Modeling the Impacts of Facility Type, Trip Characteristics, and Trip Stressors on Cyclists' Comfort Levels Utilizing Crowdsourced Data

Bryan Blanc and Miguel Figliozzi

Transportation agencies are striving to increase the comfort of their bicycle networks in an effort to improve the experience of existing cyclists and to attract new cyclists. To increase bicycle mode share is challenging and has motivated research to understand where and what types of bicycle improvements yield the maximum net benefit in terms of increased ridership, comfort, and safety. Data sets related to cyclists' comfort levels as a function of bicycle infrastructure are nonexistent at the state or local level. To fill this data gap, the Oregon Department of Transportation sponsored the development of ORcycle, a smartphone application designed to collect cyclist travel, comfort, and safety information. The research reported in this paper utilized ORcycle data to model cyclists' comfort levels as a function of bicycle facility types, sources of stress along the trip, and trip characteristics (e.g., purpose, length, frequency, and day of the week). Ordinal logistic regression models were estimated, and the results indicated that facility types such as bicycle boulevards and separated paths did have a significant positive impact on cyclists' comfort levels. Other variables (e.g., sources of stress along the trip, trip purpose, and trip distance) also were found to have significant impacts on comfort levels. A sensitivity analysis and a policy discussion highlight how important it is to reduce sources of stress along bicycle routes to increase bicycle ridership and attract new cyclists.

Bicycle transportation has become a central priority of urban areas invested in the improvement of sustainability, livability, and public health outcomes. Metropolitan areas around the United States have set aggressive bicycle mode–share objectives for their long-term transportation plans (*1*). The objective to increase bicycle mode share faces many challenges, such as constrained transportation infrastructure budgets, limited roadway space in dense and congested urban areas, the legacy of many decades of automobile-oriented development and street design, and the difficulty involved in the successful conversion of short automobile trips to bicycle trips through the attraction of new cyclists. These constraints and challenges have motivated research to understand where and what types of bicycle improvements yield the maximum net benefit in terms of ridership and safety. The literature consistently reports that comfort levels and perceptions of safety are key factors in increasing bicycle mode shares among current or potential riders, especially among those who are not highly competent or confident cyclists.

Although transportation agencies increasingly collect more bicycle data, information remains scant on the adequacy of existing bicycle facilities. To fill this data gap, the Oregon Department of Transportation (DOT) decided in 2013 to finance a research project (SPR 768) to develop a system to collect bicycle and network use and locate areas with low connectivity or poor user experience (*2*). This research project resulted in ORcycle, a smartphone application launched in November 2014 to collect data to understand cyclists' bicycle infrastructure preferences and safety issues. More information about the project and its goals, as well as about ORcycle and its features, is available at the Portland State University website (*3*).

The research reported in this paper utilized data crowdsourced with ORcycle to model cyclists' comfort levels as a function of bicycle facility types, sources of stress along the trip, and trip characteristics such as purpose, length, frequency, and day of the week. The models and results were novel, because this research effort was the first to use detailed revealed preference GPS-based route data to model cyclists' stated comfort levels. As detailed in the literature review section of this paper, other research efforts have collected detailed data about bicyclists, but the data collection efforts, analyses, or both, did not focus on the relationships between cyclists' comfort levels and bicycle infrastructure. The following sections describe the data collection and analysis tools, sample description, modeling results, and conclusions.

LITERATURE REVIEW

For nearly three decades, transportation engineers and planners have been attempting to estimate bicyclists' safety, comfort, stress levels, or level of service. Some metrics, such as the bicycle level of service of the *Highway Capacity Manual 2010* (*4*), are complex, because they aim to describe the performance (e.g., comfort, safety, operation) of bicycle facilities and reflect travelers' perceptions with the utilization of data directly measured in the field (*5*). A limitation of the *Highway Capacity Manual 2010* bicycle level of service is the lack of consideration for cyclists' differential preferences or trip characteristics [e.g., a parent that commutes to work can have a different comfort level if he or she travels (part of) the route with a son or daughter on the way to primary school].

B. Blanc, Nelson\Nygaard Consulting Associates, 621 Southwest Morrison Street, Suite 1250, Portland, OR 97205. M. Figliozzi, Department of Civil and Environmental Engineering, Maseeh College of Engineering and Computer Science, Portland State University, P.O. Box 751–CEE, Portland, OR 97207-0751. Corresponding author: M. Figliozzi, figliozzi@pdx.edu.

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The term "stress" is commonly understood as the opposite of "comfort"; a definition of "comfortable" in the Merriam-Webster Dictionary is "free from stress or tension." An estimation of bicycle level of stress was first attempted in 1994 as a function of safety levels, physical or mental effort, and age (*6*). More recently, the term "level of traffic stress" (LTS) has been used to refer to an evaluation method that takes into account not only traffic and geometric characteristics of the riding environment but also the suitability of the environment for different user groups within the population (*7*). The LTS term can be used to delineate islands of low-stress network connectivity, which highlight disconnections and especially stressful links within a bicycle network. Neither bicycle level of service nor LTS actually have their basis in empirical measurements of the stress of cyclists along a route. To measure physiological stress levels for real-world, on-road cyclists is possible, but quite complex, as recent research results indicate (*8*).

