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Bicyclist Link Evaluation: A Stated-Preference Approach

K. W. AXHAUSEN AND R. L. SMITH, JR.

The purpose of this study is to develop a methodology for evaluating bicycle route choice and to test the individual link preference component of the methodology. The focus is on the relationships between the qualitative factors that describe an individual link of a bicycle route and the overall evaluation of that route. It is demonstrated that it is possible to use functional measurement to estimate one of the partial utility functions of the hypothesized overall utility function of route choice. The utility of the individual links is estimated as a function of six link attributes. All but one of the attributes have significant main effects at the 5 percent level of confidence.

During the last 10 years transportation planners and engineers have rediscovered the bicycle as a mode of transportation. This rediscovery has been caused by a number of factors. Probably the single most important factor was the energy crisis of 1973–1974 and the following boom in bicycle sales. In addition, the environmental movement sharpened the awareness of the need for energy-efficient and pollution-free solutions to transportation problems. Increased health awareness was a third factor in the promotion of the bicycle. Changes in professional attitude are illustrated by the inclusion of bicycles in traffic counts and travel surveys. What was once viewed as a children's toy is now viewed as a legimate mode of transportation.

Most research and planning efforts in recent years have been concentrated on solving the practical problems of the increased number of bicycle accidents and the design of bicycle facilities. Many cities built new bike paths, signed new bike lanes, and marked new bike routes in addition to rehabilitating old facilities. Still, many expectations for the new facilities were not fulfilled because the facilities did not fit the needs of the intended user groups.

This disappointment resulted in part from a lack of understanding of bicyclists and their route choice. Not much effort was spent studying the behavior of bicyclists and the factors that influence route choice. Only accidents involving bicyclists have been studied extensively during the last decade.

As is the case with automobile drivers, there is little knowledge of bicyclists' trade-offs between travel time and travel costs and qualitative factors such as bicycle facilities or surface quality. Qualitative factors have an obvious role in the route choice of bicyclists, who are more exposed to environmental influence than are car drivers. Research on the attitudinal factors of automobile driver route choice *(1, 2)* showed that qualitative factors also influence them.

There are two basic approaches to estimating such trade-offs. The estimates can be performed on revealed-preference data on actual route choices or on stated-preference data from the results of a controlled experiment (simulation of choice). Given the problems inherent in collecting the qualitative and quantitative data on the bicycle networks required for the first approach, only the second approach was feasible within the constraints of this study.

In recent years a number of methods have been developed for collecting and analyzing revealed-preference data. The most prominent methods are conjoint analysis and functional measurement. On the basis of a review of the relevant literature, it was decided to employ the technique of functional measurement, which has been developed by Anderson *(3)* and Louviere et al. *(4)*. [An introduction to functional measurement is given in Kocur et al. *(5)*.] The primary advantages of functional measurement are the ease of data analysis and the availability of good statistical tests of significance of the model parameters.

The purpose of this study is to develop a methodology for evaluating bicycle route choice and to test the individual link preference component of the methodology. The focus of the study is on the relationships between the qualitative factors that describe an individual link of a bicycle route and the overall evaluation of that link. Following a short literature review, the approach and the aims of the study are explained in more detail and the design of the survey is outlined. The analysis of the survey is divided into two

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parts. In the first part the respondents are described in terms of their socioeconomic characteristics. The analysis of the relationships between the qualitative factors and the overall evaluation of the link is presented in the second part. An attempt is also made to segment the link preference function by socioeconomic characteristics.

LITERATURE REVIEW

Four recent studies are devoted exclusively to the question of the route choice of bicyclists: Upcott *(6)*, Teichgraeber *(7)*, Krause *(8)*, and Bradley and Bovy *(9)*. The work of Teichgraeber and Krause concentrates on bicyclists' sensitivity to avoiding detours and on the general factors that affect route choice. Teichgraeber documents the strong effects intersections can have on the route choice of bicyclists. Upcott applies a shortest path and a stochastic route choice assignment model to the route choice of bicyclists. Both models perform satisfactorily, but it is difficult to generalize the results because the study is based on a survey of high school students in a small English town. Bovy and Bradley's paper is based on a current major study of the route choice of bicyclists in The Netherlands. Using functional measurement, the authors estimate a utility function for the route choice of bicyclists using four factors: length of trip, surface quality, traffic volumes, and bike facilities. The influence of trip length and surface quality is approximately equal and nearly twice as large as the influence of traffic volumes and bike facilities. The authors surveyed only regular bicyclists. The model used by Bovy and Bradley assumes that the levels of the three qualitative variables are constant over the length of the trip and that intersections have no significant influence. More research is needed to determine if these strong assumptions are valid.

In addition, there are a number of studies that focus on the effects of bike lanes and bike paths: Kroll and Ramey *(10)*; Walsh *(11)*; Kroll and Sommer *(12)*; Lott, Tardiff, and Lott *(13)*; and Ambrosius *(14)*. These studies document the increase in subjective safety that most bicyclists experience when using bike lanes and paths. Ambrosius shows the positive influence of a complete bicycle infrastructure on the modal share of the bicycle.

