BICYCLING PREFERENCES AND BEHAVIOR IN SALT LAKE CITY

by

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A thesis submitted to the faculty of
The University of Utah
in partial fulfillment of the requirements for the degree of

Master of Science

Department of Geography

The University of Utah

August 2015

The University of Utah Graduate School

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ABSTRACT

Improving our understanding of cycling behaviors in urban areas is an important step in producing a more sustainable transportation system. Based on a stated preference survey in Salt Lake City, Utah, this paper studies the influence of attitudes on bicycling behavior. A travel preference factor analysis indicates four attitudinal factors concerning bicycling: safety, direct benefits, comfort, and timesaving. The decision to cycle is positively correlated with the timesaving and convenience factors, whereas preferences on travel comfort level negatively affected bicycling frequencies. Besides attitude factors, bicycling level is the highest among groups with higher education, single and living without a family, do not have access to a car, and who have a positive attitude on bicycling. We also apply a route optimization method to further analyze bicyclists' route choice behavior and preferences toward transportation link level characteristics (e.g., bike lane, slope, traffic speed). The results indicated an influential effect of separated bike lanes. These findings indicate that attitudes, bike lanes, and other demographic factors have a strong impact on bicycling behaviors.

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ACKNOWLEDGEMENTS

I wish to give my sincere thanks to the members of my committee, Tom Cova and Simon Brewer, for all the advice and feedback of my thesis research. I give special thanks to my advisor, Steve Farber. Thank you for providing the opportunity to work with you, teaching me how to do research, write papers, and mentoring me through this process.

Thanks to Dapeng Li, Scott Barrel, and Xiao Li for sending out the surveys to friendly strangers and bearing the lovely summer weather. Thanks to all the volunteers in the Salt Lake City Bicycle Collective who have provided survey locations as well as giving valuable suggestions of my study design. I am truly inspired by your devotion and passion. I would also like to thank all my friends in the Geography Department for your help and encouragement that got me this far.

Finally I would like to thank my husband Xing, who has given me enormous support way beyond debugging codes, proofreading papers, and listening to my strange thoughts. I am more than lucky to have you and I look forward to the exciting future ahead of us.

CHAPTER 1

INTRODUCTION

Bicycling is a healthy mode of transportation and an efficient exercise activity. Increasing bicycle utilization will benefit a sustainable transportation system by reducing problems caused by extensive automobile use. For example, studies have found that as bicycling levels increase, traffic injury rates fall, making bicycling safer and therefore providing societal benefits over and above those pertaining to personal health (Elvik, 2009; Jacobsen, 2003; Robinson, 2005). Additionally, both air and noise pollution can be reduced and controlled by increasing bike use in densely populated areas (Elvik, 2009).

The research literature indicates the necessity to increase bicycle use through well-established biking infrastructures, good safety records, and policies that facilitate cycling (Pucher et al., 2010). However, attitudes toward cycling is a less considered factor that may influence ridership. Recent literature has revealed that attitudes and habits significantly influence bicycling behavior and should receive further attention (Gatersleben and Appleton, 2007; Heinen et al., 2011). Current works on attitude and values tend to focus on the impact of attitudinal factors on transportation mode choice. However, a more specific focus on cycling frequency and route choice is still needed. The causal relationship between positive bicycling attitude and bicycling behaviors is not clear.

The main purpose of this paper is to perform a comprehensive analysis on factors influencing bicycling frequency. We present findings from a bicyclist preferences survey conducted in Salt Lake City, 2013, which simultaneously collected stated preferences data for cycling frequency and revealed bicycle routes for each respondent. Factor analyses and ordered probit models were applied to analyze bicycling frequency differences with respect to rider attitudes. The influence of travel purposes and social-demographic factors were also analyzed in these models. We further analyzed bicyclists' preferences for on-route facilities and cycling conditions with a newly proposed route choice method. This approach is able to model travel routes by simultaneously minimizing generalized travel cost while optimizing a cost function of road links.

The remainder of the thesis is structured as follows. Chapter 2 contains a brief review of previous research in this area. Data and methods are described in Chapter 3 and 4. Chapter 5 reports on the analytical results and conclusions are made in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

Generally, mode and route choice decisions have been found to be influenced by factors relating to the cycling environment, socio-demographics, and attitudes (Heinen et al., 2011; Stinson et al., 2003). Because of these multiple influencing factors, cycling behaviors can be complex and difficult to predict. This chapter will first review the three categories of factors that influence the choice to bicycle. The last part of this chapter will discuss previous research on methods of analyzing bicycle route choice behaviors.

2.1 Built Environment Factors

Link-level factors are a category of environmental factors referring to the attributes of the built environment that constitute the transportation system. Specifically, bike facilities, traffic volume, and grade are identified to have an evident relationship with bicycle use. Preference surveys have been used to evaluate the influence of traffic on bicyclist route choice behavior. Respondents generally prefer using bicycling facilities in low traffic volume routes (Stinson & Bhat, 2003). In recent years, a number of new regional policies have been put into place to encourage commuting cyclists. The most effective inducement is to increase the number of bike lanes, especially lanes that are separated from automobile traffic (Broach et al., 2012; Parkin et al., 2008; Wang et al. 2012). Apart from bicycle routes and lanes, point-of-destination facilities provided at school, workplace, or other attractions also encourage people to use bicycles as their means of transportation. Examples include bicycle parking, changing and showering facilities, and bike sharing programs (Pratt et al., 2012).

2.2 Social-Demographic Factors

Socio-demographic characteristic is another category of factors that will influence bicycling frequency and route choice. When focused on commuting trips, income obviously has a determining role in one's travel mode. Bicycle use is found higher among groups with annual household income less than $50,000 (Krizek & Johnson, 2006). Ownership of a car greatly reduces the likelihood of both walking and bicycling (Pucher & Renne, 2003). However, distinction has to be made between voluntary and nonvoluntary cyclists. A major number of bicyclists choose this transportation mode voluntarily, for recreational or exercising purpose, and therefore attitudes toward cycling must also be considered (Kuzmyak et al., 2014). Education level also influences perceptions of bicycle use and choice of travel mode. Bicycling rates are the highest among those in the lowest education group, presumably due to income effects, and highest education group, presumably due to preferences (Kuzmyak et al., 2014). Similar to the situation of income analysis, there is an obvious relationship between travel purpose and bicycling frequency among groups with different education levels. People with higher education levels are likely to ride more often for transportation rather than recreation, which may be due to a working or studying population at local university or college who live within bicycling distance (Xing et al., 2010). Furthermore, gender may play an important role in influencing individual choices to participate in cycling activities. One study found that 65% of male cyclists who cycle to work do so even though they perceive risks associated with cycling, while only 50% of female cyclists with similar perceptions do so (Wang et al., 2012). This result is consistent with gender-related attitudes toward risk aversion in route choice behaviors: female commuter cyclists prefer to use routes with maximal separation from motorized traffic. Improved bicycling facilities in the form of bicycle paths and lanes that provide a high degree of separation from motor traffic is likely to be important for increasing cycling activity among women (Garrard et al., 2008).

2.3 Attitudinal Factors

Aside from physical environment characteristics and social-demographic factors, public health research suggests that attitudinal factors are as important in analyzing physical activities including bicycling (Handy, 2005). Specifically, attitudes toward benefits gained by cycling are identified to directly impact bicycling behavior. Previous research found that individual attitude variables including preference for cycling activity, and perceived health and mental benefits are highly related to bicycle use (Handy et al., 2010; Heinen et al., 2011). These finding suggests that educational programs can play an important role in increasing both bicycle ownership and daily usage.

Drawing on the previous literature, this study further analyzes the influence of the three categories of factors influencing bicycling frequency with ordered probit models. Link-level characteristics and attitudes were considered as explanatory variables of the model, while demographics are included as controls. Specifically, factor analyses were conducted to explore latent structures in a wide range of attitudes and values towards the bicycling environment. The specific approaches taken will be further described in Section 2.4 below.

2.4 Bicycle Behavior Modeling

Various modeling methods have been applied to understand how bicyclists make their travel decisions. Burbidge and Goulias (2009) completed a thorough literature review of recent research on active travel behavior models. They pointed out that these models usually concern responses to environmental factors, especially the attributes of the transportation network. Yet little has been done to incorporate the "self-selection" factor that considers individual preferences over built environment. In other words, it becomes important to determine whether the built environment is having a direct effect on cycling, or if those with positive attitudes toward cycling relocate to areas in the city where good cycling facilities exist.

Aggregate-level analysis has been used in transportation modeling for decades to study travel demand. An aggregate model generally calculates the inflow and outflow of each selected region within a city, and then uses regression models to test correlations between transportation flows and other variables (Barnes et al., 2006). Based on census data, aggregate level models provide a quantitative method for analyzing traffic flows. When applied to cycling behavior studies, these models help to demonstrate the significant positive impact bicycle facilities in central cities have on activity (Barnes et al., 2006; Dill & Carr, 2003). While it may play a significant role in understanding overall demand, aggregate level analysis cannot adequately address the problem of individual mode or route choice.

Recently, researchers have applied spatial network analysis to model travel route choice. This individual level model analyzes the geometry and topography of selected routes as well as their connections to the whole transportation network (Cervero & Duncan, 2003; Pucher et al., 2010; Wang et al., 2012). Some studies have incorporated stated preference survey data in order to map cyclists' route networks and compare them to the shortest paths (Pucher et al., 2010; Wang et al., 2012). Unfortunately, there is a study that reveals that respondents may occasionally report behaviors and perceptions inconsistent with actual behavior (Pratt et al., 2012).

A more accurate method uses GPS to track cycling routes, and further simulate route choice mode by assigning specific attributes and rule sets to each cycling pathway (Broach et al., 2012). Although this research represents an improvement on previous models, most studies using GPS modeling have not included an evaluation component that would provide evidence of the impact of the intervening factors on the amount of bicycling (Pucher et al., 2010).

We have proposed a route optimization method in this paper to evaluate the individual preference of link level factors on route choice behaviors. The observed routes were reported in the bicycle preference survey conducted in Salt Lake City, Utah. A cost function was specified to evaluate the influence of bicycling facilities on link attractiveness. By minimizing travel cost, we were able to compare the observed routes to shortest cost routes, and to calibrate a cost function to better match the actual traveled routes.

CHAPTER 3

DATA COLLECTION

Bike routes and preferences were acquired using a survey of cyclists. We used an intersect-recruitment strategy at public events using bike-valet services and at popular cycling destinations on the University of Utah campus. Participants were recruited in these events through convenience sampling. The survey consisted of three components: a detailed description of the most recently cycled route, a survey of socio-demographic characteristics, and a survey of values and attitudes toward cycling. These sections of the survey will be described in-turn below.

Each respondent was asked to provide a detailed verbal and illustrated description of the most recently cycled route, and the routes were geocoded using Esri ArcMap 10.1 during postprocessing. Specific questions regarding the origin and destination of the trip were used to pin-point exact endpoints. However, the locations of trip origins for mapping purposes are geocoded to the nearest block to protect respondents' privacy.

This survey also contained a questionnaire about values and attitudes toward cycling, which included eight questions on cycling motivations and 15 questions on bicycling conditions. Value statements and attitudes were measured using 5-point Likert scales. The questions were drawn from the 2012 Utah Household Travel Survey so that a future comparison to statewide characteristics could be made.

