM, and local), while controlling for spatial autocorrelation between segments.

Bike lanes and other bicycling-specific infrastructure had the strongest and most consistently positive associations with Ride Report scores, while indicators of large roads had the strongest negative associations. Even the combination of all environmental variables, however, was able to explain only a modest fraction of the variance in Ride Report scores, underscoring the complexity both of cyclists' perceptions of quality and of the environmental characteristics that contribute to them. These results suggest that a streamlined LTS method might focus on bicycle infrastructure and road size variables. Unsurprisingly, these are already some of the key variables driving existing LTS methods. Thus, both the theoretical framework laid out by LTS systems, and our empirical results, support the view that planners ought to prioritize bicycling-specific infrastructure and smaller, less trafficked roadways in order to improve the quality of cycling networks.

I. INTRODUCTION

Improvement of bicycling infrastructure is expected to increase bicycling and to foster concomitant environmental sustainability and health benefits. As a result, significant attention has turned to understanding and measuring the quality of streets for bicycling. The "Level of Traffic Stress" (LTS) framework has become a widely used approach for analyzing bicycling quality along individual street segments and communicating opportunities to improve comfort, safety, and connectivity.[10] The framework has quickly permeated active transportation planning. For example, recent plans prepared for agencies in Berkeley, CA, Washington, D.C., Montgomery County, MD, and Colorado have used LTS to assess current conditions and the impacts of proposed improvements.[11]

LTS attempts to measure the suitability of street segments for bicycling, particularly for individuals concerned about safety related to interactions with motor vehicles. LTS levels are based on factors understood to feel more or less stressful for cyclists, including speed limit, number of traffic lanes, width of bicycle and parking lanes, presence of a center line, and frequency of bicycle lane blockage. The levels are also linked to presumed thresholds of comfort for cyclists with different degrees of experience. Streets classified as LTS 1, such as bicycle boulevards and neighborhood streets, should feel comfortable even for inexperienced cyclists and children, whom Geller refers to as "interested but concerned" cyclists.[12] Mid-range LTS levels, exemplified by bicycle lanes along streets with speeds above 25 mph and with various degrees of separation from traffic, should be comfortable for "enthused and confident" cyclists, who have some experience with cycling but varying levels of comfort with traffic. Streets classified as LTS 4, such as high-speed, multi-lane streets with mixed traffic, should feel comfortable only for the most experienced, "strong and fearless" cyclists. Thus, key features of LTS include its intuitive organization, coordination with Geller's "types of cyclists," transparency of application, and ease of communicability.

Despite LTS's intuitive appeal, practitioners face several notable challenges when applying and interpreting LTS analyses. In addition to Mekuria et al.'s "original" LTS classification method,[13] herein referred to simply as the *Mekuria* method, a number of alternative methods have developed in order to accommodate data limitations (e.g. the Conveyal method), to address localized context (e.g., the Montgomery method),[14] or to better represent how bicyclists perceive stress (e.g., Furth's "LTS 2.0").[15]

While well-intentioned in their development, the diversity of LTS methods can be confusing. Most of the methods produce similarly-labeled outputs: a four-tiered ordinal structure referred to as levels 1 through 4. These scales are not, however, necessarily identical across methods; "LTS 2" could have an entirely different meaning depending on the method and source data used to derive it. Moreover, while LTS levels are numeric, the scale is ordinal; they do not describe *how much* better successive levels are from one another. While such an ordinal scale is not theoretically problematic, it can easily be misinterpreted, and often is by practitioners who are not intimately familiar with LTS methods. It is all too easy to misinterpret LTS levels as representing equally-spaced values on a continuous scale. Mekuria et al. might have introduced LTS levels as "A, B, C, D" in order to reinforce their non-numeric ordinality. Today, it would be difficult to encourage adoption of an alternative nomenclature because the numeric levels are so widely-used in planning practice.

One reason why LTS is attractive is that it aggregates many different factors into a single scale. This also, however, makes it difficult to tell which individual factors are most associated with cyclist satisfaction. This project addresses each of these challenging questions—the agreement of classificaiton results between different LTS methods and data sources, the association between LTS and continuous measures of cycling satisfaction, and the association of individual environmental factors with cyclist satisfaction—through three core objectives.

OBJECTIVE 1: AGREEMENT OF LTS RESULTS ACROSS DIFFERENT CLASSIFICATION METHODS AND DATA SOURCES

The study's first objective was to examine the agreement of classifications based on different LTS methods and using data from different sources. For streets in Portland, Oregon and in Austin, Texas, seven LTS measures were calculated (Table 2), three times each with three sources of data: audits conducted by the authors and research assistants; OpenStreetMap (OSM); and local agencies' GIS databases (in Portland only). The resulting ordinal outcomes were then compared. Portland and Austin were chosen because these cities were best represented in the crowdsourced dataset used to address the second and third study objective; moreover, these cities offered a degree of difference in bicycling infrastructure provision and local cycling culture, with Portland representing one of the most cycling-oriented cities in the U.S. Portland also offered unusually detailed datasets from local agencies that accounted for nearly all variables used by LTS analyses, allowing for a direct comparison of local agency data to audited and OSM data.

Table 2. LTS Methods Evaluated in This Study

Author(s)	Abbreviated Name	Year	Input Variables
Conveyal[16]	Conveyal	2015	4
Furth[17]	Furth	2017	6
Lowry, Furth, and Hadden-Loh[18]	Lowry	2016	4
Mekuria, Furth, and Nixon[19]	Mekuria	2012	18
Montgomery County, Maryland[20]	Montgomery	2017	12
Oregon Department of Transportation[21]	ODoT	2017	15
People For Bikes[22]	PFB	2017	6

OBJECTIVE 2: ASSOCIATIONS BETWEEN LTS AND A MEASURE OF USER SATISFACTION

The second objective was to investigate the association between LTS levels and a continuous measure of user satisfaction. LTS methods have defined levels based on plausible a priori assumptions about what roadway characteristics result in more or less stress for cyclists. This contrasts notably with the Highway Capacity Manual's Bicycle Level of Service (BLoS),[23] which was based on regression models estimating relationships between bicycling infrastructure and user ratings.[24] LTS methods' a priori definitions have allowed them to be sensitive to factors, such as detailed intersection treatments, whose associations with cyclist satisfaction, especially in combination with one another, might be difficult to detect in noisy empirical data. Because LTS levels were not defined in relation to an indicator of user satisfaction, they offer no way to interpret *how much* better or worse one LTS level is than another in terms of user satisfaction. This study compared LTS levels to Ride Report scores to examine the strength and linearity of relationships between LTS and a continuous measure of user satisfaction.

OBJECTIVE 3: ASSOCIATIONS BETWEEN CYCLING ENVIRONMENT VARIABLES AND USER SATISFACTION

While new LTS methods have tended to be developed to accommodate data constraints, it may also be prudent to develop LTS classification methods that concentrate on factors most strongly related to user satisfaction. The third objective of this study was to examine relationships between individual cycling environment variables and Ride Report scores to identify which variables might represent the greatest opportunities for bicycle network improvements.

II. BACKGROUND

Since its inception in 2012, the LTS concept has become popular among researchers and practitioners. LTS evaluations in research literature have included analyses of San Jose, California by Mekuria et al.;[25] San Diego, California by Scrivener;[26] Atlanta, Georgia by Mingus;[27] Seattle, Washington by Lowry, Furth, and Hadden-Loh;[28] and Washington, D.C. by Semler et al.[29]

LTS analyses are also prevalent in planning documents prepared by agencies and consultants. These have included plans for Berkeley, CA; Washington, D.C.; Montgomery County, MD; and the State of Colorado.[30] Informal discussions with transportation planning practitioners have revealed familiarity with and interest in LTS, including a desire to incorporate LTS into future work at agencies where it has not yet been used.[31]

Researchers and agencies use LTS to assess current conditions and describe the impacts of proposed improvements. Notably, LTS analyses tend to reveal substantial discontinuities in low-stress networks—clusters of internally-connected low-stress "islands" separated from each other by high-stress streets—between major neighborhoods and key destinations. LTS patterns are also frequently mapped spatially.[32] For example, maps of low-stress islands and separating high-stress corridors may be used to identify opportunities for infrastructure improvements that provide low-stress "bridges" between islands.

LEVEL OF TRAFFIC STRESS (LTS) CLASSIFICATION METHODS

The Original LTS

The first LTS classification method was developed by Mekuria, Furth, and Nixon.[33] The method used 21 variables arranged in decision matrices to identify an LTS level for each street segment in a network, along a four-point scale, where 1 represented the lowest stress and 4 the highest. Qualitatively, Mekuria et al. defined LTS 1 as "suitable for children"; LTS 2 was "the traffic stress that most adults will tolerate" according to Dutch bikeway design criteria;[34] LTS 3 and 4 represented "greater levels of stress."[35]

LTS was framed as a simpler, more intuitive alternative to the Bicycle Level of Service (BLoS) scale, which was adopted by the Highway Capacity Manual and uses a linear model fed by data that are not commonly available in existing datasets (e.g., FHWA's pavement condition rating).[36] Nevertheless, the original LTS approach still relied on a large number of variables, many of which tend not to be available from existing, public sources (e.g., the lengths of right-turn lanes). Thus, many researchers and practitioners have looked for ways to further streamline the operationalization of the approach, reducing the need to collect custom data for LTS studies.

Adaptations of LTS

The Conveyal LTS method represented an extreme simplification, drawing solely from data that were widely available from OpenStreetMap (OSM).[37] The Conveyal method used four variables, and assumed that three of these could be inferred from the fourth—

highway class—in the case of missing data. The meaningfulness of distinctions between LTS classes was substantially diluted by calculating them based on such limited data; however, this approach did allow application almost anywhere in the world without collecting additional data.

Lowry et al. developed an LTS method based on four variables similar to those used by Conveyal, but which were collected from a local agency (their study was in Seattle, WA) and were therefore more specific (e.g., separate binary indicators were used to represent three different types of bike lanes instead of all bike lanes being represented by same indicator).[38]

People for Bikes (PFB) also developed a classification method intended to be used with OSM data.[39] Similarly to Conveyal, they provided a set of assumptions with which to fill missing data. They used six variables to calculate a two-level scale (low and high stress), which reflected the imprecision of their inputs.

The Montgomery County, Maryland LTS method was also designed to use local agency data and therefore presumed higher-quality input data.[40] It used fourteen variables, including variables not used by other LTS methods, such as the number of driveways along a segment, presumably because these data were conveniently available through Montgomery County-specific dataset. It also increased the apparent precision of classification by adding a fifth mid-level class: LTS 2.5. The addition of this fractional level increases the risk of misinterpreting LTS levels as representing a continuous scale, with LTS being “halfway between” LTS 2 and LTS 3 in terms of stress level.

The Oregon Department of Transportation (ODoT) developed a customized LTS based on 18 variables, most of them overlapping with those used in the Mekuria method.[41] The ODOT method was focused more on precision than simplification, requiring additional variables related to left-turn lanes, and including many of the turning-lane variables of the Mekuria LTS, even though these data are some of the least widely available, often requiring manual auditing of each street segment.

Furth, a co-author on the studies that developed the Mekuria and Lowry methods, later developed “LTS 2.0,” which required only nine variables and did not account for intersection treatments, significantly reducing the complexity of conducting an LTS analyses.[42] This method drew on traffic volumes, lane counts and speed limits as key inputs, while omitting metrics that do not tend to be available from secondary sources, such as the frequency of bike lane blockage.

Other LTS classification methods have been developed for analyzing specific cities. The city of Auckland, New Zealand, for example, developed a tool for evaluating quality of service which had many similarities to LTS frameworks. Although it was infeasible for us to analyze all LTS methods developed to date, the seven methods included in this study represent the breadth of LTS methods developed for both generalized and specific contexts, and with both extensive and minimal data requirements.

III. LITERATURE REVIEW

As outlined above, the primary goals of this study included evaluation of the correspondence of different LTS methods to one another (Objective 1), of correlations between LTS levels and a measure of user satisfaction (Objective 2), and of the correlations between individual environmental variables and a measure of user satisfaction (Objective 3). Our study harnesses data crowdsourced from the mobile app Ride Report as a measure of user satisfaction. To the authors' knowledge, no study had previously examined correspondence between different LTS methods, so this literature review focuses on the latter two objectives. Objective 2 is situated within a body of research that compares LTS to behavioral and perceptual outcomes, while Objective 3 is related to studies investigating the role of individual variables in either promoting or impeding bikeability. Both of these objectives are related to previous bicycling research utilizing crowdsourced data, some of which involved LTS.

THE PREDICTIVE VALIDITY OF LTS (OBJECTIVE 2)

Prior research has explored whether LTS classifications can predict several behavioral outcomes related to bicycling. Questions investigated have included: whether LTS predicts the propensity to bicycle or not bicycle; whether LTS predicts the use of bikeshare programs; and whether LTS correlates with safety outcomes.

Travel Behavior

Wang et al. found mixed evidence for an association between LTS and travel behavior, finding that correlations between LTS and bicycling are dependent on how bicycling was measured.[43] Exploring the case of the Salem-Keizer, Oregon region, they found LTS did not predict bicycle mode share as measured by the U.S. American Community Survey. However, LTS was significantly associated with the number of bicycle trips as measured with the Oregon Household Activity Survey (OHAS). Notably, the OHAS captures bicycle trips for all purposes, while census data only measures commuting.

Fitch, Handy, and Thigpen found that the presence of more comfortable, lower-stress routes was positively associated with children's bicycling to school.[44] Studying schools in Davis, California, they found that the greater the availability of LTS 1 and LTS 2 routes to a school, the greater the number of parked bicycles observed during rack counts. Their modeling suggests that if students had no comfortable bicycle routes to school, then bicycling rates would be far below the current city average. They conclude that traffic stress "is likely one of the primary ways in which the urban environment influences bicycling to school."

Both the Wang et al. study and the Fitch, Handy, and Thigpen study explored the relationship between bicycle trips and traffic stress as calculated using the original Mekuria LTS method.

Cyclist Safety

Chen et al. aggregated ten years of bicycle-automobile crash data for four New Hampshire cities to determine whether LTS can be effective in estimating crash risk for locations without historical records of crashes.[45] Their analysis centered on four goals: (1) identifying the relationship between traffic stress and injury severity; (2) identifying the relationship between traffic stress and crash frequencies; (3) establishing if an increase in traffic stress leads to an increase in crash severity; and (4) measuring the relationship between crowdsourced data and LTS.

The researchers developed a mixed logit model with independent variables including roadways characteristics, speed limits, vehicle volumes, LTS (Mekuria method), and crash history locations. Results from the model showed that LTS could effectively predict crash severity. LTS levels could also indicate where bike lanes might be added or removed to improve crash safety, with a focus on locating bike lanes on roadways classified as LTS 1, 2, or 3.

Bikeshare Usage

Prabhakar and Rixey explored the relationship between LTS and bikeshare ridership within the Capital Bikeshare network in Montgomery County, Maryland.[46] They used linear regression to model and predict the relationship between bikeshare ridership and low-stress bicycle connections between stations and to estimate total trips per year. They determined that, between pairs of bikeshare docking stations, lower-stress roadways were associated with higher bikeshare ridership, and that longer detours required to achieve a low-stress route were associated with lower bikeshare ridership. They conclude that providing more low-stress connections could better enable trips between origins and destinations that have other characteristics favorable to bicycling, such as in places with high activity density and origin-destination pairs with relatively short travel distances.

VALIDITY OF LTS INPUTS (OBJECTIVE 3)

LTS methods draw on variables that are commonly recognized as being important influences on bicyclists' perceptions and behaviors.[47] However, additional variables that are also associated with bicycling behavior may be neglected by LTS methods. Potential blind spots of LTS include characteristics of the built and natural environment, measures of the mental difficulty of routes, and traffic volumes; these are all variables which were not included in the Mekuria method, but have since been included in others.[48] In a discussion about LTS with the authors, a practitioner also expressed concern about the absence of demographic variables, which have not been included in any known LTS methods.[49]

CROWDSOURCED APP DATA IN BICYCLE RESEARCH AND PLANNING

The cyclist satisfaction data used in this study were derived from crowdsourced scores collected with the Ride Report app. Crowdsourcing provides an opportunity to collect larger samples of responses from more geographically dispersed and heterogeneous locations than do conventional approaches to gathering cycling quality data, such as intercept surveying or capturing ratings from a closed sample of recruited participants.[50]

The present study is not the first to examine associations between LTS and crowdsourced app data. Chen et al. explored correlations between LTS and cycling volume data from the STRAVA app.[51] While Chen et al. use STRAVA (note that it has been used by other researchers and agencies), they also discuss a potential deficiency of STRAVA: its user base is biased toward highly-experienced recreational cyclists. App developers aiming to market their data for planning purposes have substantial incentive to design their products in such a way that they capture a more diverse spectrum of cyclists. The Ride Report data used in this study were likely more representative of inexperienced cyclists than many crowdsourced data sources because the Ride Report app was used to track participation in events that encourage inexperienced cyclists to try cycling more, such as National Bike Month. Nonetheless, it is unlikely that apps with large-volume user bases will ever be able to account and control for detailed characteristics, such as cyclists' demographics and other personal factors, to the same extent as traditional travel surveys, which demand substantial interaction between respondents and researchers.

Other studies have harnessed crowdsourced bicycling data outside of the context of LTS. Molina identified five general ways in which municipalities have harnessed crowdsourced data, including bicycling demand modeling, network planning, safety analysis, suitability, and route choice modeling.[52] For the specific purpose of planning practice and research, several agencies have utilized the CycleTracks app, which was developed by the San Francisco County Transportation Authority (SFCTA), or its derivatives.[53] CycleTracks was designed specifically to appeal to utilitarian cyclists as opposed to recreational riders.

IV. METHODS

CYCLING ENVIRONMENT DATA

Data necessary to determine LTS classes according to each of the six evaluated methods were collected from three types of sources: OpenStreetMap (OSM); local agencies; and a Google Street View-enabled audit conducted by the authors and research assistants. Table 3 summarizes these sources for each of 23 variables. Substantial effort was put into identifying measures that were similar across each of the sources. In cases where comparable measures were not available or contained missing records, assumptions were used to fill missing values. These assumptions are outlined in Table 3 and reported in detail in Appendix A.

OSM data were downloaded in June and September of 2018, for all streets in Portland and Austin respectively. These data were processed into relevant variables using a custom Python module developed by the authors, providing records for 30,487 non-freeway street segments in Portland, and 36,936 in Austin. The OSM data and their processing is further described in the next section, titled "*OpenStreetMap Data*."

Data from local agencies were collected only for Portland, and were compiled from GIS shapefiles representing bikeways, pavement maintenance, pavement markings, parking slots, street signs, speed limits, traffic signals, average weekday traffic volumes, zoning districts, and traffic islands (Table 3). All of these datasets, with the exception of traffic volumes, were publicly available from the City of Portland's Portland Maps Open Data portal. The latest revision dates for each of these datasets are included in Table 4. Traffic volumes were acquired directly from the Portland Bureau of Transportation (PBoT). The local datasets and their processing are further described in the section titled "Local Agency Data," below.

Audits were conducted using the most recent Google Street View in both Portland (n = 635 street segments) and Austin (n = 445 street segments), along segments selected through stratified random sampling aimed at representing streets of varying sizes, within varying built environment contexts, and with varying Ride Report scores. The same audit protocol was used in bot Portland and Austin. A subsample of streets in each city were audited by multiple auditors to evaluate inter-rater reliability (see the section titled "Assessing Inter-Rater Reliability", below). The audits were considered to be the most reliable data source. Comparisons between audited measures and corresponding OSM and local data measurements are summarized in Table 3. The audit protocol and sampling approach are further described in the section titled "Audited Data," below.