APPROACH AND AIM OF STUDY

The decision process of bicyclists can be formulated in the following form, which has been proposed for other choice problems by Louviere and Meyer *(15)*:

$$X_{ij} \to x_{ij} \to U_i \to R_i \to C_i$$

where

- X_{ij} = a vector of the j observable characteristics or attributes describing the ith alternative,
- x_{ij} = the vector of the perceived or psychological values of the observable attributes,
- U_i = the vector of the utility of the i alternatives,
- R_i = the vector of stated evaluations of the i alternatives as generated by a laboratory experiment, and
- C_i = the behavioral response to alternative i as observable in the field.

The response could be the choice frequency of, in this case, a route.

The utility of the ith alternative is related to the observable attributes by

$$U_i = F[f_j\,(X_{ij})] \qquad (1)$$

Also, the stated response or evaluation (R_i) is related to the utility (U_i) by a simple mathematical transformation:

$$R_i = a + bU_i \qquad (2)$$

This assumption allows use of the results of the analysis of the stated-response experiment for the prediction of the C_i's. The behavioral response (C_i) can be predicted from the values of the U_i's depending on the assumptions made about the distribution of the error terms of the U_i's.

The set of attributes or characteristics that are important for bicycle route choice, as found in the literature, includes: (*a*) overall travel time, (*b*) travel time of the individual links and other link attributes, and (*c*) average waiting time at intersections and other intersection attributes. For the purpose of this study it is assumed that it is possible to decompose the overall route attributes (X_{ij}) into individual link and intersection attributes so that

$$X_{ij} = [T_i, (t^n, L^n{}_{ik}), (w^m, I^m{}_{il})] \qquad (3)$$

where

- T_i = travel time of route i,
- t^n = travel time of link n,
- $L^n{}_{ik}$ = kth attribute of link n,
- w^m = average wait time at intersection m, and
- $I^m{}_{il}$ = lth attribute of intersection m.

It is also assumed that it is possible to estimate the utility functions of a partial set of route attributes so that

$$U_i = F[u_1\,(T_i), u_2\,(t^n, L^n{}_{ik}), u_3\,(w^n, I^n{}_{il})] \qquad (4)$$

where the u_i's are the partial utility functions.

The aim of this research was to test the usefulness of this approach by developing one of the partial utility functions as a first step toward the development of a route choice model for bicyclists. The partial utility functions are the building blocks of the overall utility functions. The research here is limited to the estimation of the partial utility function of bicyclists' evaluation of the individual links.

Preliminary studies and the literature review show that three basic concepts provide the framework for the evaluation of a route: (*a*) traffic volumes, (*b*) control of movement, and (*c*) comfort of the ride. "Control of movement" describes the wish of the bicyclist to travel safely at the desired speed without too much interference in the form of traffic controls or other traffic. At the link level bicycle facilities are the main variable that describes this concept. "Comfort" relates to the quality of the ride and the quality of the environment. The slope of the link, the surface quality of the link, and the abutting land use were chosen to represent this concept. The last variable needed to complete the description was the length of the link. For each of the six variables—traffic volumes, length, surface quality, slope, land use, and bike facilities—three levels were chosen to span the range of values typically found in urban areas (Table 1).

TABLE 1 VARIABLES OF THE FACTORIAL DESIGN AND THEIR LEVELS

Variable	Level 0	Level 1	Level 2
Length of link (blocks)	2	1	1/2
Slope (%)	6	3	0
Traffic volumes	High	Medium	Low
Abutting land use	Industrial	Residential	Park
Bike facilities	None	Bike lane	Bike path
Surface quality	Low	Medium	High

An experimental design was required that would give an estimate of the relative importance of the six factors and all two-way interactions because it was impossible to exclude certain interactions on the basis of the literature.

DESIGN OF THE SURVEY

The questionnaire consisted of two main parts: the factorial design experiment needed for the estimation of the partial utility function and general socioeconomic questions.

Conner and Zelen *(16)* include an experimental design that met the specifications: a 1/3 3^6 factorial design with nine blocks of 27 questions each. Every respondent would have to evaluate one of the blocks. This blocking requires the assumption that there is no effect associated with the blocks.

The values of the levels were explained or illustrated with local examples in the questionnaire for the variables slope, surface quality, and bike facilities. Preliminary testing had shown that the respondents had very similar conceptions of low, medium, and high traffic volumes. Therefore the levels of the factor "traffic work or university on a 20-point scale with 20 being the most desirable link and zero the least desirable link to ride on.