Finally, socio-demographic characteristics were also collected. Questions include respondents' gender, race, educational attainment, working status, marital status and household formation, car ownership, and household income.

The survey was conducted during the period from 29th August to 4th October in 2013. The data collection team intercepted riders at the Salt Lake City Farmer's Market and a number of Twilight Concert Series events at Pioneer Park in downtown Salt Lake City, as well as several locations on the University of Utah Campus. We collected 160 surveys, although 26 participants did not sufficiently complete the questionnaire, leaving 132 usable surveys. Among the valid surveys, nearly 85% of the data came from the Pioneer Park events in downtown Salt Lake City. A complete transcript of the survey instrument appears in the appendix.

Table 1 shows the demographic profile of the respondents. In comparison to a statistically representative sample of Salt Lake County cyclists reported in (Burbidge, 2012), this sample contains a higher percentage of male cyclists, and is a more highly educated sample, with the majority having a university degree. In general, the sample consists primarily of young, highly educated, full-time workers, who overwhelmingly have access to a vehicle for transportation. Thus, most of these cyclists can be considered discretionary riders.

The bicycling frequency question indicates how many days in the past 2 weeks respondents had made bicycling trips. As the survey was distributed specifically to cyclists, all respondents had biked at least once, with a fairly even distribution of cycling frequency across the four categories.

Table 1 Sample characteristics (*n* = 132)

Demographic Characteristic	Number of respondents	Percentage of Respondents
Gender		
Female	53	40.2%
Male	79	59.8%
Age		
20 or younger	3	2.3%
20-30	63	47.7%
30-40	43	32.6%
40-60	19	14.4%
60 or older	4	3.0%
Education		
Community and lower	39	29.5%
University and higher	93	70.5%
Employment status		
Unemployed or student	22	16.7%
Part time	20	15.2%
Full time	82	62.1%
Homemaker or other unpaid work	8	6.0%
Car ownership		
Have access to an automobile and the ability to drive it	115	87.1%
Do not have access to an automobile or unable to drive one	17	12.9%
Marital status		
Married or living with partner	55	41.7%
Single or not living with partner	77	58.3%
Income level		
Less than $20,000	29	22.0%
$20,000-$40,000	25	18.9%
$20,000-$60,000	22	16.7%
More than $60,000	42	31.8%
Do not know/refusal	14	10.6%
Bike Frequency		
Less than 1 day per week	25	18.9%
2–3 days per week	37	28.0%
4–5 days per week	28	21.2%
6–7 days per week	42	31.8%

A Salt Lake City bikeway shapefile containing bike lanes, shared use paths, and signed shared roadways was used to attribute the collected cycling routes. This dataset is continually maintained and provided by the Salt Lake City Department of Transportation. The Utah road system GIS data provided by the Utah Department of Transportation (UDOT) data portal were also utilized to add link-level attributes, including grade, traffic lights, speed limits, and road classification.

CHAPTER 4

METHODS

4.1 Attitude and Value Analysis

Factor analysis was used to identify the latent structure in categorical attitudinal and values questions. Each statement about attitudes and values was considered as a covariate. For example, attitude toward the statement “I can avoid traffic congestion” when cycling is scored based on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The exploratory factor analysis method is usually used to study variations among observed correlated variables in response to a potentially smaller set of unobserved latent factors (Fabrigar et al., 1999). The variables were hypothesized as linear combinations of the latent factors with an error term. Factor scores were calculated to provide information on the contribution of each variable on each identified latent factor. Through a comparison of factor scores with revealed route choices and stated cycling frequencies, we can detect attitudes and values that affect the valuation of link-level factors or that may increase travel frequency.

4.2 Bicycling Frequency Model

Using the latent attitudinal and value factors created in the factor analysis, ordered probit models are used to explore their influence on bicycling frequencies among participants (McKelvey & Zavoina, 1975). Individual and household demographic characteristics are also entered into the model (Figure 1).

To ensure model parsimony, each group of independent variables is modeled with a stepwise method to eliminate insignificant variables. Insignificant variables were eliminated from the final model according to the Akaike information criterion (AIC) score of the ordered probit model in each step.

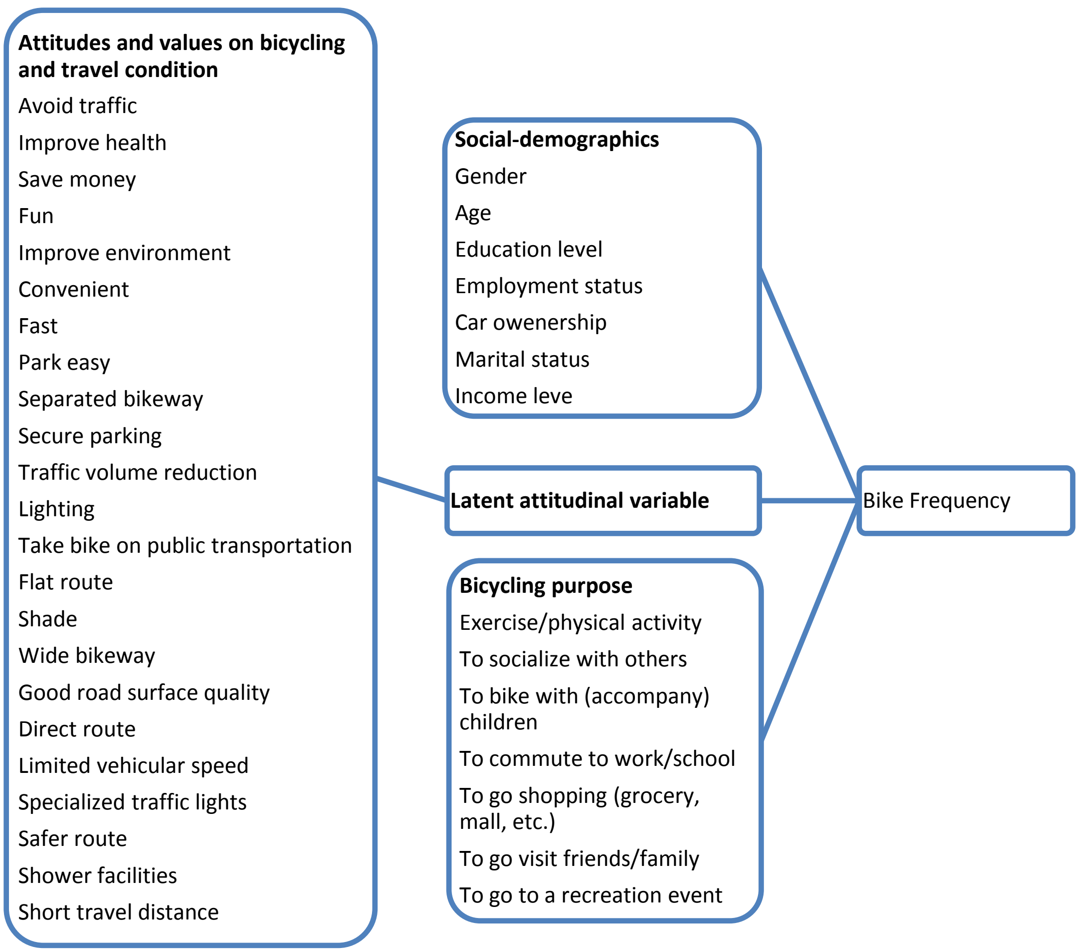

Figure 1. Explanatory variables in the bicycling frequency mode

4.3 A proposed Route Optimization Method

Recent bicyclist's route choice behavior analyses (Aultman-Hall et al., 1997; Harvey et al., 2008) suggest that multiple environmental variables influence bicycling decisions to various degrees. For example, bicyclists will take a deviation from the shortest route to seek for or avoid certain route features, suggesting that they may have preferences for different bicycling facilities or conditions.

To establish the rationale underlying the route optimization method, we consider travellers making bicycling trips between known origins and destinations in an urban area. Generally all links in the road network will be considered when making travel decisions. The bicyclists will evaluate the road link set according to certain link criteria and their own preferences. It is then assumed that travelers try to minimize the generalized cost spent by finding the lowest cost path through the network. To estimate the travel preferences in bicycling, we propose a route optimization method that will match the least cost routes to the observed ones in order to model route choice behaviors.

The assumption here is that travelers choose their least cost routes with certain "trade-off" decisions. One such example is making a detour to pursue more attractive road sections. Unlike most route choice methods, the traveler's search is based on the entire network of links instead of a limited route choice set. It is assumed that bicyclists estimate the link cost according to travel preferences, and will minimize total cost in the entire trip when they make travel decisions.

According to previous research on bicycling frequency analyses, timesaving is the most influential attitude and value factor that affects the decision to cycle in an urban transportation system. This may be because the most common travel purpose for city bicyclists is to make commute trips, and commuters in general are very sensitive to travel times. As bicyclists have preferences over link characteristics or will avoid unattractive road sections to reach a certain travel comfort level, compromise decisions are likely to be made. For example, a bicyclist would prefer to use a bike lane even though this could result in detours. Because of this kind of “trade off” decisions, the link attributes were multiplicatively combined into a generalized cost function with an exponential parameter to modify cost based on link distance.

For each link in the transportation network, we apply a cost function in the following form: $C_i = D_i * x_{1i}^a * x_{2i}^b * x_{3i}^c$ ..., where C_i is the generalized cost for link i, and x_{ji} is a link attribute that could be a factor influencing cost estimation. D_i is the distance, considered as the base cost for link i. Exponential parameters such as a, b, c are weighting parameters within a certain range, typically between -1 and 1 to ensure that they do not cause too much detour from the shortest path.

In order to find the cost-function parameters, we use a brute-force parameter sweep method. For each parameter state, we compare the shortest cost paths to the observed paths, and compute the overlapping distance percentage as a goodness-of-fit score. It is assumed that the cost function is appropriately calibrated when the estimated shortest cost paths are closely matched with the observed routes. In our case, there were many solutions that achieved a similar level of correspondence, and so we investigate the parameter distributions that achieved the highest levels of fit, rather than just the single best set of parameters.

The implementation of the route optimization method was as follows:

1) Define attributes for network dataset links based on empirical analyses and

descriptive statistics of survey results.

2) Define cost function $C_i = D_i * x_{1i}^a * x_{2i}^b * x_{3i}^c \ldots$ for network dataset links based on selected attributes.

3) Set initial value for exponential parameters and a step size for each parameter to change, assuring to cover all possible combinations in a given range. For example, in a three attribute variable function $C_i = D_i * x_{1i}^a * x_{2i}^b * x_{3i}^c$ where the range of a, b, and c are between -1 and 1, set all initial values as -1 and increase by 0.1.

4) For all origin-destination pairs, calculate the least cost paths using generalized costs. Compare least cost routes to corresponding observed routes to calculate overlapping link counts and overlapping distances.

5) Repeat step 4 until all values in the n dimensional set of exponential parameters are traversed, where n stands for the number of attributes in the defined cost function. Estimate parameter values based on top 1% overlapping ratio.

6) Expand exponential parameter space as needed. If the estimation value is close to the explored parameter boundary, expand the range to a larger space and confine step size to ensure more accurate results. Repeat steps 5-7 until each estimated value is no longer near the boundary of the parameter space.