Other researchers have conducted stated preference studies to determine which factors most affect bicyclist comfort and travel preferences. A 2005 random phone survey ($N = 503$) in Portland, Oregon, was used to explore the relationship between cycling rates, demographics, the built environment, perceptions about the built environment, and attitudes (*9*). Key findings indicated that perceptions about the availability of comfortable bicycle infrastructure were a stronger determinant of cycling than objectively measurable characteristics about the availability of comfortable bicycle infrastructure. A 2006 survey of more than 1,400 current and potential cyclists in Vancouver, British Columbia, Canada, evaluated motivators and deterrents to cycling. Key factors that affected the stated likelihood of cycling were safety, ease of cycling, weather conditions, route conditions, and interactions with motor vehicles (*10*). In 2008, researchers in Austin, Texas, administered a statewide, web-based survey that elicited stated preference information on bicycle route choice (*11*). Model results indicated that bicyclists preferred routes with minimal on-street parking, continuous bicycle facilities, lower traffic volumes and speeds, and fewer intersections.

Another line of research used portable GPS units to record and later analyze cyclists' routes. A 2006 study in Minneapolis, Minnesota, analyzed the GPS data of 55 bicycle commuters over the course of 3 weeks (*12*). The study compared the preferred route of each cyclist with the calculated shortest route on the basis of trip distance and bicycle facility type (i.e., off-street path, on-street bike lane, road with no designated bicycle facility). Participants also reported demographic characteristics and their "cycling comfort" on a scale of 1 through 5: 1 indicated that the cyclist was comfortable only to ride on off-street paths, while 5 indicated that the cyclist was comfortable to ride on urban streets with heavy traffic. A linear regression model was tested to model the difference in length between the chosen route and the shortest route as a function of several predictors. The only independent variable found to be statistically significant was a cyclist's reported comfort level. Other variables (e.g., bicycle facility type, historical route safety, traffic control type, number of intersections along route, cycling comfort level, gender, age) were not significant. The authors posited that this finding indicated that cyclists with lower comfort levels were more willing to travel out of their way to use a preferred route rather than the shortest one. In 2007, researchers examined the cycling behavior of 164 participants in the Portland, area with the use of GPS tracking methods (*13*). The purpose of each trip was reported by the cyclists, and only utilitarian (i.e., nonexercise) trips were kept in the data set used for analysis. The results indicated that cyclists were willing to travel significantly out of their way (estimated 17.9% of trip distance) to use bicycle boulevards, while they were willing to travel even farther out of their way (estimated 72.3% trip distance) to avoid a path with a 2% to 4% upslope. Overall, the results indicated several significant characteristics associated with route choice within the sample, namely, distance, turn frequency, slope, intersection control type, traffic volumes, and bicycle facility type. A 2009 study in Zurich, Switzerland, compared chosen routes with the alternative shortest-path routes over a number of characteristics and exposed differences in the grade of the route chosen (i.e., routes chosen were less steep) and the proportion of the route chosen along dedicated bicycle facilities (i.e., routes chosen included a higher portion of dedicated bicycle facilities) (*14*). Model results also indicated that topography had a statistically significant negative impact on cyclists' utility: cyclists were choosing routes with gentler topography even if they were longer. Route length also was found to have a statistically significant impact on cyclist utility, although this finding was typical for nearly all route choice models (*14*). In 2010, GPS data were collected for 100 cyclists in Waterloo, Ontario, Canada, in combination with stated preference survey data (*15*). Five route characteristics were used as predictive variables in the route choice model: (*a*) the length of each link in the network, (*b*) the posted auto speed of each link, (*c*) the auto volume of each link, (*d*) the gradient (elevation change) of each link, and (*e*) the presence or absence of a cycling lane (*16*). The stated preference survey showed that convenience was the top motivation for cycling, while safety was the primary consideration used in route selection.

Other studies have utilized smartphone applications, but data collection and analyses have not focused on cyclist comfort levels. Instead, the research has focused on smartphone data applications to bicycle route choice models (*17*), shortest path analysis and network deficiencies (*18*), user characteristics and online participation (*19*), and injury risk modeling (*20*).

To the best of the knowledge of the authors of this present study, no research has focused on cyclists' levels of comfort with the utilization of empirical GPS-based route data and bicycle network facility data. This present study was a first step to fill this research gap.

DATA COLLECTION AND PROCESSING

In 2014, researchers at the Transportation, Technology, and People (TTP) Laboratory at Portland State University began to work in conjunction with the Oregon DOT to develop a smartphone application to collect bicycle data. The goal of this research effort was to crowdsource information from cyclists to understand empirically where they ride, why they ride, and what improvements could make their cycling experience safer and more comfortable.

In November 2014, the ORcycle application was launched, which is available for Android and iOS platforms. E-mail messages and flyers were used to promote ORcycle within Oregon by transportation agencies (i.e., the Oregon DOT, some cities, some counties). The sample analyzed here is a convenience sample of opt-in users; no targeted recruiting or incentives were used to ensure user participation. GPS trajectories were collected for each trip with a frequency of approximately 60 Hz (one coordinate per second). The raw GPS trajectory of each trip was matched to the Portland metropolitan area bicycle and street network with the use of Python scripts developed for a previous bicycle GPS study conducted by Broach et al. in the Portland region (*13*). These scripts are based on algorithms developed by Schuessler and Axhausen (*21, 22*). The data used in this present study were collected between November 2014 and May 2015, and this subset contained only Portland metropolitan area trips. Trips shorter than 0.25 mi were not included in the final data set. The final data set used for modeling here contained 729 trips from 170 unique users.

The survey questions utilized in the comfort model are detailed in the next four paragraphs. In line with the implementation of previous applications, trip purpose was selected after a trip was completed. The available trip purpose categories are outlined (one option only must be chosen):

- Commute,
- School,
- Work-related,
- Exercise,
- Social or entertainment,
- Shopping or errands,
- Transport access, or
- Other.

