USDOT Region V Regional University Transportation Center Final Report

NEXTRANS Project No. 171OSUY2.2

Tracking Bicyclists' Route Choices,
Case Study: The Ohio State University

By

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DISCLAIMER

Funding for this research was provided by the NEXTRANS Center, Purdue University under Grant No. DTRT12-G-UTC05 of the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

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TECHNICAL SUMMARY

NEXTRANS Project No. 171OSUY2.2 Final Report, August, 2017

Tracking Bicyclists' Route Choices, Case Study: The Ohio State University

Introduction

Bicycles have low access costs and moderate travel speeds, reduce congestion, help protect the environment and bring many health benefits (Clifton & Akar, 2009). Within these considerations, several researchers have explored the factors associated with bicycling choice to understand the needs of bicyclists and increase bicycle mode share. Existing literature identified socio-demographics, built environment, road conditions and land-use patterns as factors associated with bicycling choice in general (Pucher et al., 2011; Dill and Carr, 2003). Among these, presence of bicycle facilities, motor vehicle traffic characteristics, surface quality, neighboring land-uses are cited as factors affecting bicycling route choices (Broach et al. 2012).

There is increasing interest among colleges and universities in ways to reduce local congestion, contributions to greenhouse gases, and provide leadership in sustainable transportation. This study brings these two emerging areas together: analyzing campus transportation patterns and identifying the factors associated with bicycle trip generation and bicycle route choices using state-of-the-art data collection techniques at a large university campus, The Ohio State University (OSU). The origins, destinations and routes of bicycle trips are collected through a cell phone app: *CycleTracks*[(1)]. This app is developed by SFCTA (San Francisco County Transit Authority) to collect data on users' bicycle trip routes and times, and display maps of their rides using smartphone GPS.

This study has two major components: (i) an online survey with questions on bicycling decisions and personal attitudes associated with those decisions, (ii) collecting bicycle trip data (origins, destinations and routes) using a cell phone app (CycleTracks) and route choice analyses.

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[1] http://www.sfcta.org/modeling-and-travel-forecasting/cycletracks-iphone-and-android

Findings

The first part of this study uses data from the 2015 Campus Travel Pattern Survey. We collaborated with OSU's Transportation & Traffic Management Department on this survey. The focus of the survey is on individuals' bicycling choices as an alternative commute mode to campus. This study performs analyses with the data on respondents' travel origins to draw out practical information on the bicycling environment along actual roads to and from campus. Using survey respondents' residential locations and data on Bicycle Level of Service (BLOS) received from MORPC (Mid-Ohio Regional Planning Commission), we construct a dataset that consists of respondents' travel origins and shortest routes to OSU campus. Since the 2015 survey data reveal that those who live within 1-5 miles from campus are more likely to be bicycle users, we categorize those who live within 5 miles from the campus area as potential bicyclists and a target group for promoting bicycling to commute. We include these respondents in our detailed analyses.

We assume the respondents ride to a central campus location using the shortest path. First, we geocode each respondent's residential location into coordinates on an ArcGIS layer. Second, we transform the Ohio street system into a network of nodes and arcs (or road segments) using Python and MS Excel. Following these and through some data manipulation, we assign the potential number of bicycling trips to each road segment using the shortest path algorithm. We superimpose the layer of BLOS (Bicycle Level of Service) values upon this map and perform an overlay analysis. We compare the potential bicycling trips and the BLOS values at each road segment level. These two values are compared particularly for heavily used segments. The comparison results are discussed in detail in the report.

Overall, only a few roads are rated as 'Good' (11%), 16.7% are rated as 'Poor', while 37.7% are considered 'Moderate'. Most of the segments with high trip demands fall into the categories of 'Moderate' or 'Residential'. Please note that 19.1% of the road segments did not have assigned BLOS values. Potential bicyclists would encounter roads with multiple BLOSs. For instance, an individual may ride on road segments with 'moderate' or 'residential' BLOS near his/her neighborhood and close to campus, but likely face 'poor' or 'moderate' road segments in between. We provide snapshots of these different road conditions as examples. We consider BLOS values as an indicator of bicycle-friendliness, however the four categories of BLOS (i.e. Good, Moderate, Poor, and Residential) may not suffice to capture detailed components.

In the second part of this study, we analyze smart phone GPS data in an effort to analyze bicycle route preferences and their associations with facility types. Data were collected through smartphone GPS in central Columbus from September through the end of November, 2016. We recruited study participants from The Ohio State University through email invitations, fliers and advertisements on campus buses. The report details on the following five major tasks:

1) Collection of the GPS data on bicycle trips (origin, destination, purpose and route)
2) Cleaning and matching of the GPS points to a given road network
3) Developing maps illustrating the collected data
4) Comparing the chosen routes with the shortest routes
5) Discussion on future research plans

The survey respondents were asked to download a smartphone application, *CycleTracks*. These individuals recorded their bicycle trips by turning the app on and off at the beginning and end of each bicycle trip. We provided the link of our survey promotion website in our survey invitation emails and survey promotion postcards, where detailed step-by-step instructions were described with screenshots of the application (http://u.osu.edu/cycletracks). We collected data on 1,584 bicycle trips. GPS traces were matched to the network links using ArcGIS custom routines and a high-resolution network reconstructed to include all possible links available for bicycling.