CHAPTER 5

RESULTS AND DISCUSSION

In this chapter, we report the results of our various analyses. First, we present descriptive statistics for the cycling routes, cycling purposes, and different types of attitudes. Then we delve into bivariate analysis of trip frequencies, followed by the multivariate analysis of latent attitudes and values. Afterward, the multivariate model of trip frequency is presented. Finally, the route choice model results are presented.

5.1 Description of Cycling Route Characteristics

Table 2 reports the summary statistics of observed route characteristics. According to the 132 reported bicycle routes, the average distance traveled is around 4 kilometers, which is a 16-minute ride if we assume the average bicycling speed is 15 km/h. The longest cycle trip was about 10.6 kilometers. The distribution of trips is positively skewed, indicating that most trips in the survey were short distance trips.

Two types of bike lanes were analyzed in this study, those separated from traffic, and those that are not. Separated lanes include bike lanes, cycle tracks, and buffered bike lanes that are painted with special bicycle symbols and signs and may not be used by motor vehicles. The others are shared lanes and signed bike routes, which are shared

Table 2 Observed route characteristics

Attribute	Minimum	Maximum	Mean	Standard Deviation
Length (meters)	665	10648	3988	196
Bike Lanes Proportion				
Any Bike lane	0%	98.7%	48.6%	0.03
Mixed traffic bike lane	0%	98.2%	27.4%	0.02
Separated traffic bike lane	0%	82.9%	21.1%	0.02
Slope Proportion				
Steep slope (≥3°)	3.5%	99.4%	36.3%	0.02
Low slope (<3°)	5.9%	99.6%	63.6%	0.02
Speed Limit Proportion				
High speed link (>30MPH)	11.1%	100%	69.3%	0.02
Low speed link (≤30MPH)	0%	88.9%	30.7%	0.02

with traffic.

Since a bicycle trip is composed of a mixture of link types, such as bike lanes and shared lanes, we analyzed route characteristics at the link level, in which a trip reported in the survey is treated as a combination of a series of road links. Among all links traversed in all trips, 48% of them have bike lanes, with a slightly higher usage of mixed traffic bike paths than separated traffic bike lanes. This is probably caused by a lower implementation rate of separated bike lanes in Salt Lake City.

Data on link-level slopes and speed limits are also presented in Table 2. Slopes are computed regardless of direction in the present research. Based on the distribution of links traveled in the survey data, we choose 3% as the cutoff value between steep and low slopes to ensure an equal distribution in the two categories. The equal split approach is to avoid bias in route choice modeling when the attributes of samples are not evenly distributed. There is a higher usage on low slope links, suggesting a preference for flatter routes. For link-level speed limits, we took a similar approach to choose the cutoff value of 30MPH. We find that bicyclists tend to travel more on links with higher speed limits.

This is somewhat counterintuitive since high-speed streets are perceived to be more dangerous. We further plot the distributions of different route types in Figure 2. Summary statistics suggests that 58% of bike lanes are on high-speed routes, despite that high-speed routes only account for 13% of all streets in the city. The high usage of higher speed limit links is likely caused by the high percent of overlap between bike lanes and high-speed links on city arterials.

5.2 Bicycling Purpose of Cyclists in Salt Lake City

Figure 3 presents the distribution of the bicycling purpose responses. Respondents were asked to select all the reasons why they choose to cycle. As shown in the figure, the most frequently selected purpose for bicycling is to exercise, which indicates that improving fitness and physical health might be a compelling motivator for people to cycle. Following this are the purposes to use bicycling to reach various destinations, such as to go to school, work, and recreation events. As we can see from the figure, these purposes are also quite common and rank close to the purpose of the exercise/physical activity. This suggests that the purpose to commute also plays an important role in motivating people to bike.

Aside from the reasons listed in the figure, some respondents pointed out purposes such as that cycling for fun, mountain biking, and cycling with dogs also served as frequent bicycling reasons.

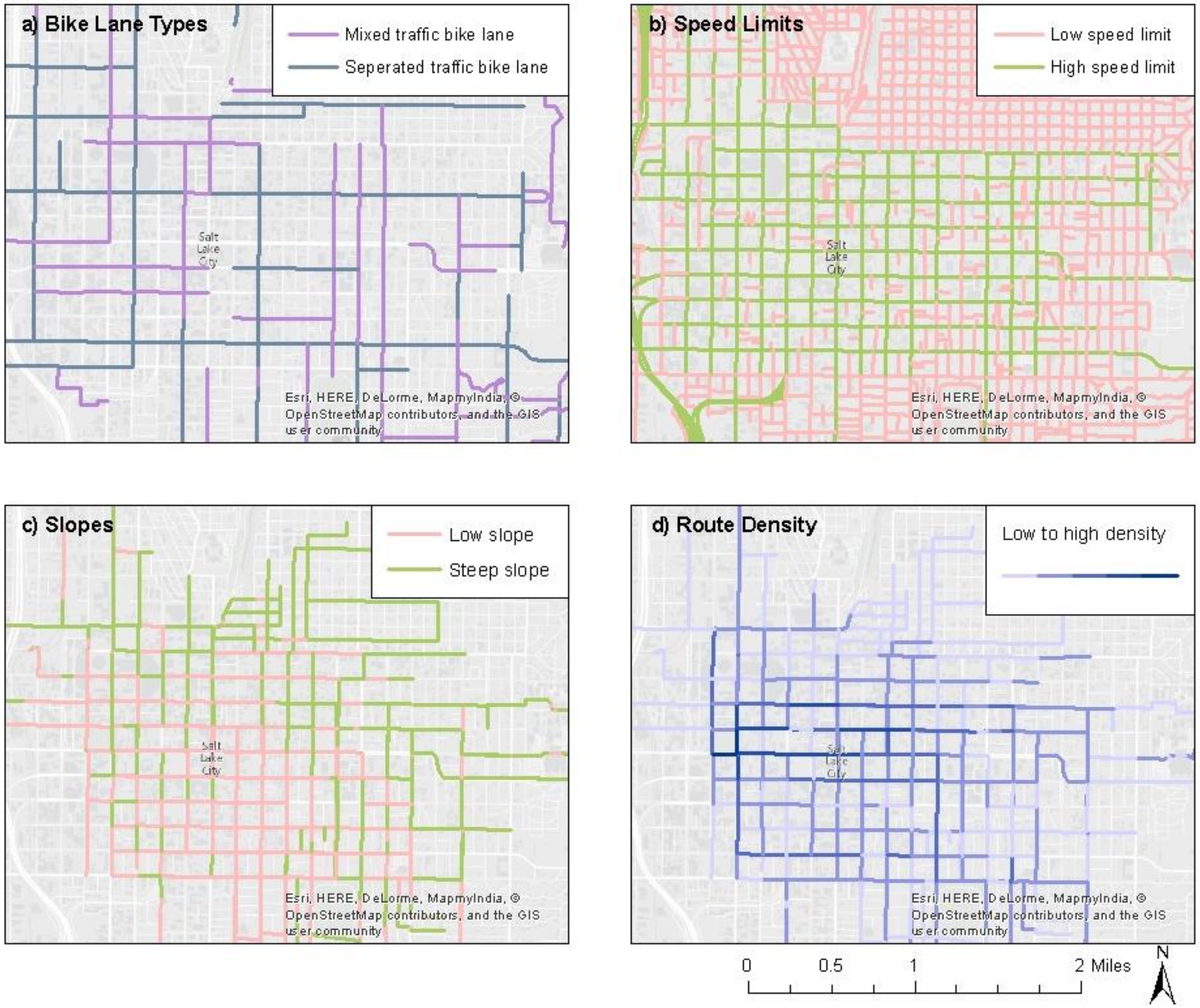

Figure 2. Study area route characteristics of a) bike lane types, b) speed limits, c) slopes, and d) route density

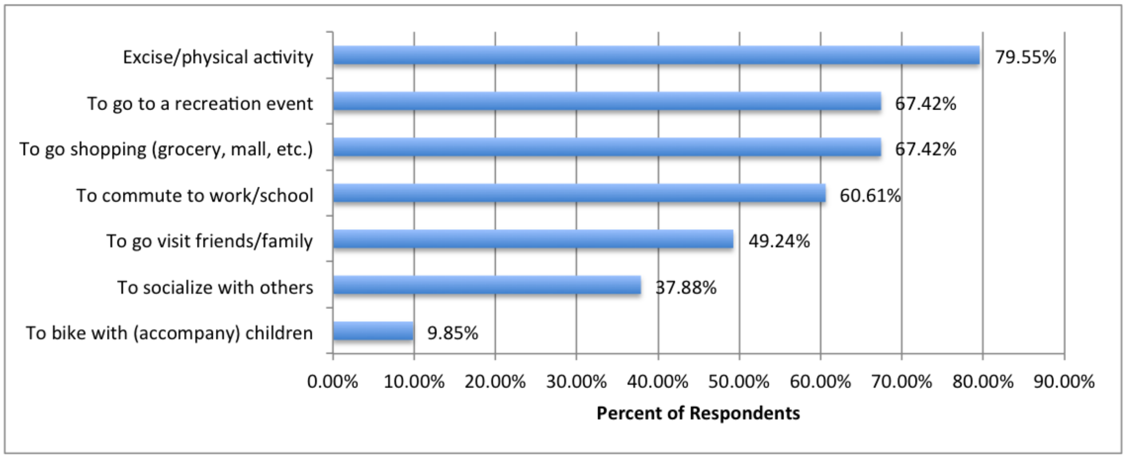

Figure 3. Bicycling purposes for bicyclists in Salt Lake City

5.3 Attitudes on Bicycling Motivation for Cyclists in Salt Lake City

Participants were also asked to rate how strongly they agree or disagree with the statements considering cycling motivations. The results are presented in Figure 4. It shows that more than 75% of respondents strongly agree that they bike out of environmental concern or that they bike for fun. Other strong motivations include convenient parking, travel expenses, and health concerns. Nearly half of the participants responded neutral or negatively to statements such as bicycling is faster, suggesting that bicycling, compared to other transportation mode, is not generally perceived as a fast and convenient way of travelling, even amongst those who cycle.

5.4 Attitudes on Travel Environment for Cyclists in Salt Lake City

Another component of the survey is to rate the bicycling environment. The question is whether the participant would choose to bike more often if certain conditions were satisfied. Five levels of attitudes range from strongly negative to strongly positive to reflect attitudes on route characteristics and other bicycling facilities. The results are

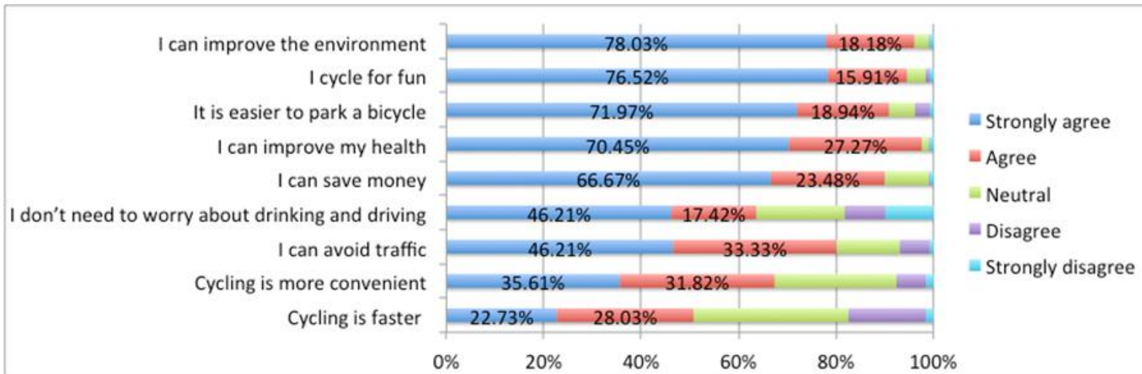

Figure 4. Attitudes on bicycling motivations for bicyclists in Salt Lake City

presented in Figure 5.