Table 3. Summary of Data Collected From Audit, OSM, and Local Sources

Variable	OSM Source	Local Source	Audit Source
Bike facility buffer width (continuous)	Numeric value from 'cycleway:buffer:*' tag *or assumed based on 'Separated Bike Lane'* Pearson correlation with audit data: 0.52 (Portland), 0.51 (Austin)	*Assumed based on 'Separated Bike Lane'* Pearson correlation with audit data: 0.34 (Portland)	Measured from Google Maps imagery
Bike facility width (continuous)	Numeric value from 'cycleway:*:width' tag *or assumed based on 'Bike Lane' or 'Separated Bike Lane'* Pearson correlation with audit data: 0.07 (Portland), 0.22 (Austin)	*Assumed based on 'Bike Lane' and 'Separated Bike Lane'* Pearson correlation with audit data: 0.17 (Portland)	Measured from Google Maps imagery
Bike lane (binary)	Yes if 'cycleway:*' tag equals 'lane' or 'opposite_ lane', otherwise No Agreement with audit data: 97% (Portland), 86% (Austin)	City of Portland Bike Network Shapefile (2017) Agreement with audit data: 94% Portland	Identified from Google Maps imagery or Street View
Buffered bike lane* (binary)	*Not available*	City of Portland Bike Network Shapefile (2017) Used as intermediary	Identified from Google Maps imagery or Street View
Cycle track* (binary)	*Not available*	City of Portland Bike Network Shapefile (2017) Used as intermediary	Identified from Google Maps imagery or Street View
Separated bike lane* (binary)	Yes if 'cycleway:*' tag equals 'track', 'opposite_ track' or 'buffered_lane', otherwise No Agreement with audit data: 96% (Portland), 96% (Austin)	City of Portland Bike Network Shapefile (2017) Agreement with audit data: 94% (Portland)	Combination of 'Buffered Bike Lane' and 'Cycle Track'
Bicycle boulevard* (binary)	*Not available*	City of Portland Bike Network Shapefile (2017) Agreement with audit data: 86% (Portland)	Identified from Google Maps imagery or Street View
Center turn lane* (binary)	Yes if 'turn:lanes:both_ways' tag equals 'left', otherwise No Agreement with audit data: 96% (Portland), 90% (Austin)	*Not available*	Identified from Google Maps imagery or Street View
Curb-to-curb width (continuous)	Numeric value from 'width' or 'est_width' tags, or assumed based on 'Lanes' and 'Parking' Pearson correlation with audit data: 0.37 (Portland), 0.51 (Austin)	City of Portland Pavement Maintenance Shapefile (2018) Pearson correlation with audit data: 0.54 (Portland)	Measured from Google Maps imagery

Variable	**OSM Source**	**Local Source**	**Audit Source**
Lanes (count)	Numeric value from 'lanes' tag, or assumed based on 'highway' tag Pearson correlation with audit data: 0.42 (Portland) 0.54 (Austin)	City of Portland Pavement Maintenance Shapefile (2018) Pearson correlation with audit data: 0.73 (Portland)	Counted from Google Maps imagery or Street View
One way (binary)	Yes if 'oneway' tag equals 'yes' or '-1', otherwise No Agreement with audit data: 98% (Portland), 100% (Austin)	*OSM values assumed*	Identified from Google Maps imagery or Street View
Left turn lanes (count)	Count of 'left' or 'slight_left' within 'turn:lanes:*' tag Pearson correlation with audit data: 0.52 (Portland), 0.44 (Austin)	*No direct measure or proxy available. Assumed to be 0 for all segments.*	Counted from Google Maps imagery or Street View
Right turn lanes (count)	Count of 'right' or 'slight_ right' within 'turn:lanes:*' tag Pearson correlation with audit data: 0.19 (Portland), 0.09 (Austin)	City of Portland Pavement Marking Symbols Shapefile (2018) Pearson correlation with audit data: 0.00 (Portland)	Counted from Google Maps imagery or Street View
High speed right turn lane (binary)	*No direct measure available. Assumed based on 'highway' tag.*	*No direct measure available. Assumed based on OSM 'highway' tag.*	Identified from Google Maps imagery or Street View
Parking (binary)	Yes if 'marked,' 'parallel,' 'inline,' 'perpendicular,' 'orthogonal' or 'diagonal' in 'parking:lane:*' tag, otherwise No Agreement with audit data: 90% (Portland), 64% (Austin)	City of Portland Parking Slots Shapefile (2018); City of Portland Signs Shapefile (2018) Agreement with audit data: 91% (Portland)	Identified from Google Maps imagery or Street View
Speed limit (continuous)	Numeric value in 'maxspeed:*' tag, or assumed based on 'highway' tag	City of Portland Speed Limit Shapefile (2018) Pearson correlation with OSM data: 0.81 (Portland)	*Local values assumed*
Traffic signal (binary)	Yes if 'traffic_signals' in 'highway' tag of either end node, otherwise No Agreement with audit data: 82% (Portland), 98% (Austin)	City of Portland Traffic Signals Shapefile (2017) Agreement with audit data: 80% (Portland)	Identified from Google Maps imagery or Street View
ADT (continuous)	*Assumed based on 'highway' tag*	Portland Bureau of Transportation 2015 Average Weekday (AWD) traffic volume shapefile *or assumed based on OSM 'highway' tag*	*Local values assumed*
Residential street (binary)	Yes if 'residential' in 'highway' tag, otherwise No Agreement with audit data: 64% (Portland), 49% (Austin)	City of Portland Zoning Shapefile (2017) Agreement with audit data: 88% (Portland)	Identified from Google Maps imagery or Street View

Variable	OSM Source	Local Source	Audit Source
Bike lane obstructed (binary)	*No direct measure available. Assumed to be Yes for all segments.*	Assumed from zoning categories including ‘Mixed,’ ‘Central,’ and ‘High’, City of Portland Zoning Shapefile (2017) Agreement with audit data: 40% (Portland)	Identified from Google Maps imagery or Street View
Bike lane aligned through intersection (binary)	*No direct measure available. Assumed based on ‘highway’ tag.*	*No direct measure available. Assumed based on OSM ‘highway’ tag.*	Identified from Google Maps imagery or Street View
Bike lane continuous through intersection (binary)	*No direct measure available. Assumed to be Yes for all segments with bike lanes.*	*No direct measure available. Assumed to be Yes for all segments with bike lanes.*	Identified from Google Maps imagery or Street View
Pedestrian refuge across cross street (binary)	*No direct measure or proxy available. Assumed to be No for all segments.*	City of Portland Traffic Islands and Circles Shapefile (2018) Agreement with audit data: 95% (Portland)	Identified from Google Maps imagery or Street View

Note: Italics denote assumptions based on other variables. “Agreement” between binary datasets is measured as the percent of records from the dataset represented by that column that have the same value in the other specified dataset. See Appendix A for more detailed information about data sources, processing, and assumptions.

* Not required for LTS. Collected as an intermediary for calculating other variables or for analysis of correlations with Ride Report scores.

OPENSTREETMAP DATA

OpenStreetMap (OSM) is a worldwide repository of free, vector-based geodata. Historically it has focused on highway systems, though it increasingly includes additional data about land uses, landforms, and other common topographic geodata. All OSM data are volunteered to the system, so they are often referred to as Volunteered Geographic Information (VGI).[54] As a result, OSM data can be detailed and comprehensive in some places while being sparse in others. Bicycle facilities, which are often mapped in OSM quite soon after installation, exemplify the type of infrastructure that may be well accounted for by OSM. A 2015 study evaluating the completeness of OpenStreetMap bicycle infrastructure found that approximately 95% of Portland bicycle lanes mapped in the OpenStreetMap database corresponded to actual existing bike lanes, as confirmed by examination of aerial photos.[55]

OSM data representing streets and intersections were gathered throughout Portland and Austin using the Overpass Application Programming Interface (API) through the OSMnx Python package (Boeing, 2017). Freeways, alleys, driveways, and off-street pedestrian and bicycle paths were removed from the dataset.[56] OSMnx was used to restructure the street network datasets so that each block-length street segment between neighboring intersections (excluding alleys and private driveways) was represented by a single line. These block-length units were used throughout the study as the consistent geometric units of analysis onto which attributes from other datasets were attached.

Attribute data in the OSM database are referred to as “tags.” The authors developed a Python module for parsing common tag:value pairs into categorical, binary, and continuous attributes for each street segment. The parsing rules are summarized in Appendix A. Parsing explicit values from OSM (e.g., definite presence or absence of a bike lane, as opposed to implicitly inferring absence based on lack of “cycleway” tag for that segment) yielded a wide range of levels of attribute completeness (Table 4). To produce a usable dataset across the study cities, assumptions were used to fill missing values (see variables beginning with ‘osm_assumed_’ in Appendix A). There were several key types of assumptions:

- All null values were set equal to 0 or “no.”
    - (E.g., because there were no data related to pedestrian refuges in the OSM data, all intersections were assumed to have no pedestrian refuge.)
- Values were based on closely-related variables.
    - (E.g., if there was a bikeway separated from traffic by a buffer, but no information about the width of the buffer, its width was assumed to be 2 ft.)
- Values were based on the ‘highway’ tag.
    - (E.g., missing speed limits were assumed to be the 75th percentile of speeds from Portland Metro’s speed limit dataset within that ‘highway’ tag.)

Full definitions for all assumed variables are included in Appendix A.

Assumed versions of OSM variables facilitated the application of these variables in citywide LTS classification and other analyses, but the assumptions they are founded on inevitably reduce confidence in their accuracy. Assumptions were intended to provide conservative (i.e., producing relatively high LTS classes) yet plausible estimates of real values. Table 4 demonstrates that certain variables (e.g., speed limit and number of traffic lanes) were much more likely to be based on explicit attributes than others. For example, despite the existence of OSM tagging conventions for bike facility width and bike facility buffer width, no segments in either Portland or Austin had these tags applied with standard values. Thus, bike facility widths and buffer widths were always assumed based on the presence of a bike lane or separated bike lane.

Table 4. Attributes Available from Explicit Tag Values in Portland and Austin OSM Datasets

Attribute	Street Segments with Attribute Values Backed by Explicit Tag Values (Not Null) in the OSM Datasets * Number of Segments (% of Segments) Portland	Austin
Highway class (categorical)	30,487 (100%)	36,936 (100%)
Bike lane (binary)	2,931 (10%)	2,903 (8%)
Separated bike lane (binary)	45 (<1%)	566 (2%)
Bike facility width (continuous)	0 (0%)	0 (0%)
Bike facility buffer width (continuous)	0 (0%)	0 (0%)
One way (binary)	4,107 (13%)	8,529 (23%)
Lanes (continuous)	8,192 (27%)	4,253 (12%)
Right turn lanes (continuous)	295 (1%)	443 (1%)
Left turn lanes (continuous)	881 (3%)	1,398 (4%)
Center turn lane (binary)	207 (1%)	148 (<1%)
Parallel parking (binary)	63 (<1%)	252 (1%)
Perpendicular parking (binary)	7 (<1%)	22 (<1%)
Curb-to-curb width (continuous)	14 (<1%)	0 (0%)
Speed limit (continuous)	23,326 (77%)	2,798 (8%)
Traffic signal (binary)	3,336 (11%)	3,561 (10%)

Note: While it is possible for tags related to binary variables (e.g., “One way”) to have explicitly negative values (e.g., “No”), it appeared to be more common for negative values to be implied by the lack of a tag, based on visual inspection of satellite imagery. Thus a low proportion of explicit values does not necessarily indicate substantial missing data.

There is a notable semantic difference between OSM bikeway tags and conventional U.S. classifications, particularly with regard to bikeways that are separated from traffic by a painted or physical buffer or barrier. In U.S. bicycle planning, the term “bike lane” refers to an exclusive lane for bicycles that is separated from traffic by a painted line. This is consistent with the OSM tagging convention, “cycleway”:“lane.” However, U.S. bicycle planning further distinguishes between ‘buffered bike lanes’ and ‘cycle tracks,’ both of which are separated from traffic, the former by a painted buffer, and the latter by a more substantive, physical buffer, such as by bollards, planters, or raised pavement. OSM tagging conventions do not distinguish between these types. The “cycleway”:“track” tag is most frequently used to describe further separation. Some contributors have started using “cycleway”:“buffered_lane” in Austin, though not in Portland. Due to the inconsistent distinction between buffered lanes and cycle tracks, they were collectively defined as “separated bike lanes.” Unfortunately, this did not allow for identification of potential benefits due to the further separation provided by cycle tracks. It did, however, enable a consistent definition across the data sources.

Local Agency Data

Local governments are common sources for built-environment data at citywide scales. Most cities provide GIS datasets representing streets and bicycle networks. In order to compare OSM and audited data, and in order to identify reasonable assumptions for missing OSM attributes, relevant GIS datasets were collected from the City of Portland's 'PortlandMaps' online data portal. These included shapefiles representing bicycle facilities; pavement characteristics (e.g., width, lanes); pavement markings (e.g., turn lane symbols); marked and metered parking slots; street signs (e.g., No Parking signs); speed limits; traffic signals; zoning districts; and traffic islands (e.g., medians). Average weekday (AWD) traffic volume estimates from 2015 were also acquired directly from the Portland Bureau of Transportation (PBoT). Relevant variables were extracted from these datasets and spatially joined to the OSM street segments.

Due to the exceptional quality and availability of data offered by local agencies in Portland, including datasets that either matched or approximated nearly all attributes contributing to LTS classifications, the analysis of local agency data was focused on Portland. No local agency data for Austin for gathered or examined.

Attributes attached to linear features (e.g., center lines) were spatially joined using a customized algorithm that used Hausdorff distances to identify related features based on the similarity of their spatial envelopes. Compared with conventional spatial joining techniques relying on nearest neighbors, this approach improved the accuracy of matches between features with different lengths and in situations where the datasets represented large streets with different combinations of single and dual carriageways.

Point and polygon features were matched based on proximity to OSM street segments. For the parking variable, it was necessary to combine multiple local datasets in order to infer parking status. 'No Parking This Block' signs were isolated within the traffic signs dataset, and it was assumed that a street had no parking if at least one of these signs was located along both sides of a street segment. Furthermore, marked and metered parking slots were matched to each segment, and a given segment was assumed to have no parking if all slots for the segment were labeled as 'No Parking.' All other segments were assumed to have street parking.

Binary classes and continuous units of all local variables were coded to maintain consistency with similar OSM variables.

Audited Data

As a third data source, detailed audits (also known as inventories and ground-truths) of a subsample of street segments were gathered within both Portland and Austin. The same auditing approach was used in each city to reduce the likelihood of systematic measurement bias between the two cities. Because audit data were collected based on the authors' own, detailed criteria, they were considered the most reliable data source. Figure 3 outlines the workflow used to identify subsamples of street segments for auditing, to develop and apply the auditing protocol, and to process the resulting data.

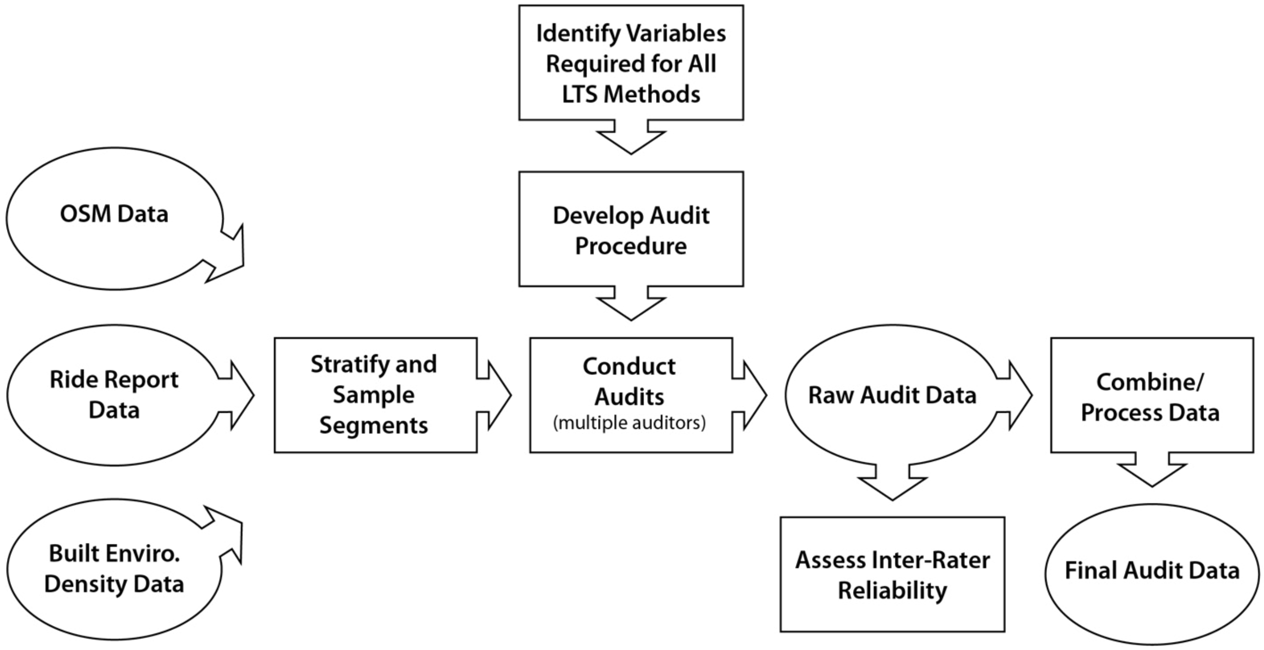

Figure 3. Auditing Workflow

Audits were conducted with Google Street View and Google Maps aerial imagery in order to complete the auditing quickly and efficiently. The efficacy of Street View as a transportation-environment auditing tool has been previously evaluated, and it has been deemed to be reasonably accurate while being substantially more time- and resource-efficient than in-person auditing.[57] The distance measurement tool in Google Maps also provided an efficient mechanism for measuring variables such as curb-to-curb width, parking lane width, and right-turn lane length, which would have been difficult and dangerous to measure in the field. Google Maps aerial imagery and the majority of Street View imagery in both Portland and Austin was from within the last two years and was sufficiently high-resolution to identify street markings and signs.

Previous audits have been conducted for various units of analysis. Rodriguez and Vergel-Tover audited block faces and blocks,[58] Zegeer et al. audited intersections,[59] and others have focused exclusively on street segments.[60] For this study, street segments, defined as block-length street areas bounded by the nearest cross street in each direction, were the units of analysis used for audits. The audited segments corresponded with the geographical units for which Ride Report scores were available; thus, the same units were used for the audit as were used for all measurement and analyses throughout the study.

Segments to be audited were sampled in each city through a stratified random process. Firstly, the pool of segments was limited to those for which Ride Report scores were available and whose lengths were between 100 and 500 m (328 and 1640 ft). The pool was then stratified according to three criteria: highway functional classes based on OSM highway tags; Ride Report score; and built environment density measure based on the continuity of building facades along each block face. Three functional classes were defined: “local” (OSM “highway” equaled “residential” or “unclassified”); “collector” (OSM “highway” equaled “tertiary”); and “arterial” (OSM “highway” equaled “secondary” or “primary”). Ride

Report scores were categorized into poorly-scoring segments (Ride Report score < 0.8) and relatively well-scoring segments (Ride Report score ≥ 0.8). Built environment density was defined based on 'street wall continuity,' the proportion of block faces along both sides of each street segment that were lined with buildings:[61] if both sides of a segment were continuously lined with facades (within 200 m of the center line), continuity would be 1.0; if only one side had continuous facades, continuity would be 0.5; if no facades were within 200 meters a segment, continuity was 0.0. Continuity measurements were made using a Python script and based on OSM building footprint data, which was fairly complete along candidate segments in Portland and Austin, as judged by visual comparisons with aerial imagery. Continuity followed a fairly normal distribution among segments in both cities. Two density classes, 'low' and 'high,' were defined for each city, with the boundary being the mean value for that city (0.50 in Portland; 0.43 in Austin).

This 3x2x2 stratification yielded twelve groups (Table 5). Approximately 60 segments were randomly sampled from each group. Some groups offered a pool of fewer than 60 segments, in which case all available segments were sampled.

The final audit samples in Portland and Austin were assigned to auditors in a random order. Auditors were provided with the street name and cross street names for each segment in order to define the spatial extent of their audit. They were also provided with custom Google Maps and Street View links that were automatically centered on each segment.

Table 5. Stratified Sampling of Audit Segments within Portland and Austin

	Portland			Austin		
Group	**Pool**	**Sample**	**Audited***	**Pool**	**Sample**	**Audited***
Local, low R.R., low dens.	63	60	57	10	10	7
Local, low R.R., high dens.	64	60	51	40	40	25
Local, high R.R., low dens.	558	60	58	130	60	44
Local, high R.R., high dens.	1040	60	59	149	60	53
Collector, low R.R., low dens.	61	60	48	41	41	26
Collector, low R.R., high dens.	64	60	52	141	60	50
Collector, high R.R., low dens.	422	60	54	201	60	51
Collector, high R.R., high dens.	419	60	54	299	60	54
Arterial, low R.R., low dens.	64	60	57	22	22	15
Arterial, low R.R., high dens.	58	58	49	63	60	40
Arterial, high R.R., low dens.	147	60	41	109	60	46
Arterial, high R.R., high dens.	96	60	55	75	60	34
Total	**3159**	**768**	**635**	**1285**	**615**	**445**

** Counts of audited segments account only once for segments that were inadvertently audited twice. Thus, these are counts of unique segments, not audits.*

Auditors were trained in the data collection protocol in order to ensure high reliability. A training session was conducted to provide guidance on the protocol and the ratings system, with a visual guide prepared for each audit question. The training included particular examples of situations, in order to increase homogeneity of ratings across auditors. Throughout the auditing process, auditors asked for clarifications on how to address questions in the context of certain segments; responses to these questions were shared with all auditors in order to promote consistency in interpretation. All audits were conducted by student researchers.

The audit consisted of 40 questions, including fields for tracking auditor name, identifying information for the segment and cross streets. Several questions were only shown based on responses to an earlier question, and questions about intersection treatments were shown twice in order to audit each end of a given segment. Questions capturing core built environment data were either multiple choice or open response requiring the answer to be a number (e.g., number of through-traffic lanes). All questions required either an explicit response (e.g., “Yes” or “No”) or a null responses (e.g., “Unable to Identify”). The audit was operationalized with Google Forms, enabling audit responses to be automatically collected in a Google Sheets spreadsheet. Each audit took approximately five minutes to complete.

Segments were randomly assigned to auditors, and approximately 10% of segments were assigned to two auditors in order to enable analysis of inter-auditor reliability (see “Assessing Inter-Auditor Reliability” below). More segments were audited redundantly than was originally intended, due to an erroneous interpretation of each direction of two-way segments as being unique segments.[62] This strengthened the ability to determine inter-auditor agreement, but diminished the effective audit sample size by approximately 12% in Portland and 25% in Austin. These sample reductions were spread fairly evenly across the stratification groups.

Assessing Inter-Auditor Reliability

The reliability of an instrument refers to whether it yields similar results every time it is applied in the same context and circumstances. This assessment of inter-auditor reliability aimed to determine the degree to which two different, trained raters agreed regarding their assessment of the environment using the audit instrument. Higher agreement meant higher inter-auditor reliability. Percentage agreement is often used as an indicator of agreement, although it is often criticized because it does not correct for chance agreement. For this assessment, kappa coefficients were used to describe agreement among binary variables, weighted kappa coefficients for categorical and ordinal variables,[63] and concordance statistics for continuous variables.[64] Both weighted kappa coefficients and concordance statistics correct for chance agreement and range between 0 and 1, with higher values denoting higher agreement. The weights used in the weighted kappa coefficients penalize responses that are more distant over responses that are closer together. Percent agreement is also reported because it is a helpful descriptor in cases where features have a low prevalence and agreement is not perfect; in those circumstances kappa coefficients and concordance statistics may be low, but agreement may be quite high. The criteria by Landis and Koch were used to interpret agreement,[65] with values of zero indicating no agreement, 0–0.20 indicating slight agreement, 0.21–0.40 indicating fair agreement, 0.41–0.60 indicating moderate agreement, 0.61–0.80 indication substantial agreement, and 0.81–1 indicating almost perfect agreement.

Agreement could not be determined for audit items that did not vary across segments (i.e. that always took the same value). This assessment focused solely on audit items that had variation in the sample for a given auditor. Agreement was analyzed across 142 segments in both Portland and Austin that were examined by multiple auditors. Overall, most of the audited measures had adequate inter-auditor agreement according to the Landis and Koch criteria (Table 6). The salient exceptions were bicycle facility width (concordance = 0.321) and measured width of the buffer between the bicycle facility and the road, if present (weighted kappa = 0.27; agreement = 74.7%). There was fair to moderate agreement for measures of number of traffic lanes on the cross street (weighted kappa = 0.30) and whether or not there was a center line (kappa = 0.42). All other measures examined had either substantial or almost perfect agreement, indicating high inter-auditor reliability.