The following questions, which related to route comfort, trip frequency, route choice factors, and route stressors, were not included in other applications. The route comfort question asked is as follows: "In terms of comfort, this route is. . . ." The available responses are provided here (one option only must be chosen):

- Very bad (unacceptable for most riders),
- Bad (for confident riders only),
- Average,
- Good (for most riders), and
- Very good (even for families and children).

The route comfort question was designed to match the level of traffic stress scale and description (*7*) and the classification used in the Oregon DOT *Analysis Procedures Manual* (*23*). User familiarity with a route may have had an effect on route comfort. A route frequency question asked is as follows: "How often do you ride this route?" The available answers to this question are given here (one option only must be chosen):

- Several times per week,
- Several times per month,
- Several times per year,
- Once per year or less, or
- First time ever.

An innovation in ORcycle is the question that asks about sources of stress along a user's bicycle route. This question is as follows: "Along this route, are you concerned about conflicts/crashes with . . . ?" Users can select more than one option with the exception of "not concerned," which cannot be selected simultaneously with any of the other options:

- Not concerned,
- Auto traffic,
- Large commercial vehicles (trucks),
- Public transport (buses, light rail, streetcar),
- Parked vehicles (being doored),
- Other cyclists,
- Pedestrians, and
- Other.

In the latest version of ORcycle, these questions are now mandatory. However, some responses were missing to questions that were not mandatory in the first version of the applications. These missing responses were imputed with the use of the R package missForest (a multiple imputation algorithm) (*24*). The trips included in the model were weighted, because some users repeated similar trips multiple times. Trips taken by the same user, for the same reported trip purpose (mandatory question on trip completion), in the same direction, with the utilization of 90% or more of the same network links (i.e., streets, bikeways), were considered similar and were weighted on the basis of the following weighting formula:

$$\text{model weight of particular trip} = \frac{1}{\text{number of similar trips} + 1}$$

For example, if two similar trips were found, each trip counted only for half of a trip (model weight = 0.5) within the model. After the application of this similarity weighting, the total number of trips included in the model was reduced to 593.9 weighted trips. Of these weighted trips, 133.9 (23%) had the route comfort question imputed from other available survey responses.

As with respect to all travel surveys, there were biases in the data, which resulted from the user sample and the data collection method. The data set was collected between the beginning of November 2014 and the end of May 2015. Although the winter of 2014 to 2015 was relatively mild in Oregon, winter cyclists typically have preferences different from their fair-weather counterparts (*25, 26*). In addition, potential biases resulted from the method of data collection, namely, that it was necessary to have access to an iOS or Android smartphone to download the application and participate in the data collection. In a companion study, user sample bias was analyzed and quantified by comparing the smartphone sample with a sample of bicycle commuters in a traditional travel survey (*27*). Results indicated that the ORcycle sample used here was representative of the ethnicity and income distributions of Portland area cyclists, but participants were younger (on average) and more likely to be male than were the Portland area cycling population. The sample data were likely to be representative of the year-round cycling population in Portland, as opposed to the more casual or fair-weather riders.

DATA DESCRIPTION

The trip purpose distribution across the trip sample is illustrated in Table 1. More than 60% of the trips were indicated to have been commuting trips with the next highest categories as follows: shopping or errands (16%), social or entertainment (8%), and exercise (5%). Trip purpose did have an impact on trip length (Table 1). The lengths of exercise trips were significantly longer than lengths for other trip purposes. Trips to access transit or other vehicles were significantly shorter than for other trip purposes. The mean length of all trips in the data set was 5.15 mi.

The route frequency distribution indicated that nearly half of all trips (47%) were biked several times per week. The correlation was high between trips biked several times a week and trips whose purpose was to commute. Other trips were biked several times a month (22%) and several times a year (18%).

The route stressors' distribution across the trip sample is illustrated in Figure 1. Users could select more than one response to this question. The average number of responses per trip was 1.8. For

TABLE 1 Trip Purpose and Trip Length Distribution

Trip Purpose	Proportion of Sample (%)	Distance (mi) Minimum	25th Percentile	Median	Mean	75th Percentile	Maximum
Commute	61.2	0.6	4.3	4.7	5.6	6.5	22.1
Shopping or errands	15.6	0.3	1.4	3.1	3.5	4.8	19.4
Social or entertainment	7.9	0.6	1.9	3.1	3.6	4.3	19.3
Exercise	4.5	2.0	4.8	9.7	10.3	13.1	29.2
Work-related	4.2	0.7	2.4	4.0	4.3	6.1	9.0
Other	3.1	0.3	2.4	3.5	3.8	4.7	11.5
School	3.0	1.2	3.0	3.8	4.2	4.9	11.4
Transportation access	0.4	0.4	1.1	1.8	1.4	1.9	2.1

approximately 38% of the trips, there was no answer (this question was optional and some users declined to provide this information), but on most trips (57%) users indicated that they were concerned about conflicts with automobile traffic. Other high categories of concern included large commercial vehicles (27%) and parked vehicles (32%). Cyclists indicated that they were not concerned about any stressors for roughly 8% of the trips (Figure 1).

The analyzed roadway categories follow:

- Primary arterials. Multilane roads that carry high traffic volumes at high speeds,
- Minor arterials. Two-lane or multilane roads that carry moderate traffic volumes at moderate speeds,
- Residential streets. Two- or one-way streets primarily used for residential access, and
- Other. Streets that do not fit into the other three categories.