From Figure 5, we can see that in general bicyclists desire less interaction with the traffic and may be willing to ride more often if in a safer environment. The most preferred characteristic is to have bike lanes separated from the traffic. More than 68% of the participants respond strongly positive to the provision of separated bike lanes. Bicyclists also responded positively about improvements on other aspects related to safety, including specialized signage, reduction in traffic, and overall safer route. Secure bicycle parking is also identified as an important motivator. It is suggested that 67% of bicyclists are willing to bike more often if secure parking facilities are provided. As a result, developing policies and facilities to make bicycling safer and decrease the risk of theft is likely to increase bicycle usage.

The majority of bicyclists prefer to be able to take bikes on public transportation. Although bikes are allowed on light rail and buses in Salt Lake City, the number of bikes that can be taken on each vehicle is limited. More than 56% of the bicyclists wish to be able to complete their bicycling trips using public transportation. Developing a public

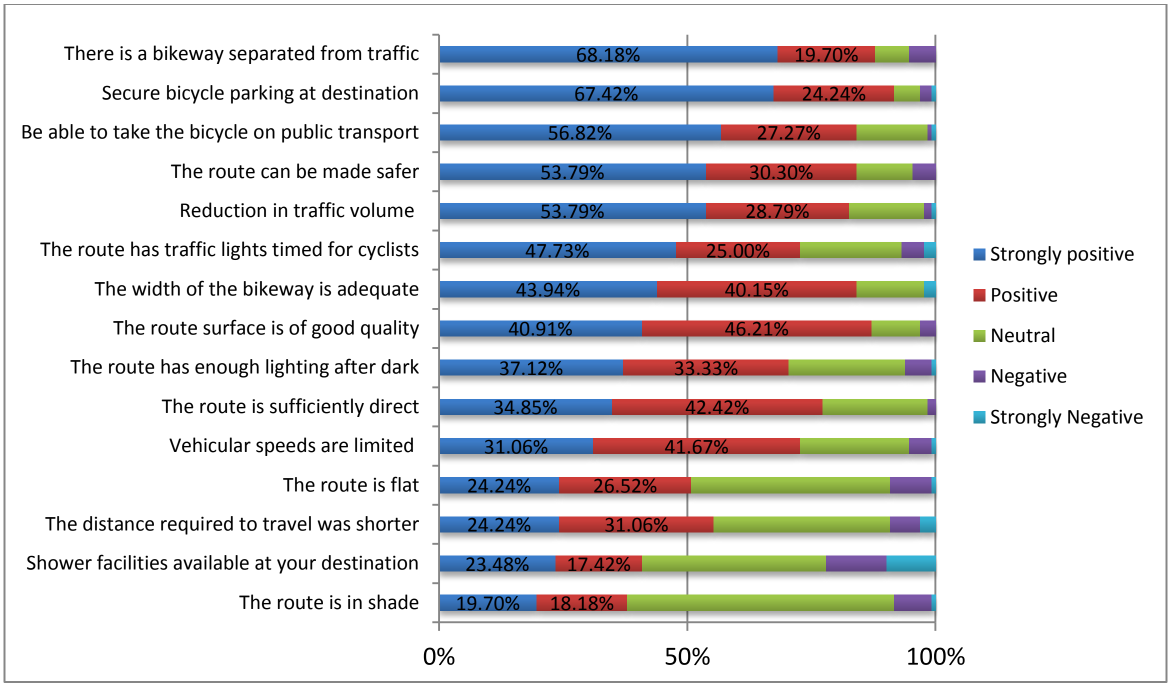

Figure 5. Attitudes on bicycling condition for bicyclists in Salt Lake City

transportation system well integrated with bicycling facilities is also likely to motivate increased cycling behavior.

5.5 Statistical Analyses of Bicycling Frequency

The statistical analysis of bicycling frequency is presented in this section. *T*-tests (for binary variables) and one-way analysis of variance (ANOVA) models (for polychotomous variables) were used to analyze differences in cycling frequencies amongst demographic and attitude perception groups. For now, we are assessing differences by the numeric representation of actual bike frequencies. So bicycling frequency 1 accounts for the option “I bike less than 1 day per week," and 2, 4, and 6, each account for “I bike 2–3 days per week,” “I bike 4–5 days per week,” and “I bike 6–7 days per week." When we move on to the ordered probit models, the categorical nature of the data is treated more appropriately.

The results indicate that all of the socio-demographic variables, except for educational attainment, are significantly related to cycling frequency (see more details in Appendix B). Bicycling frequencies were found the highest among groups who were male, age 20 or younger, homemaker or other unpaid work, single not living with family, and had limited access to a car.

Cycling purpose was also investigated using *T*-tests. Each variable was categorized as a binary value to represent yes or no responses to typical bicycling purpose. The results suggest that the purpose to commute to school or work, to go shopping, and to go visit friends or family have significant positive effects. Interestingly, although the purpose to exercise was the most selected bicycling reason, it is not significantly related to cycling frequency.

ANOVA tests were conducted to examine how attitudes on bicycling motivations influence bicycling frequency. Studies examining the relationship between attitudes and bicycle use have repeatedly demonstrated a significant influence of attitude, value, and individual habit factors (Gatersleben & Appleton, 2007; Heinen et al., 2010, 2011). The results indicated a significant relationship between concerns for convenience (bicycling is more convenient compared to other transportations modes) and bicycle frequency ($p < .01$), suggesting that significant bicycle use variance exists among groups with different levels of convenience perception. The attitude on "bicycling is fast" in five levels also had a significant influence on bicycling level ($p < .05$).

5.6 Attitude and Value Analysis

Exploratory factor analysis is performed on the survey data in order to identify the latent structures underlying attitude question responses. Furthermore, ANOVA tests were used to analyze attitudinal differences between different demographic groups, to discover the extent to which attitudes and values are independent from socio-demographic characteristics.

Maximum-likelihood factor analysis was performed using R programming language. A varimax rotation of the factors was applied to clarify the structure of factor loadings (Kaiser, 1958). In this model, the goodness-of-fit is tested by optimizing the log likelihood of factor loadings as the data are normally distributed (Fabrigar et al., 1999). Furthermore, factor scores were reported using the weighted least squares method (Bartlett, 1937).

The analysis reveals four attitudinal and value factors related to cycling that we name: safety, direct benefits, comfort, and timesaving. The identified factors explained nearly 50.3% of the variance (Table 3). Adding a fifth factor only explains 3.2% more variance, so the interpretation of more factors was not meaningful. The indicator “bike to avoid drinking and driving” is deleted according to its low absolute values of factor score on all identified factors (<0.1), leaving 23 attitude and value variables to test for latent factors. As we do not assume hypothesis for exploratory factor analysis, some variables may fit in multiple categories. For example, some may argue that “Avoid traffic” can also be treated as safety. Yet factors are defined based on the majority of their variables.

The first factor is labeled “safety” as it is constructed mainly of the travel safety characteristics, including traffic volume, travel speed, and parking safety. It also concerns

Table 3 Factor scores of the attitudes and values towards bicycling

	Factor			
	Safety	Direct benefit	Comfort	Timesaving
Secure parking	0.758			
Specialized traffic lights	0.721			
Separated bikeway	0.685			
Lighting	0.685			
Traffic volume reduction	0.636			
Limited vehicular speed	0.536			
Wide bikeway	0.533		0.429	
Good road surface quality	0.498		0.432	
Shower facilities	0.458			
Take bike on public transportation	0.456			
Safer route	0.448			
Improve health		0.837		
Save money		0.76		
Improve environment		0.758		
Fun		0.654		
Avoid traffic		0.494		
Park easy		0.424		
Convenient		0.409		0.763
Shade			0.796	
Flat route			0.735	
Short travel distance			0.57	
Direct route			0.497	
Fast				0.8
Proportion of variance explained	0.187	0.135	0.115	0.065
Cumulative variance explained	0.187	0.323	0.438	0.503

Note: Absolute values below 0.4 are not reported.

bicycle facilities and road characteristics that increase riding safety. The variables with high scores on the “direct benefits” factor are health improvement, money benefit, and environment improvement. Note that environment improvement may be regarded as being direct benefit because of the specific situation of high air pollution levels in Salt Lake City. Ranked high in America’s most dangerously polluted cities (American Lung Association, 2014), the city’s environment is raising more and more concern in recent years. Local administration and news media have been advocating non-motorized transportation means, including bicycling. Therefore, people are likely to be more aware of the environmental benefit of bicycling, and will connect the resulting air quality improvement to personal health improvement. The third factor, labeled “comfort,” has high scores on routes being flat and shaded, which mainly contribute to a pleasant biking environment. The “timesaving” factor comprises of only two characteristics, convenient and fast, yet the high factor score (>0.75) and the explained proportion (0.065) suggest it as an important and easily interpretable factor.

Having identified the four attitudes and values factors, independent sample *t*-tests and one-way ANOVAs are then applied to examine whether the mean perception scores of these four factors differed significantly according to the weekly bicycle frequency and demographic characteristics of the respondents. The results (see Appendix B) suggest that gender is the most influential demographic characteristic, with males having higher scores on the timesaving factor and lower scores for comfort and safety. This result is consistent with gender-related attitudes toward risk aversion in route choice behaviors: female commuter cyclists prefer to use routes with maximal separation from motorized traffic (Garrard et al., 2008).

The other demographic factors with statistically significant influence are marital status, with married individuals being more concerned with safety and less concerned with timesaving, and income, with a nonmonotonic relationship with comfort. Overall, and especially after taking gender into consideration, it appears that attitudinal and value factors are actually quite decoupled from demographics, This result supports that attitude factors can be only explained to a limited extent by social-demographics (Heinen et al., 2011), indicating the importance of collecting such factors in future research.

The final variable considered in ANOVA analysis is bicycling frequency, which is shown to be significantly related to the timesaving factor. It suggests that those who consider bicycling as a faster and more convenient transportation mode are likely to bike more often.

5.7 Bicycling Frequency Model

Ordered probit models are used to explore cycling frequencies among participants. Given the relatively small sample size, groups of variables are sequentially investigated, and final models are selected using a stepwise approach. The Akaike information criterion (AIC) score is used to assess goodness of fit.

The first model solely estimates the effect of demographic variables on cycling frequency. This model suggests that the following factor levels are associated with increased cycling frequency: being male, higher educated, single, without a car, and only part-time employed. Interestingly, income and age have no significant impact on frequency.

Following model 1, a stepwise search returns five significant factors that are subsequently tested in models 2-5. These are gender, education status, employment status, car ownership, and marital status. These five variables were entered into the following models to reduce the confounding effects caused by demographic variations.