Table 6. Inter-Auditor Agreement of Street Segment Data

	Agreement Measure			
Audited Variable	**Percent Agreement**	**Kappa**	**Weighted Kappa**	**Concordance**
Bike facility (check all that apply): None, Sharrow, Paved Shoulder, Lane, Sidepath	90.1%		0.91	
Number of through lanes	98.6%		0.87	
Street is one way (y/n)	98.6%	0.95		
Street center line (y/n)	69.0%	0.42		
Center turn lane (y/n)	95.8%	0.74		
Number of residential driveways/ curb cuts				0.906
Number of commercial driveways/curb cuts				0.799
Presence of parking (none, one side, both sides)	84.5%		0.85	
Moving cars based on Google Street View				0.804
Moving cars based on Google Street View, truncated at 5+	93.0%	0.72		
Curb-to-curb width (feet)				0.852
Number of cross street traffic lanes	83.1%		0.30	
Bike lane on cross street (no bike lane, dropped bike lane, straight bike lane)	94.4%	0.87		
Bike lane approach to intersection (no bike lane, dropped bike lane, straight bike lane)	97.2%		0.93	
Bike facility buffer width (feet; smallest of either side)	73.7%		0.27	
Bike facility width (feet; smallest of either side)				0.321

Audit Data Processing

Raw audit data were transformed into binary and continuous variables consistent with those provided by the OSM and local data sources (Appendix A). Null values were interpreted as 0 for continuous measures (e.g., ‘Left Turn Lanes’ == ‘None’ → 0) and ‘No’ for binary measures (e.g., ‘Median Refuge’ == ‘Unable to Identify’ → ‘No’). Data for segments that were audited multiple times, either by different auditors or due to the segment directionality issue, were aggregated by taking the maximum value from each segment in order to maintain the most conservative (i.e., highest-stress) observation. Because LTS classifications take as inputs intersection-related variables from one or the other end of a segment (rather than classifying LTS separately at each end), intersection-related variables were also aggregated as the maximum among both ends of a segment.

EPA Smart Location Data

Data from the U.S. Environmental Protection Agency (EPA) Smart Location Database (SLD) were used to account for neighborhood-scale social and built environmental characteristics in statistical models developed to address Objective 3.[66] The EPA provides SLD variables for every census block group in the U.S. Fifteen of these variables were gathered for this study, including the National Walkability Index, which was accessed from a separate data file (Table 7). These variables were then each spatially joined to the street segments within a given block group. Segments along the boundary between two block groups, or which traversed multiple block groups, were assigned the average of each variable among those block groups, in order to summarize their combined characteristics.

Table 7. EPA Smart Location Database (SLD) Variables

Descriptive Variable Name	EPA SLD Field Code or Description of Derivation
Percent of zero-car households	Pct_AO0
Housing units per acre	Calculated by dividing housing units (CountHU) from unprotected land area (Ac_Unrp)
Population per acre	Calculated by dividing population (TotPop) from unprotected land area (Ac_Unrp)
Jobs per acre	Calculated by dividing employment (TotEmp) from unprotected land area (Ac_Unrp)
Jobs per household	D2a_JpHH
Employment entropy	D2b_E5Mix
Employment and household entropy	D2a_EpHHm
Trip production/attraction equilibrium	D2c_TripEq
Street network density	D3a
Pedestrian-oriented street network density	D3apo
Intersection density	D3b
Pedestrian-oriented intersection density	D3bpo3
Proportion of block group jobs within ½ mile of a fixed guideway transit stop	D4b050
Regional Centrality Index	D5dei
National Walkability Index	Separate Data File

LTS CLASSIFICATION

Authors of LTS methods tend to describe them as being straightforward, but in fact operationalizing them can be fairly complex. The Mekuria method was defined by a series of seven lookup tables related to different combinations of bike lane presence, parking presence and intersection treatments. Within each table, LTS values were identified by cross-referencing potential combinations of roadway attributes (See Appendix C). Many of the tables also included footnotes that added additional levels of decision making complexity, sometimes including additional variables. Multiple tables might have be applicable to a given street segment. Following the "weakest link" principle, each segment was assigned the maximum LTS value derived from any relevant table. While the table system was fairly intuitive for manual classification, it did not translate efficiently into a coding algorithm. Other LTS systems were also documented by similar series of lookup tables.

After exploring decision tree-based approaches for classification, the authors instead choose to implement a rule-based approach that provided greater interpretability and flexibility. Classification was driven by a sequence of conditional ("if…then…") rules, each leading to a specific LTS class if the rule tested positive. Once all rules were applied to each street segment, the highest candidate LTS class was assigned to the segment, similar to the "weakest link" principle used by the Mekuria method.

The classification process was operationalized in Python. Each classification operation was fed by three tables containing: (1) street segment-level source data; (2) assumptions necessary to link that source data with a specific method; and (3) rules for classifying the assumption-transformed data into LTS classes (Figure 4).

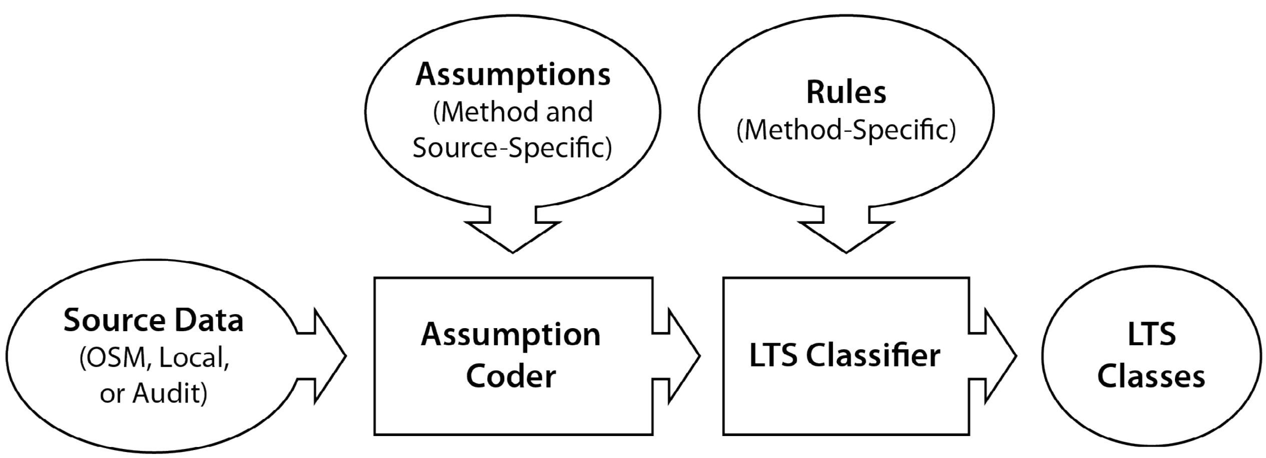

Figure 4. LTS Classification Workflow

Classification rules were developed for seven LTS methods:

1. *Conveyal* – This method was developed by the transportation consultancy and software development firm Conveyal and was designed explicitly to require minimal data inputs, almost all of which were available through OSM.[67] The Conveyal method was developed in partnership with the World Bank in an effort to provide high-level analyses in nearly any location worldwide.

2. *Furth* – Furth published this method, which he called "LTS 2.0," in order to streamline data requirements and improve geographic generalizability.[68]

3. *Lowry* – This method with streamlined data inputs was published within a broader study on bicycle facility stress.[69]

4. *Mekuria* – This was the "original" LTS method, developed by a Mineta Transportation Institute research project.[70]

5. *Montgomery* – Montgomery County, MD developed their own LTS method to support their 2018 Bike Master Plan.[71]

6. *ODoT* – The Oregon Department of Transportation (ODoT) developed their own LTS method to support bicycle planning within Oregon.[72]

7. *PFB* – This method was developed by People for Bikes (PFB) in order to conduct LTS analyses throughout the United States using OSM data.[73]

Table 8 summarizes the number of rules and input variables for each LTS method.

Table 8. Classification Rules and Variables for Each of the LTS Methods

Method	Rules	Variables
Conveyal	7	Functional Class (Categorical) Lanes (Count) Speed Limit (Ratio) Bike Lane (Binary)
Furth	134	Bike Lane Width (Continuous) Parking Lane Width (Continuous) Center line (Binary) ADT (Count) Speed Limit (Continuous) One Way (Binary)
Lowry	37	Residential Land Use (Binary) Lanes (Continuous) Speed Limit (Continuous) Bike Facility (Categorical)

Method	Rules	Variables
Mekuria	61	Bike Lane Width (Continuous) Right Turn Lanes (Count) Right Turn Lane Length (Continuous) Bike Lane Continuous at Intersection (Binary) Bike Lane Aligned Through Intersection (Binary) Right turn lane speed (Continuous) Parking Lane Width (Continuous) Lanes Per Direction (Count) Residential Land Use (Binary) High Parking Turnover (Binary) Speed Limit (Continuous) Bike Lane Frequently Blocked (Binary) Raised Median (Binary) Center line (Binary) Pedestrian Refuge at Intersections (Binary) Traffic Signal at Intersections (Binary) Cross Street Speed Limit (Continuous) Cross Street Lanes (Count)
Montgomery	94	Bike Facility Width (Continuous) Bike Facility Type (Categorical) Speed Limit (Continuous) Parking Lane Width (Continuous) Parking (Binary) High Parking Turnover (Binary) Center line (Binary) ADT (Count) Residential Land Use (Binary) Bike Facility Buffer Type (Categorical) Many Driveways (Binary) Raised Median (Binary)
ODoT	75	Bike Lane Width (Continuous) Parking Lane Width (Continuous) Speed Limit (Continuous) Lanes per Direction (Count) Bike Lane Frequently Blocked (Binary) Center line (Binary) Right Turn Lanes (Count) Right Turn Lane Length (Continuous) Right Turn Lane Speed (Continuous) Bike Lane Aligned Through Intersection (Binary) Left Turn Lanes (Count) Traffic Signal at Intersections (Binary) Pedestrian Refuge at Intersections (Binary) Cross Street Speed Limit (Continuous) Cross Street Lanes (Count)
PFB	26	Bike Facility (Categorical) Residential Land Use (Binary) Speed Limit (Continuous) Lanes per Direction (Count) Parking (Binary) Curb-to-Curb Width (Continuous)

The Mekuria method produced a four-level classification scheme, with segments being classified as LTS 1, LTS 2, LTS 2, or LTS 4. The majority of alternative methods have followed suit. Two of the methods, however, produced different numbers of levels. The Montgomery system was designed to produce seven levels: LTS 0, LTS 1, LTS 2, LTS

2.5, LTS 3, LTS 4, and LTS 5. To simplify comparison with other systems, the authors elected to combine Montgomery LTS 0 with LTS 1, LTS 2.5 with LTS 2, and LTS 5 with LTS 4, producing a more traditional four-level scheme. The PFB method was designed to produce only two levels: “low” and “high.” Because it would have been problematic to artificially refine these into four levels, this two-level structure was maintained.

RIDE REPORT DATA

Crowdsourced scores reflecting cycling satisfaction were acquired from Knock Software Inc. (hereafter referred to as “Knock”), the makers of the Ride Report app, for all street segments in Portland and Austin with sufficient data. Ride Report is available for public download on the iOS and Android mobile phone operating systems. Users agree to have their movement analyzed based on information collected by the smartphone. Once the app detects a bicycling trip it automatically records the route; the app also detects the end of each trip and stops recording automatically. Shortly after the trip has ended, the app prompts the user to rate their satisfaction with the trip on a binary scale (thumbs-up, thumbs-down). The app then transmits the trip route and rating to Knock. If a user declines to rate a trip, the route is still transmitted to Knock, but the trip is not scored.

To derive segment-level scores, Knock assigns the overall trip satisfaction score to each segment in the route. For a given segment, Knock reports the proportion of ratings of a trip that shared the segment that were positive. Thus, a segment for which all routes that traversed it rated positively would have a score of 1; a segment with all negative ratings would have a score of 0. The assumption is that as the number of users increases, the score of each segment will uniquely reflect segment-level conditions. Ride Report scores were based on ratings recorded prior to November 2017. In Portland, Ride Report began collecting data in December of 2014 and usership peaked in May 2017, coinciding with the League of American Bicyclists’ *National Bike Month*, for which Ride Report has been used to track commuting competitions, with approximately 1,800 unique users who made cycling trips. Data collection in Austin began in April of 2015, and peaked in November of 2016 with approximately 200 cycling users. Ride Report continues to collect data with increasing large user bases in both cities.

The vast majority of ratings were positive, so the distributions of segment-level scores were substantially left-skewed. The average score among all users in Portland was 0.90 and among all users in Austin was 0.88. Scores were only calculated if there were minimum of 20 ratings along a given segment. This preserved anonymity of users and ensured that the segment scores were reliable. All scores were calculated by Knock prior to being delivered to the authors, so the authors had access only to aggregated segment-level scores rather than to individual routes or ratings. No attributes other than segment-level scores were made available.

Knock’s segments were also based on OSM streets and were predominantly block-length, but in some cases had slightly different lengths than the analysis segments. Knock segments were spatially joined to the study segments, and when there was more than one Ride Report score joined to a study segment, their scores were averaged. This process resulted in 8,198 segments with Ride Report scores in Portland, and 2,104 in Austin.

Customized Ride Report "Queries"

In Portland, Knock also prepared customized Ride Report scores based on subsets of ratings representing various cyclist characteristics (Table 15). Because other scores were based on ratings made by only a subset of riders, they were available for only for the segments along which these riders rode and for which there were a critical number of ratings to reliably determine a score. Because Ride Report usership was smaller in Austin than in Portland, Knock could only reliably calculate these subset scores in Portland. They were not available for Austin.

Knock used metadata about app users and the spatiotemporal attributes of rides to compile subsets of ratings for certain types of riders (e.g., male riders) or rides (e.g., during inclement weather). They used these rating subsets to calculate customized scores reflective of those conditions (e.g., scores based on male riders or trips during inclement weather). The customized ratings are herein referred to as "queries."

Gender-based queries relied on data collected from surveys conducted for National Bike Challenge events, connections between the Ride Report app and the iOS or Android health apps, or gender estimates based on user email addresses using the Gender API (with only matches with >90% confidence being used). Age-based queries relied on data gathered from the National Bike Challenge surveys and app connections. It was notable that no segments had sufficient ratings from cyclists over the age of 65 with which to compute reliable scores. This may have been because few users were over the age of 65, because few of these older users provided their age, or because older cyclists did not travel along sufficiently-overlapping routes to provide reliable scores.

Socioeconomic disadvantage queries relied upon the starting and ending points of rides relative to Community of Concern areas, as defined by TriMet, the Portland area transit agency.[74] If more than 25% of trip staring or ending points for a given rider were within a Community of Concern, the rider was assumed to be socioeconomically disadvantaged or regularly exposed to a disadvantaged community. This was a highly imprecise measure, but was the best available proxy for considering disadvantaged populations and their communities given the extremely limited person-level data.

Queries related to cycling strength were based on two measures: speed and cycling frequency. Slow and fast riders were identified based on their average trip speed (total trip distance / total trip time) over their entire history as Ride Report users. High, medium, and low-frequency riders were identified based on their average weekly cycling trip count. The boundaries used to define each category are reported in the "Definition" column of Table 15.

Queries based on ride distance were based on distances computed along the OSM street network between ride start and end points. Queries based on time of day and date were based on metadata automatically recorded for each ride. Ride dates allowed them to be categorized by season. Queries based on weather at time of each ride were calculated by linking ride times and dates with National Weather Service data.

A notable shortcoming of the Ride Report app was that it could sometimes misidentify transportation modes. In the authors' personal use of the app, it reported false positives (e.g., the app estimated that you were riding a bicycle when you were actually riding the bus) much more frequently than false negatives (e.g., the app estimated that you were riding a bus when you were actually riding a bicycle). The authors presumed that users were much more likely to supply a rating when the app detected bicycle riding correctly. Because scores were based only on rated trips, they assumed that classification errors did not substantially affect scoring.

Ride Report ratings tended to be positive, with the average segment score receiving a thumbs up 90% of the time.

STATISTICAL ANALYSES

Objective 1: Agreement of LTS Results Across Different Classification Methods and Data Sources

Kappa coefficients were computed in order to assess the similarity of different LTS methods (e.g., Mekuria, Conveyal, Furth) while holding data sources constant. Kappa coefficients were also used to compare different data sources (e.g., audit, OSM, local agency) while holding LTS methods constant. Because audit data were only available for a subset of street segments, additional sets of kappa coefficients were calculated using only audited streets, facilitating direct comparisons between methods on the same sample of streets. A kappa coefficient of 1 would indicate perfect agreement, while 0 would indicate no more agreement than would be expected due to chance (e.g., random matches between four-class sets would likely yield 25% correct matches). A Negative kappa coefficient would indicate that agreement is lower than random. Thus, kappa coefficients provided a more robust measure of methods' similarity than would "percent agreement," by correcting for chance agreement.

Weighted kappa coefficients are appropriate when categorical variables are ordinal rather than nominal, so that disagreements between proximate levels (e.g., 1 and 2) are weighted less heavily than disagreements between more distant levels (e.g. 1 and 4). Linear weighting applies a linearly decreasing weight to successively greater disagreements, assuming that that the importance of an additional unit of disagreement is constant no matter the degree of disagreement. Kappa coefficients were interpreted based on the ranges suggested by Landis and Koch (1977): 0–0.2: poor agreement; 0.2–0.4: fair agreement; 0.4-0.6: moderate agreement; 0.6–0.8: substantial agreement; and 0.8–1.0: almost perfect agreement.

Objective 2: Associations Between LTS and Crowdsourced Bicycle User Satisfaction

Additionally, the degree of correlation between LTS levels and Ride Report ratings was examined using Spearman's rank correlation coefficient (ρ), a non-parametric approach appropriate for ordinal variables. Spearman coefficients summarize the degree to which two variables can be described using a monotonic function. This contrasts with the more commonly-used Pearson correlation coefficient (r), which assesses continuous rather than ordinal relationships. Like the Pearson correlation, values of the Spearman rank correlation range between -1 (inversely correlated) and 1 (positively correlated).[75] For the sake of intuitiveness, Spearman coefficients between LTS (for which lower values represent greater comfort) and Ride Report scores (for which higher values represent greater comfort) were multiplied by -1 so that positive coefficients indicated conceptual agreement about cycling satisfaction.

Objective 3: Associations Between Cycling Environment Variables and User Satisfaction

Grouped logistic regression models were developed to evaluate associations between individual cycling environment variables and Ride Report scores.[76] Since Ride Report ratings were aggregations from individual binary ratings, the effect of contextual environmental variables on the proportion of positive ratings was estimated for each segment.

The regression models built on the following form:

$$Y_i = SatisfactoryRatings_i \,/\, TotalRatings_i = f(Z(X_i))$$

where Y_i is the proportion of ratings for each segment, i, that are satisfactory, and $Z(X_i)$ is a vector of contextual environmental characteristics.

Because nearby street segments were likely to have unobserved similarities that might have affected their Ride Report scores, the models included terms to account for spatial autocorrelation using a technique developed by Clapp et al.[77] This involved including second-order Taylor expansion terms of two-dimensional spatial coordinates (longitude and latitude) in the regression equation. The full models, with these terms included, took the form:

$$Y_i = SatisfactoryRatings_i \,/\, TotalRatings_i = f(Z(X_i), Lat_i, Lon_i, Lat_i^2, Lon_i^2, Lat_i \times Lon_i)$$

where the additional terms are Lat_i, the latitude of the segment; Lon_i, the longitude of the segment; their squares; and their product. Intuitively, these terms control for the impact of spatial proximity among segments on Ride Report outcomes.

V. RESULTS

OBJECTIVE 1: AGREEMENT OF LTS RESULTS ACROSS DIFFERENT CLASSIFICATION METHODS AND DATA SOURCES

For the same street, different classification results could be obtained depending on the LTS method used, as well as on the data source used. Figure 5 shows how the shapes of LTS distributions sometimes varied substantially across methods (rows) and data sources (columns). If all LTS methods and data sources had produced the same classification outcome, all distributions in black (representing audited segments) within each city (Portland, n=633; Austin n=445) would have had similar shapes, as would all distributions in blue (representing all segments; Portland: n=30,487; Austin: n=36,936). Instead, methods and data sources produced a variety of distributions.

Unsurprisingly, the distributions were largely right-skewed, with a greater proportion of segments classified as LTS 1 and 2, and lower proportions at higher LTS values. This skew is especially pronounced within the all-segment (blue) samples, in which the vast majority of segments were residential streets. These distributions were representative of the true distributions of traffic stress within the population of Portland and Austin streets. The audited (black) samples, in contrast, were purposefully chosen to represent a range of traffic stresses, so they were more evenly distributed across LTS levels.

Looking down the first column of Figure 5, which shows how audited streets were classified based on audit data in Portland (n=633), it can be seen that there were limited similarities between LTS methods. The Conveyal and Lowry distributions both decreased monotonically, but at different rates. The Conveyal method identified substantially more LTS 4 segments than did any other method, suggesting that it erred toward higher classification. The Furth, and ODoT methods were bimodal and had similar distributions, identifying relatively large numbers of LTS 1 and LTS 3 segments. Many of the distributions in the second and fourth columns, based on same sample of streets but classified using OSM vs. Local data, had different modes and overall shapes compared with those in the first column, demonstrating the non-equivalence of these data sources. The high degree of variability makes it difficult to make generalizations concerning whether certain methods or data sources were biased toward certain distributions. Outcomes appeared to be highly sensitive to both methods and data sources.

One exception is the Conveyal method, which offered fairly consistent classifications across each of the three data sources. Within both Portland and Austin, the Conveyal distributions based on audit and OSM data were highly similar. The local data in Portland appeared to displace some LTS 2 segments into LTS 3, but produced similar counts of LTS 1 and LTS 4 segments. This consistency was unsurprising given the Conveyal method's simplicity: it was based on only seven rules and taking as inputs only four variables—functional class, lane count, speed limit, and bike lane presence—that were widely available or could be reliably estimated (e.g., assumptions about lane count and speed limit based on functional class). This simplicity, however, may also make the Conveyal results imprecise compared with methods accounting for more detailed features, such as intersection infrastructure.