Bicycle facilities follow:

- Bicycle lanes. Dedicated road space for cyclists delineated only by striping, with no lateral separation between bicyclists and motor vehicle traffic.
- Buffered bicycle lanes. Similar to bicycle lanes, with extra buffer space allocated on the roadway through the use of striping to increase the lateral separation between bicyclists and motor vehicle traffic.
- Bicycle boulevards. Low-traffic streets designated for bicycle travel. They feature bicycle route signage and pavement markings, traffic-calming features (e.g., traffic circles, speed humps), and motor vehicle traffic diversion at major intersections.
- Cycletracks. Lateral separation is enforced through some physical buffer (e.g., planters, plastic posts, parked cars, raised concrete barriers) or other treatments.
- Separated paths. Facilities on which motor vehicle traffic is prohibited, but bicycle traffic is allowed or encouraged.
- No bicycle facility. No bicycle facility exists on the particular link that matches any of the bicycle facilities described here. In such case, bicyclists share the traffic lane with motor vehicle traffic, and no special consideration is given to bicyclists.

The summary of the bicycle facility and the roadway type of the links used on each trip is shown in Figure 2. This figure is relevant in the next section in which comfort models are discussed. Most of the trip miles in the model were concentrated on residential

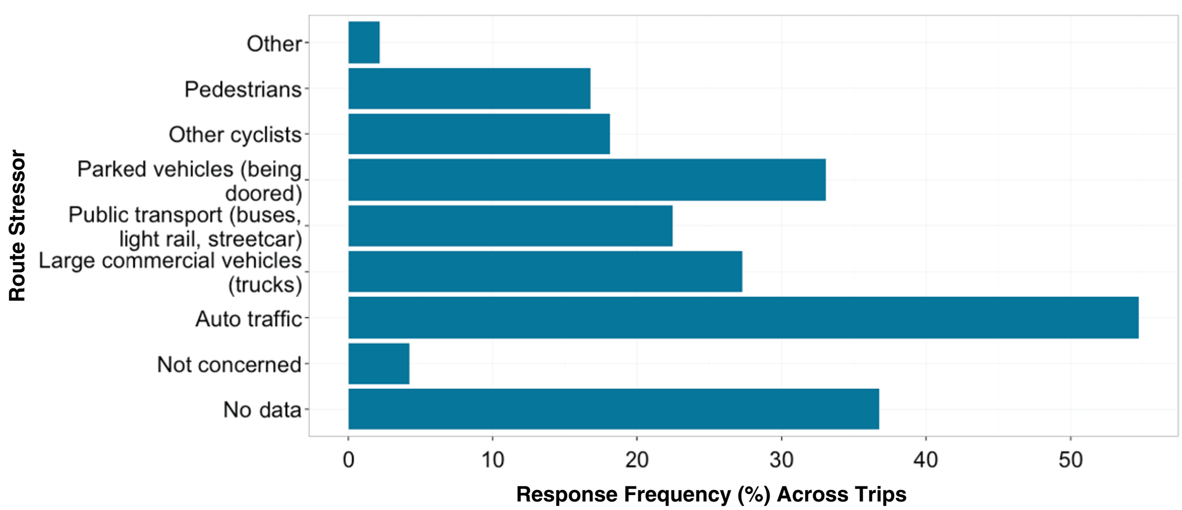

FIGURE 1 Trip stressors distribution (route stressor number of trips = 729).

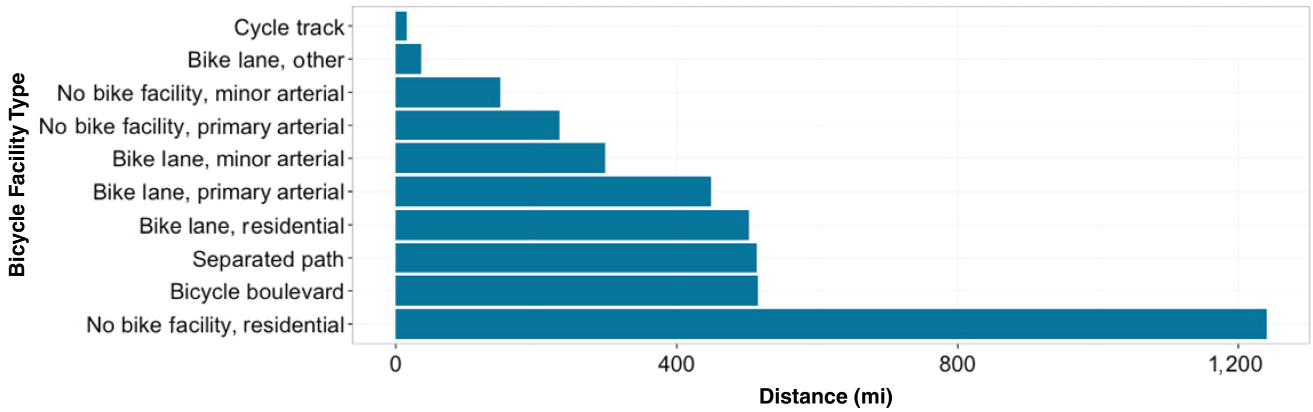

FIGURE 2 Bicycle facility type distribution.

streets with and without bicycle facilities, bicycle boulevards, and separated paths.

DATA ANALYSIS

A goal of this research was to test the feasibility of the use of ORcycle data to study cyclists' comfort levels. The utilization of revealed preference GPS route data to study cyclists' comfort levels had never been attempted. As a preliminary exploratory analysis, route comfort was compared with each independent variable available separately, with the use of an ordinal logistic regression model. Ordinal logistic regression has been used in several level-of-service models (*28–30*). Ordinal logistic regression models (also known as cumulative logistic regression models) are suitable for this research, because they are used to model categorical dependent variables of an ordered nature. The ordinal logistic regression model results presented here were calculated with the use of the R package ordinal (*31*).