Model 2 evaluates the relationship between stated cycling purposes and bicycling frequencies while controlling for demographic variables. Bicycling to participate in social activities, to accompany children, to visit friends, and to commute were identified as significant factors that influence bicycle frequency. It is worth mentioning that the employment status variable showed little significant effect in this model, once purposes are controlled for more directly.

Attitude and value variables were analyzed in model 3 while controlling for demographics. Two attitudinal variables, comfort and timesaving, are found to be significant. Those who value timesaving are more likely to ride, while valuing comfort has a negative effect.

Model 4 considers all previous identified variables as independent indicators, and the stepwise output of the forth model was shown in model 5. The final model outputs for model 5 are found in Table 4 (see Appendix B for full results of all models).

Only seven variables remained after stepwise elimination. The main results presented in the final model suggest that bicycling purpose has a strong influence on the propensity to bike more often. Specifically, everyday commute need has a strong positive influence on bicycling frequencies, but other utilitarian trip purposes such as going shopping or visiting friends does not seem to motivate cycling as much. In addition, biking to accompany children will significantly increase biking frequencies.

The models report a significant effect of the attitude and value variables on bike use.

Table 4 Ordered probit model results for bicycling frequencies

	Regression Coefficient	***P*-Value**
Demographics		
Education		
University and higher (base)		
Community and lower	-0.6498	0.006
Car ownership		
Do not have access to an automobile (base)		
Have access to an automobile and the ability to drive it	-1.2737	7.52e-04
Marital status		
Married or living with partner (base)		
Single or not living with partner	0.3996	0.065
General biking purpose		
Bike with children	0.6084	9.18e-02
Commute to work/school	0.9853	7.77e-06
Shopping (grocery, mall, etc.)	0.3888	8.11e-02
Attitudes and Values		
Comfort	-0.1466	0.124
Timesaving	0.3153	0.001
Intercept		
0|1	- 1.4159	0.002
1|2	- 0.2967	0.504
2|3	0.5099	0.254
Log Likelihood	-143.297 (*df*=11)	

The most important factor is perception of time benefit gained by using bicycles, while the effect of other attitudes is less clear. Surprisingly, the safety factors did not suggest statistical significance, pointing to the possibility of indirect effect of bicycle infrastructure. It is likely that people will bike even though there are few bike lanes on their route because of utilitarian reasons such as commuting. We expect that bike route characteristics will, however, have a more significant impact on route choice than overall bicycling frequency.

The ordered probit model results also reveal how bicycle frequency varies among different demographic groups. Gender, education, car ownership, and marital status were significantly related to bicycling frequency. Previous statistical analyses indicated similar results for these variables, except that the ANOVA test between education status and tendency to bike did not reveal a significant relationship. The results can be summarized as follows:

Gender: males are more likely to bike compared to females, which is consistent with literature suggesting that men are more likely to engage in cycling activities in United States (Steinbach et al., 2011).

Education: bicycling frequency is lower among lower education groups, including community college, high school, and less than high school. A cursory analysis of relationship between education and bicycling factors showed that people with better education have higher perception scores on environment and health concern variables, indicating that they are more aware of environmental issues or place higher importance on personal physical health, as stated by Besser and Dannenberg (2005).

Car ownership: access to automobile has a significant negative impact on bicycle use. Those who do not have access to a car are more likely to bike more often because of the necessity to perform daily activities.

Marital status: whereas the need to bike with children will increase bicycling frequencies, the results show that individuals who are single or live alone are more likely to bike. This makes sense because automobiles are still the major transportation means for most couples with children, who are less likely to bike.

5.8 Application of the Proposed Route Optimization Approach

In this study, we choose link attributes from the available dataset based on our descriptive analyses above. Four variables were chosen aside from the base cost link distance (Table 5). The cost function is represented as $\mathrm{C_i} = \mathrm{D_i} * \mathrm{AvgSlope_i^a} * \mathrm{OnRouteLane_i^b} * \mathrm{SeparatedLane_i^c} * \mathrm{SpeedLimit_i^d}$. For comparison between exponential parameters, all attribute variables except distance were converted to binary forms, which were determined by their distribution in the observed routes. As the cost function is in a multiplicative form, attributes were represented by 1 and 2 to avoid zero assignment of link cost values. For example, the existence of an on route bike lane is represented by 1 and otherwise by 2. Also, since using bike lanes is assumed to be preferred, only the positive interval of exponential parameter spaces need to be considered. In this way, the amount of calculation will be notably decreased, especially in cases with large numbers of attribute variables. Although it is unlikely in theory, the range may still be expanded to

Table 5 Link attribute definitions

Attribute	Value	Description
AvgSlope	1	Average slope between two link ends is smaller than or equals to 3
	2	Average slope between two link ends is larger than 3
OnRouteLane	1	There is a bike lane on route which is mixed with traffic
	2	There is not a bike lane on route which is mixed with traffic
SeparatedLane	1	There is a bike lane on route which is separated from traffic
	2	There is not a bike lane on route which is separated from traffic
SpeedLimit	1	The speed limit on route is smaller than or equals to 30
	2	The speed limit on route is larger than 30

negative values if the estimation of the exponential parameter is close to 0.

As seen in Table 5, more desirable link attributes are coded with 1s, indicating no additional cost of travel on that link, while less desirable characteristics are coded with 2s, indicating some additional cost of travel (to be determined by the exponential parameter). The parameter values were all set to 0 at initiation and increased by 0.1 to 1.

Figure 6 shows an example of a path that starts at the University of Utah and ends at Pioneer Park. The results of route simulation as well as the actual traveled route are reported in the map. In this example, the overlapping distance ratio is 49.43%, while the ratio of each model simulation reported next is calculated as the average value over all simulated routes.

The relationship between overlapped distance and the exponential parameter combinations is illustrated in Figure 7. The baseline is set when *a*, *b*, *c*, and *d* equals to

Figure 6. Route simulation example

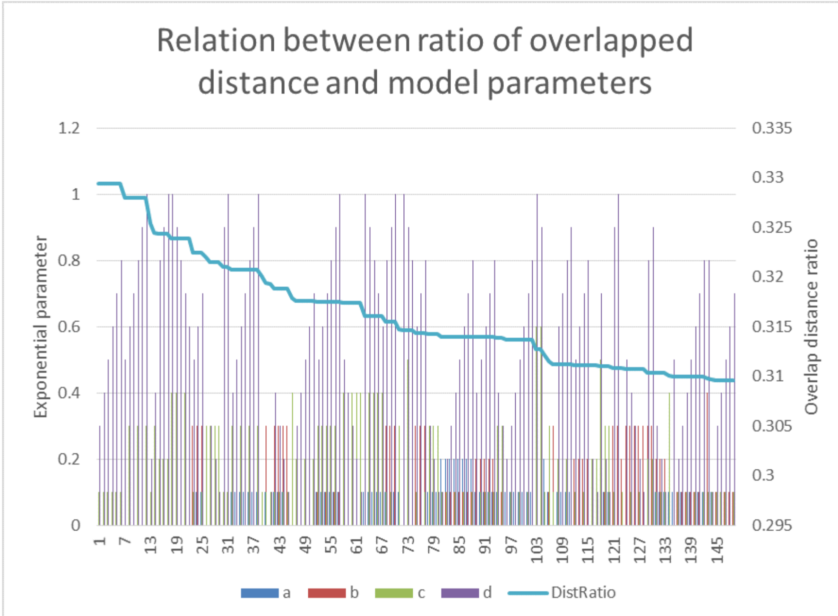

Figure 7. Distribution of model parameter at top 1% overlapped ratio among 10000 model runs, with 0< a <1, 0< b <1, 0< c <1, 0< d <1. (The left axis shows the value of exponential parameters combinations in the model, while the right axis shows the overlap distance ratio of the corresponding model)

zero, indicating no additional cost on selected attributes. The corresponding average overlap ratio is 29.9% according to model simulation, which is below the average of modeled results. As a result, the route optimization approach may describe route choice behavior better than distance-based models. We estimated the parameter values according to the top 1% of overlapped distance ratio. The largest overlapped distance to total observed route distance is 32.9% with 952 overlapped links. The figure suggests that there is little variance among the value of a and b, and the values were close to 0.1. So we refine the range of these two parameters to (0, 0.1) and change by 0.01 in the next estimation step. The figure also shows that the value of d is considerably unstable among the top 1% of results, which may imply that the fourth variable of speed limit on route is unlikely to affect travel choice given the value of a, b and c. Therefore, we ruled out the speed limit variable in the next model run.

Figure 8 further illustrates the distribution of model parameters with histograms. Parameter *d* has even distributions in the four categories, supporting the assumption that the speed limit variable may not be an influencing factor in the model. Besides, the values of parameter a falls mainly in 0 and 0.1, while 0.1 is also the most common value for parameter b. Since we estimate parameters based on their average value, the parameter space will be refined if the mean values fall in categories with little variances. As a result, we adjust the range of parameter a and b to (0, 0.1) and change by 0.01 in the next estimation step for more precise outputs.

The correlation matrix is presented in Table 6, revealing that there is little significant

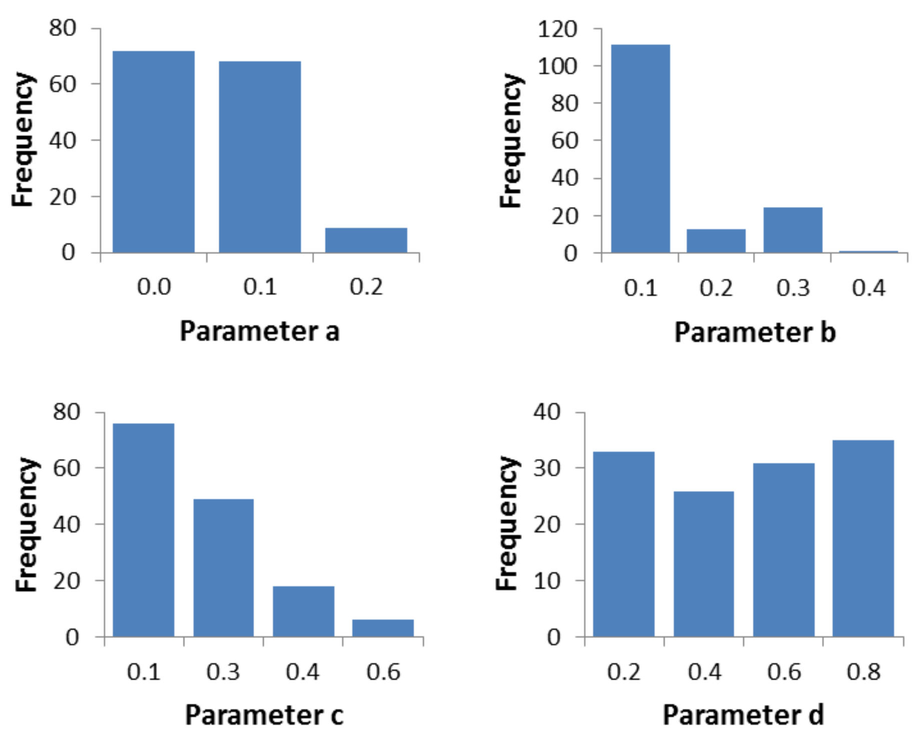

Figure 8. Distribution of model parameters at the 1% overlapped ratio

Table 6 Correlation matrix of model parameters at the 1% overlapped ratio

	a	b	c	d
a (AvgSlope)	1			
b (OnRouteLane)	0.094	1		
c (SeparatedLane)	-0.211	-0.535	1	
d (SpeedLimit)	-0.132	-0.039	0.188	1

correlation between the estimated parameters. However, there is a negative correlation between parameter b and c, suggesting that bicyclists who are more attracted to bike lanes separated from traffic will put less weight on mixed traffic bike lanes.