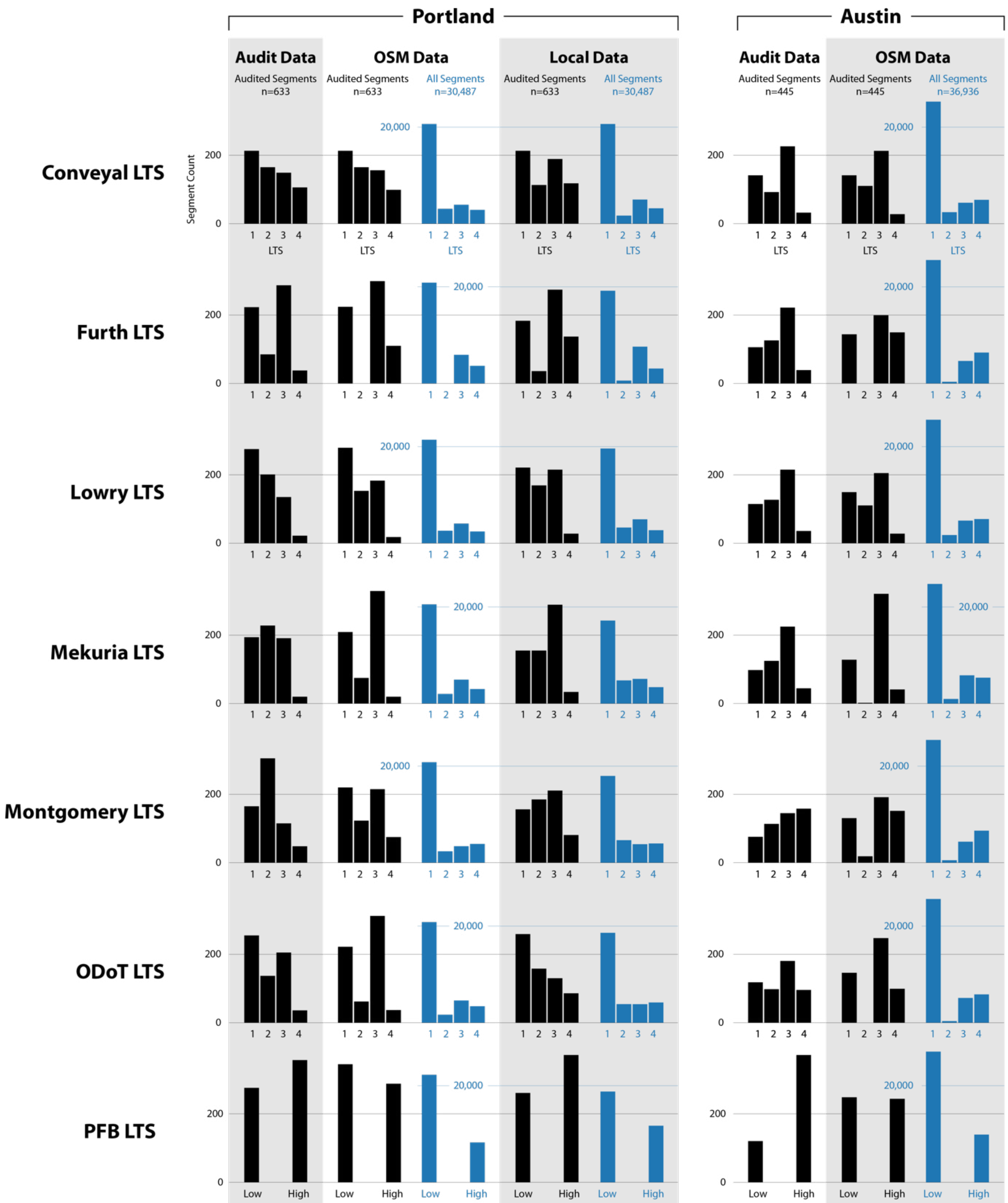

Figure 5. Distributions of LTS Levels Derived from Various Classification Methods and Data Sources

It is notable that the People for Bikes (PFB) method, despite being fairly simple, with only six input variables, 26 rules, and two LTS outcome levels (as opposed to the standard four), yielded inconsistencies in modal values between audit and OSM data in both Portland and Austin. This was likely because of its high sensitivity to minor differences in certain variables. For example, the presence or absence of parking in the PFB method often makes the difference between a Low and a High classification. Yet parking is one of the most difficult variables to account for explicitly in OSM and local datasets. In many cases, parking must be assumed based on a proxy, resulting in variability among the segments where parking is either known or estimated to occur. Where classification rules hinge on parking, variations in the quality of parking data may substantially influence LTS outcomes. To reduce this impact, LTS methods might avoid using variables that are inconsistently available, or at least minimize the extent to which these variables play decisive roles in swinging classifications in one direction or another.

Another notable trend across several of the methods was that fewer segments were classified as LTS 2 based on OSM and local data than with audit data. The Furth method, for example, produced no LTS 2 segments when using OSM data in Portland, and nearly none in Austin, even though a moderate number of segments were considered LTS 2 based on the audit data. This discrepancy was due to the way that the Furth method differentiated between LTS 1, 2, and 3 based on variables related to speed, volume, and center line presence. If all of these were low, it classified as LTS 1, while if all are high, it classified as LTS 3. To be LTS 2, these variables needed to have mixed levels. However, because OSM attributes were sparse, these variables were often estimated based on the same proxies, such as the OSM highway tag, leading to highly colinear assumptions that drove LTS to either low or high extremes rather than the LTS 2 middle ground. Appendix D (available in the online supplementary materials) shows which rules had the greatest influence on classification for each method, demonstrating that different rules were influential depending on data sources. Many segments classified as LTS 2 according to audit datasets were classified as LTS 3 according to OSM and local data due to conservative assumptions about speed, volume, and center lines. In particular, center line assumptions appeared to be a substantial driver of LTS 3 classifications using OSM and local datasets, both of which poorly represented this variable.

Consistency between LTS classifications across methods and data sources was also evaluated with Cohen's kappa coefficients. Table 9 shows kappa coefficients comparing pairs of LTS methods (Method A vs. Method B) while data sources were held constant. Separate kappa coefficients for each data source in each city are reported in each column.

The most notable trend among kappa coefficients was that classifications were most similar between LTS methods when they were based on OSM data (typically around 0.9, or 'almost perfect' similarity) and least similar when based on audit data (typically between 0.2 and 0.5, or 'fair' to 'moderate' similarity). This was surprising, given that audit data were considered the most reliable data source and OSM the least reliable. Sense can be made of this discrepancy, however, by considering that audit data resulted from highly detailed, segment-by-segment measurements that contained substantial classification heterogeneity, whereas OSM data were more generalized, with many missing data points that were filled by assumptions, resulting in greater homogeneity in classification. The detailed audit data, therefore, resulted in more varying classifications due to subtle differences between methods. In essence, there was more granular evidence on which to base different interpretations of traffic stress. With the more general OSM data, classifications were instead based on assumptions derived from major characteristics, such as highway class.

Table 10 shows Kappa coefficients between LTS classifications with different data sources (Data Source A vs. Data Source B) while LTS methods were held constant. Classifications from the Conveyal method, across all data source pairs, had notably greater similarity than those from any other method. Across all of the methods, no data source pairs had strikingly more or less similarity than any others. Trends in kappa coefficients were associated chiefly with methods, not data sources. However, it was notable that kappa coefficients in Portland were universally higher when all segments (n=30,487) were accounted for than with only audited segments (n=633). This was likely due to the preponderance of LTS 1 segments (as demonstrated by Figure 5), which may have been more likely than higher levels to be classified similarly no matter the method or data source.

The broad takeaway from Table 9 and Table 10 is that most pairs of methods and data sources, with the notable exception of comparisons of data sources involving the Conveyal method, had only moderate agreement (kappa coefficients between 0.4 and 0.6). As such, LTS methods were not readily comparable with one another, and most methods were sensitive to differences in data sources. If OSM data were used, different LTS methods yielded more similar classifications compared with audited data. Agreement was lower, but still either moderate or substantial, when comparing audited and local data.

Table 9. Linearly Weighted Cohen's Kappa Coefficients Comparing Pairs of LTS Methods with Data Sources Held Constant

		Weighted Kappa Coefficient				
		Portland			Austin	
LTS Method A	LTS Method B	Audit Data n=633	Local Data n=30,487	OSM Data n=30,487	Audit Data n=445	OSM Data n=36,936
Conveyal	Furth	0.60	0.76	0.83	0.67	0.89
	Lowry	0.50	0.85	0.91	0.86	0.95
	Mekuria	0.54	0.78	0.89	0.61	0.92
	Montgomery	0.51	0.78	0.87	0.46	0.89
	ODOT	0.52	0.65	0.88	0.53	0.90
	PFB	0.41	0.59	0.70	0.39	0.97
Furth	Lowry	0.39	0.72	0.82	0.61	0.91
	Mekuria	0.48	0.75	0.89	0.58	0.94
	Montgomery	0.47	0.79	0.90	0.49	0.98
	ODOT	0.57	0.66	0.90	0.61	0.96
	PFB	0.38	0.55	0.63	0.05	0.58
Lowry	Mekuria	0.68	0.85	0.90	0.66	0.92
	Montgomery	0.59	0.85	0.90	0.52	0.91
	ODOT	0.37	0.67	0.89	0.51	0.92
	PFB	0.39	0.61	0.67	0.38	0.95
Mekuria	Montgomery	0.66	0.90	0.94	0.59	0.95
	ODOT	0.61	0.75	0.96	0.65	0.96
	PFB	0.32	0.60	0.46	0.07	0.52
Montgomery	ODOT	0.54	0.70	0.94	0.59	0.96
	PFB	0.18	0.60	0.56	-0.17	0.60
ODOT	PFB	0.27	0.47	0.47	0.03	0.58

Table 10. Linearly Weighted Cohen's Kappa Coefficients Comparing Pairs of Data Sources with LTS Methods Held Constant

			Weighted Kappa Coefficient		
			Portland		Austin
LTS Method	Data Source A	Data Source B	Audited Segments (n=633)	All Segments (n=30,487)	Audited Segments (n=445)
Conveyal	Audit	Local	0.89		
	Audit	OSM	0.99		0.91
	Local	OSM	0.89	0.92	
Furth	Audit	Local	0.64		
	Audit	OSM	0.64		0.58
	Local	OSM	0.68	0.81	
Lowry	Audit	Local	0.65		
	Audit	OSM	0.69		0.80
	Local	OSM	0.63	0.79	
Mekuria	Audit	Local	0.59		
	Audit	OSM	0.61		0.57
	Local	OSM	0.67	0.77	
Montgomery	Audit	Local	0.67		
	Audit	OSM	0.66		0.82
	Local	OSM	0.63	0.80	
ODOT	Audit	Local	0.36		
	Audit	OSM	0.65		0.57
	Local	OSM	0.40	0.60	
PFB	Audit	Local	0.43		
	Audit	OSM	0.41		0.37
	Local	OSM	0.59	0.67	

To illustrate how different classification methods and input datasets yielded different LTS outcomes, example segments were identified to represent each of the four LTS levels according to the Mekuria method using audit data. Examples were purposefully chosen with high heterogeneity in LTS levels across methods and data sources.

Figure 6 and Table 11 show the LTS 1 example segment. Classifications based on each of the method-data combinations are reported at the top of the table, with the variables used as inputs for LTS classification listed below. The "R" numbers in parentheses next to each LTS level identify the rules, according to each method, that were responsible for that classification. These rule numbers can be cross-referenced with the tables in Appendix D (available in the online supplementary materials) for detailed analysis of which variables were chiefly responsible for shaping the results.

In this first example, the Mekuria classification was driven by the lack of a bicycle lane, number of lanes, and speed limit. Because the audit did not collect speed limits, due to the lack of speed limit signs available on each block, speed limit was assumed to be the value available from the local dataset: 25mph. Given this speed limit, two through lanes, and residential land use, the segment was classified as LTS 1.

The Conveyal method, by contrast, classified this same segment as LTS 4 because it did not have a bicycle lane and was labeled as a secondary street in OSM. The Furth method responded to the segment's relatively high traffic volume, nearly 9,000 vehicles per day on average, to result in an LTS 3 classification.

Classifications within the same methods tended to be fairly similar between data sources, though some minor differences resulted from differences in the assumptions used to fill in missing data, tending to bias results toward more conservative (i.e., higher) LTS levels. When using OSM and local data, for example, the Mekuria method drew on assumptions about non-residential land use and the presence of a center line to classify this segment as LTS 2.

Figure 7 and Table 12 show a segment in downtown Portland that was classified as LTS 2 by the Mekuria method with audit data, owing to its lack of a bicycle lane and mixed land use context. However, because this street was labeled 'residential' by OSM, had a low speed limit, and had no center line, other methods classified it as LTS 1. This segment demonstrated how a single input variable defined in slightly different ways by different datasets could have a dramatic effect on LTS level. The PFB method, for example, classified this segment's stress level as "High" based on the audit data, because auditors identified the land use as non-residential. With OSM data, however, the segment was considered "Low" because the street was labeled "residential," the only available indicator of contextual land use. Imprecisely-defined terms, such as "residential," cannot necessarily be assumed to mean the same thing from one context to another, and LTS methods did not included definitions for input data with sufficient detail to discriminate what should qualify as "residential."

The segment described in Figure 8 and Table 13 was classified as LTS 3 with the Mekuria method with audit data, as a result of the bicycle lane being blocked by construction. While an indicator of lane blockage was not available from the OSM data, the Mekuria method still resulted in LTS 3 due to the assumption of a right-turn lane on a primary street (see Appendix A), though based on the more reliable audit data, there was no such lane. The local data provided the same result for yet another reason: the speed limit was assumed to be 35 mph due to the street classification, in lieu of an explicitly-defined speed limit in the local dataset. This demonstrated how the same LTS level may result from different rules within the same method. It also showed how assumptions used to fill missing data could play a substantial role in shaping LTS outcomes, and how these assumptions may nevertheless produce coincidentally consistent outputs.

The final example, illustrated in Figure 9 and Table 14, was classified as LTS 4 by the Mekuria method using audit data, and showed how criteria related to right turn lanes had a substantial influence on the Mekuria method. With the audit data, which identified two right turn lanes, this segment was automatically classified as LTS 4. None of the other data sources explicitly captured or assumed any right turn lanes, so their results were based on other criteria, mostly resulting in lower LTS levels.

Figure 6. LTS 1 Example: NW Glisan St Between 19th Ave and 18th Ave in Portland

Source: Google.

Table 11. LTS 1 Example: NW Glisan St Between 19th Ave and 18th Ave in Portland

	Data Source		
	Audit	OSM	Local
LTS Method			
Conveyal	LTS 4 (R7)	LTS 4 (R7)	LTS 4 (R7)
Furth	LTS 3 (R23)	LTS 3 (R65)	LTS 3 (R23)
Lowry	LTS 1 (R1)	LTS 2 (R6)	LTS 2 (R6)
Mekuria	**LTS 1 (R32)**	LTS 2 (R33)	LTS 2 (R35)
Montgomery	LTS 2 (R37)	LTS 2 (R38)	LTS 2 (R39)
ODoT	LTS 1 (R29)	LTS 2 (R30)	LTS 1 (R29)
PFB	High (R18)	High (R18)	High (R18)
Input Variable			
Bike facility buffer width (ft)	0	0	
Bike facility width (ft)	0	0	
Bike lane (binary)	False	False	False
Buffered bike lane (binary)	False		
Cycle track (binary)	False		
Separated bike lane (binary)	False	False	False
Bicycle boulevard (binary)	False		False
Center turn lane (binary)	False	False	
Center line (binary)	True		False
Curb-to-curb width (ft)	37		
Lanes (count)	2	2	2
One way (binary)	True	True	
Left turn lanes (count)	0	0	
Right turn lanes (count)	0	0	0
High speed right turn lane (binary)	False		
Parking (binary)	True		True
Parking lane width (ft)	0		
Speed limit (mph)		25	25
Traffic signal (binary)	1	1	1
ADT			8626
Residential street (binary)	True		False
Bike lane obstructed (binary)	False		
Bike lane aligned through intersection (binary)	False		
Bike lane continuous through intersection (binary)	False		
Pedestrian refuge across cross street (binary)	False		False
Cross street lanes (count)	2		1
OSM highway tag		secondary	

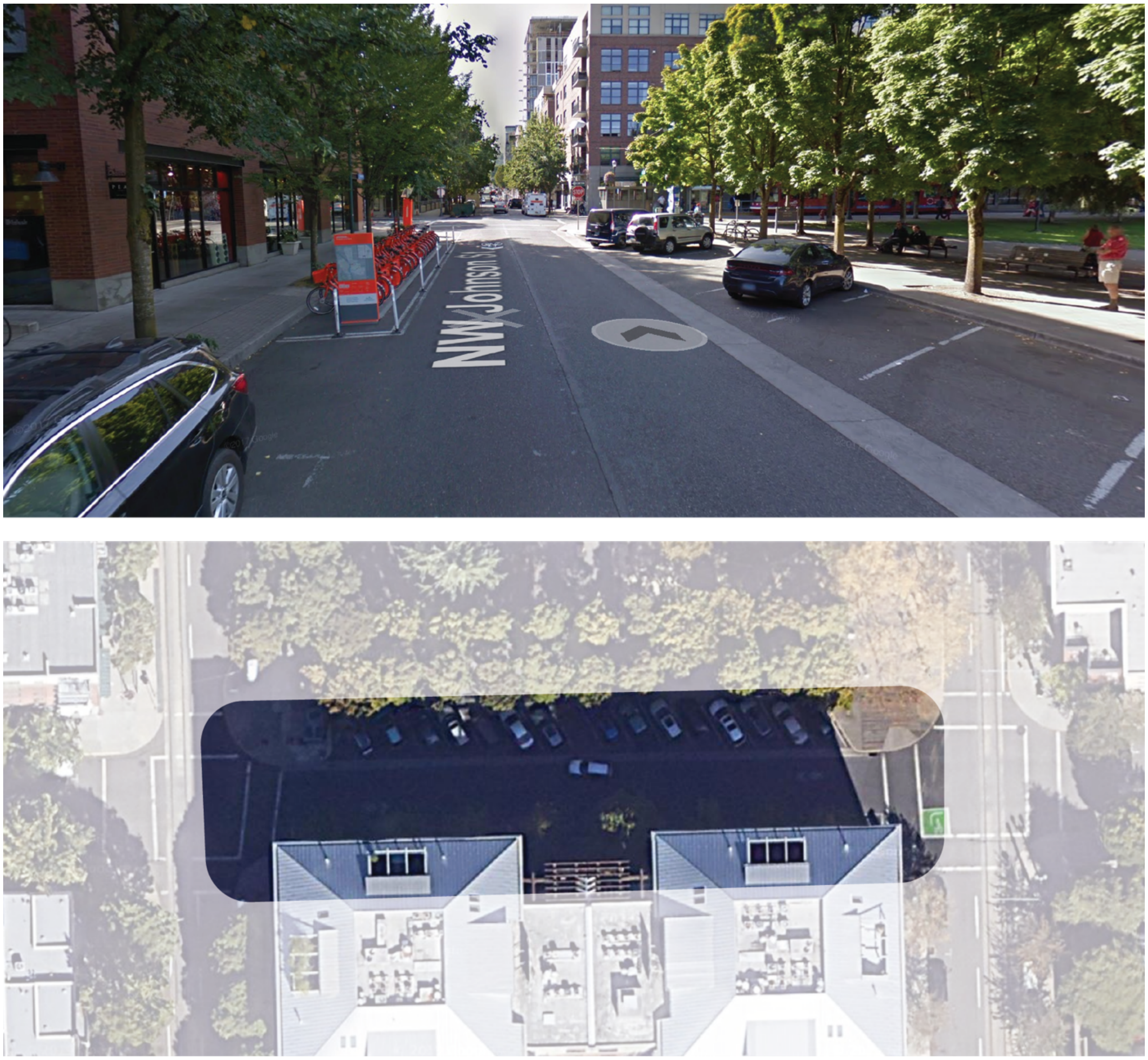

Figure 7. LTS 2 Example: NW Johnson St Between NW 10th Ave and NW 11th Ave in Portland

Source: Google.

Table 12. LTS 2 Example: NW Johnson St Between NW 10th Ave and NW 11th Ave in Portland

	Data Source		
	Audit	**OSM**	**Local**
LTS Method			
Conveyal	LTS 1 (R1)	LTS 1 (R1)	LTS 1 (R1)
Furth	LTS 1 (R9)	LTS 1 (R9)	LTS 3 (R58)
Lowry	LTS 2 (R6)	LTS 1 (R1)	LTS 2 (R6)
Mekuria	**LTS 2 (R35)**	LTS 1 (R32)	LTS 2 (R33)
Montgomery	LTS 2 (R39)	LTS 1 (R33)	LTS 2 (R38)
ODoT	LTS 1 (R29)	LTS 1 (R29)	LTS 4 (R40)
PFB	High (R18)	Low (R19)	High (R18)
Input Variable			
Bike facility buffer width (ft)	0	0	
Bike facility width (ft)	0	0	
Bike lane (binary)	False	False	False
Buffered bike lane (binary)	False		
Cycle track (binary)	False		
Separated bike lane (binary)	False	False	False
Bicycle boulevard (binary)	False		False
Center turn lane (binary)	False	False	
Center line (binary)	False		True
Curb-to-curb width (ft)	29		
Lanes (count)	2		2
One way (binary)	False	False	
Left turn lanes (count)	0		
Right turn lanes (count)	0		1
High speed right turn lane (binary)	False		
Parking (binary)	True		True
Parking lane width (ft)	0		
Speed limit (mph)		25	
Traffic signal (binary)	False	False	False
ADT			
Residential street (binary)	False		False
Bike lane obstructed (binary)	False		
Bike lane aligned through intersection (binary)	False		
Bike lane continuous through intersection (binary)	False		
Pedestrian refuge across cross street (binary)	False		False
Cross street lanes (count)	2		2
OSM highway tag		residential	

Figure 8. LTS 3 Example: N Couch St Between NE MLK Blvd and NE Grand Ave in Portland

Source: Google.