The results of the exploratory analysis were promising and intuitive (Table 2). In terms of route stressors, an answer of not concerned increased comfort levels, while the other stressors decreased comfort levels. Trip miles along bicycle facilities such as separated paths increased comfort levels, whereas trip miles along links with no bike facilities or arterials tended to decrease comfort levels. Trip purpose (with commute used as a reference) indicated that shopping trips tended to be associated with higher comfort levels. Caution must be used to interpret these results, however. Some variables showed significant correlation with each other. For example, commute trip purpose was highly correlated with frequency levels of several times a week, weekday trips, and higher than average trip speeds.

Pooled models were then tested to establish the optimal set of predictors of route comfort. Pooled models were selected by grouping variables with statistically similar coefficients, dropping variables that were not significant, and utilizing a backwards stepwise selection procedure on the basis of the Akaike information criterion.

The final models are shown in Table 3. Bicycle facilities were included in the comfort models as a proportion of total trip length, or as the number of miles in the trip on that type of facility. If a trip consisted of 2 mi on arterials streets and 3 mi on separated path facilities, the separated path variable was input as 0.6 = 3/5 for the proportion model and input as 3 for the distance model. Most variables were significant at the $p < .01$ level, with the remainder significant at the $p < .05$ level.

TABLE 2 Single Variable Exploratory Models

Model	Independent Variable	Influence on Route Comfort
Trip statistics	Average trip speed of cyclist	Decrease
	Trip distance	Decrease
Temporal characteristics	Weekday trip	Decrease
Trip survey responses	Route frequency	Increase
	Route stressors: not concerned	Increase
	Route stressors: large commercial vehicles or trucks	Decrease
	Route stressors: public transport	Decrease
	Route stressors: parked vehicles + being doored	Decrease
	Route stressors: pedestrians	Decrease
	Trip purpose: exercise	Increase
	Trip purpose: shopping or errands	Increase
Bicycle facility and street type	No bike facility, primary arterial	Decrease
	No bike facility, other	Decrease
	Bike lane, primary arterial	Decrease
	Bike lane, minor arterial	Decrease
	Separated path	Increase

TABLE 3 Pooled Regression Model Specification

Variable or Characteristic	Results by Model: Proportional	Distance-Based
Separated path	2.897*** (0.560)	0.304*** (0.066)
Bicycle boulevard	NA	0.558** (0.256)
Bicycle boulevard (squared)	NA	–0.212** (0.089)
Arterial (with and without bike lanes)	–1.496*** (0.388)	–0.205*** (0.042)
Total trip distance	–0.194*** (0.062)	na
Total trip distance (squared)	0.007** (0.003)	na
Trip purpose: exercise	1.530*** (0.432)	1.470*** (0.415)
Trip purpose: shopping or errands	0.890*** (0.233)	0.890*** (0.229)
Not concerned about stressors on route	1.030** (0.442)	1.081** (0.446)
Stressed by auto traffic on route	–1.347*** (0.217)	–1.436*** (0.215)
Stressed by large commercial vehicles	–1.681*** (0.222)	–1.711*** (0.219)
Stressed by other cyclists on route	0.617*** (0.219)	0.638*** (0.220)
Observations	594	594
Log likelihood	–594. 932	–600.458
Threshold values		
Very bad | bad	–6.088 (0.405)	–5.605 (0.352)
Bad | average	–3.752 (0.306)	–3.282 (0.242)
Average | good	–1.653 (0.267)	–1.177 (0.199)
Good | very good	2.132 (0.290)	2.555 (0.242)

NOTE: NA = not available because variable was not significant at .05 p level; na = not applicable. Standard errors of coefficients are shown in parentheses.
$^{**}p < .05$; $^{***}p < .01$.

Threshold values were reported in the model results calculated in R and presented in Table 3. Arterial distances with and without bike lanes were pooled in the final models, because the effects of each variable were similar and likely pointed to the minimal comfort benefits of bicycle lanes on arterial roadways.

The variables associated with trip purpose and route stressors were similar in both models. The estimated coefficients associated with these variables were stable and barely changed when the bike facilities and distance variables were grouped or removed. This result indicated the robustness of the predictive power of route stressor and trip purpose variables within the sample. When users reported that they were not concerned about conflicts or crashes along the route, comfort levels increased significantly. When users indicated they were concerned about automobile traffic, comfort levels decreased significantly. The decrease was even larger if users were concerned about large commercial vehicles (trucks). If users were concerned about other cyclists, the overall comfort level increased. The interpretation was that other cyclists were a nuisance only on facilities with a high number of cyclists. This type of facility in Portland tends to be a separated path or a bicycle boulevard, both of which are associated with higher comfort levels. Another interpretation was the safety in numbers effect in which a route with a high number of cyclists was perceived to be safer than a similar route on the same type of facilities but with less bicycle traffic (*32*).

With respect to trip purpose, exercise had a high positive comfort influence. Several interpretations were possible: exercise trips were taken by more confident riders, and exercise trips tended to take place during weekends or off-peak traffic periods when traffic volumes were lower. For some exercise trips, a high proportion used more comfortable bicycle facilities (e.g., the Springwater corridor with nearly 40 mi of separated path bicycle facilities). The trip purpose to shop or run errands also had a positive coefficient, which may have been the result of the increased likelihood of cycling in residential areas, at off-peak times, or both. Commuter trips (not significant in the final models) tended to be repeated frequently and correlated to travel during weekdays and peak traffic periods.