In the second model, the cost function is set as: $\mathrm{C_i} = \mathrm{D_i} * \mathrm{AvgSlope_i^a} * \mathrm{OnRouteLane_i^b} * \mathrm{SeparatedLane_i^c}$. According to the parameter estimation results in the first model, a and b ranged from 0 to 0.1 and changed by 0.01. Furthermore, the parameter space of separated bike lane was refined from 0 to 0.6 to reduce amount of calculation. After this, a third model was proposed to add back the previously dropped variable to test if performance improved with more precise values of the other parameters.

The results of the three models are revealed in Table 7. The coefficients of variation (CV) are also reported in the table. The overall route overlap rate of the three models remains similar; the third model showed a slightly higher average overlapped distance ratio of 33%, suggesting that it performs better at representing travel choices.

Among the three models, the value of average slope parameter (a) is largely influenced by the speed limit parameter (d). In models 1 and 3, its value is about 0.05, while in model 2, its value drops to 0.006, essentially adding very little cost. This may indicate covariance between these two variables.

Table 7 Cost function parameter estimation result (based on top 1% of overlapped distance ratio)

Parameter		Model 1	Model 2	Model 3
a (AvgSlope)	Mean	0.058	0.006	0.048
	CV	0.086	0.500	0.104
b (OnRouteLane)	Mean	0.090	0.089	0.070
	CV	0.010	0.034	0.057
c (SeparatedLane)	Mean	0.209	0.100	0.176
	CV	0.526	0	0.040
d (SpeedLimit)	Mean	0.528		0.561
	CV	0.045		0.044
Largest Overlapped Distance ratio		32.9%	32.6%	33.4%
Average Overlapped Distance ratio		31.6%	32.0%	32.9%

As suggested in model 3, the speed limit parameter (d) showed the largest estimation value and may indicate significant increase of cost on high-speed road sections. Additionally, the third variable of on route bike lane is a significant factor that influences travel choice. Traveling on a route without such bike lanes will increase travel cost. Compared to on street bike lanes, the model parameter for bike lanes that are separated from traffic is increased by 151%, suggesting that bicyclists would add higher cost over road sections without a separated bike lane. Since bicyclists prefer bike lanes separated from the traffic for safety reason, the result is expected.

CHAPTER 6

CONCLUSIONS

This study has analyzed the preferences and travel behavior of cyclists in Salt Lake City, Utah. Specifically, we explored the influences of attitude and values on bicycling frequencies by identifying four latent attitudinal factors relating to cycling. Then independent sample *t*-tests and ANOVA tests were applied to examine effects of demographic characteristics on attitude and values. Next, a series of ordered probit models examined relationships between bicycling frequencies and variables including attitudinal factors and demographics. Finally, a route choice model was used to improve our understanding of how cyclists value link-level characteristics, such as speed limits and bike lanes.

The analysis suggests an influential role of attitudes in making bicycling decisions. Bicycling frequency is largely affected by a belief that cycling can be a timesaving mode of travel. This is consistent with the literature on mode choice analysis, that people base their travel decision on benefits in terms of flexibility (Heinen et al., 2011).

An analysis of gender differences found that men and women place different levels of importance on safety and timesaving. As suggested by previous research, females are more likely to avoid the risks associated with cycling, and men seem to value timesaving more than women. One study found that 65% of male cyclists who cycle to work do so even though they perceive risks associated with cycling, while only 50% of female cyclists with similar perceptions do so (Wang et al., 2012). Yet more than 83% of the frequent bicyclists, regardless of gender, suggest that they would bike more often if the route were made safer. Furthermore, among all the safety related characteristics, the most desired facility is bike lane separated from traffic.

Aside from gender, other demographic factors including education status, car ownership, and marital status are also found to influence bicycling behavior. Specifically, car ownership has the most significant impact on bicycle usage among all the demographic variables. Possession of a car decreases the use of bicycle as a commute mode. There is also a significant difference in cycling frequency among different education groups. Our results echo previous studies that have found that bicycling rates are the highest among college degree or higher education levels group, possibly because of higher environmental concern of this group of people (Kuzmyak et al., 2014).

As discussed in the data collection section, the sample collected from the survey is biased, because of the survey distribution locations and method. The sample represents more of a recreational bicycling population, rather than utilitarian cyclists. Although there may be some overlap in the two categories, further research should utilize a more statistically representative sample.

In general, the bicycling frequency model offers insights into the influence of individual attitude factors and social-demographic components in explaining bicycle use, and points out some further research topics. First, individual attitude of timesaving is identified to play a significant role in promoting bicycle use. However, there is still a need to research on attitude influence on bicycling, since the effect of safety and direct benefit concerning health and cost savings are also found to be importance in some cases (Heinen et al., 2011). The significant role of individual attitudes may vary according to residential environment or other personal experiences not controlled for in the present study. Second, potential relationships between suggested policies and bicycle use need to be explored through modeling or before-after studies. The empirical effects of educational programs and improvements in bicycle facilities need to be examined to further identify effective strategies.

Finally, we present a route optimization method to analyze bicycling route choice behaviors regarding link level characteristics. Streets with higher speed limits are traveled more often. However, that is because most direct routes are city arterials with high speed limits while there are very few direct routes that have low speed limits. Our model shows a strong preference for lower speed limit streets. Thus, we believe there is a great need for bike routes that are both direct and with low speed limits.

When it comes down to categories of bicycle routes, the model result suggests a preference for bike lanes separated from traffic. Given the relatively low use of this type of bike facility due to limited supply, the result has further proved the importance and demand for safer bicycle facilities.

The estimated least cost routes show a relatively low overlap rate with observed routes. This is likely because only four variables were evaluated in the route choice model, which is limited by data availability and computational ability. Besides, in a grid transportation network such as Salt Lake City, there are few differences in trip distance when comparing observed routes to shortest paths, making it difficult to estimate route preferences because often more and less desirable routes will have the exact same length.

We expect that adding more detailed link-level characteristics will help the model perform better on matching observed travel routes.

Route choice models have often focused on generating a universal set of alternative routes and evaluating discrete choices among the generated choice set. The proposed route choice modeling method assumes that travelers will estimate the cost of the links according to their preferences. It is able to consider all the alternative links in the network and allows travelers to synthetically evaluate all environmental factors and make decisions accordingly.

One open question with this research is the definition of the cost function. The rational of multiplicative representation is to modify the perceived distance of trips by small increments. However, the binary assignment of route characteristic variables can be arbitrary and easily influenced by the data distribution. Implementations of continuous variables into the model needs to be studied and compared with the current model. Other forms of the cost function are also yet to be studied and compared to evaluate feasibility. One interesting follow-up study is to investigate the role of attitudes and demographics on parameter estimates in the cost function. This should surely provide a closer fit than the global cost functions investigated herein.

Based on the selected cost function, an iterative search method was used in this study to traverse parameter space and to explore the parameter combinations that perform the best. This is a rather straightforward method that can be easily implemented in the route optimization approach. However, it takes a long time to traverse the whole parameter space and compute routes for each combination. The complexity of this algorithm is exponential, so the operation time will increase extremely fast by adding more variables.

Furthermore, in a travel behavior such as bicycling, the route choice behavior is generally affected by many more complex variables than those demonstrated in this paper. Therefore, a systematic variable selection method needs to be developed to ensure acceptable running time of this algorithm.

Validation methods need be developed to better evaluate the route choice model. Overlapping ratio is used as a goodness-of-fit indicator in this approach, and we have found that model 3 performs better than model 2, with a 1% increase in overlapping ratio. However, model 3 requires an additional variable, increasing its complexity, so further study may focus on comparing between models through other statistical test such as likelihood-ratio test or AIC measure.

This study associated a revealed choice route survey with a stated preference survey and analyzed bicycling behaviors as well as individual attitudes. We can use results from this study as policy implications for the transportation planners, to promote bicycling by improving policies and facilities to make bicycling faster and more convenient. Some approaches include implementation of specialized signage and traffic control, provision of cycling priority boxes at intersections, or better integration of bicycling with the public transit systems. Combining the results of the two experiments shows interesting findings. Even though timesaving is the most dominant factor in attitudes toward bicycling choices, bicyclists prefer low speed limit streets in their route choices, indicating a concern for safety. As on street bike routes are already broadly implemented in the case of Salt Lake City, the more impending need may be off-street bike lanes in parallel with city arterials. Besides, improved bicycling facilities in the form of bicycle paths and lanes that provide a high degree of separation from motor traffic are also important for increasing cycling activity, especially among women (Garrard et al., 2008). Closing this gender gap by providing people with safer means to bicycle should result in increased health equality between genders, whereas for places that have less bicycling infrastructures, the importance of "timesaving" attitude should be taken into consideration in bicycling planning.

Applying attitudes and values in this travel behavior study indicates that these factors have a strong impact on bicyclists' riding decisions. However, we found that the actual routes they take sometimes differ from routes that would be chosen based on their stated attitudes, suggesting various preferences. As a future direction to increase the understanding of the relationship between attitudes and actual travel behavior, one could apply techniques such as GPS collection to gather more accurate and larger amount of data to compare actual routes with stated preference travel surveys. Applying attitudes and values in this travel behavior study indicates that these factors have a strong impact on bicyclists' riding decisions. However, we found that the actual routes they take sometimes differ from routes that would be chosen based on their stated attitudes, suggesting various preferences. As a future direction to increase the understanding of the relationship between attitudes and actual travel behavior, one could apply techniques such as GPS collection to gather more accurate and larger amount of data to compare actual routes with stated preference travel surveys.

APPENDIX A

BICYCLING PREFERENCE SURVEY

Bicycling Preference Survey

The following questionnaire has been developed to assist student's thesis research in University of Utah. Your cooperation in honestly completing this study would be greatly appreciated. **Please do not sign your name on your survey. All responses will be kept confidential.** Please omit any questions you do not wish to answer. Please feel free to add comments or clarifications to any of the questions.

1. Where were you when you started your trip (home, work, out for dinner, etc.)?

    ____
    _

2. Using as much detail as possible, please describe and/or draw the route taken here today. Please include portions of the trip that you may have travelled by different modes of transportation (bus, Trax, FrontRunner, or automobile) to get here. It is essential that we learn which streets you rode on, where you turned, and whether you made stops along the way.