RESPONDENTS

The survey was distributed to two groups: students of two civil engineering classes and the members of the local bicycle touring club (Bombay Bicycle Club). Neither of the groups is representative of the bicycling public as a whole, but this study did not attempt to be representative. Both groups should, however, be representative of two segments of the bicycling public: university students and older, regular bicyclists. The survey was distributed to the students the third week of February 1984. The principal author explained the survey and remained in the classroom to answer further questions. A total of 124 complete questionnaires were obtained from the students. The questionnaire with a cover letter explaining the purpose of the survey and a stamped return envelope was sent to a systematic sample of one-third of the members of the bicycle club. By the end of the third week following the mailing (third week of February 1984) 69 of the 130 mailed questionnaires had been returned complete.

Table 2 gives a summary of the most important characteristics of the two groups. The members of the bicycle club are older and own more cars, but they use the bicycle more often than do the students for their work or school trips. Both groups use five- or ten-speed bicycles almost exclusively.

TABLE 2 CHARACTERISTICS OF RESPONDENTS

Characteristic	Students[a]	Bicycle Club Members[a]
Average age (yr)	22.0 (0.2)	34.0 (1.2)
Male (%)	82	70
Female (%)	18	30
Own one or more cars (%)	56	88
Own one or more bicycles (%)	92	99
Mode most frequently used for school or work trip during good weather months		
Car (%)	13	22
Bicycle (%)	33	65
Walking (%)	41	6
Average years of bike ownership	11.0 (1.0)	17.0 (1.3)
Average years of regular bike use[b]	5.9 (0.4)	6.2 (0.6)
Self-evaluation of experience as bicyclist[c]		
Average	4.6 (0.1)	5.3 (0.2)
Distribution (%)		
≤ 3	14	11
4,5	60	35
≥ 6	26	54

[a]Standard errors in parenthesis.
[b]Regular use was defined as 10 or more bike trips per week.
[c]Scale of 0 to 7 with 7 as most experienced.

The greater use of the bicycle by bicycle club members is reflected in the self-evaluation of the two groups. The students evaluate their experience as a bicyclist 0.7 points lower than do the members of the bicycle club on a 7-point scale (0 = not at all experienced, 7 = extremely experienced). The use of self-evaluation for the measurement of experience is not completely satisfactory, but for this research it was the best way to estimate this important variable. The self-evaluation is correlated with the length and intensity of bicycle ownership and use, but the correlations are not especially high.

ESTIMATION OF UTILITY FUNCTIONS

Analytical Procedure

Although the size of the blocks was relatively large (27 alternative links), only a small number of students did not complete the tasks and only a very small number of alternatives were not evaluated.

As the data in Table 1 indicate, the variables were coded to produce positive coefficients in the regression analysis. For example, high traffic volumes were coded as zero because it could be assumed that the utility of traffic volumes decreases with increasing traffic volumes.

To assure comparability of the individual responses, the analysis was performed on the normalized responses. For every respondent the mean and standard deviation of the responses were calculated and the responses normalized. In this way it is possible to compare the sensitivity of the respondents to the various variables using a common metric. Comparison of the results for the normalized responses with those for the unnormalized data showed no differences in the conclusions to be drawn from the analysis.

The analysis was carried out in two separate stages for both the student and the bicycle club data sets. In the first stage the significance of the variables (factors) was tested and in the second stage the partial utility function was estimated with linear and piecewise linear multiple regression. Attempts were also made to segment the partial utility function for each data set on the basis of socioeconomic characteristics.

Significance Tests

For the normalized responses the design consists of one random factor—the respondents—and six fixed factors—the design variables. For this case of a repeated-measurement design the correct test of significance of a factor is not the F-ratio of mean square of the factor to mean square of the error but

$$F(Factor) = MS(Factor)/MS(Factor*Respondents).$$

For a large data set, such as the student data set, it is either computationally infeasible or too expensive to test interactions in this way. [In the course of the anaysis one two-way interaction was tested with the GLIM package on a SIEMENS 7880 mainframe. A work region of 7,000 KByte and about 60 min CPU time was necessary.] Louviere and Woodworth *(17)* suggest as an alternative to adjust the degrees of freedom of the standard t-test of the regression coefficients from degrees of freedom (DOF) = number of respondents times number of questions to DOF = number of respondents. This adjustment underestimates the significance of the factors but is on the safe side. Tables 3 and 4 give the results of both tests for the two data sets. The regression equations used to calculate the t-values included the interaction terms of interest.

The results for both groups show the high significance of all but one factor, length. This result is explained in part by the interaction between length and traffic volumes as will be explained shortly. As shown by the t-values, all of the factor impacts have the expected positive sign. Comparison of the two significance tests confirms the conservative nature of the DOF adjustment. The underestimation of significance leads in two cases to rejection of the null hypothesis (land use and bicycle facilities in Table 4). It is preferable to use the F-test, but for large data sets only the t-test is computationally feasible.