Table 13. LTS 3 Example: N Couch St Between NE MLK Blvd and NE Grand Ave in Portland

	Data Source		
	Audit	OSM	Local
LTS Method			
Conveyal	LTS 3 (R6)	LTS 3 (R6)	LTS 3 (R6)
Furth	LTS 3 (R23)	LTS 3 (R65)	LTS 4 (R67)
Lowry	LTS 1 (R7)	LTS 1 (R7)	LTS 3 (R31)
Mekuria	**LTS 3 (R19)**	LTS 3 (R3)	LTS 3 (R17)
Montgomery	LTS 2 (R6)	LTS 2 (R6)	LTS 4 (R54)
ODoT	LTS 3 (R3)	LTS 4 (R40)	LTS 2 (R6)
PFB	LTS 1 (R10)	LTS 4 (R12)	LTS 4 (R2)
Input Variable			
Bike facility buffer width (ft)	0	0	
Bike facility width (ft)	5	0	
Bike lane (binary)	True	True	True
Buffered bike lane (binary)	True		
Cycle track (binary)	False		
Separated bike lane (binary)	False	False	False
Bicycle boulevard (binary)	False		False
Center turn lane (binary)	False	False	
Center line (binary)	True		True
Curb-to-curb width (ft)	35		
Lanes (count)	2	2	2
One way (binary)	False	True	
Left turn lanes (count)			
Right turn lanes (count)	0		
High speed right turn lane (binary)	False		
Parking (binary)	True		1
Parking lane width (ft)	8		
Speed limit (mph)		25	
Traffic signal (binary)	True	True	True
ADT			18865
Residential street (binary)	False		False
Bike lane obstructed (binary)	True		
Bike lane aligned through intersection (binary)	True		
Bike lane continuous through intersection (binary)	True		
Pedestrian refuge across cross street (binary)	False		False
Cross street lanes (count)	3		4
OSM highway tag		primary	

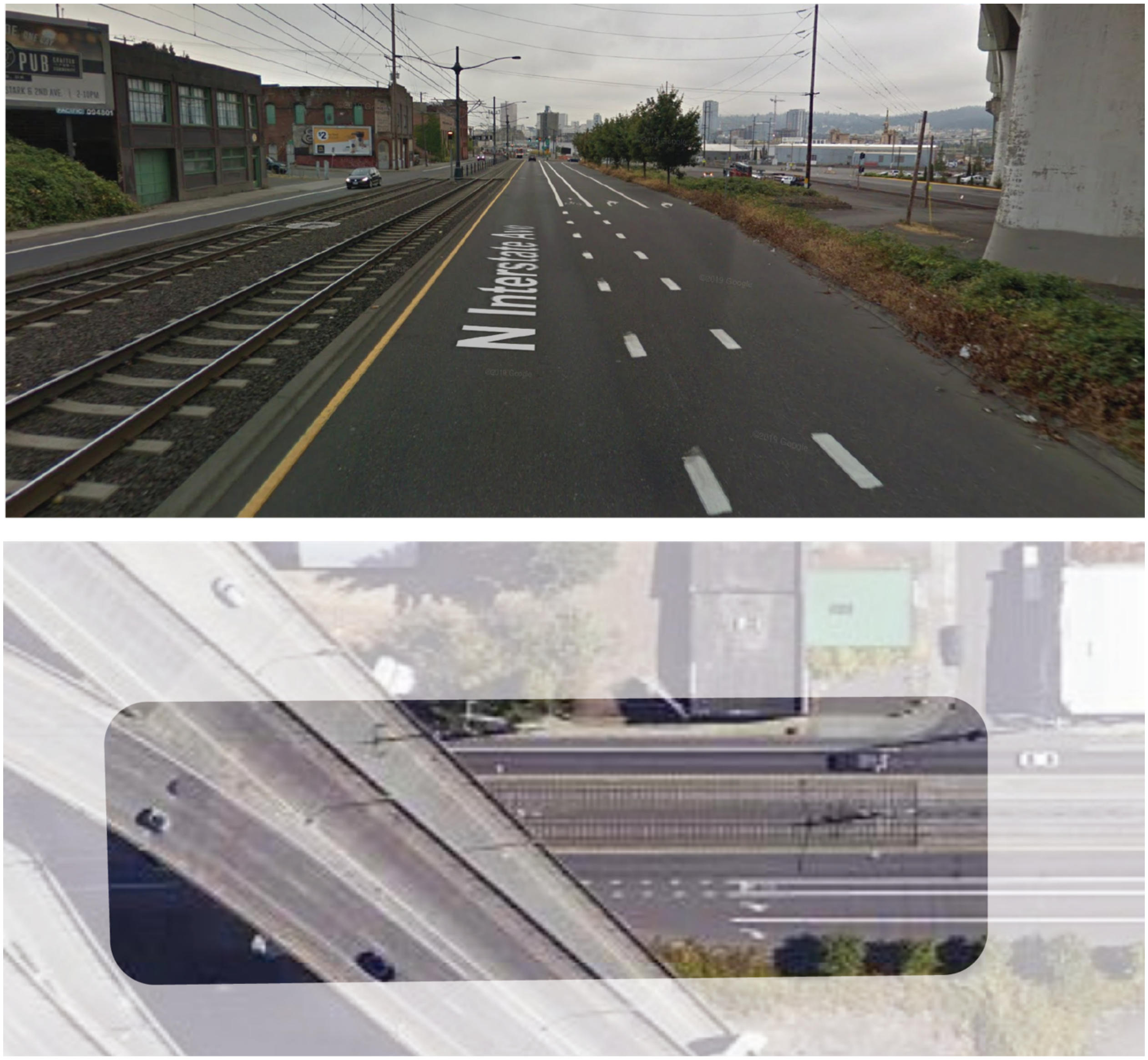

Figure 9. LTS 4 Example: N Interstate Ave Between N Graham St and N Knott St in Portland

Source: Google.

Table 14. LTS 4 Example: N Interstate Ave Between N Graham St and N Knott St in Portland

	Data Source		
	Audit	OSM	Local
LTS Method			
Conveyal	LTS3 (R6)	LTS3 (R6)	LTS3 (R6)
Furth	LTS2 (R91)	LTS4 (R73)	LTS4 (R73)
Lowry	LTS2 (R19)	LTS3 (R27)	LTS3 (R27)
Mekuria	**LTS4 (R4)**	LTS3 (R19)	LTS3 (R19)
Montgomery	LTS3 (R49)	LTS4 (R51)	LTS4 (R51)
ODoT	LTS4 (R41)	LTS3 (R5)	LTS2 (R4)
PFB	LTS1 (R9)	LTS4 (R12)	LTS4 (R7)
Input Variable			
Bike facility buffer width (ft)	0	0	
Bike facility width (ft)	7	0	
Bike lane (binary)	True	True	True
Buffered bike lane (binary)	True		
Cycle track (binary)	False		
Separated bike lane (binary)	False	False	False
Bicycle boulevard (binary)	False		False
Center turn lane (binary)	False	False	
Center line (binary)	True		True
Curb-to-curb width (ft)	86		
Lanes (count)	2		4
One way (binary)	False	True	
Left turn lanes (count)			
Right turn lanes (count)	2		
High speed right turn lane (binary)	False		
Parking (binary)	False		True
Parking lane width (ft)	0		
Speed limit (mph)		30	30
Traffic signal (binary)	False	False	False
ADT			13130
Residential street (binary)	False		False
Bike lane obstructed (binary)	False		
Bike lane aligned through intersection (binary)	True		
Bike lane continuous through intersection (binary)	True		
Pedestrian refuge across cross street (binary)	False		False
Cross street lanes	2		3
OSM highway tag		secondary	

OBJECTIVE 2: ASSOCIATIONS BETWEEN LTS AND CROWDSOURCED BICYCLE USER SATISFACTION

Bivariate relationships between LTS levels and Ride Report scores were examined in order to analyze whether LTS levels realistically expressed user satisfaction. In addition to analyzing “overall” Ride Report scores based on ratings from all riders and rides, analyses in Portland were repeated with queried Ride Report scores that representing specific rider and ride characteristics. Table 15 reports summary statistics for each of the queried score sets in comparison with the overall scores (first row).

Differences between queried scores tended to be small. Scores based on longer distance rides, presumably made by stronger riders, were higher than for shorter rides. Scores based on rides during colder seasons and with colder weather were slightly lower than those made during warmer times, consistent with the expectation that cold weather riding was relatively unpleasant. Scores based on female riders, however, were higher on average than those from male riders, despite evidence that female cyclists tend to be more concerned with infrastructure safety than their male counterparts. It is speculated that Ride Report users may tend to choose safer or otherwise more pleasurable routes, accounting for this result. The larger number of segments with reliable scores based on male riders (4,210) compared with female riders (2,889) was consistent with research showing that males cycle at higher rates than females.

Older riders produced slightly higher scores than younger riders, and those who cycled occasionally produced higher scores than those who cycled frequently. Surprisingly, there was no notable difference in scores between fast and slow cyclists. Cyclists presumed to be socioeconomically disadvantaged produced higher scores than those who weren’t. Many of these differences were small enough, however, that it was difficult to conclude whether different types of cyclists had substantially different interpretations of what constituted a high quality route.

Table 15. Portland Ride Report Query Summaries

Category	Name	Definition	Segment Count	Average Ride Report Score
Overall	Overall		8,198	0.90
Gender	Male	Gender = Male	4,210	0.89
	Female	Gender = Female	2,889	0.93
Age	Young Age	Cyclist Age < 25	244	0.91
	Young Middle Age	25 ≤ Cyclist Age < 45	3,810	0.92
	Older Middle Age	45 ≤ Cyclist Age < 65	1,375	0.93
	Older	Cyclist Age ≥ 65	0	NA
Distance	Short Distance	Trip Distance ≤ 1 mi	646	0.88
	Mid-Distance	1 mi < Trip Distance < 5 mi	5,742	0.90
	Long Distance	Trip Distance ≥ 5 m	4,636	0.91
Time of Day	Late Night	Trip Starts 10 PM - 4 AM	787	0.97
	Early Morning	Trip Starts 4 AM - 7 AM	805	0.95
	Morning Commute	Trip Starts 7 AM - 11 AM	3,740	0.89

Category	Name	Definition	Segment Count	Average Ride Report Score
	Midday	Trip Starts 11 AM - 3 PM	2,980	0.90
	Afternoon	Trip Starts 3 PM - 7 PM	4,607	0.88
	Evening	Trip Starts 7 PM - 10 PM	2,235	0.93
Season	Winter	Trip in Dec, Jan, or Feb	1,940	0.88
	Spring	Trip in Mar, Apr, or May	5,031	0.92
	Summer	Trip in June, Jul, Aug	3,723	0.90
	Fall	Trip in Sep, Oct, Nov	3,746	0.88
Weather	Hot	Trip While Temp > 80° F	1,609	0.91
	Warm	60° F < Trip While Temp ≤ 80° F	5,323	0.90
	Cool	45° F < Trip While Temp ≤ 60° F	5,301	0.89
	Cold	Trip While Temp ≤ 45° F	1,987	0.88
	Not Rainy	Trip while it is not raining	7,702	0.91
	Rainy	Trip while it is raining	2,667	0.87
Socioeconomic Disadvantage	Not Disadvantaged	Cyclists that have fewer than 25% of their trip ends (start or end) within a TriMet Community of Concern	5,871	0.90
	Disadvantaged	Cyclists that have at least 25% of their trip ends (start or end) within a TriMet Community of Concern	4,740	0.91
Cycling Speed	Fast	Cyclists with an average trip speed (total dist. / total time) of ≥ 12 mph	5,626	0.90
	Slow	Cyclists with an average trip speed (total dist. / total time) of < 12 mph	4,645	0.90
Cycling Frequency	High Frequency	Cyclists who have ridden ≥ 4 days per week on average throughout their use of the Ride Report App	4,052	0.91
	Medium Frequency	Cyclists who have ridden more than 1 day but less than 4 days per week on average throughout their use of the Ride Report App	4,161	0.92
	Low Frequency	Cyclists who have ridden 1 day or less per week on average throughout their use of the Ride Report App	3,306	0.93

Table 16 shows the Spearman rank correlation coefficients between Ride Report scores and LTS levels for each of the seven LTS methods, in Portland and Austin, all of which were calculated with audited data. Sample sizes for each correlation corresponded with the number of segments along which the corresponding Ride Report query provided reliable scores. Correlations involving small samples (<50% of segments in the “overall” Ride Report sample) or which were not statistically significant with 95% confidence, were omitted from the table.

None of the Spearman rank correlations were especially high ($\max(r_s) = 0.35$ among overall Ride Report scores; $\max(r_s) = 0.53$ among filtered scores), indicating that the relationship between LTS levels and perceived quality of bicycling facilities, as measured by Ride Report, was generally weak. If the measures had correlated strongly, this would have been further evidence of their mutual efficacy. These results, however, either suggested that LTS poorly represented cyclist experiences, that Ride Report poorly captured those experiences, or both.

The strength of correlations was moderate, but higher in Portland than in Austin. In Portland, Ride Report scores' correlations with the Conveyal LTS were also stronger than with the other LTS methods, suggesting that simpler methods might better represent cyclist perceptions than more complex methods. This trend did not, however, hold in Austin, where the Furth method was most strongly correlated with Ride Report scores. This difference underscores how indicators of infrastructure quality, and the needs of residents, may vary between cities.

Given the large number of unknown factors that might contribute to Ride Report users' ratings of a given route, and the highly generalizing approach through which these ratings were aggregated into segment-specific scores, it was unsurprising that Ride Report scores were not perfectly correlated with LTS. Ride Report scores were expected to be noisy, affected by numerous influences (such as weather, or someone simply having a bad day) that were entirely unrelated to LTS. In some ways, then, it was impressive that Ride Report and LTS were even moderately correlated in some cases. Ride Report's efficacy as an indicator of user satisfaction was clearly better than random.

The relatively high correlations for some filtered Ride Report scores, particularly in contrast to overall scores, suggested that LTS may better represent the experiences of certain types of cyclists. Correlations with midday (11am-3pm) Ride Report scores, for example, tended to be almost twice as strong as those from other times of day; the authors speculate that midday cycling may potentially be a proxy for more cautious, less experienced cyclists. Substantial differences in correlations based on fast cyclists (lower correlations) and slow cyclists (higher correlations) also suggested that LTS was more representative of less experienced cyclists, consistent with Mekuria et al.'s original intention.[78]

Table 16. Spearman Correlations Between LTS Levels and Ride Report Scores

	LTS Method (All Calculated with Audit Data)						
Ride Report Query	**Conveyal**	**Furth**	**Lowry**	**Mekuria**	**Mtgmry.**	**ODoT**	**PFB**
Overall (Portland) (n=633)	0.35	0.26	0.28	0.28	0.20	0.21	0.26
Overall (Austin) (n=445)	0.14	0.25	0.14	0.11	0.17	0.18	-0.05
Gender (Portland)							
Male (n=538)	0.25	0.14	0.17	0.18	*	0.11	0.21
Female (n=394)	0.20	0.14	0.15	0.22	0.19	0.18	0.19
Age (Portland)							
Young (n=20)	*	*	*	*	*	*	*
Young-middle (n=503)	0.18	*	0.11	0.15	*	*	0.09
Older middle (n=191)	*	*	*	*	*	*	*
Older (n=0)	*	*	*	*	*	*	*
Distance (Portland)							
Short (n=94)	*	*	*	0.23	*	0.23	*
Medium (n=606)	0.32	0.20	0.24	0.26	0.15	0.17	0.28
Long (n=508)	0.22	0.19	0.11	0.15	0.12	0.16	

Ride Report Query	LTS Method (All Calculated with Audit Data)						
	Conveyal	**Furth**	**Lowry**	**Mekuria**	**Mtgmry.**	**ODoT**	**PFB**
Time of Day (Portland)							
Late night (n=108)	*	*	*	*	0.20	*	*
Early morning (n=98)	*	*	*	*	*	*	0.20
Mrng. commute (n=482)	0.29	0.23	0.14	0.20	0.14	0.15	0.16
Midday (n=429)	0.53	0.36	0.47	0.47	0.38	0.32	0.37
Afternoon (n=633)	0.26	0.17	0.20	0.19	0.11	0.11	0.19
Evening (n=346)	0.26	0.18	0.16	0.21	0.12	0.16	0.22
Season (Portland)							
Winter (n=304)	*	*	*	*	*	*	*
Spring (n=586)	0.38	0.26	0.30	0.31	0.21	0.18	0.25
Summer (n=527)	0.12	*	*	0.11	*	0.11	0.10
Fall (n=525)	0.44	0.38	0.28	0.32	0.27	0.27	0.26
Weather (Portland)							
Hot (n=226)	*	*	*	*	*	*	*
Warm (n=618)	0.25	0.14	0.18	0.19	0.11	0.14	0.20
Cool (n=603)	0.34	0.27	0.23	0.27	0.19	0.21	0.21
Cold (n=300)	0.47	0.37	0.30	0.31	0.26	0.25	0.20
Not Rainy (n=633)	0.35	0.26	0.27	0.28	0.20	0.21	0.25
Rainy (n=415)	0.34	0.20	0.23	0.26	0.14	0.18	0.19
Socioeconomics (Portland)							
Not disadv. (n=607)	0.27	0.18	0.17	0.18	0.08	0.12	0.24
Disadvantaged (n=569)	0.36	0.28	0.30	0.29	0.25	0.22	0.21
Cycling Speed (Portland)							
Fast cyclists (n=595)	0.29	0.18	0.22	0.22	0.09	0.12	0.22
Slow cyclists (n=568)	0.38	0.22	0.32	0.31	0.28	0.23	0.25
Cycling Frequency							
Frequent cyclists (n=519)	0.37	0.29	0.34	0.32	0.26	0.24	0.25
Medium Freq. (n=538)	0.10	*	*	0.09	0.10	*	*
Infreq. cyclists (n=448)	0.33	0.27	0.30	0.24	0.18	0.12	0.21

All correlations were multiplied by -1 so positive values represent expected directionality of relationship.
* *Considered unreliable:* Spearman rank correlation not significantly different from 0 with 95% confidence, or query-specific Ride Report scores available for fewer than 50% (n < 317) of audited Portland street segments

To examine whether associations between LTS and user satisfaction were linear, 95% confidence intervals were calculate for average Ride Report scores among segments with each LTS level (Figure 10). Ride Report scores mostly decreased monotonically across successive LTS levels, though there were some cases where the average Ride Report score for LTS 2 was less than that for LTS 3. This suggested that differences between the middle LTS classes were less meaningful than differences at the extremes of the LTS scale. Potentially, a three-level system that combined the middle two classes would provide more consistent differentiation between levels. This may have been one of the reasons why PFB used a two-level LTS system, though these two levels still were not highly differentiable based on Ride Report scores.

The confidence intervals plotted in Figure 10 demonstrate that differences between successive LTS levels were not typically significant, particularly within the smaller, audited samples of street segments (black bars). The Furth LTS calculated with audited data in Austin provided some of the best separation with this smaller sample size, offering nearly non-overlapping confidence intervals for all but the middle two levels, which had nearly the same average. There was more separation between LTS levels with the full-city samples (blue bars), which had narrower confidence intervals. The Conveyal LTS with OSM data in Portland, Lowry LTS with OSM and local data in Portland, and Mekuria LTS with local data in Portland had significantly different mean Ride Report scores at all of their levels.

The range in Ride Report score associated with the full range of LTS levels was approximately 0.05 to 0.1, depending on LTS method and data source. Assuming a monotonic decrease, which is more reasonable an assumption with some LTS methods than others, this describes an increase in Ride Report score of between 0.017 and 0.033 points for every one-level decrease in LTS. Assuming a causal relationship between LTS level and Ride Report score, a one-level LTS decrease might result in an approximately 2–3% higher probability of a Ride Report user providing a satisfactory (thumbs-up) rating for a route that included that segment. Because the distribution of Ride Report scores was quite narrow, this would constitute an improvement of the mean Ride Report score from the initial median score to between the initial 65th and 75th percentiles. While this interpretation is contingent on a number of assumptions, it suggests that decreasing an LTS level might translate into a sizable increase in the percentage of cyclists who are would give a positive rating for a ride along that segment.

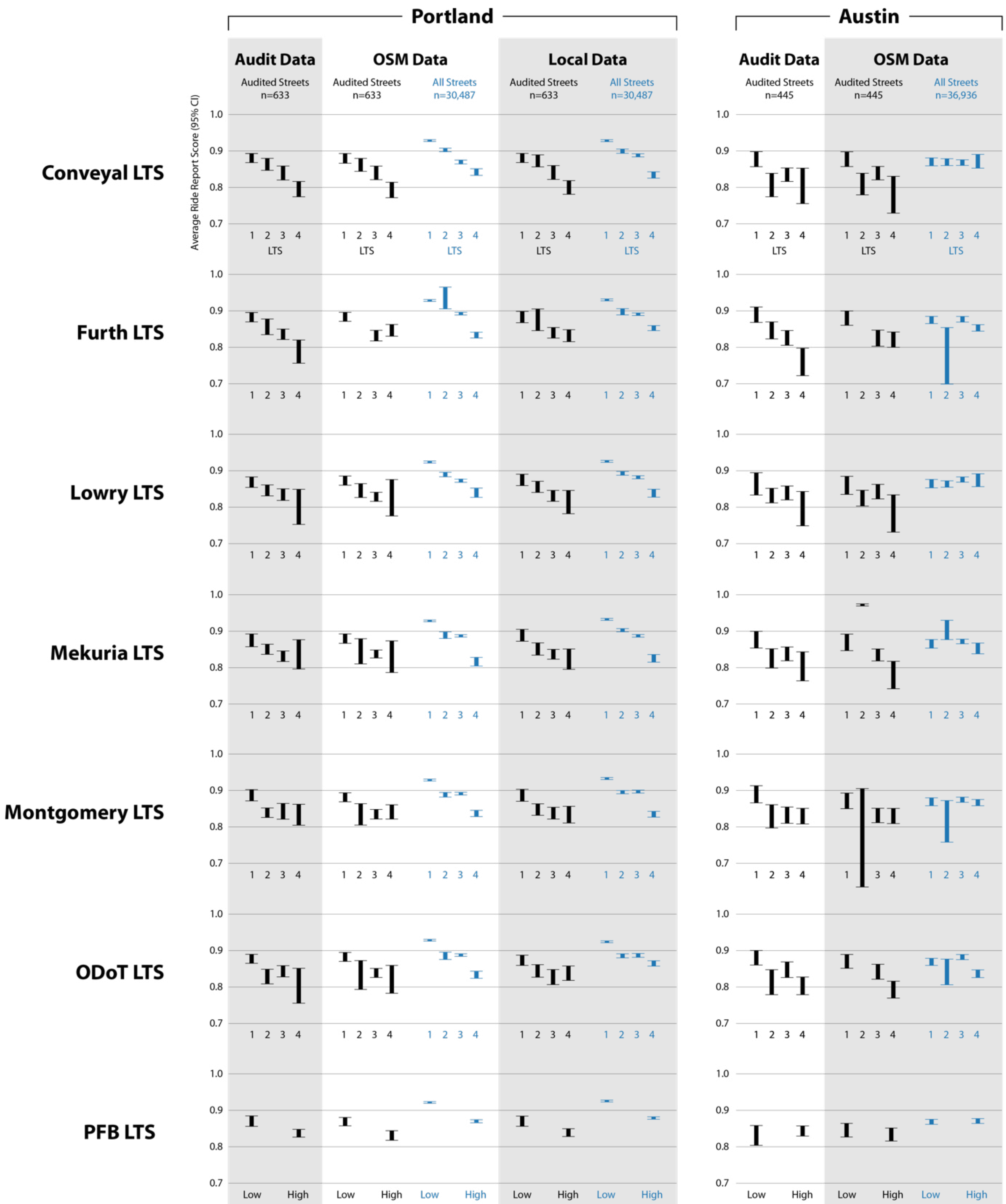

Figure 10. Confidence Intervals (95%) on Average Ride Report Scores by LTS Level

OBJECTIVE 3: ASSOCIATIONS BETWEEN SPECIFIC CYCLING ENVIRONMENT VARIABLES AND USER SATISFACTION

To investigate which street environment variables might be most useful for improving user satisfaction, and therefore be useful as inputs for an LTS classifier, Ride Report scores in Portland were regressed onto street environment variables from each of the three data sources (Table 17). Model variations based on each data source and sample size (audited segments vs. all segments) were compared to null models that included only a constant term and control terms for spatial autocorrelation. The aim of modeling was to compare estimates across samples and data sources, not to maximize predictive power or parsimony. Thus, all relevant and available variables were entered for each model, especially to the extent that they facilitated meaningful comparisons. Terms were removed using a backwards stepwise process until all terms were significant at a 95% confidence level. The traffic signal variable was retained in Model 1.1 because it was nearly significant at this level (P=0.07).