3. You identify your gender as
    - o Female
    - o Male
    - o ________

4. What is your year of birth? _______________

5. What is the highest degree or level of school you have completed? If currently enrolled, highest degree received.
    - o No schooling completed

- ○ High school or the equivalent (for example: GED)
- ○ Community college diploma or the equivalent
- ○ Bachelor’s degree
- ○ Master’s degree
- ○ Doctorate degree

6. What is your current employment status?
- ○ Unemployed and not a student, but currently seeking work
- ○ Student
- ○ Employed part-time (<30 hours per week)
- ○ Employed full-time (≥30 hours per week)
- ○ Homemaker or other unpaid work

7. Over the LAST TWO WEEKS, how many days did you go on a bike ride?
- ○ 6–7 days per week
- ○ 4–5 days per week
- ○ 1–3 days per week
- ○ 1 day in the last two weeks
- ○ none

8. Typically, what are the reasons that you go on a bike ride? Please select all that apply.
- ○ Exercise/physical activity
- ○ To socialize with others (bike club, training group, coworkers, etc.)
- ○ To bike with (accompany) children
- ○ To commute to work/school
- ○ To go shopping (grocery, mall, etc.)
- ○ To go visit friends/family
- ○ To go to a recreation event (a concert, a sporting event, etc.)
- ○ Other, please specify: ____

9. How strongly do you agree or disagree with each of the following statements about your cycling motivations?

	Strongly agree	**Agree**	**Neutral**	**Disagree**	**Strong disagree**
I can avoid traffic congestion	○	○	○	○	○
I can improve my health	○	○	○	○	○
I cycle for fun	○	○	○	○	○
I can save money	○	○	○	○	○
I can improve the environment/air quality	○	○	○	○	○
Cycling is more convenient than other travel modes	○	○	○	○	○
Cycling is faster than other travel modes	○	○	○	○	○
It is easier to park a bicycle	○	○	○	○	○

10. How do you feel about biking more often if each of the following conditions were satisfied?

	Strongly positive	Positive	Neutral	Negative	Strong Negative
There is a bikeway separated from traffic	○	○	○	○	○
Secure bicycle parking at destination	○	○	○	○	○
Reduction in traffic volume	○	○	○	○	○
The route has enough lighting after dark	○	○	○	○	○
Be able to take the bicycle on public transport	○	○	○	○	○
The route is flat	○	○	○	○	○
The route is in shade	○	○	○	○	○
The width of the bikeway is adequate	○	○	○	○	○
The route surface is of good quality	○	○	○	○	○
The route is sufficiently direct	○	○	○	○	○
Vehicular speeds are limited	○	○	○	○	○
The route has traffic lights timed for cyclists	○	○	○	○	○
The route can be made safer	○	○	○	○	○
Shower facilities available at your destination	○	○	○	○	○
The distance required to travel was shorter	○	○	○	○	○

11. Do you own or otherwise have reasonable access to an automobile and the ability to drive it? YES/NO

12. What do you think is the single most important barrier for why YOU don’t cycle more often?

- ○ Poor/unpredictable weather
- ○ Too busy (didn’t have time)
- ○ Need/want to use vehicle for work/school/other reasons (instead of biking)
- ○ Feel unsafe biking in traffic
- ○ Too few off-street bike paths or trails
- ○ Too few on-street marked bike lanes
- ○ Takes too long to bike to the places I go
- ○ No showers/changing facilities to use after biking
- ○ Do not like/enjoy biking
- ○ My health (or health of someone in my household) doesn’t allow me to bike
- ○ Do not own a bike
- ○ Other, please specify: ____

13. What do you think is the single most important barrier for why OTHERS don't cycle more often?
- o Poor/unpredictable weather
- o Too busy (didn't have time)
- o Need/want to use vehicle for work/school/other reasons (instead of biking)
- o Feel unsafe biking in traffic
- o Too few off-street bike paths or trails
- o Too few on-street marked bike lanes
- o Takes too long to bike to the places I go
- o No showers/changing facilities to use after biking
- o Do not like/enjoy biking
- o Their health (or health of someone in their household) doesn't allow them to bike
- o Do not own a bike
- o Other, please specify: ____

14. Which of the following describes your marital status?
- o Married or currently living with a spouse or partner
- o Single and/or not living with a spouse or partner

15. If you have children, please list the age of each of your children.

____

16. If you have children, please indicate the age of each child that lives at home with you.

____

17. To the best of your ability, please provide us with an estimate of your household income to the nearest $10,000.

____

18. Would you describe your race/ethnicity as (circle one or more): <u>White / Black / Hispanic / Asian / Other</u>
If other, please specify: ____

Thank you!

APPENDIX B

COMPLETE STATISTICAL ANALYSIS RESULTS

Table 8 Relations between cycling frequencies and demographic/attitude perception groups.

Variable	Mean bicycling frequencies
Gender[a]	
Female	2.849
Male	3.886
p-value	0.003 **
Age[b]	
20 or younger	6.000
20-30	3.556
30-40	3.279
40-60	3.632
60 or order	1.500
p-value	0.055 .
Education[b]	
Community and lower	3.153
University and higher	3.602
p-value	0.264
Employment status	
Unemployed or student	4.227
Part time	4.100
Full time	3.012
Homemaker or other unpaid work	4.500
p-value	0.009 **
Car ownership[a]	
Have access to an automobile	3.250
Do not have access to an automobile	4.940
p-value	0.004 **
Marital status[a]	
Married or living with partner	2.872
Single or not living with partner	3.896
p-value	0.004 **

Variable	Mean bicycling frequencies
Income level[b]	
Less than $20,000	3
$20,000-$40,000	4.517
$40,000-$60,000	3.12
More than $60,000	3.273
Do not know/refusal	3.214
p-value	0.0343 *
Exercise/physical activity[a]	
Yes	3.524
No	3.259
p-value	0.579
To socialize with others[a]	
Yes	3.420
No	3.500
p-value	0.823
To bike with children[a]	
Yes	4.231
No	3.387
p-value	0.163
To commute to work/school[a]	
Yes	4.275
No	2.231
p-value	5.574e-10 ***
To go shopping (grocery, mall, etc.)[a]	
Yes	3.899
No	2.581
p-value	2.058e-4 ***
To go visit friends/family[a]	
Yes	4.076
No	2.881
p-value	5.375e-4 ***

Variable	Mean bicycling frequencies
To go to a recreation event[a]	
Yes	3.607
No	3.186
p-value	0.269
I can avoid traffic congestion[b]	
Strongly agree	3.525
Agree	3.568
Neutral	3.235
Disagree	2.875
Strongly disagree	4.000
p-value	0.880
I can improve my health[b]	
Strongly agree	3.366
Agree	3.806
Neutral	3.000
Disagree	--
Strongly disagree	2.000
p-value	0.601
I cycle for fun[b]	
Strongly agree	3.455
Agree	3.792
Neutral	2.000
Disagree	--
Strongly disagree	2.000
p-value	0.252

Table 8 (continued)

Variable	Mean bicycling frequencies
I can save money[b]	
Strongly agree	3.511
Agree	3.710
Neutral	2.667
Disagree	--
Strongly disagree	2.000
p-value	0.409
I can improve the environment[b]	
Strongly agree	3.408
Agree	3.458
Neutral	5.500
Disagree	--
Strongly disagree	2.000
p-value	0.197
Cycling is more convenient[b]	
Strongly agree	4.106
Agree	3.571
Neutral	2.667
Disagree	3.125
Strongly disagree	1.000
p-value	0.008 **
Cycling is faster[b]	
Strongly agree	4.033
Agree	3.892
Neutral	2.905
Disagree	3.238
Strongly disagree	1.500
p-value	0.048 *

Variable	Mean bicycling frequencies
It is easier to park a bicycle[b]	
Strongly agree	3.674
Agree	3.000
Neutral	3.429
Disagree	2.000
Strongly disagree	2.000
p-value	0.291
Variable	**Mean bicycling frequencies**
I don’t need to worry about drinking and driving[b]	
Strongly agree	3.344
Agree	3.739
Neutral	3.292
Disagree	3.636
Strongly disagree	3.769
p-value	0.882

Notes: This table provides complete results for discussions in Section 5.5
Variables labeled “a” were evaluated using *t*-tests. Variables labeled “b” was evaluated using ANOVA tests.
* Significant at the 5% level; ** Significant at the 1% level; *** Significant at the 0.1% level.

Table 9 Relationships between demographics, attitudes, and cycling frequency

	Mean factor score			
	Safety	Direct benefit	Comfort	Timesaving
Gender[a]				
Female	0.283	-0.008	0.233	-0.243
Male	-0.19	0.005	-0.157	0.163
p-value	0.01534 **	0.9518	0.05198 .	0.03823 *
Age[b]				
20 or younger	0.007	0.031	0.17	0.063
20-30	-0.103	0.037	-0.232	0.151
30-40	0.359	-0.352	-0.044	-0.222
40-60	-0.42	0.39	-0.154	-1.272
60 or order	-0.396	0.526	0.245	-0.384
p-value	0.495	0.503	0.481	0.114
Education[b]				
Community and lower	0.085	0.081	-0.0313	0.024
University and higher	-0.202	-0.192	0.075	-0.057
p-value	0.1967	0.3084	0.6205	0.69
Employment status				
Unemployed or student	0.048	-0.078	-0.074	-0.058
Part time	-0.356	0.168	-0.129	-0.157
Full time	0.265	0.076	0.255	0.519
Homemaker or other unpaid work	-0.178	0.146	0.478	0.267
p-value	0.276	0.755	0.375	0.137

Table 9 (continued)

	Mean factor score			
	Safety	Direct benefit	Comfort	Timesaving
Car ownership[a]				
Have access to an automobile and the ability to drive it	-0.347	-0.166	0.138	0.168
Do not have access to an automobile	0.051	0.024	-0.02	-0.024
p-value	0.1521	0.5097	0.5822	0.5463
Marital status[a]				
Married or living with partner	0.214	0.062	0.078	-0.282
Single or not living with partner	-0.153	-0.044	-0.056	0.202
p-value	0.05152 .	0.5588	0.512	0.01331 *
Income level[b]				
Less than $20,000	0.037	0.266	0.821	0.1
$20,000-$40,000	- 0.125	0.134	-0.045	0.42
$40,000-$60,000	0.093	-0.113	-0.193	-0.05
More than $60,000	-0.106	0.141	0.03	-0.177
Do not know/refusal	0.075	-0.188	-0.112	-0.201
p-value	0.915	0.526	0.0662 .	0.177
Bike frequency[b]				
Less than 1 day per week	0.178	-0.01	0.134	-0.546
2–3 days per week	0.152	-0.099	0.251	-0.115
4–5 days per week	-0.184	0.331	-0.107	-0.129
6–7 days per week	-0.118	-0.128	-0.229	0.5121
p-value	0.45	0.317	0.242	0.00087 ***

Notes: This table provides complete results for discussions in Section 5.6
Variables labeled “a” were evaluated using *t*-tests. Variables labeled “b” were evaluated using ANOVA tests.
. Significant at the 10% level.
* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

Table 10 Ordered probit model results for bicycling frequencies considering four latent attitude factors (full model)

	Model 1 Demographic Coefficients (*p*-value)	**Model 2 Cycling Purpose Coefficients (*p*-value)**	**Model 3 Attitude and Value Coefficients (*p*-value)**	**Model 4 All refined Coefficients (*p*-value)**	**Model 5 Stepwise Output of Model 4 Coefficients (*p*-value)**
Demographics	`				
Gender					
Female (base)					
Male	0.5185 (0.013)	0.5060 (0.019)	0.3995 (0.062)	0.304 (0.166)	
Age					
20 or younger	5.0520 (0.937)				
20-30 (base)					
30-40	0.1008 (0.691)				
40-60	0.3960 (0.211)				
60 or older	-0.6462 (0.317)				

Table 10 (continued)