Plots of the marginal means of the factors (Figures 1 and 2) show that for both students and club members reductions in traffic volumes and slopes result in an approximately linear increase in the evaluation. The improvement in the other three significant factors has a nonlinear impact on increases in the evaluation. For these three factors the first improvement is much more important than the second. For example, the change from riding through an industrial area to riding through a residential area is about three (students) to eight (Bombay Bicycle Club) times greater than the change from residential to park areas. The members of the bicycle club are also in relative terms more sensitive to the change from no facility to a bike lane than are the students, whereas the students are more sensitive to the change from bike lane to bike path. For both groups surface quality is the most important variable. The largest overall increase in the evaluation is due to improvements in surface quality.

Identification of Interaction

As the data in Table 4 indicate, the two significance tests give different results for the significance of the interaction terms. None of the adjusted t-values for the interaction terms are significant at the 0.05 level; however, the F-test gives three interaction terms that are significant at the 0.05 level and one at the 0.10 level. The results from the adjusted t-value test are supported by the minimal increase in explained variance provided by the four significant F-test interaction terms. Also, none of the interaction terms for the student data set (Table 3) has significant adjusted t-values at the 0.05 level. Nevertheless, nonlinearities in the factor relationships may distort the analysis of the interaction terms. Thus it is useful to examine the significant interactions graphically using plots of the marginal means.

Figures 3–6 show the nature of the significant interactions identified by the F-test in Table 4. In general, the interactions are small and many of the underlying relationships are nonlinear. The

TABLE 3 SIGNIFICANCE TESTS FOR THE NORMALIZED RESPONSES OF STUDENTS

Factor	F-Test $MS(F)$	$MS(F*R)$	F	Adjusted t-Value	Marginal Means 0	1	2
L: Length	0.3	0.3	0	—[a]	.00	.02	−.02
V: Volume	73.0	0.7	104[b]	2.44[c]	−.28	.05	.23
S: Slope	126.2	0.7	180[b]	3.33[b]	−.36	.05	.31
LU: Land use	122.9	1.1	112[b]	2.77[c]	−.37	.12	.26
BF: Facilities	108.2	0.8	135[b]	2.62[c]	−.35	.12	.23
SQ: Surface	238.1	1.2	199[b]	4.23[b]	−.51	.11	.40
DOF	2	244		122			
Interactions		—[d]		—[e]			

[a]Not significant at $\alpha = 0.05$ for unadjusted t.
[b]Significant at $\alpha = 0.005$.
[c]Significant at $\alpha = 0.05$.
[d]Not computed for reasons stated in the text.
[e]Not significant at $\alpha = 0.05$ for adjusted t.

TABLE 4 SIGNIFICANCE TESTS FOR THE NORMALIZED RESPONSES OF THE BOMBAY BICYCLE CLUB

Factor	F-Test MS(F)	MS(F*R)	F	Adjusted t-Value	Marginal Means 0	1	2
L: Length	0.1	0.2	0	–[a]	–.02	.02	.03
V: Volume	78.1	0.6	130[b]	3.46[b]	–.37	.02	.34
S:Slope	17.1	0.5	38[b]	1.64[c]	–.17	.01	.16
LU:Land use	45.2	0.7	65[b]	1.54	–.31	.13	.19
BF: Facilities	47.8	1.1	42[b]	1.51	–.32	.15	.18
SQ: Surface	200.7	1.2	167[b]	4.07[b]	–.63	.15	.48
DOF	2	134		67			
L*V	1.3	0.5	3d	–[a]			
L*S	0.3	1.1	0	–[a]			
L*LU	0.1	0.3	0	–[a]			
L*BF	0.3	0.5	1	–[a]			
L*SQ	0.2	0.3	1	–[a]			
V*S	2.9	2.7	1	–[e]			
V*LU	1.5	2.4	1	–[a]			
V*BF	2.6	0.3	9[b]	–[e]			
V*SQ	0.7	1.0	1	–[a]			
S*LU	2.4	3.0	1	–[a]			
S*BF	0.5	0.2	2c	–[a]			
S*SQ	1.4	1.6	1	–[a]			
LU*BF	1.7	0.5	4b	–[a]			
LU*SQ	0.7	1.3	0	–[e]			
BF*SQ	0.3	0.2	1	–[a]			
DOF	4	268		67			

[a]Not significant at $\alpha = 0.05$ for unadjusted t.
[b]Significant at $\alpha = 0.005$.
[c]Significant at $\alpha = 0.1$.
[d]Significant at $\alpha = 0.05$.
[e]Not significant at $\alpha = 0.05$ for adjusted t.