Which variables were retained in the models was likely affected by high multicollinearity between certain variables. The average variance inflation factor (VIF) among independent variables in the models ranged from 1.8 to 13.7. VIFs for variables associated with street size, such as lane count, curb-to-curb width, and speed limit, were especially high, ranging from 14.0 to 61.1, in models based on local agency data (Models 3.1 and 3.2). Due to this multicollinearity, the absence of certain variables from the final models did not necessarily suggest that these variables were unrelated to Ride Report, but rather that covariates may have masked these relationships.

Comparisons of fit across the models suggested that individual variables had minimal influence on Ride Report scores. Baseline models had McFadden R^2 statistics of 0.11 and 0.14 for "audited segments" and "all segments" models respectively.[79] Comparable models with audited, OSM, and local data had only slightly improved fit, with McFadden R^2 ranging from 0.21 to 0.22. Based on the Akaike information criterion (AIC), the best models were those using OSM data (Models 2.1 and 2.2). By another metric, the area under the curve (AUC) of the receiver operator characteristic (ROC), models that included segment-level variables had only marginally more predictive power (ROC AUC = 0.61 and 0.62, for Models 2.1 and 2.2 respectively) than the null models (ROC AUC = 0.58 and 0.60, for Models 0.1 and 0.2 respectively).[80] In sum, available street environment variables had fairly weak associations with Ride Report scores, suggesting that other factors, such as weather or personal preferences, may have had greater influences on Ride Report users' ratings than roadway characteristics.

The directionality-of-effect estimates for independent variables were generally consistent with expectations. Bicycle-oriented infrastructure, such as bike lanes and bicycle boulevards, were positively correlated with Ride Report scores. These infrastructure variables also had some of the strongest correlations. Similarly, some street configuration variables were significant. Increased buffer widths and parking lane width (Model 1.1) were positively correlated, while roadway width (lane count and curb-to-curb width) and variables related to large streets (center line, 'large street,' median, and right turn lanes/length) were negatively correlated. Intersection density, the only EPA variable whose effect was statistically significant in any of the models, was positively correlated with Ride Report scores, consistent with existing research on relationships between bicycling and the built environment.[81]

Several variables had notably inconsistent or counterintuitive estimated effects. Negative associations between one-way traffic flow and Ride Report scores across different models suggested that a segment being one-way was an unreliable indicator of rider satisfaction. Speed limit and cross-street speed limit had small but positive correlations in models where these variables had statistically significant effects. Counterintuitively, this suggested that bicyclists might prefer streets with higher speed limits. This might be explained, in part, by confounding relationships between speed limit and other indicators of street size, such as width, center line, or a ‘large street’ label. Alternatively, it might suggest that cyclists prefer larger streets that may be more engaging places or have desired land uses along them (e.g., the quintessential ‘Main Street’). In the model based on audit data (Model 1.1), cross-street lane count was negatively correlated with Ride Report scores, as expected, but the version estimated with local data (Model 3.1) indicated a positive correlation. This discrepancy might be explained by the audited data’s being more reliable than those from PBoT’s dataset.

Several cross-street and intersection factors had unexpected associations with Ride Report scores. Median refuges and traffic signals, for example, had a fairly substantial negative associations with Ride Report score, despite being potentially valuable assets for bicyclists negotiating busy crossings. Median refuges might, however, have simply indicated the need to cross a large street, which was less preferred than crossing a smaller street even if a median refuge or signal was provided. Unfortunately, median refuges and signals simply did not occur at small street crossings, leading to unbalanced levels in observations that made it difficult to estimate their effect statistically while holding street size constant. Alternatively, crossing large cross streets might have compelled riders to be less critical of the relatively low-stress segments they were riding on. This might explain not only the negative associations between crossing infrastructure and Ride Report scores, but also the counterintuitive positive associations between Ride Report scores and “large” cross streets (Models 2.1 and 2.2).

Table 17. Logistic Regression Models Estimating Overall Ride Report Scores

	Base Case		Audit Data	OSM Data		Local Data	
	Audited Segments n=633	All Segments n=8,198	Audited Segments n=633	Audited Segments n=633	All Segments n=8,198	Audited Segments n=633	All Segments n=8,198
	Model 0.1	**Model 0.2**	**Model 1.1**	**Model 2.1**	**Model 2.2**	**Model 3.1**	**Model 3.2**
Independent Variables	**Regression Coefficient Estimates**						
Segment							
Bike lane (binary)			0.22	0.33	0.78	0.34	0.10
Separ. bike ln. (binary)				0.20	0.16	0.12	0.11
Cycle track (binary)			0.54				
Buffered bike ln. (binary)			0.36				
Bike blvd (binary)			0.49			0.59	0.22
Sharrow (binary)				0.57	0.24		
Bike ln. buffer width (ft)			0.01				
Bike ln. obstruct. (binary)			-0.31				
Lanes (count)						-0.02	-0.06
Curb-to-curb width (ft)			-0.05			0.004	-0.01
Parking lane width (ft)			0.05				
Speed limit (mph)						0.01	
One way street (binary)			-0.24	0.11	-0.04		
Center line (binary)			-0.25			-0.08	-0.20
Large street (binary)†				-0.27	-0.46		
Median (binary)			-0.35				
Right turn lanes (count)			-0.03				
Right turn ln. length (ft)			-0.03				
Cross Street							
Median refuge (binary)			-0.28				
Lanes (count)			-0.02			0.04	0.04
Traffic signal (binary)			-0.03*			-0.12	-0.10
Large street (binary)				0.03	0.03		
Speed limit (mph)						0.01	0.003

	Base Case		Audit Data	OSM Data		Local Data	
	Audited Segments n=633	**All Segments n=8,198**	**Audited Segments n=633**	**Audited Segments n=633**	**All Segments n=8,198**	**Audited Segments n=633**	**All Segments n=8,198**
	Model 0.1	**Model 0.2**	**Model 1.1**	**Model 2.1**	**Model 2.2**	**Model 3.1**	**Model 3.2**
Independent Variables	**Regression Coefficient Estimates**						
EPA intersection density			0.09	0.001	0.001	0.001	0.001
Longitude	0.76	0.58	0.55	0.61	0.42	0.54	0.42
Latitude	0.79	0.45	0.67	0.72	0.40	0.67	0.39
Longitude^2	0.37	-0.12	0.30	0.25	-0.04	0.22	-0.07
Latitute^2	0.23	-0.08	0.18	0.20	-0.05	0.16	-0.09
Longitude x latitude	0.81	-0.03	0.66	0.69	0.02	0.64	0.07
Constant	2.16	2.56	2.14	1.61	2.25	1.24	2.64
Model Summary							
McFadden R^2	0.11	0.14	0.21	0.22	0.21	0.21	0.21
AIC	20467.72	173086.52	18273.03	17927.17	158563.45	18263.72	159457.95
Log-Likelihood	-10228	-86537	-9113.5	-8950.6	-79269	-9114.9	-79713
ROC Area Under Curve	0.58	0.60	0.61	0.61	0.62	0.60	0.62
Average VIF	3.8	1.8	4.5	2.9	1.7	13.7	11.8

** p=0.07. All other parameter estimates are significant at the P<0.05 (95%) level.*

† Includes OSM 'highway' tags with values of 'trunk,' 'primary,' or 'secondary'

Note: Cell colors are coordinated with shading in Figure 11 to facilitate interpretation.

The curves in Figure 11 graphically represent associations between the predictor variables with the largest and most consistent associations with Ride Report scores. Curve colors are coordinated with the cells in Table 17 that contain associated effect estimates. The curves illustrate the estimated change in Ride Report score based on change in that variable while all other independent variable were held constant at their mean (for continuous variables) or mode (for categorical variables). Curves representing each audited-segment model were plotted side by side in order to facilitate comparison; these curves had different intercepts owing to the different mean or mode values for other variables in each model.

The leftmost panel in Figure 11 shows that adding a bike lane was estimated to improve Ride Report score by between 0.02 and 0.04. Because the Ride Report scores have a low variance, this represents a shift of the initial median Ride Report score from its initial value to between the initial 67th and 85th percentiles, a substantial improvement. A separated bike lane, likewise, might improve the Ride Report score between 0.01 and 0.05, or a shift of the median from its initial value to between the initial 59th and 91st percentiles, with the latter estimate representing audited cycle tracks. A bike boulevard was associated with a score increase of between 0.04 and 0.06, or a shift of the median from its initial value to between the initial 85th and 95th percentiles. A larger street, by contrast, was estimated to reduce Ride Report score by between 0.01 and 0.04, or a shift of the median downward from the its initial value to between the initial 43rd and 28th percentiles. These results suggest that bicycle infrastructure and street size had sizable and predictable associations with user perceptions.

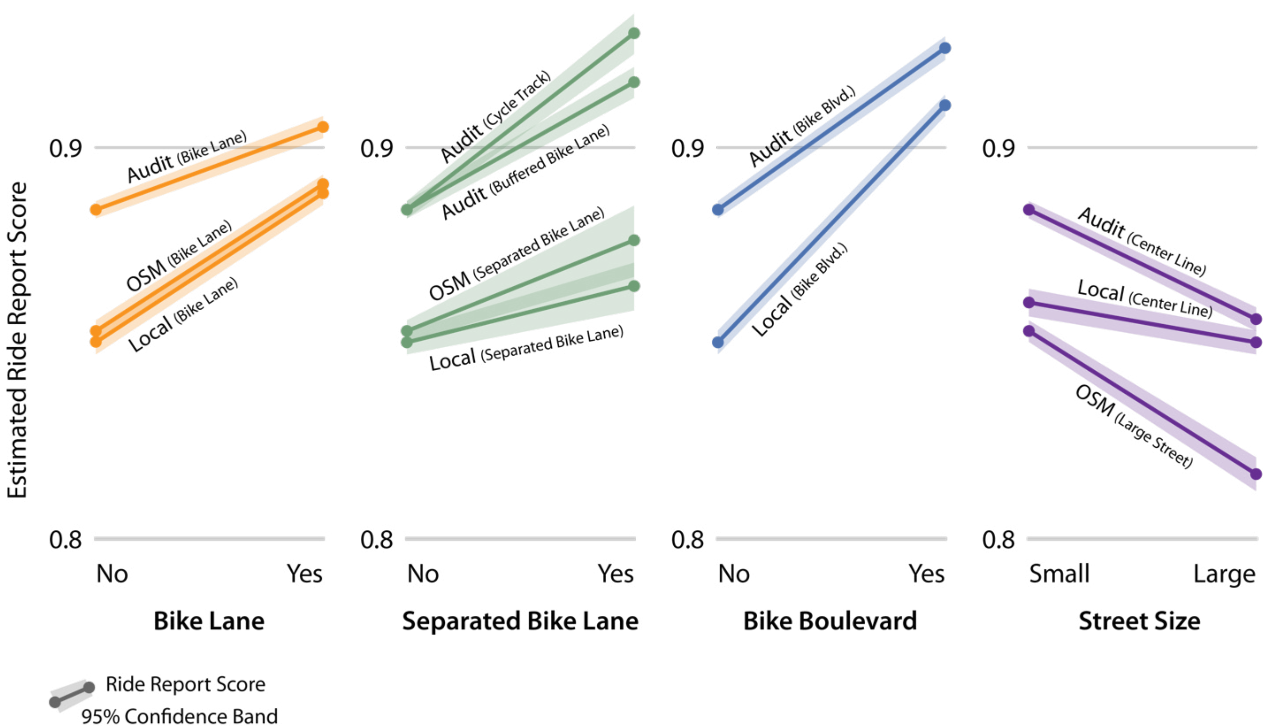

Figure 11. Marginal Associations Between Segment Variables and Ride Report Scores

Based on logistic regression models. Estimates assume average or modal values of all other independent variables in a given model. Separate estimates are presented for models based on audit, OSM, and local data sources. All estimates are based on models developed from the "audited segments" sample in Portland (n=633). Colors coordinate with shading on coefficients in Table 16.

VI. CONCLUSIONS

The Level of Traffic Stress (LTS) framework offers a concise metric for characterizing the quality of urban streets for bicycling, aggregating diverse infrastructure variables into an intuitive ordinal scale. Consequently, it has been widely embraced by planners in order to streamline analyses of bicycle network quality and communicate these findings to decisionmakers and the public. LTS's concision, however, can also risk misinterpretation: what, exactly, *is* "LTS 2"? Different LTS methods, developed in order to facilitate analyses with different data needs, in different geographies, or with updated understandings of what constitutes bikeability, have led to diverse definitions of LTS levels. Different data sources that offer varying levels of precision, or require assumptions to fill missing data, can also dramatically affect LTS outcomes. LTS levels can also be easily misinterpreted as a continuous scale, implying that the degree of improvement is consistent between sequential levels. Because LTS levels result from combinations of variables, it can also be difficult to interpret which specific variables might have the greatest influence on cycling quality.

This study examined each of these issues, providing an empirical foundation for more precise interpretation of LTS analyses. Firstly, it found that LTS outcomes can vary substantially depending on the methods and data sources used. The implications of this finding could be interpreted in two ways: either differences between LTS methods and data sources ought to be clearly acknowledged to reduce the likelihood of inappropriate comparison, or results that differ from the those of the original Mekuria LTS might be considered "wrong." The authors prefer the former approach because it allows for LTS to be adaptable to evolving contexts and improvements in theory and evidence about what constitutes high-quality cycleways. If multiple LTS methods are going to coexist, however, they need to be clearly differentiated in order to avoid apples-to-oranges comparisons.

Taking a cue from Furth's "LTS 2.0," the authors recommend that planners adopt more careful naming conventions in order to distinguish variants. This report demonstrates an author name-based convention: e.g., *Mekuria* LTS, or *ODoT* LTS. Key data sources should also be noted prominently. Methods and data sources ought to be emphasized in titles, abstracts, and introductions so that readers more thoroughly understand that an analysis reflects a particular interpretation of the LTS concept, and not a universal method. For example, an analysis might be titled: "Using the Lowry LTS with OpenStreetMap Data to Identify Low-Stress Cycleways in Oakland, CA." A simpler version—"Using LTS to Identify Low-Stress Cycleways…"—would inappropriately imply that LTS is a universally-defined method. Because LTS methods are so varied, they require more specific labeling.

This study also demonstrated the value of comparing LTS methods in order to better understand what methodological and data differences influence their results. In many cases, it is beyond the reasonable scope of an LTS study to apply multiple methods and compare their results. If resources are constrained, planners might nonetheless begin a study by comparing several methods along a small subset of streets, drawing on both audited and existing data to understand how different methods and data sources might unintentionally bias results. Such a pre-study might reveal the importance of more widespread auditing of critical variables for the full-scale analysis, or reveal the utility of one LTS method over another for revealing important case-specific factors. At a minimum, it would provide awareness of data gaps and methodological differences that could be used to contextualize more widespread results. If sufficient data are available, analysts are encouraged to calculate LTS levels across their full study area using several methods, allowing them to determine points of ambiguity or conflict, and which of the methods best represents users' interpretations of the cycling network. The Python code provided alongside this study can help analysts efficiently apply the seven LTS methods examined here. While different LTS methods and data sources may produce substantially different outcomes, it is important to confront these differences transparently, and comparing them may enrich LTS analyses.

Another key finding was that LTS levels derived from most methods and data sources were consistently correlated, albeit weakly, with an independent measure of cyclist satisfaction: Ride Report score. This suggested that LTS may serve as a reasonable indicator of satisfactory facilities. A one-level decrease in LTS was, on average, associated with a shift from the median of Ride Report Scores from its initial value to between the initial 65th and 75th percentiles, a substantial improvement. However, differences in average Ride Report scores between successive LTS levels, and even LTS extremes, did not tend to be statistically significant. Therefore, it would be imprudent for planners to claim that LTS 1 segments are necessarily more satisfactory than LTS 4 segments, though they did tend to be more satisfactory on average for most of the methods, data sources, and geographies analyzed.

An important related finding was that relationships between LTS levels and Ride Report scores were fairly linear. This provides some vindication for interpreting LTS as a continuous variable in analytical contexts where this would be useful, such as in weighting streets in a network analysis based on their LTS levels. However, analysts should still strive to interpret LTS as an ordinal variable whenever possible in order to maintain consistency with its theoretical and definitional roots. The approximate linear relationship between LTS level and percentage of satisfied riders is an empirical, not theoretical finding, and may not be valid for certain methods, data sources, or contexts. Linearity was more apparent for some methods and geographies than others. For example, Conveyal LTS levels showed a highly linear association with Ride Report scores in Portland, but not in Austin. If possible, analysts should compare their LTS results to an independent continuous measure, such as Ride Report scores or the results of a customized user survey, before using interpreting them as a continuous variable.

Thirdly, this study reinforced that certain infrastructural variables were more indicative of cyclist satisfaction than others. Measures of cycling-specific infrastructure, such as bike lanes and bicycle boulevards, exhibited some of the strongest positive correlations with Ride Report scores. A bike lane or separated bike lane corresponded with an improvement in the median Ride Report score from its initial value to between the initial 59th and 91st percentiles, depending on the facility type and data source. Bicycle boulevards corresponded with even larger improvements. Unsurprisingly, large, heavily-trafficked streets corresponded with decreases in median Ride Report score from its initial value to between the initial 43rd and 28th percentiles.

These findings show that measures of bicycle-specific infrastructure and indicators of large, heavily-trafficked streets may be the most crucial variables to include in an LTS framework. Analyses with limited capacity to collect high-quality data might prioritize these variables, or identify reliable indicators of them, and use an LTS framework that focuses on these basic criteria. For example, one reason that the Conveyal LTS may have corresponded so closely with Ride Report scores, despite being the simplest method included in this study, was that its key input variable was highway class, a close proxy for roadway size and volume. By heavily leveraging this single type of widely-available data, it out-performed, on average, much more complex methods that relied on more obscure variables with more missing or low-quality data. The tradeoff for Conveyal's high-level performance, however, was that it could not account for nuanced characteristics, such as aspects of intersection design that were captured by the Mekuria method assuming that complete and high-quality data were available.

Because street size and bicycle infrastructure were most strongly and consistently associated with Ride Report scores, planners might also prioritize these characteristics in their recommendations for actionable improvements. Unsurprisingly, these are the same conclusions that might be drawn from close examination of LTS methods. According to most of the LTS methods evaluated, reducing traffic lanes and turning lanes, reducing speed limits, reducing traffic volume, and adding bicycle-specific infrastructure are some of the clearest ways to reduce LTS levels. This conclusion may be frustrating for planners looking for ways to maintain auto-oriented streets while providing for bicycles: "how do I make this arterial into an LTS1 1?" The study's empirical findings, and the theoretical frameworks provided by LTS methods, show that this is a very unrealistic goal. The best way to reduce cyclists stress along a large, auto-oriented street is to remove traffic and dedicate more space to cyclists.

While this study provides a useful foundation for critiquing LTS variants, future work could offer several important improvements. Foremost, research could be expanded to additional cities. Portland and Austin were selected for this study on the basis of data availability, but these cities are not highly representative of the U.S. or global context. Portland is an eminent bicycling city within the U.S., and has been used heavily as a case study in bicycling research.[82] A potential benefit of studying Portland is that the results are comparable to this broad array of existing work.[83] Austin was included to improve the generalizability of the analysis, but this city also has unusually high levels of bicycle ridership and infrastructure compared with major U.S. cities.[84] However, aspects of the Portland analysis involving local agency data and customized Ride Report queries could not be completely replicated in Austin due to data limitations. Discrepancies in findings between the two cities reveal the importance of examining additional geographies to better understand how different cities are represented by LTS framework. Hopefully, the tools the authors have developed for efficient LTS classification will enable future analyses across a more diverse set of cities.

A more sophisticated approach for comparing LTS methods would be to investigate the degree of network connectivity they estimate, rather that comparing segment-by-segment classifications. Mekuria et al. emphasized how LTS could be used to identify discontinuities in low-stress networks, resulting in low stress "islands."[85] One way to judge the agreement of LTS methods might be to examine differences in the shapes of low-stress islands, or the degree of low-stress connectivity. Whereas direct comparisons of segment-based LTS levels effectively equalize the importance of each segment, comparing connectivity would emphasize key segments that may be responsible for linking, or separating, large portions of the network to either side. Methods that appear to be quite similar in terms of overall classification might nonetheless show substantially different connectivity if they classify only a few key segments differently. Summarizing LTS results in this way might also be more useful for planners looking to identify focused interventions.

Further development of precise and efficient methods for measuring user satisfaction is a key area for future work on bicycling research at-large. Ride Report offered a novel approach for gathering ratings from many cyclists along a large sample of street segments. However, because it relied on aggregation of binary ratings across partially-overlapping trips, it was an imprecise metric that provided only limited accountability for personal and trip characteristics. Because users contributed ratings voluntarily, it also had substantial potential for response bias. Conventional survey methods, such as randomized travel surveys or intercept surveys, cannot feasibly capture similarly-large samples of respondents or street segments, but they would likely provide deeper and more controlled insights about user perceptions. Future research should look for opportunities to improve the precision and richness of crowdsourced data, or combine it with data from more traditional surveys in order to account for user satisfaction in more precise ways.

This study helps practitioners and researchers understand the limitations of LTS methods, the extent to which they relate to cyclist satisfaction, and the individual variables that most strongly relate to cyclist satisfaction. It also provides a computational toolset for researchers and practitioners to efficiently calculate LTS levels based on a variety methods and data inputs. With these methods, analysts can evaluate the agreement LTS results derived from different methods and data sources, and their associations with other indicators of cycling quality in diverse locations. Hopefully, this will facilitate increased awareness of LTS's inherent limitations, as well as of opportunities to use it responsibly to promote lower-stress cycling infrastructure.

APPENDIX A: VARIABLE DEFINITIONS

Style Key

Monospaced: Variable name or value, OSM tag, Python-style logical statement

Italics: Audit question (see Appendix **)

*: Wildcard (any value) in OSM tag

Bike Facility Buffer Width (feet)

Audit

audit_bike_facility_buffer_width: Direct from *Bike Facility Buffer Width (lowest of both sides)* audit question. Maximum value among redundant audits.