For bicycle facilities, both models clearly showed that separated bicycle facilities had a major positive impact on cyclists' comfort levels. However, arterials had a significant negative impact on cyclists' comfort levels. Bicycle boulevards had a significant nonlinear impact on the distance-based model. The highest positive impact took place when the distance on bicycle boulevards was equal to 1.32 mi, and the positive impact disappeared when the distance exceeded 2.63 mi. As points of reference, the 75th and 90th percentiles for distances on bicycle boulevards are 1.02 mi and 2.16 mi, respectively. Hence, the impact of bicycle boulevards on comfort levels was predominantly positive. Other bicycle facility types were not significant. This result was likely not because the remaining bicycle facilities did not have a significant positive or negative impact but because of the limitation of the sample size. With a larger sample size, it may be possible to separate the effects of bicycle lanes, residential streets, and different types of arterials.

The distance variable is present in the proportional model only; distance has a negative impact between 0 and 27.7 mi. As a point of reference, the longest trip in the data set was 29.2 mi and, as shown in Table 1, trips longer than 8 mi were predominantly exercise trips. The negative impact of distance can be interpreted in different ways: as a higher disutility associated with longer travel distances (i.e., as in route choice models), or as the higher likelihood of encountering poor bicycle facilities or conditions as the trip becomes longer.

Table 4 outlines the relative importance of each variable in the final models through utilization of a procedure in which each variable was removed ceteris paribus to obtain the difference in log likelihood between the full model and the model with one variable removed. This difference in log likelihood indicated which variables had the most predictive power in the final model.

TABLE 4 Pooled Regression Model Variable Rank

	Distance Model		Proportion Model	
Variable Rank	Variable	Log Likelihood Difference Removed Ceteris Paribus	Variable	Log Likelihood Difference Removed Ceteris Paribus
1	Stressed by large commercial vehicles	175.82	Stressed by large commercial vehicles	167.58
2	Arterial (with and without bike lane)	150.26	Separated path	145.94
3	Stressed by auto traffic on route	148.71	Stressed by auto traffic on route	142.69
4	Separated path	146.82	Trip purpose: shopping or errands	138.60
5	Trip purpose: shopping or errands	143.97	Trip purpose: exercise	136.77
6	Stressed by other cyclists on route	140.15	Arterial (with and without bike lane)	136.52
7	Trip purpose: exercise	140.10	Total trip distance	135.39
8	Not concerned about stressors on route	138.88	Total trip distance (squared)	135.39
9	Bicycle boulevard	133.77	Stressed by other cyclists on route	133.87
10	Bicycle boulevard (squared)	133.77	Not concerned about stressors on route	133.39

Large commercial vehicles were the strongest factor in the ORcycle data to affect users' comfort negatively. They also constituted the most important variable in each model (Table 4). Overall, the stressor variables (commercial vehicles, automobile traffic) ranked highest in terms of predictive power in both the proportion and the distance models. Trip purpose variables (exercise and shopping) also had relatively high explanatory power. Of the facility variables, only arterial and separated path ranked in the top five in terms of explanatory power. The former was associated with low levels of comfort and the latter with high levels of comfort.

DISCUSSION AND POLICY IMPLICATIONS

Overall, the results tended to agree with previous research studies. In terms of comfort, a trade-off was observed between shorter trips that utilized arterials and longer trips on more specialized facilities such as separated paths. Novel contributions included the quantification of the impacts on comfort levels of trip purpose and sources of stress along a route. These impacts are analyzed in more detail in this section.

Sensitivity Analysis

The impact of the variables that represent sources of stress can be understood better if they are applied to a typical route. Assume, for example, that a typical commuter route for ORcycle users consists of 1.5 mi on bicycle boulevards, 1.5 mi on separated facilities, and 3 mi on arterials. The mileages assumed are close to the typical (median) travel distances on bicycle boulevards, separated facilities, and arterials, as well as to the median total trip distance for commuters. For the sake of simplicity, an integer value (6 mi) is utilized for total trip distance. This scenario is the baseline. Of the cyclists, 70% would rate this trip as good or very good, according to the proportional model, and 80% would rate this trip as good or very good, according to the distance model (Table 5, baseline probability rows). Assume four scenarios:

1. No sources of concern along the route,
2. Automobile traffic is the unique source of concern,
3. Commercial vehicle traffic is the unique source of concern, and
4. Vehicle and commercial traffic are sources of concern.

TABLE 5 Impact of Route Stressors on Comfort Levels

	Result by Rating				
Probability	Very Bad	Bad	Average	Good	Very Good
Distance Model					
Baseline probabilities (%)	0	3	17	71	9
Change in probabilities					
Add: no concerns	0	–2	–10	–1	13
Add: traffic concerns	1	8	23	–25	–6
Add: commercial vehicle	1	10	27	–31	–7
Add: traffic + commercial vehicle	6	32	27	–57	–8
Proportional Model					
Baseline probabilities (%)	0	4	25	65	5
Change in probabilities					
Add: no concerns	0	–3	–13	9	8
Add: traffic concerns	1	10	21	–29	–4
Add: commercial vehicle	2	15	23	–36	–4
Add: traffic + commercial vehicle	9	38	14	–55	–5

How do these four scenarios affect changes in comfort levels? Displays change across comfort level categories. For example, in the first scenario, the likelihood that users will rate the trip as good or very good will increase 12% for the distance model and 17% for the proportional model. The comfort of the facility decreases rapidly as traffic, commercial vehicles, and automobile traffic and commercial vehicles are added to the baseline scenario. According to ORcycle users, the fourth scenario was reserved for mostly confident riders (35% and 42% probability in the distance model and proportional model, respectively) and in some cases was unacceptable by most riders (6% and 9% probability in the distance model and proportional model, respectively). The ORcycle data set was captured during the winter and early spring, and most users described themselves as regular commuters, who cycled all year round. It is possible to predict that Scenarios 2 through 4 would have had an even more dramatic impact on people who were not regular cyclists.