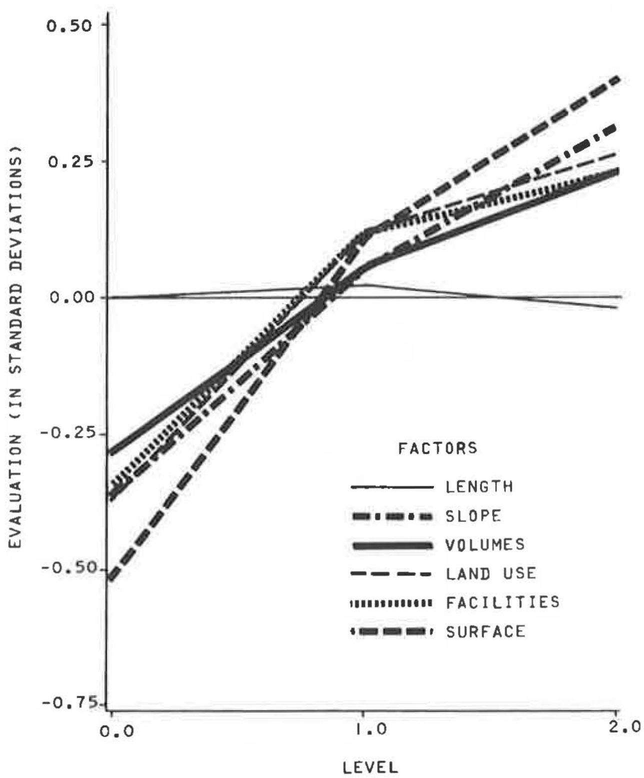

FIGURE 1 Marginal means by factor (students).

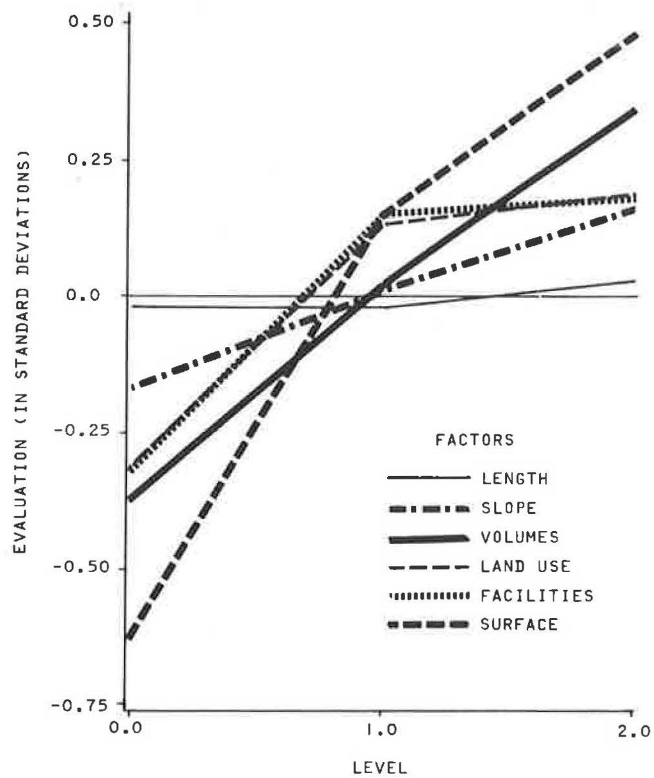

FIGURE 2 Marginal means by factor (Bombay Bicycle Club).

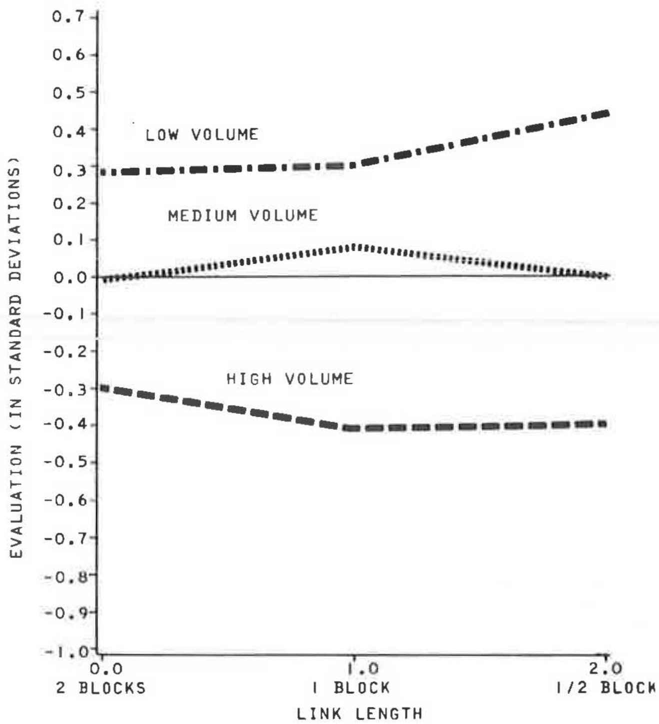

FIGURE 3 Interaction of link length and traffic volume (Bombay Bicycle Club).