OSM

osm_bike_facility_buffer_width: Direct from cycleway:buffer:* if this tag has a numeric value. Meters converted to feet. Otherwise, NaN.

osm_assumed_bike_facility_buffer_width: Direct from osm_bike_facility_buffer_width if explicitly available. Otherwise, assumed to be 2 if osm_separated_bike_lane is explicitly positive. Otherwise, assumed to be 0.

Portland Local

local_assumed_bike_facility_buffer_width: Assumed to be 2 if local_separated_bike_lane is explicitly positive. Otherwise, assumed to be 0.

Bike Facility Width (feet)

Audit

audit_bike_facility_width: Direct from *Bike Lane Width (lowest of both sides)* audit question. Maximum value among redundant audits.

OSM

osm_bike_facility_width: Direct from cycleway:width or cycleway:*:width if this tag has a numeric value. Meters converted to feet. Otherwise, NaN.

osm_assumed_bike_facility_width: Direct from osm_bike_facility_width if explicitly available. Otherwise, assumed to be 4 if osm_bike_lane is explicitly positive. Otherwise, assumed to be 6 if osm_separated_bike_lane is explicitly positive. Otherwise, 0.

Portland Local

local_assumed_bike_facility_width: Assumed to be 2 if local_bike_lane is explicitly positive. Otherwise, assumed to be 6 if local_separated_bike_lane is explicitly positive. Otherwise, 0.

Bike Lane (1: Yes, 0: No)

Audit

audit_bike_lane: 1 if *lane* is checked on *Bike Facility (check all that apply)* audit question. Otherwise, 0. Maximum value among redundant audits.

OSM

osm_bike_lane: 1 if lane or opposite_lane within any of the following tags: {cycleway, cycleway:backward, cycleway:right, cycleway:left, cycleway:both}. Otherwise, NaN.

osm_assumed_bike_lane: 1 if osm_bike_lane is explicitly positive. Otherwise, assumed to be 0.

Portland Local

local_bike_lane: 1 if (Facility == 'BL') and (Status == 'ACTIVE') in the City of Portland Bike Network shapefile. Otherwise, NaN.

local_assumed_bike_lane: 1 if local_bike_lane is explicitly positive. Otherwise, assumed to be 0.

Separated Bike Lane (1: Yes, 0: No)

Audit

audit_separated_bike_lane: 1 if *lane* is checked on *Bike Facility (check all that apply)* audit question and audit_bike_facility_buffer_width > 0. Otherwise, 0. Maximum value among redundant audits.

OSM

osm_separated_bike_lane: 1 if track, opposite_track or buffered_lane within any of the following tags: {cycleway, cycleway:backward, cycleway:right, cycleway:left, cycleway:both}. Otherwise, NaN.

osm_assumed_separated_bike_lane: 1 if osm_separated_bike_lane is explicitly positive or if osm_bike_facility_buffer_width is explicitly positive. Otherwise, assumed to be 0.

Portland Local

local_separated_bike_lane: 1 if (Facility in ['BBL','PBL']) and (Status == 'ACTIVE') in the City of Portland Bike Network shapefile. Otherwise, NaN.

local_assumed_separated_bike_lane: 1 if local_separated_bike_lane is explicitly positive. Otherwise, assumed to be 0.

Center Turn Lane (1: Yes, 0: No)

Audit

audit_center_turn_lane: 1 if *lane* is checked on *Center Turn Lane (at segment midpoint)* audit question. Otherwise, 0. Maximum value among redundant audits.

OSM

osm_center_turn_lane: 1 if left in turn:lanes:both_ways tag. Otherwise, NaN.

osm_assumed_center_turn_lane: 1 if osm_center_turn_lane is explicitly positive. Otherwise, assumed to be 0.

Curb-to-Curb Width (feet)

Audit

audit_curb_to_curb_width: Direct from *Curb-to-Curb Width (ft)* audit question. Maximum value among redundant audits.

OSM

osm_curb_to_curb_width: Direct from width or est_width if this tag has a numeric value. Meters converted to feet. Otherwise, NaN.

osm_assumed_curb_to_curb_width: Direct from osm_curb_to_curb_width if explicitly available. Otherwise, assumed to be (osm_assumed_lanes * 10) + (osm_assumed_parallel_parking * 16).

Portland Local

local_width: Direct from RoadWidth attribute in the City of Portland Pavement Maintenance shapefile. Otherwise, NaN.

local_assumed_width: Direct from local_width if explicitly available. Otherwise, coded as a function of osm_highway class based on 75 percentile width among known widths within each class:

80 if osm_highway == ‘trunk’

70 if osm_highway == ‘primary’

55 if osm_highway == ‘secondary’

45 if osm_highway == ‘tertiary’

35 if oms_highway in [‘residential’, ‘unclassified’]

20 if osm_highway == ‘living_street’

Lanes (count)

Audit

audit_lanes: Direct from *'Through Traffic Lanes (at segment midpoint, in all directions)'* audit question. Maximum value among redundant audits.

OSM

osm_lanes: Direct from lanes tag if it has a numeric value. Meters converted to feet. Otherwise, NaN.

osm_assumed_lanes: Direct from osm_lanes if explicitly available. Otherwise, coded as a function of OSM highway classes based on 75 percentile among known local_lanes within each class:

2 if osm_highway in ['trunk', 'tertiary' ,'residential', 'unclassified', 'living_street']

4 if osm_highway in ['primary', 'secondary']

Portland Local

local_lanes: Direct from NumberOfLa attribute in the City of Portland Pavement Maintenance shapefile. Otherwise, NaN.

local_assumed_lanes: Direct from local_lanes if explicitly available. Otherwise, coded as a function of osm_highway class based on 75 percentile among known local_lanes within each class:

2 if osm_highway in ['trunk', 'tertiary' ,'residential', 'unclassified', 'living_street']

4 if osm_highway in ['primary', 'secondary']

One Way (1: Yes, 0: No)

Audit

audit_oneway: Direct from *'One Way'* audit question. Maximum value among redundant audits.

OSM

osm_oneway: 1 if 'yes' or -1 in the oneway tag. 0 if 'no' in the oneway tag. Otherwise, NaN.

osm_assumed_oneway: Direct from osm_oneway if explicitly available. Otherwise, assumed to be 0.

osm_oneway_based_on_parallel: Direct from osm_assumed_oneway but adjusted to 0 for segments that have a closely aligned parallel segment (i.e., a dual carriageway). These segments are classified as one way in the OSM database for routing purposes, but are actually just one side of a larger, two way street with a median. This aligns better with the definition of one way streets used by the audit.

Left Turn Lanes (count)

Audit

audit_left_turn_lanes: Direct from *'Left Turn Lanes (Sample Street)'* audit question. Maximum value among redundant audits and ends of each audited segment.

OSM

osm_left_turn_lanes: Count of instances of left or slight_left within values of the following tags: {turn:lanes, turn:lanes:forward, turn:lanes:backward}. Otherwise, NaN. Values for these tags take the following form: turn:lanes=left|through|right|right, which denotes a left turn lane, a through lane, and two right turn lanes.

osm_assumed_left_turn_lanes: Direct from osm_left_turn_lanes if explicitly available. Otherwise, assumed to be 0.

Portland Local

local_assumed_left_turn_lanes: No data available. Assumed to be 0 for all segments.

Right Turn Lanes (count)

Audit

audit_right_turn_lanes: Direct from *'Right Turn Lanes (Sample Street)'* audit question. Maximum value among redundant audits and ends of each audited segment.

OSM

osm_right_turn_lanes: Count of instances of 'right' or 'slight_right' within values of the following tags: {turn:lanes, turn:lanes:forward, turn:lanes:backward}. Otherwise, NaN. Values for these tags take the following form: turn:lanes=left|through|right|right, which denotes a left turn lane, a through lane, and two right turn lanes.

osm_assumed_right_turn_lanes: Direct from osm_right_turn_lanes if explicitly available. Otherwise, assumed to be 1 if osm_highway == 'primary'. Otherwise, assumed to be 0.

Portland Local

local_right_turn_lanes: 1 if right arrow symbol (SymbolStyl == 'AR') from the City of Portland Pavement Marking Symbols shapefile within 20 meters of a segment center line. Otherwise, assumed to be 0.

High Speed Right Turn Lane (binary)

Audit

audit_high_speed_right_turn: 1 if 'Rounded Corner (>15 mph)' marked for *'Right Turn Radius (Sample Street)'* audit question. Otherwise, 0. Maximum value among redundant audits.

OSM

osm_assumed_high_speed_right_turn: 1 if osm_highway in ['trunk', 'primary']. Otherwise, assumed to be 0

Portland Local

local_assumed_high_speed_right_turn: 1 if osm_highway in ['trunk', 'primary']. Otherwise, assumed to be 0

Parking (1: Yes, 0: No)

Audit

audit_parking: 1 if 'One Side' or 'Both Sides' in response to *'Parking'* audit question. Otherwise, 0. Maximum value among redundant audits.

OSM

osm_parallel_parking: 1 if 'marked', 'parallel' or 'inline' within any of the following tags: {parking:lane:right, parking:lane:left, parking:lane:both}. Otherwise, NaN.

osm_assumed_parallel_parking: Direct from osm_parallel_parking if explicitly available. Otherwise, assumed to be 0 if osm_highway in ['primary', 'secondary', 'tertiary']. Otherwise, assumed to be 1.

osm_perpendicular_parking: 1 if 'perpendicular', 'orthogonal' or 'diagonal' within any of the following tags: {parking:lane:right, parking:lane:left, parking:lane:both}. Otherwise, NaN.

osm_assumed_perpendicular_parking: Direct from osm_perpendicular_parking if explicitly available. Otherwise, assumed to be 0

Portland Local

local_parking: 0 if all parking slots in the City of Portland Parking Slots shapefile, on both sides of a segment, are labeled 'no parking' (ParkingDur == 'NOPARKING'). Otherwise, 0 if 'No Parking This Block' signs in the City of Portland Signs shapefile (SignCode == 'P1060') are on both sides of a segment. Otherwise, assumed to be 1.

Speed Limit (mph)

OSM

osm_speed_limit: Direct from maxspeed, maxspeed:forward or maxspeed:backward tags if they have a numeric value. Kilometers per hour converted to miles per hour, as necessary (units parsed from value suffixes). Otherwise, NaN.

osm_assumed_speed_limit: Direct from osm_speed_limit if explicitly available. Otherwise, coded as a function of osm_highway class based on 75 percentile among known local_speed_limit within each class:

45 if osm_highway == 'trunk'

35 if osm_highway in ['primary', 'secondary']

30 if osm_highway == 'tertiary'

25 if oms_highway in ['residential', 'unclassified']

15 if osm_highway == 'living_street'

Portland Local

local_speed_limit: Direct from SpeedLimit field of the City of Portland Speed Limits shapefile. Otherwise, NaN.

local_assumed_speed_limit: Direct from local_speed_limit if explicitly available. Otherwise, coded as a function of osm_highway class based on 75 percentile among known local_speed_limit within each class:

45 if osm_highway == 'trunk'

35 if osm_highway in ['primary', 'secondary']

30 if osm_highway == 'tertiary'

25 if oms_highway in ['residential', 'unclassified']

15 if osm_highway == 'living_street'

Traffic Signal (1: Yes, 0: No)

Audit

audit_traffic_signal: 1 if 'Stop Light' or 'RRFB' marked in *'Intersection Control'* audit question. Otherwise, 0. Maximum value among redundant audits and ends of each audited segment.

OSM

osm_traffic_signal: 1 if 'traffic_signals' within the highway tag of the node at either end of a segment. Otherwise, NaN.

osm_assumed_traffic_signal: Direct from osm_traffic_signal if explicitly available. Otherwise, 0.

Portland Local

local_traffic_signal: 1 if a traffic signal point from City of Portland Traffic Signals shapefile is within 30 meters of either end of a segment. Otherwise, 0.

Highway Class (categorical)

OSM

osm_highway: Direct from highway tag of each segment.

ADT (count)

OSM

osm_assumed_adt: coded as a function of osm_highway class based on 75 percentile among known local_awd within each class:

30000 if osm_highway == 'trunk'

20000 if osm_highway == 'primary'

10000 if osm_highway == 'secondary'

5000 if osm_highway == 'tertiary'

1500 if oms_highway in ['residential', 'unclassified']

500 if osm_highway == 'living_street'

Portland Local

local_awd: Direct from AWD_volume field of the '2015_AWD_volumes' shapefile from the Portland Bureau of Transportation (PBoT). Otherwise, NaN.

local_assumed_adt: Direct from local_awd if explicitly available. Otherwise, coded as a function of osm_highway class based on 75 percentile among known local_awd within each class:

30000 if osm_highway == 'trunk'

20000 if osm_highway == 'primary'

10000 if osm_highway == 'secondary'

5000 if osm_highway == 'tertiary'

1500 if oms_highway in ['residential', 'unclassified']

500 if osm_highway == 'living_street'

Residential Street (1: Yes, 0: No)

Audit

audit_residential: 1 if 'Residential' or 'Bike Boulevard/Neighborhood Greenway' marked in *'Street Type'* audit question. Otherwise, 0. Maximum value among redundant audits.

OSM

osm_highway_residential: 1 if osm_highway == 'residential'. Otherwise, 0.

Portland Local

local_residential: 1 if ('Dwelling' in CMP_DESC) and ('High' not in CMP_DESC) from City of Portland Zoning districts adjacent to each segment. Otherwise, 0.

Bike Lane Obstructed (1: Yes, 0: No)

Audit

audit_bike_lane_obstructed: 1 if 'Yes' in *'Bike Lane Obstructed'* audit question. Otherwise, 0. Maximum value among redundant audits.

OSM

osm_assumed_bike_lane_obstructed: 1 if for all segments.

Portland Local

local_high_intensity: 1 if ('Mixed' in CMP_DESC) or ('Central' in CMP_DESC) or ('High' in CMP_DESC) from City of Portland Zoning districts adjacent to each segment. Otherwise, 0.

Bike Lane Aligned Through Intersection (1: Yes, 0: No)

Audit

audit_bike_lane_aligned: 1 if 'Straight' in *'Bike Lane Approach to Intersection (Sample Street)'* audit question. Otherwise, 0. Maximum value among redundant audits and ends of each audited segment.

OSM

osm_assumed_bike_lane_aligned: 1 if osm_highway in ['trunk','primary']. Otherwise, 0.

Portland Local

local_assumed_bike_lane_aligned: 1 if osm_highway in ['trunk','primary']. Otherwise, 0.

Bike Lane Continuous Through Intersection (1: Yes, 0: No)

Audit

audit_bike_lane_continuous: 1 if ‘Straight’ or ‘Skewed’ marked (but not `Dropped`) in *‘Bike Lane Approach to Intersection (Sample Street)’* audit question. Otherwise, 0. Maximum value among redundant audits and ends of each audited segment.

OSM

osm_assumed_bike_lane_continuous: 1 if osm_bike_lane or osm_separated_bike_lane are explicitly positive. Otherwise, 0.

Portland Local

local_assumed_bike_lane_continuous: 1 if local_bike_lane or local_separated_bike_lane are explicitly positive. Otherwise, 0.

Pedestrian Refuge Across Cross Street (1: Yes, 0: No)

Audit

audit_cross_street_island: 1 if ‘Yes (>6 ft wide)’ marked in *‘Median Refuge (Cross Street)’* audit question. Otherwise, 0. Maximum value among redundant audits and ends of each audited segment.

OSM

osm_assumed_cross_street_island: 0 for all segments.

Portland Local

local_cross_street_island: 1 if a pedestrian refuge point (IslandType == 3340) from the City of Portland Traffic Islands and Circles shapefile within 20 meters of either end of a segment. Otherwise, 0.

APPENDIX B: STREET SEGMENT AUDIT FORM

LTS Segment Attributes

* Required

1. **Auditor Name** *

2. **Segment ID** *

3. **Street Name** *

4. **Street Type** *
Mark only one oval.
- ◯ Residential
- ◯ Bike Boulevard/Neighborhood Greenway
- ◯ Neighborhood Commercial
- ◯ Downtown Commercial
- ◯ Suburban/Strip Commercial
- ◯ Industrial
- ◯ Other
- ◯ Unable to Identify

5. **Bike Facility (check all that apply)** *
Mark only one oval.
- ◯ None *After the last question in this section, skip to question 22.*
- ◯ Route *After the last question in this section, skip to question 22.*
- ◯ Sharrow *After the last question in this section, skip to question 22.*
- ◯ Paved Shoulder
- ◯ Lane
- ◯ Sidepath *After the last question in this section, skip to question 22.*
- ◯ Unable to Identify *After the last question in this section, skip to question 22.*

6. **Through Traffic Lanes (at segment midpoint, in all directions)** *

7. **One Way** *
Mark only one oval.

- Yes
- No
- Unable to Identify

8. **Centerline** *
Mark only one oval.

- Yes
- No
- Unable to Identify

9. **Center Turn Lane (at segment midpoint)** *
Mark only one oval.

- Yes
- No
- Unable to Identify

10. **Raised Median** *
Mark only one oval.

- Yes
- No
- Unable to Identify

11. **Residential Driveways (count) (both sides)** *

12. **Commercial Driveways (count) (both sides)** *

13. **Moving Cars (Street View) (count)** *

14. **Moving Cars (Aerial Image) (count)** *

15. **Curb-to-Curb Width (ft)** *

16. **Parking** *
Mark only one oval.

- One Side
- Both Sides
- None

17. **Parking Lane Width (lowest of both sides)** *
Mark only one oval.

- No Parking
- No Lane Markings (but parking along curb)
- 5 ft
- 6 ft
- 7 ft
- 8 ft
- 9 ft
- 10 ft
- 11 ft
- 12 ft
- 14 ft
- 15 ft
- > 15 ft
- Unable to Identify

Bike Lane Specifics

"Lane" here includes sidepaths and paved shoulders

18. **Bike Lane Obstructed** *
Mark only one oval.

- Yes
- No
- Unable to Identify

19. **Bike Lane Width (lowest of both sides)** *
Mark only one oval.

- 1 ft
- 2 ft
- 3 ft
- 4 ft
- 5 ft
- 6ft
- 7ft
- 8 ft
- 9 ft
- 10 ft
- > 10 ft
- Unable to Identify

20. **Bike Lane Buffer (check all that apply)** *
Check all that apply.

- [ ] No Buffer
- [ ] Painted
- [ ] Contrasting Pavement
- [ ] Flexible Bollards
- [ ] Rigid Bollards
- [ ] Bumps
- [ ] Curb/Narrow Median
- [ ] Continuous Wall/Fence
- [ ] Parked Cars
- [ ] Raised
- [ ] Unable to Identify

21. **Bike Facility Buffer Width (lowest of both sides)** *
Mark only one oval.

- No Buffer
- 1 ft
- 2 ft
- 3 ft
- 4 ft
- 5 ft
- 6ft
- 7ft
- 8 ft
- 9 ft
- 10 ft
- > 10 ft
- Unable to Identify

Intersection 1

22. **Cross Street Name** *

____

23. **Intersection Control** *
Check all that apply.

- [ ] None (or Yield)
- [ ] Four Way Stop Sign
- [ ] Sample Street Stop Sign (Cross street does not stop)
- [ ] Cross Street Stop Sign (Sample street does not stop)
- [ ] Stop Light
- [ ] Bike/Ped Warning Light (e.g., RRFB)
- [ ] Roundabout
- [ ] Curb Bumpout
- [ ] Unable to Identify

24. **Right Turn Radius (Sample Street)** *
Mark only one oval.

- Tight Corner (<15 mph)
- Rounded Corner (>15 mph)
- Unable to Identify

25. **Right Turn Lanes (Sample Street)** *
Mark only one oval.

- None
- 1
- 2
- 3
- >3
- Unable to Identify

26. **Right Turn Lane Length (ft) (Sample Street)**

____

27. **Bike Lane Approach to Intersection (Sample Street)** *
Mark only one oval.

- No Bike Lane
- Dropped
- Straight
- Skewed
- Unable to Identify

28. **Left Turn Lanes (Sample Street)** *
Mark only one oval.

- None
- 1
- 2
- 3
- >3
- Unable to Identify

29. **Traffic Lanes (Cross Street)** *

____

30. **Median Refuge (Cross Street)** *

Mark only one oval.

- Yes (>6 ft wide)
- No
- Unable to Identify

Intersection 2

31. **Cross Street Name** *

____

32. **Intersection Control** *

Check all that apply.

- [ ] None (or Yield)
- [ ] Four Way Stop Sign
- [ ] Sample Street Stop Sign (Cross street does not stop)
- [ ] Cross Street Stop Sign (Sample street does not stop)
- [ ] Stop Light
- [ ] Bike/Ped Warning Light (e.g., RRFB)
- [ ] Roundabout
- [ ] Curb Bumpout
- [ ] Unable to Identify

33. **Right Turn Radius (Sample Street)** *

Mark only one oval.

- Tight Corner (<15 mph)
- Rounded Corner (>15 mph)
- Unable to Identify

34. **Right Turn Lanes (Sample Street)** *

Mark only one oval.

- None
- 1
- 2
- 3
- >3
- Unable to Identify

35. **Right Turn Lane Length (ft) (Sample Street)**

____

36. **Bike Lane Approach to Intersection (Sample Street)** *
Mark only one oval.

- ◯ No Bike Lane
- ◯ Dropped
- ◯ Straight
- ◯ Skewed
- ◯ Unable to Identify

37. **Left Turn Lanes (Sample Street)** *
Mark only one oval.

- ◯ None
- ◯ 1
- ◯ 2
- ◯ 3
- ◯ >3
- ◯ Unable to Identify

38. **Traffic Lanes (Cross Street)** *

____

39. **Median Refuge (Cross Street)** *
Mark only one oval.

- ◯ Yes (>6 ft wide)
- ◯ No
- ◯ Unable to Identify

Segment Notes

40.

____
____
____
____
____

APPENDIX C: ORIGINAL CLASSIFICATION TABLES FOR LTS METHODS

Conveyal [86]

Webpage: https://blog.conveyal.com/better-measures-of-bike-accessibility-d875ae-5ed831

Javascript code: https://github.com/conveyal/r5/blob/master/src/main/java/com/conveyal/r5/labeling/LevelOfTrafficStressLabeler.java

Rules Summary:

Does not allow cars: LTS 1

Is a service road: Unknown LTS

Is residential or living street: LTS 1

Has 3 or fewer lanes and max speed 25 mph or less: LTS 2

Has 3 or fewer lanes and unknown max speed: LTS 2

Is tertiary or smaller road:

- Has unknown lanes and max speed 25 mph or less: LTS 2
- Has bike lane: LTS 2
- Otherwise: LTS 3

Is larger than tertiary road

- Has bike lane: LTS 3
- Otherwise: LTS 4

Furth [87]

Webpage: http://www.northeastern.edu/peter.furth/criteria-for-level-of-traffic-stress/

Classification Tables:

Level of Traffic Stress Criteria for Road Segments, version 2.0, June, 2017

Mixed traffic criteria

Number of lanes	Effective ADT*	Prevailing Speed ≤ 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 3	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

Bike lanes and shoulders not adjacent to a parking lane

Number of lanes	Bike lane width	Prevailing Speed ≤ 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.