In the baseline scenario, the very good category received relatively meager probabilities of 9% and 5% (in the distance model and proportion model, respectively). What would it take to increase these numbers significantly according to the model results? It would take a combination of three criteria: (*a*) no sources of stress, (*b*) travel mostly on separated facilities or bicycle boulevards, and (*c*) relatively short and direct routes (i.e., no significant increase in travel distance). Unfortunately, many origin–destination pairs do not satisfy these criteria. It is possible to speculate that it will be difficult to increase bicycle mode share significantly (e.g., to reach Portland's goal of a 25% bicycle mode share for short trips by 2030) if those criteria are not met (*33*).

This type of analysis can be replicated to consider how trips with different compositions of bicycle facilities are likely to be rated by users. Once planners see how these variables affect the distribution of comfort levels among users, planners can begin to estimate roughly how the combination of different design variables will affect cyclists' comfort categories (Table 5).

Limitations

It is advisable to be mindful of the limitations of this research. The effort was an exploratory one, and the data set (e.g., users, infrastructure) was specific to the Portland metropolitan area. Year-round commuter cyclists are represented primarily in the sample data. It is not clear how the model results will transfer to other regions and urban areas. Some variables that may have a significant impact on comfort levels are not included in the model: for example, cyclists' history of crashes or confidence levels. Statistical significance does not necessarily indicate causality. Hence, the results presented here must be interpreted with due caution.

CONCLUSIONS

This research presents novel findings about cyclists' comfort levels. Cyclist comfort is a complex construct affected by many groups of variables, including bicycle facilities, trip characteristics (e.g., distance), trip purpose, and sources of stress along the route. This research was a first step toward quantifying the key variables that affect cyclists' comfort levels. The results broadly agreed with other studies in the literature that pertain to bicyclists' preferences, but the models presented here are specific to comfort levels. Hence, variable estimates and insights related to route concerns, trip purpose, and bicycle facilities are novel.

The results of the ordinal logistic regression models indicated the comfort benefits of separated paths and bicycle boulevards for cyclists. The results highlighted the prominence of route stressors: comfort levels dropped if automobile or commercial vehicle traffic, or both, were identified as stressors. Commercial vehicle traffic was the variable that had the highest predictive power in the models. The results also showed that longer trips and bicycle miles traveled on arterial roadways tended to decrease user comfort. Trips made for the purposes of exercise and to shop and run errands were, on average, more comfortable than trips made for other purposes. The model results seemed to suggest that, to increase comfort levels dramatically, three criteria should be met: (*a*) no sources of concern along the route, especially no commercial vehicle traffic; (*b*) travel mostly on separated facilities or bicycle boulevards; and (*c*) relatively short and direct routes (i.e., no significant increase in travel distance).

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REFERENCES

1. Pucher, J., R. Buehler, and M. Seinen. Bicycling Renaissance in North America? An Update and Re-Appraisal of Cycling Trends and Policies. *Transportation Research Part A: Policy and Practice,* Vol. 45, 2011, pp. 451–475.
2. Figliozzi, M. Evaluating the Use of Crowdsourcing as a Data Collection Method for Bicycle Performance Measures and Identification of Facility Improvement Needs. http://www.oregon.gov/ODOT/TD/TP_RES/docs/2014StageTwos/14-072_PEA_Crowdsourcing_Stage2.pdf. Accessed May 1, 2014.
3. ORcycle. Maseeh College of Engineering and Computer Science, Transportation Technology and People Laboratory. Portland State University, Oregon. http://www.pdx.edu/transportation-lab/orcycle.
4. *Highway Capacity Manual 2010.* Transportation Research Board of the National Academies, Washington, D.C., 2010.
5. Figliozzi, M., and B. Blanc. *Evaluating the Use of Crowdsourcing as a Data Collection Method for Bicycle Performance Measures and Identification of Facility Improvement Needs.* Final Report. SPR 768. Oregon Department of Transportation, Salem, 2015. http://www.oregon.gov/ODOT/TD/TP_RES/docs/Reports/2015/SPR768_Crowdsourcing_DataCollection.pdf. Accessed Nov. 1, 2015.
6. Sorton, A., and T. Walsh. Bicycle Stress Level as a Tool to Evaluate Urban and Suburban Bicycle Compatibility. In *Transportation Research Record: Journal of the Transportation Research Board 1438,* TRB, National Research Council, Washington, D.C., 1994, pp. 17–24.