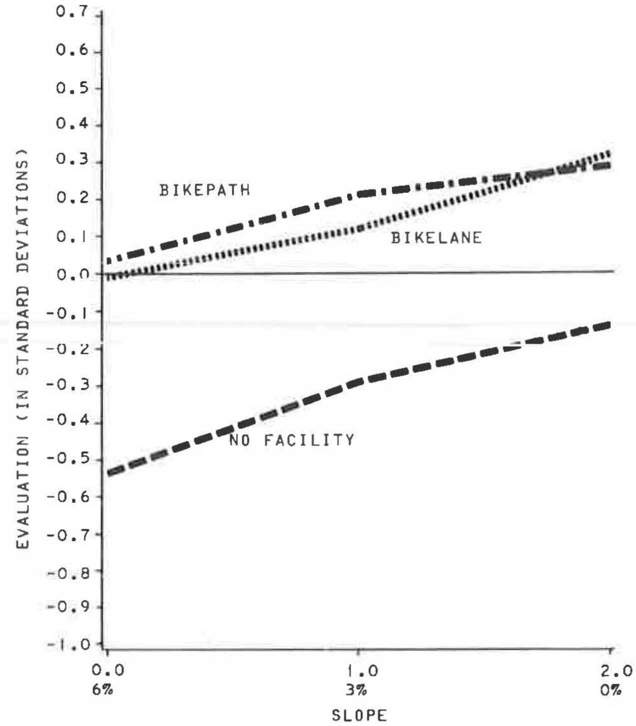

FIGURE 5 Interaction of slope and bicycle facilities (Bombay Bicycle Club).

nonlinear relationships suggest that quadratic terms may be appropriate.

An explanation for the lack of significance of length is provided by Figure 3. For low traffic volumes bicycle club members' link ratings increase as link length decreases (increases in level), and the opposite is true for high traffic volume links. The two effects cancel each other with the result that the curve for length alone is flat. The observed interaction of length and volume is logical in that the increase in the number of intersections resulting from short links would probably not cause significant delay at low volumes but would at high volumes.

The two-way interactions between bicycle facilities and the

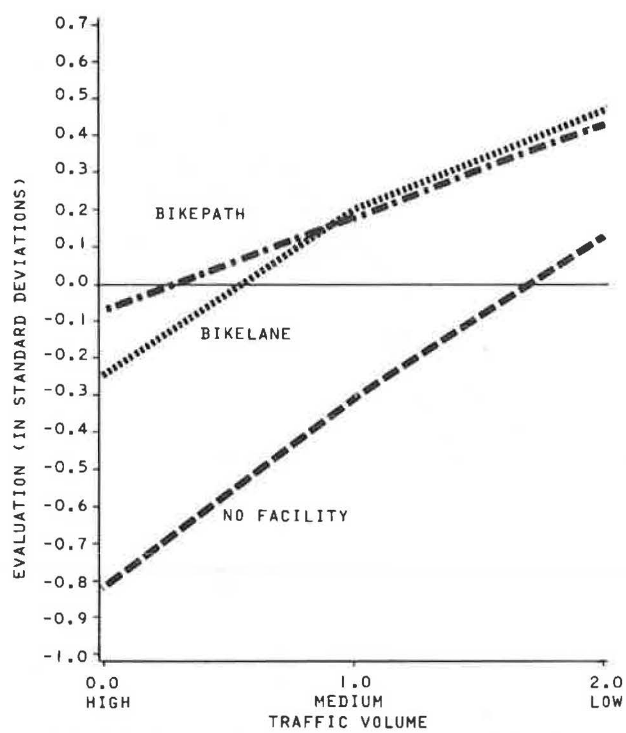

FIGURE 4 Interaction of traffic volume and bicycle facilities (Bombay Bicycle Club).

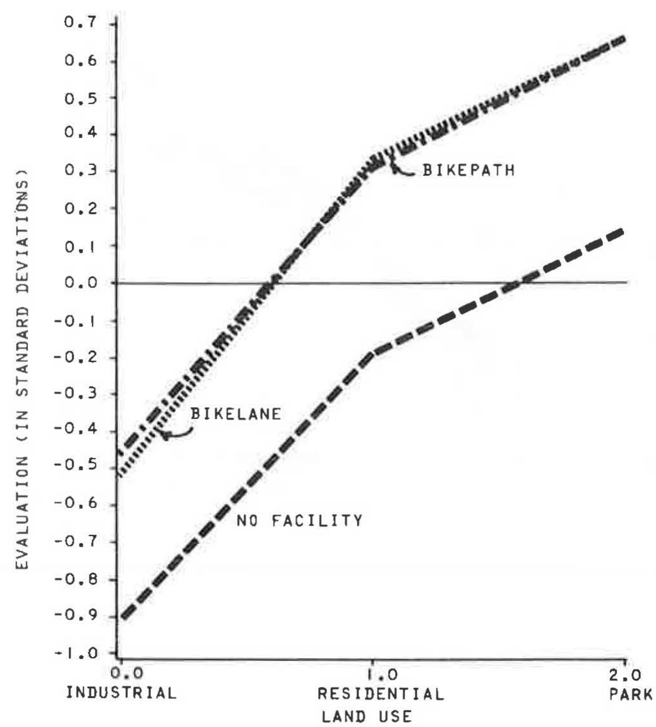

FIGURE 6 Interaction of land use and bicycle facilities (Bombay Bicycle Club).

three factors—volume, slope, and land use—are shown in Figures 4–6. In all three cases there is little difference between the curves for bike lanes and bike paths, which is consistent with the basic relationship for bicycle facilities shown in Figure 2.