Bike lanes alongside a parking lane

Number of lanes	Bike lane reach = Bike + Pkg lane width	Prevailing Speed ≤ 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.

Lowry [88]

Journal Article: https://www.sciencedirect.com/science/article/pii/S0965856416000306

Classification Tables:

Roadway Number of Lanes	Speed Limit	Roadway Stress w/out Bicycle Accommodation	Stress Reduction from Bicycle Accommodations: Bike Route 5%	Sharrows 10%	Bike Lane 50%	Buffered Bike Lane 65%	Protected Bike Lane 75%
2 lanes (residential)	Up to 25 mph	10%	10%	9%	5%	4%	3%
2 lanes (residential)	30 mph	15%	14%	14%	8%	5%	4%
2-3 lanes	Up to 25 mph	20%	19%	18%	10%	7%	5%
4-5 lanes	Up to 25 mph	35%	33%	32%	18%	12%	9%
2-3 lanes	30 mph	40%	38%	36%	20%	14%	10%
6+ lanes	Up to 25 mph	67%	64%	60%	34%	23%	17%
4-5 lanes	30 mph	70%	67%	63%	35%	25%	18%
6+ lanes	30 mph	80%	76%	72%	40%	28%	20%
2-3 lanes	35+ mph	100%	95%	90%	50%	35%	25%
4-5 lanes	35+ mph	120%	114%	108%	60%	42%	30%
6+ lanes	35+ mph	140%	133%	126%	70%	49%	35%

Level of Traffic Stress Limits

LTS 1 Limit:	10%	LTS 2 Limit:	30%	LTS 3 Limit:	60%	LTS 4 Limit:	no MRS limit

Fig. 1. Stress in terms of MRS for various types of roadway and bicycle accommodation.

Cross Street Number of Lanes	Speed Limit	Cross Street Stress w/out Bicycle Accommodation	Stress Reduction: Traffic Signal or Functional Priority 60%
2 lanes (residential)	Up to 25 mph	10%	4%
2 lanes (residential)	30 mph	15%	6%
2-3 lanes	Up to 25 mph	20%	8%
4-5 lanes	Up to 25 mph	35%	14%
2-3 lanes	30 mph	40%	16%
6+ lanes	Up to 25 mph	67%	27%
4-5 lanes	30 mph	70%	28%
6+ lanes	30 mph	80%	32%
2-3 lanes	35+ mph	100%	40%
4-5 lanes	35+ mph	120%	48%
6+ lanes	35+ mph	140%	56%

Fig. 2. Crossing stress (see Fig. 1 for stress limits).

Mekuria [89]

Report: https://transweb.sjsu.edu/research/low-stress-bicycling-and-network-connectivi-ty

Classification Tables:

Table 2. Criteria for Bike Lanes Alongside a Parking Lane

	LTS ≥ 1	LTS ≥ 2	LTS ≥ 3	LTS ≥ 4
Street width (through lanes per direction)	1	(no effect)	2 or more	(no effect)
Sum of bike lane and parking lane width (includes marked buffer and paved gutter)	15 ft. or more	14 or 14.5 ft.[a]	13.5 ft. or less	(no effect)
Speed limit or prevailing speed	25 mph or less	30 mph	35 mph	40 mph or more
Bike lane blockage (typically applies in commercial areas)	rare	(no effect)	frequent	(no effect)

Note: (no effect) = factor does not trigger an increase to this level of traffic stress.

[a] *If speed limit < 25 mph or Class = residential, then any width is acceptable for LTS 2.*

Table 3. Criteria for Bike Lanes Not Alongside a Parking Lane

	LTS ≥ 1	LTS ≥ 2	LTS ≥ 3	LTS ≥ 4
Street width (through lanes per direction)	1	2, if directions are separated by a raised median	more than 2, or 2 without a separating median	(no effect)
Bike lane width (includes marked buffer and paved gutter)	6 ft. or more	5.5 ft. or less	(no effect)	(no effect)
Speed limit or prevailing speed	30 mph or less	(no effect)	35 mph	40 mph or more
Bike lane blockage (may apply in commercial areas)	rare	(no effect)	frequent	(no effect)

Note: (no effect) = factor does not trigger an increase to this level of traffic stress.

Table 4. Criteria for Level of Traffic Stress in Mixed Traffic

	Street Width		
Speed Limit	2-3 lanes	4-5 lanes	6+ lanes
Up to 25 mph	LTS 1[a] or 2[a]	LTS 3	LTS 4
30 mph	LTS 2[a] or 3[a]	LTS 4	LTS 4
35+ mph	LTS 4	LTS 4	LTS 4

Note: [a] Use lower value for streets without marked centerlines or classified as residential and with fewer than 3 lanes; use higher value otherwise.

Table 5. Level of Traffic Stress Criteria for Pocket Bike Lanes

Configuration	Level of Traffic Stress
Single right-turn lane up to 150 ft. long, starting abruptly while the bike lane continues straight, and having an intersection angle and curb radius 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, and having an intersection angle and curb radius such that turning speed is ≤ 20 mph.	LTS ≥ 3
Single right-turn lane in which the bike lane shifts to the left but the 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 along with an option (through-right) lane.	LTS = 4

Table 6. Level of Traffic Stress Criteria for Mixed Traffic in the Presence of a Right-turn Lane

Configuration	Level of Traffic Stress
Single right-turn lane with length ≤ 75 ft. and intersection angle and curb radius limit turning speed to 15 mph.	(no effect on LTS)
Single right-turn lane with length between 75 and 150 ft., and intersection angle and curb radius limit turning speed to 15 mph.	LTS ≥ 3
Otherwise.	LTS = 4

Table 7. Level of Traffic Stress Criteria for Unsignalized Crossings Without a Median Refuge

Speed Limit of Street Being Crossed	Width of Street Being Crossed		
	Up to 3 lanes	4 - 5 lanes	6+ lanes
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

Table 8. Level of Traffic Stress Criteria for Unsignalized Crossings With a Median Refuge at Least Six Feet Wide

Speed Limit of Street Being Crossed	Width of Street Being Crossed		
	Up to 3 lanes	4 - 5 lanes	6+ lanes
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

Montgomery [90]

Website: http://www.mcatlas.org/bikestress/

Classification Tables: (right and next page)

Level of Traffic Stress Methodology for Street Segments

Posted Speed Limit (mph)	# of Through Lanes	Mixed Traffic / Priority Shared Lane Markings						Bike Lanes							Shared Use Path			Separated Bike Lanes				Bikeable Shoulders	Neighborhood Greenway	Shared Street
		No Parking		Parking				No Parking			Parking													
								Infrequenly Obstructed		Frequently Obstructed	Infrequenly Obstructed / Low Parking Turnover			Frequently Obstructed / High Parking Turnover										
		Center Line	No Center Line	Center Line & High Parking Turnover	Center Line & Low Parking Turnover	No Center Line & Non-Residential	No Center Line & Residential	Bike Lane ≤ 5.5 ft	Bike Lane ≥ 6.0 ft		Bike Lane + Parking < 14.0 ft	Bike Lane + Parking = 14.0 - 14.5 ft	Bike Lane + Parking = 15.0 ft		Sidepath with Buffer < 5 ft (and no railing) OR Many Driveways	Sidepath with Buffer ≥ 5 ft (or railing) AND Few Driveways	Independent ROW	Flex Posts	Separated Bike Lanes with Buffer < 5 ft (and no railing) OR Many Driveways	Separated Bike Lanes with Buffer ≥ 5 ft (or railing) AND Few Driveways	Parked Cars			
	2-3	3 (2^{c})	2 (1^{d})	2.5	2	2.5	2 (1^{d})	2	1	2.5	2.5 (2^{a})	2	1	2.5	2 (1^{a})			1				2		
≤25	4-5	3	n/a	3	3	n/a	n/a	2.5 (2^{b})	2.5 (2^{b})	2.5	3				2	1	0	2	2	1	1	2.5 (2^{b})	1	1
	≥6	4	n/a	4	4	n/a	n/a	3			3				2			2.5				3		
	2-3	3	2	3	3	2.5	2	2	2	2.5	2.5	2	2	2.5	2 (1^{a})			2				2		
30	4-5	4	n/a	4	4	n/a	n/a	2.5 (2^{b})	2.5 (2^{b})	2.5	3				2	1	0	2.5	2	1	1	2.5 (2^{b})	1	1
	≥6	4	n/a	4	4	n/a	n/a	3			3				2			2.5				3		
	2-3																	2						
35	4-5	4	n/a	4	4	n/a	n/a	3			3				2	1	0	2.5	2	1	1	3	1	1
	≥6																	2.5						
	2-3							3														3		
40	4-5	4	n/a	4	4	n/a	n/a	4 (3^{b})			n/a				2.5	2 (1^{e})	0	2.5	2.5	2 (1^{e})	n/a	4 (3b)	1	1
	≥6							4														4		
	2-3																							
≥45	4-5	5	n/a	5	5	n/a	n/a	4			n/a				2.5	2 (1^{e})	0	2.5	2.5	2 (1^{e})	n/a	4	1	1
	≥6																							

Notes
- a if road is residential or posted speed limit is < 25 mph
- b if there is a raised median
- c if ADT < 6,000 ADT
- d if ADT < 3,000 ADT
- e if buffer is wide

Industrial roads -- For roads that are classified as "industrial" in a master plan, the LTS is the higher of 1) the result in the segment table or 2) 2.5

Level of Traffic Stress Methodology for Intersections

Traffic Stress at Unsignalized Intersections

LTS is the more stressful of:

1. Intersection Approach Link

Posted Speed Limit on Street Being Crossed	# of Lanes of Street Being Crossed					
	No Median Refuge			Median Refuge (≥6 ft wide)		
	2 to 3	4 to 5	6+	2 to 3	4 to 5	6+
≤25	1	2	4	1	1	2
30	2	2.5	4	1	2	2.5
35	2.5	3	4	1	2.5	3
≥40	3	4	4	2	2.5	4

or

2. Street LTS (see link methodology)

Traffic Stress at Signalized Intersections

LTS of street is carried through the intersection.

Traffic Stress for Bikeways in Independent Rights-of-Way

When a bikeway in an independent right-of-way (aka a trail) crosses a street at:

1. an unsignalized location, use the above table to determine the LTS, unless there are no traffic conflicts.
2. a signalized location, the LTS is 1

Oregon Department of Transportation (ODoT) [91]

Manual: https://www.oregon.gov/ODOT/Planning/Documents/APMv2_Ch14.pdf

Classification Tables:

Exhibit 14-3 Bike Lane with Adjacent Parking Lane Criteria

1 Lane per direction				≥2 lanes per direction	
Prevailing or Posted Speed	**≥ 15' bike lane + parking**	**14' – 14.5' bike lane + parking**	**≤ 13' bike lane + parking or Frequent blockage[1]**	**≥ 15' bike lane + parking**	**≤ 14.5' bike lane + parking or Frequent blockage[1]**
≤25 mph	LTS 1	LTS 2	LTS 3	LTS 2	LTS 3
30 mph	LTS 1	LTS 2	LTS 3	LTS 2	LTS 3
35 mph	LTS 2	LTS 3	LTS 3	LTS 3	LTS 3
≥40 mph	LTS 2	LTS 4	LTS 4	LTS 3	LTS 4

[1]Typically occurs in urban areas (i.e. delivery trucks, parking maneuvers, stopped buses).

Exhibit 14-4 Bike Lane without Adjacent Parking Lane Criteria

1 Lane per direction					≥2 lanes per direction	
Prevailing or Posted Speed	≥ 7' (Buffered bike lane)	5.5' – 7' Bike lane	≤ 5.5' Bike lane	Frequent bike lane blockage[1]	≥ 7' (Buffered bike lane)	<7' bike lane or frequent blockage[1]
≤30 mph	LTS 1	LTS 1	LTS 2	LTS 3	LTS 1	LTS 3
35 mph	LTS 2	LTS 3	LTS 3	LTS 3	LTS 2	LTS 3
≥40 mph	LTS 3	LTS 4	LTS 4	LTS 4	LTS 3	LTS 4

[1]Typically occurs in urban areas (i.e. delivery trucks, parking maneuvers, stopped buses).

Exhibit 14-5 Urban/Suburban Mixed Traffic Criteria

Prevailing Speed or Speed Limit (mph)	**Unmarked Centerline**	**1 lane per direction**	**2 lanes per direction**	**3+ lanes per direction**
≤ 25[1]	LTS 1	LTS 2	LTS 3	LTS 4
30	LTS 2	LTS 3	LTS 4	LTS 4
≥ 35	LTS 3	LTS 4	LTS 4	LTS 4

[1]Presesence of "sharrow" markings may reduce the LTS by a level for 25 mph or less sections depending on overall area context.

Exhibit 14-6 Right Turn Lane Types

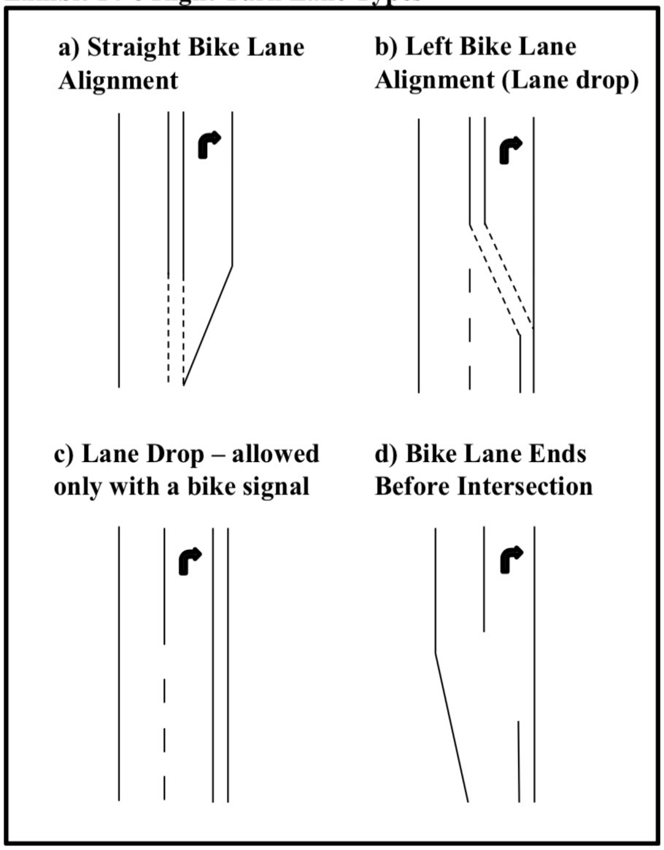

Exhibit 14-7 Right Turn Lane Criteria

Right-turn lane configuration	Right-turn lane length (ft)	Bike Lane Approach Alignment	Vehicle Turning Speed (mph)[2]	LTS
Single	≤ 150	Straight	≤ 15	2
Single	>150	Straight	≤ 20	3
Single	Any	Left	≤ 15	3
Single[1] or Dual Exclusive/ Shared	Any	Any	Any	4

[1]Any other single right turn lane configuration not shown above.
[2]This is vehicle speed at the corner, not the speed crossing the bike lane. Corner radius can also be used as a proxy for turning speeds.

Exhibit 14-8 Left Turn Lane Criteria

Prevailing Speed or Speed Limit (mph)	No lane crossed[1]	1 lane crossed	2+ lanes crossed	Dual shared or exclusive left turn lane[2]
≤25	LTS 2	LTS 2	LTS 3	LTS 4
30	LTS 2	LTS 3	LTS 4	LTS 4
≥ 35	LTS 3	LTS 4	LTS 4	LTS 4

[1]For shared through left lanes or where mixed traffic conditions occur (no bike lanes)
[2]Any other single left turn lane configuration not shown above.

Exhibit 14-9 Unsignalized Intersection Crossing Without a Median Refuge Criteria[1]

Prevailing Speed or Speed Limit (mph)	Total Lanes Crossed (Both Directions)[2]		
	≤ 3 Lanes	**4 -5 Lanes**	**≥ 6 Lanes**
≤ 25	LTS 1	LTS 2	LTS 4
30	LTS 1	LTS 2	LTS 4
35	LTS 2	LTS 3	LTS 4
≥ 40	LTS 3	LTS 4	LTS 4

[1]For street being crossed.
[2]For one-way streets use Exhibit 14-10.

Exhibit 14-10 Unsignalized Intersection Crossing With a Median Refuge Criteria[1]

Prevailing Speed or Speed Limit (mph)	Maximum Through/Turn Lanes Crossed per Direction		
	1-2 Lanes	**2-3 Lanes**	4+ **Lanes**
≤ 25	LTS 1[2]	LTS 1[2]	LTS 2
30	LTS 1[2]	LTS 2	LTS 3
35	LTS 2	LTS 3	LTS 4
≥ 40	LTS 3	LTS 4	LTS 4

[1]For street being crossed.
[2]Refuge should be at least 10 feet to accommodate a wide range of bicyclists (i.e. bicycle with a trailer) for LTS 1, otherwise LTS=2 for refuges 6 to <10 feet.

People for Bikes (PFB) [92]

Website: https://bna.peopleforbikes.org/#/methodology

Classification Tables:

Default segment assumptions

Functional class	Speed	Number of lanes	Parking	Parking lane width	Buffered bike lane width	Bike lane width (with parking)	Bike lane width (no parking)	Roadway width
Primary	40	2	Y	8 ft	6	5	4	N/A
Secondary	40	2	Y	8 ft	6	5	4	N/A
Tertiary	30	1	Y	8 ft	6	5	4	N/A
Unclassified	25	1	Y	N/A	N/A	N/A	N/A	27 ft
Residential	25	1	Y	N/A	N/A	N/A	N/A	27 ft

Default signal control assumptions*

Street classes	Signalized
Primary-Primary	Y
Primary-Secondary	Y
Primary-Tertiary	N
Primary-Residential	N
Secondary-Secondary	Y
Secondary-Tertiary	N
Secondary-Residential	N
Tertiary-Tertiary	Y
Tertiary-Residential	N
Residential-Residential	N

*Uncontrolled intersections assume a low stress crossing for travel along the higher-order roadway
(e.g. If traveling on secondary and crossing a residential, it is low stress. If traveling on residential and crossing a secondary, the stress is governed by the characteristics of the secondary roadway.)

Stress on segments (except residential or unclassified class)

Facility type	Speed	Number of lanes	Parking	Facility width	Stress
Cycle track	--------------------	--------------------	--------------------	-------------------->	Low
Buffered bike lane	> 35	> 1	--------------------	-------------------->	High
		1	--------------------	-------------------->	High
	35	> 1	--------------------	-------------------->	High
		1	Yes	-------------------->	High
			No	-------------------->	Low
	30	> 1	Yes	-------------------->	High
			No	-------------------->	Low
		1	--------------------	-------------------->	Low
	<= 25	--------------------	--------------------	-------------------->	Low
Bike lane without parking	>30	--------------------	--------------------	-------------------->	High
	25-30	> 1	--------------------	-------------------->	High
		1	--------------------	-------------------->	Low
	<= 20	> 2	--------------------	-------------------->	High
		<= 2	--------------------	-------------------->	Low
Bike lane with parking	--------------------	--------------------	-------------------->	>= 15 ft	*Treat as buffered lane*
				13-14 ft	*Treat as bike lane without parking*
				< 13 ft	*Treat as shared lane*
Shared lane	<= 20	1	--------------------	-------------------->	Low
		> 1	--------------------	-------------------->	High
	> 20	--------------------	--------------------	-------------------->	High

Stress at intersections

Intersection control	Number of crossing lanes	Crossing speed limit	Median island	Stress
None/yield to cross traffic	> 4	----------------------------------	-------------------------->	High
	4	>30	-------------------------->	High
		30	Yes	Low
			No	High
		<= 25	-------------------------->	Low
	< 4	> 30	Yes	Low
			No	High
		<= 30	-------------------------->	Low
RRFB	> 4	----------------------------------	-------------------------->	High
	4	>= 40	-------------------------->	High
		35	Yes	Low
			No	High
		<= 30	-------------------------->	Low
	< 4	> 35	Yes	Low
			No	High
		<= 35	-------------------------->	Low
Signalized, HAWK, four way stop, or priority based on class	--------------------------------------	----------------------------------	-------------------------->	Low

Stress on segments

Facility type	Speed	Number of lanes	Parking	Road width	Stress
Cycle track	----------	----------	----------	---------->	*Treat as tertiary*
Buffered bike lane	----------	----------	----------	---------->	*Treat as tertiary*
Combined bike / parking lane	----------	----------	----------	---------->	*Treat as tertiary*
Bike lane	----------	----------	----------	---------->	*Treat as tertiary*
Shared lane	>=30	----------	----------	---------->	*Treat as tertiary*
	25	>1	----------	---------->	*Treat as tertiary*
		1	One side or none	>= 19 ft	Low
				18 ft	High
				< 18 ft	High
			Both sides	>= 27 ft	Low
				26 ft	High
				< 26 ft	High
	<= 20	>1	----------	---------->	*Treat as tertiary*
		1	One side or none	>= 19 ft	Low
				18 ft	Low
				< 18 ft	Low
			Both sides	>= 27 ft	Low
				26 ft	Low
				< 26 ft	Low

APPENDIX D: STANDARDIZED RULE-BASED CLASSIFICATION TABLES FOR LTS METHODS (AVAILABLE IN ONLINE SUPPLEMENTARY MATERIALS)

ABBREVIATIONS AND ACRONYMS

ADT	Average Daily Traffic
BLos	Bicycle Level of Service
EPA	United States Environmental Protection Agency
HCM	Highway Capacity Manual
LTS	Level of Traffic Stress
PHAS	Oregon Household Activity Survey
ODoT	Oregon Department of Transportation
OSM	OpenStreetMap
PFB	People for Bikes
r_S	Spearman rank correlation coefficient
SFCTA	San Francisco County Transportation Authority
SLD	EPA Smart Location Database
VIF	Variance Inflation Factor

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PEER REVIEW

San José State University, of the California State University system, and the MTI Board of Trustees have agreed upon a peer review process required for all research published by MTI. The purpose of the review process is to ensure that the results presented are based upon a professionally acceptable research protocol.