7. Mekuria, M., P. Furth, and H. Nixon. *Low-Stress Bicycling and Network Connectivity.* MTI Report 11-19. Mineta Transportation Institute, San Jose, Calif., 2012. http://transweb.sjsu.edu/PDFs/research/1005-low-stress-bicycling-network-connectivity.pdf.
8. Caviedes, A., and M.A. Figliozzi. Measuring Stress Levels for Real-World On-Road Cyclists: Do Bicycle Facilities, Intersections, and Traffic Levels Affect Cyclists' Stress? Presented at 95th Annual Meeting of the Transportation Research Board, Washington, D.C., 2016.
9. Dill, J., and K. Voros. Factors Affecting Bicycling Demand: Initial Survey Findings from the Portland, Oregon, Region. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2031,* Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 9–17.
10. Winters, M., G. Davidson, D. Kao, and K. Teschke. Motivators and Deterrents of Bicycling: Comparing Influences on Decisions to Ride. *Transportation,* Vol. 38, No. 1, 2011, pp. 153–168.
11. Sener, I.N., N. Eluru, and C.R. Bhat. An Analysis of Bicycle Route Choice Preferences in Texas, U.S. *Transportation,* Vol. 36, No. 5, 2009, pp. 511–539.
12. Harvey, F., K.J. Krizek, and R. Collins. Using GPS Data to Assess Bicycle Commuter Route Choice. Presented at 87th Annual Meeting of the Transportation Research Board, Washington, D.C., 2008.
13. Broach, J., J. Dill, and J. Gliebe. Where Do Cyclists Ride? A Route Choice Model Developed with Revealed Preference GPS Data. *Transportation Research Part A: Policy and Practice,* Vol. 46, No. 10, 2012, pp. 1730–1740.
14. Menghini, G., N. Carrasco, N. Schüssler, and K.W. Axhausen. Route Choice of Cyclists in Zurich. *Transportation Research Part A: Policy And Practice,* Vol. 44, No. 9, 2010, pp. 754–765.
15. Casello, J., A.O. Nour, K.C. Rewa, and J. Hill. Analysis of Stated Preference and GPS Data for Bicycle Travel Forecasting. Presented at 90th Annual Meeting of the Transportation Research Board, Washington, D.C., 2011.
16. Casello, J.M., and V. Usyukov. Modeling Cyclists' Route Choice Based on GPS Data. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2430,* Transportation Research Board of the National Academies, Washington, D.C., 2014, pp. 155–161.
17. Zorn, L., E. Sall, and M. Bomber. *Completing the Cycle: Incorporating Cycletracks into Sf-Champ.* San Francisco County Transportation Authority, Calif. Presented at 4th TRB Conference in Innovations in Travel Modeling, Tampa, Fla., 2012. http://www.sfcta.org/sites/default/files/content/IT/CycleTracks/completingthecycleitm20120501finalforwebsite.pdf.
18. Hudson, J.G., J.C. Duthie, Y.K. Rathod, K.A. Larsen, and J.L. Meyer. *Using Smartphones to Collect Bicycle Travel Data in Texas.* Final report. UTCM 11-35-69. University Transportation Center for Mobility, Texas A&M Transportation Institute, College Station, 2012.
19. Misra, A., A. Gooze, K. Watkins, M. Asad, and C.A. Le Dantec. Crowdsourcing and Its Application to Transportation Data Collection and Management. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2414,* Transportation Research Board of the National Academies, Washington, D.C., 2014, pp. 1–8.
20. Strauss, J., L.F. Miranda-Moreno, and P. Morency. Mapping Cyclist Activity and Injury Risk in a Network Combining Smartphone GPS Data and Bicycle Counts. *Accident Analysis and Prevention,* Vol. 83, 2015, pp. 132–142.
21. Schuessler, N., and K.W. Axhausen. *Map-Matching of GPS Traces on High-Resolution Navigation Networks Using the Multiple Hypothesis Technique.* Working Paper 568. Swiss Federal Institute of Technology, Zurich, Switzerland, 2009.
22. Schuessler, N., and K.W. Axhausen. Processing Raw Data from Global Positioning Systems Without Additional Information. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2105,* Transportation Research Board of the National Academies, Washington, D.C., 2009, pp. 28–36.
23. Oregon Department of Transportation. *Analysis Procedures Manual.* Salem, 2015. https://www.oregon.gov/ODOT/TD/TP/pages/apm.aspx. Accessed Nov. 10, 2015.
24. Stekhoven, D.J. missForest: Nonparametic Missing Value Imputation Using Random Forest. R Package Version 1.4. https://cran.r-project.org/web/packages/missForest/missForest.pdf.
25. Damant-Sirois, G., M. Grimsrud, and A.M. El-Geneidy. What's Your Type: A Multidimensional Cyclist Typology. *Transportation,* Vol. 41, No. 6, 2014, pp. 1153–1169.
26. Ahmed, F., G. Rose, M. Figliozzi, and C. Jakob. Commuter Cyclists' Sensitivity to Changes in Weather: Insight from Two Cities with Different Climatic Conditions. Presented at 91st Annual Meeting of the Transportation Research Board, Washington, D.C., 2012.
27. Blanc, B., M. Figliozzi, and K. Clifton. How Representative of Bicycling Populations Are Smartphone Application Surveys of Travel Behavior? In *Transportation Research Record: Journal of the Transportation Research Board, No. 2587,* Transportation Research Board, Washington, D.C., 2016, pp. 78–89.
28. Jensen, S.U. Pedestrian and Bicyclist Level of Service on Roadway Segments. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2031,* Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 43–51.
29. Ali, A.T., C.M. Cristei, and A. Flannery. Using Cumulative Logistic Regression Model for Evaluating Bicycle Facilities on Urban Arterials. Presented at 91st Annual Meeting of the Transportation Research Board, Washington, D.C., 2012.
30. Foster, N., C.M. Monsere, J. Dill, and K. Clifton. Level-of-Service Model for Protected Bike Lanes. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2520,* Transportation Research Board, Washington, D.C., 2015, pp. 90–99.
31. Christensen, R.H.B. Ordinal—Regression Models for Ordinal Data. http://www.cran.r-project.org/package=ordinal/.
32. Jacobsen, P.L. Safety in Numbers: More Walkers and Bicyclists, Safer Walking and Bicycling. *Injury Prevention,* Vol. 9, No. 3, 2003, pp. 205–209.
33. Portland Bicycle Plan for 2030. Portland Bureau of Transportation, City of Portland, Oregon. http://www.portlandoregon.gov/transportation/44597.

Any errors or omissions are the responsibility of the authors.

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