The interaction between volume and bicycle facilities shown in Figure 4 is logical in that changes in traffic volumes have a greater impact on the link ratings when the bicyclists are mixed with automobile traffic (no facility) than when they are protected by a bike lane or bike path. A similar but smaller interaction between slope and bicycle facilities is shown in Figure 5. Slopes have less of an impact on the ratings when the bicyclists are using a bike lane or bike path.

Finally, the curves for the interaction between land use and bicycle facilities (Figure 6) when viewed in terms of linear approximations to the individual curves show little evidence of any significant interactions. Nevertheless, the F-test indicated significance at the 0.005 level. This inconsistency plus the low explanatory power of the interactions as a group suggest that as a first approximation the interactions can be neglected.

Linear Regression Analysis

In the second stage of the analysis the partial utility functions were estimated for both groups with piecewise-linear and linear multiple regression. The interaction terms were not included because they had been found to be generally nonsignificant. The piecewise-linear regression used two dummy variables for each factor, one for the high level and one for the low level. The coefficients therefore indicate improvement (deterioration) with respect to the middle level in multiples of the standard deviation of the responses. The results are given in Table 5.

$$R_i = \beta_0 + \beta_1{*}L + .. + \beta_6{*}SQ \quad \text{linear model}$$

$$R_i = \beta_0 + \beta_{10}{*}L_0 + \beta_{12}{*}L_2 + .. + \beta_{62}{*}SQ_2$$
piecewise-linear model

where R_i is the ith response (evaluation) to the specified link attributes L (length) through SQ (surface quality), L_0 and L_2 are the dummy variables for the zero and second levels of link length, respectively, and so forth. The constant term for the linear model reflects the worst-case situation in which the term for the linear model reflects the worst-case situation in which all of the factors are zero (lowest level) whereas in the piecewise-linear case it reflects the response in which all of the factors are at their mid-level.

As the data in Table 5 indicate, all of the linear model regression coefficients except the length coefficient are significant at the 0.05 level based on adjusted t-values and have the appropriate sign. In contrast, a number of the piecewise model coefficients are not significant, which in most cases is the result of nonlinearities in the curves. The piecewise models do have a higher explanatory power, but the increase is not large.

If the regression coefficients for the students are compared with those for the bicycle club, there appear to be some substantial differences. For example, in the linear equations the impact of the slope variable for the students is twice that for the bicycle club. Although a statistical test of the differences between the individual regression coefficients shows no significant differences, at least in general terms bicycle club members react more strongly to traffic volumes and surface quality whereas students are somewhat more sensitive to slopes, land use, and bicycle facilities. A statistical test for the overall equality of the two sets of regression coefficients was not run *(18)*.

TABLE 5 RESULTS OF REGRESSION ANALYSIS

Factor and Level[a]	Students				Bombay Bicycle Club			
	Linear		Piecewise		Linear		Piecewise	
	Coefficient	Adjusted t	Coefficient	Adjusted t	Coefficient	Adjusted t	Coefficient	Adjusted t
L: Length	—[b]	—			—[b]	—		
Low			—[b]	—			—[b]	—
High			—[b]	—			—[b]	—
V: Volume	.26	3.22[c]			.36	3.4[c]		
Low			−.35	2.1[d]			−.40	1.9[e]
High			.17	1.0			.32	1.5[f]
S: Slope	.34	4.0[c]			.17	1.6[e]		
Low			−.41	2.5[d]			−.19	0.9
High			.27	1.6[e]			.15	0.7
LU: Land use	.32	3.8[c]			.25	2.3[d]		
Low			−.49	2.9[c]			−.47	2.6[d]
High			.14	0.9			—[b]	—
BF: Facilities	.30	3.6[c]			.26	2.4[d]		
Low			−.48	2.9[c]			−.50	2.7[d]
High			.13	0.9			—[b]	—
SQ: Surface	.45	5.4[c]			.56	5.2[c]		
Low			−.62	3.8[c]			−.78	3.7[c]
High			.29	1.8[e]			.35	1.7[e]
Constant	−1.67	8.3[c]	.45	2.0[d]	−1.60	6.3[c]	.50	2.1[d]
R-square	.40[c]		.42[c]		.43[c]		.46[c]	
Total sum of squares			3321				1691	

[a]Low level = 0 and high level = 2.
[b]Not significant at $\alpha = 0.05$ for unadjusted t.
[c]Significant at $\alpha = 0.005$ for adjusted t.
[d]Significant at $\alpha = 0.05$ for adjusted t.
[e]Significant at $\alpha = 0.05$ for adjusted t.
[f]Significant at $\alpha = .25$ for adjusted t.