	Model 1 Demographic Coefficients (*p*-value)	**Model 2 Cycling Purpose Coefficients (*p*-value)**	**Model 3 Attitude and Value Coefficients (*p*-value)**	**Model 4 All refined Coefficients (*p*-value)**	**Model 5 Stepwise Output of Model 4 Coefficients (*p*-value)**
Education					
University and higher (base)					
Community and lower	-0.6698 (0.007)	-0.8131 (0.001)	-0.6513 (0.007)	- 0.7691 (0.003)	- 0.6498 (0.006)
Employment status					
Full time (base)					
Unemployed or student	0.5058 (0.144)	0.3024 (0.356)	0.5326 (0.098)	0.3736 (0.265)	
Part time	0.5766 (0.091)	0.5174 (0.100)	0.6286 (0.048)	0.5081 (0.127)	
Homemaker or other unpaid work	0.6224 (0.163)	0.5553 (0.214)	1.0197 (0.019)	0.7018 (0.120)	
Car ownership					
Do not have access to an automobile (base)					
Have access to an automobile and the ability to drive it	-1.0516 (0.007)	-1.1642 (0.003)	-1.1493 (0.003)	- 1.1457 (0.005)	- 1.2737 (7.52e-04)
Marital status					
Married or living with partner (base)					

Table 10 (continued)

	Model 1 Demographic Coefficients (*p*-value)	**Model 2 Cycling Purpose Coefficients (*p*-value)**	**Model 3 Attitude and Value Coefficients (*p*-value)**	**Model 4 All refined Coefficients (*p*-value)**	**Model 5 Stepwise Output of Model 4 Coefficients (*p*-value)**
Single or not living with partner					
Income level					
More than $60,000 (base)					
Do not know/refusal	-0.4277 (0.284)				
Less than $20,000	0.2948 (0.367)				
$20,000-$40,000	-0.4344 (0.159)				
$20,000-$60,000	-0.0614 (0.842)				
General biking purpose					
Exercise/physical activity		0.2554 (0.347)			
Socialize with others (bike club, training group, coworkers, etc.)		-0.3623 (0.101)			
Bike with children		0.9306 (0.011)		0.6122 (0.102)	0.6084 (9.18e-02)
Commute to work/school		0.8775 (1.629e-4)		0.93450 (2.522e-05)	0.9853 (7.77e-06)

Table 10 (continued)

	Model 1 Demographic Coefficients (*p*-value)	**Model 2 Cycling Purpose Coefficients (*p*-value)**	**Model 3 Attitude and Value Coefficients (*p*-value)**	**Model 4 All refined Coefficients (*p*-value)**	**Model 5 Stepwise Output of Model 4 Coefficients (*p*-value)**
Shopping (grocery, mall, etc.)		0.2131 (0.351)		0.3446 (0.127)	0.3888 (8.11e-02)
Visit friends/family		0.2068 (0.397)			
Recreation event (a concert, a sporting event, etc.)		0.1385 (0.561)			
Attitudes and Values					
Safety			-0.0784 (0.417)	-0.1160 (0.244)	
Direct benefit			-0.0599 (0.534)	-0.1206 (0.227)	
Comfort			-0.2019 (0.034)	-0.1628 (0.099)	- 0.1466 (0.124)
Timesaving			0.3287 (0.001)	0.3400 (0.001)	0.3153 (0.001)
Intercept					
0|1	-1.3682 (0.004)	-0.7528 (0.120)	-1.6311 (3.62e-4)	- 1.1433 (0.018)	- 1.4159 (0.002)
1|2	-0.3513 (0.462)	-0.3735 (0.447)	-0.6266 (0.165)	0.0200 (0.967)	- 0.2967 (0.504)
2|3	0.3594 (0.455)	1.1892 (0.017)	0.1019 (0.821)	0.8776 (0.075)	0.5099 (0.254)

Table 10 (continued)

	Model 1 Demographic Coefficients (*p*-value)	**Model 2 Cycling Purpose Coefficients (*p*-value)**	**Model 3 Attitude and Value Coefficients (*p*-value)**	**Model 4 All refined Coefficients (*p*-value)**	**Model 5 Stepwise Output of Model 4 Coefficients (*p*-value)**
AIC (stepwise)	338.42	315.29	329.31	312.25	308.42
Relative Likelihood	3.06e-7	0.03	2.91e-5	0.15	1
Log Likelihood	-159.2094 (*df*=10)	-146.6452 (*df*=11)	-152.654 (*df*=12)	-138.9677 (*df*=17)	-143.297 (*df*=11)

Note: This table provides complete results for discussions in Section 5.7
The AIC is computed for the reduced (i.e., stepwise) model outputs, but coefficients are presented for the set of predictors before stepwise variable elimination. The preferred model is the one with lower AIC scores. The relative likelihood of the model suggests relative probability that the model minimizes the (estimated) information loss. It is calculated as: $\exp((AIC_{min} - AIC_i)/2)$. In this case, the relative likelihood of model i is computed based on model 5, which has the lowest AIC score.

REFERENCES

Aultman-Hall, L., Hall, F. L., & Baetz, B. B. (1997). Analysis of bicycle commuter routes using geographic information systems: Implications for bicycle planning. *Transportation Research Record: Journal of the Transportation Research Board*, *1578*, 102-110.

Barnes, G. R., & Thompson, K. B. (2006). A longitudinal analysis of the effect of bicycle facilities on commute mode share. *Transportation Research Board 85th Annual Meeting. Transportation Research Board, Washington, DC.*

Bartlett, M. S. (1937). The statistical conception of mental factors. *British Journal of Psychology. General Section*, *28*(1), 97-104.

Besser, L. M., & Dannenberg, A. L. (2005). Walking to public transit: Steps to help meet physical activity recommendations. *American journal of preventive medicine*, *29*(4), 273-280.

Broach, J., Dill, J., & Gliebe, J. (2012). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice*, *46*(10), 1730-1740.

Burbidge, S. K. (2012). Identifying a Profile for Non-Traditional Cycle Commuters(No. UT-12.16). Retrieved May 26, 2015, from http://www.udot.utah.gov/main/uconowner.gf?n=3431812201411562

Burbidge, S., & Goulias, K. (2009). Active travel behavior. *Transportation Letters*, *1*(2), 147-167.

Centers for Disease Control and Prevention. (2010). CDC Recommendations for Improving Health through Transportation Policy. Retrieved May 26, 2015, from http://www.cdc.gov/transportation/docs/final-cdc-transportation-recommendations-4-28-2010.pdf.

Dill, J., & Carr, T. (2003). Bicycle commuting and facilities in major US cities: If you build them, commuters will use them. *Transportation Research Record: Journal of the Transportation Research Board*, *1828*, 116-123.

Elvik, R. (2009). The non-linearity of risk and the promotion of environmentally sustainable transport. *Accident Analysis & Prevention*, *41*(4), 849-855.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*(3), 272-299.

Federal Highway Administration. (2007). "Interim Report to the U.S. Congress on the Nonmotorized Transportation Pilot Program SAFETEA-LU Section 1807." Washington, DC.

Garrard, J., Rose, G., & Lo, S. K. (2008). Promoting transportation cycling for women: The role of bicycle infrastructure. *Preventive Medicine*, *46*(1), 55-59.

Gatersleben, B., & Appleton, K. M. (2007). Contemplating cycling to work: Attitudes and perceptions in different stages of change. *Transportation Research Part A: Policy and Practice*, *41*(4), 302-312.

Handy, S. (2005). Critical assessment of the literature on the relationships among transportation, land use, and physical activity. *Transportation Research Board and the Institute of Medicine Committee on Physical Activity, Health, Transportation, and Land Use.* Resource paper for TRB Special Report, 282.

Handy, S. L., Xing, Y., & Buehler, T. J. (2010). Factors associated with bicycle ownership and use: A study of six small US cities. *Transportation*, *37*(6), 967-985.

Heinen, E., Maat, K., & Wee, B. V. (2011). The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. *Transportation Research Part D: Transport and Environment*, *16*(2), 102-109.

Heinen, E., van Wee, B., & Maat, K. (2010). Commuting by bicycle: An overview of the literature. *Transport Reviews*, *30*(1), 59-96.

Jacobsen, P. L. (2003). Safety in numbers: more walkers and bicyclists, safer walking and bicycling. *Injury Prevention*, *9*(3), 205-209.

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. *Psychometrika*, *23*(3), 187-200.

Krizek, K. J., & Johnson, P. J. (2006). Proximity to trails and retail: Effects on urban cycling and walking. *Journal of the American Planning Association*, *72*(1), 33-42.

Kuzmyak, J. R., Walters, J., Bradley, M., & Kockelman, K. M. (2014). Estimating Bicycling and Walking for Planning and Project Development: A Guidebook (No. Project 08-78). Retrieved May 27, 2015, from http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_770.pdf

McKelvey, R. D., & Zavoina, W. (1975). A statistical model for the analysis of ordinal level dependent variables. *Journal of Mathematical Sociology, 4*(1), 103-120.

Parkin, J., Wardman, M., & Page, M. (2008). Estimation of the determinants of bicycle mode share for the journey to work using census data. *Transportation*, *35*(1), 93-109.

Pucher, J., Dill, J., & Handy, S. (2010). Infrastructure, programs, and policies to increase bicycling: An international review. *Preventive Medicine*, *50*, S106-S125.

Pucher, J., & Renne, J. L. (2003). Socioeconomics of urban travel: Evidence from the 2001 NHTS. *Transportation Quarterly, 57*(3), 49-77.

Pratt, R. H., Evans, I. V., John, E., Levinson, H. S., Turner, S. M., Jeng, C. Y., & Nabors, D. (2012). Pedestrian and bicycle facilities. In *Transit Cooperative Highway Research Program (TCRP) Report 95: Traveler Response to Transportation System Changes*. *Transportation Research Board*, Washington, D.C., Chap 16.

Robinson, D. L. (2005). Safety in numbers in Australia: More walkers and bicyclists, safer walking and bicycling. *Health Promotion Journal of Australia*, *16*(1), 47-51.

Steinbach, R., Green, J., Datta, J., & Edwards, P. (2011). Cycling and the city: A case study of how gendered, ethnic and class identities can shape healthy transport choices. *Social Science & Medicine*, *72*(7), 1123-1130.

Stinson, Monique, & Bhat, Chandra. (2003). Commuter Bicyclist Route Choice: Analysis Using a Stated Preference Survey. *Transportation Research Record: Journal of the Transportation Research Board*, *1828*, 107-115.

Utah Department of Health. (2012). Utah Bicycle and Pedestrian Master Plan Design Guide. Retrieved May 27, 2015, from http://walkbikeplan.com/wp-content/uploads/2012/03/UDOH-Bike-Ped_Final_11-1-11.pdf

Wang, J. Y., Mirza, L., Cheung, A. K., & Moradi, S. (2012). Transforming Auckland into a bicycle-friendly city: Understanding factors influencing choices of cyclists and potential cyclists. In *Australasian Transport Research Forum (ATRF)*, 35th, 2012, Perth, Western Australia, Australia.

Xing, Y., Handy, S. L., & Mokhtarian, P. L. (2010). Factors associated with proportions and miles of bicycling for transportation and recreation in six small US cities. *Transportation Research Part D: Transport and Environment, 15*(2), 73-81.