TABLE 6 RESULTS OF SEGMENTATION ANALYSIS

	Inexperienced Students[a]		Experienced Students[b]	
Factor	Coefficient	Adjusted t	Coefficient	Adjusted t
L: Length	–[c]	–	–[c]	–
V: Volume	.40	1.6[d]	.24	2.8[e]
S: Slope	.35	1.4[d]	.34	3.8[f]
LU: Land use	.27	1.1	.32	3.7[f]
BF: Facilities	.27	1.1	.30	3.5[f]
SQ: Surface	.27	1.1	.48	5.4[f]
Constant	–1.55	2.6[e]	–1.69	8.0[f]
R-square	.34		.41	
Total sum of squares	416		2,805	
Respondents	16		106	
F-value		22.9		

[a]Self-evaluation ≤ 3.
[b]Self-evaluation ≥ 4.
[c]Not significant at $\alpha = 0.05$ for unadjusted t.
[d]Significant at $\alpha = 0.25$ for adjusted t.
[e]Significant at $\alpha = 0.05$ for adjusted t.
[f]Significant at $\alpha = 0.005$ for adjusted t.

Segmentation Analysis

It was possible to segment the students according to their self-evaluation using an F-test for the equality of sets of coefficients in two regression equations *(18)*. Linear regression equations were used for the segmentation because their explanatory value is not much smaller than the value for the piecewise-linear regression. The students with a self-evaluation of three and below had a set of coefficients significantly different from the students with a self-evaluation of four and above at the 5 percent level. Although segmentation of the students hardly increased the explanatory power of the resulting equations, segmentation is important to see the differences between the two groups. Segmentation based on age, sex, or car ownership was not possible.

Comparison of the two subgroups in Table 6 shows that certain variables gain or lose importance with increasing experience: Traffic volumes and the change from bike lanes to bike paths lose importance. Surface quality, land use, and the change from no facility to a bike lane gain importance. Experienced bicyclists are less afraid of sharing the street with other traffic but are sensitive to environmental influences, such as the abutting land use or the surface quality of the road. In comparison with the members of the Bombay Bicycle Club, the more experienced students are not as sensitive to traffic and much more sensitive to slopes.

The segmentation analysis was also performed for the responses of the Bombay Bicycle Club. It was not possible to detect any significant differences between subgroups for any of the available variables. In contrast with the student data set, it was not possible to test for the differences between members with self-evaluation of three and below and the rest of the sample because too few members had classified themselves in the low category.

The relative importance of the variables in this study can be compared with the results of Bradley and Bovy's study *(9)* by using the results for both the experienced students and the members of the Bombay Bicycle Club. For both groups the variable "surface quality" has approximately twice the importance of the variables "traffic volumes" and "bike facilities," which is consistent with Bradley and Bovy's results.

CONCLUSIONS

The study demonstrated that it is possible to use functional measurement to estimate one of the partial utility functions of the hypothesized overall utility function of route choice. The utility of the individual links was estimated as a function of six link attributes. All but one of the attributes have significant main effects at the 5 percent level.

Three different groups of bicyclists were identified: inexperienced students; experienced students; and older, experienced bicyclists. The results showed that traffic volume, which can be viewed as a surrogate for safety, is the most important factor for inexperienced bicyclists. In contrast, the experienced bicyclists stress surface quality, which is a surrogate for the ability to travel at higher speeds.

The student responses are similar with respect to slope, land use, and bicycle facilities. Overall, students are much more sensitive to slope than are older, experienced bicyclists. Differences between the students' and the older, experienced bicyclists' responses to land use and bicycle facilities are small. The experienced students, however, are much less sensitive to traffic volume than are the older, experienced bicyclists.

Application of both F- and t-tests indicated that two-way interaction terms were generally not significant. Graphic analysis of the four significant interactions from the F-test showed that magnitudes were small and subject to logical explanations. As a first approximation, interaction effects can be ignored, which greatly reduces the size of the experimental design required for future research.

The results of this study indicate the need for bicycle planning based on the various subgroups of bicyclists. Bike lanes or paths through residential neighborhoods can help inexperienced and older, experienced bicyclists who want to avoid high traffic volumes but are less likely to be attractive to the more experienced student bicyclists who want high-quality surfaces that are relatively flat.

The next steps in the effort to develop a route choice model for bicyclists are the estimation of the partial utility function for the evaluation of intersections and the incorporation of these two parts into the overall utility function. By using the overall route choice work by Bradley and Bovy *(9)* as a basis, it may be possible to go directly to estimation of the overall utility function, again using functional measurement. Key methodological issues include the representation of intersection characteristics, specification of a partial utility function for a sequence of nonhomogeneous links in a route, and integration of partial functions for both intersections and sequences of links into an overall route utility function. Validation of this last step will require the collection of an extensive set of revealed-preference data. The repetition of this study with a representative sample of bicyclists would be necessary to identify all subgroups of bicyclists and their specific needs.

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