The preliminary results show that the most frequently used street segments among the chosen routes and the shortest routes are different in terms of their locations and characteristics. These suggest that riders preferred different segments as compared to those predicted by the shortest path algorithm. Many of the participant bicyclists used the pedestrian walkways near the central university library and the streets where many university buildings and facilities are located. Several riders also preferred exclusive bicycle trails which are close to the campus area. In general, riders preferred road segments with higher levels of bikeability.

Recommendations

To analyze bicyclists' route choice behaviors more accurately, a small number of studies have employed revealed preference surveys on commute routes using GPS-based route tracking applications. In this study, we collect GPS data using a smart phone app and conclude that this method is effective in capturing information about bicycle trips. The data collection methodology and analysis techniques introduced in this study can help other researchers conduct similar studies. We conclude our study by setting the ground for future work that will identify the factors closely associated with the route choices and the degree of diversion from shortest paths.

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Introduction

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This study has two major components: (i) an online survey with questions on bicycling decisions and personal attitudes associated with those decisions, (ii) collecting bicycle trip data (origins, destinations and routes) using a cell phone app (CycleTracks) and route choice analyses.

Part 1. Campus Travel Pattern Survey

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Part 2. Analyses of Bicycle Routes

In the second part of this study, we analyze smart phone GPS data in an effort to analyze bicycle route preferences and their associations with facility types. Data were collected through smartphone GPS in central Columbus from September through the end of November, 2016. We recruited study participants from The Ohio State University through email invitations, fliers and advertisements on campus buses. The report provides details on the following five major tasks:

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The survey respondents were asked to download a smartphone application, *CycleTracks*[2]. These individuals recorded their bicycle trips by turning the app on and off at the beginning and end of each bicycle trip. We provided the link of our survey promotion website in our survey invitation emails and survey promotion postcards, where detailed step-by-step instructions were described with screenshots of the application (http://u.osu.edu/cycletracks). We collected data on 1,584 bicycle trips. GPS traces were matched to the network links using ArcGIS custom routines and a high-resolution network reconstructed to include all possible links available for bicycling.

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PART 1.

Bicycling Decisions, Personal Attitudes and Shortest Routes to Campus

Introduction: 2015 Campus Travel Pattern Survey

a. About the Survey

The purpose of the *2015 Ohio State University (OSU) Campus Travel Pattern Survey* is to provide insights on campus travel patterns. The survey was conducted online from Apr 27, 2015 to May 11, 2015. It was distributed to a stratified random sample of 15,088 faculty, staff, graduate/professional students, and undergraduate students by email with survey links to the survey instrument website. A total of 1,574 responses were received, which correspond to about 1.7% of the campus population. The survey questionnaire includes questions on socio-demographic characteristics, individuals' attitudes towards their own neighborhood characteristics, commute mode choices and behaviors, perceptions of commuting environments and two intersecting streets nearest to respondents' residential locations. The core questions associated with bicycling travel patterns include 27 bicycling-specific attitudinal questions designed to be answered on a Likert scale of 1 ("strongly disagree") to 5 ("strongly agree").

b. Main Findings

Of the 1,574 respondents, the final sample used in empirical analysis includes 677 individuals with correct address records and complete responses to every survey question included in the analyses. The respondents were asked to report how many times per week (i.e., never, one to two days a week, three to four days a week, or five or more days a week) they use different modes for their commute to campus. The survey provided the following options for mode choice:

- Auto (drive alone)
- Carpooling (with 1 or more people)
- CABS bus (Campus Area Bus Service)
- COTA bus (Central Ohio Transit Authority)
- Bicycle
- Walking
- Bicycle & Bus (in the same trip)
- Bicycle & Auto (in the same trip)
- Auto & Bus (in the same trip)
- (If you used any other mode of transportation to campus, please specify.)

Table 1 provides the summary of basic characteristics of survey respondents and the distribution of commuter cyclists across university affiliation (faculty, staff, and students), gender, commute distance, age, flexibility in arrival times and their responses to the question on residential self-selection (‘Bicycling conditions were a factor in choosing where I live’). Residential self-selection refers to the situation where individuals select themselves into certain neighborhoods based on their predetermined preferences for specific modes.

A commuter cyclist in this study is defined as one who commutes to campus by bicycle at least once a week. Based on this classification, 12.6% of the analysis sample is classified as bicycle commuters.

About 33.3% of those who live within a mile of campus are bicyclists and 24.6% of those within 5 miles of campus are bicyclists. This percentage gets significantly lower as commute distance increases.

About 19.3% of the respondents agreed with the statement on residential self-selection. About 35% of those who agreed with the statement, ‘Bicycling conditions were a factor in choosing where I live,’ and 60.8% of those who strongly agreed with the same statement are found to be bicycle commuters.

In addition to the sociodemographic information, the survey respondents were asked to rate bicycling-related environmental factors on a scale of 1 to 5 (1 being ‘strongly disagree’ and 5 being ‘strongly agree’). Tables 2 and 3 show the analysis results on individuals’ evaluations about environmental factors and neighborhood conditions associated with bicycling decisions. Table 2 presents the average ratings by university affiliation and gender. The numbers in bold are the top five factors for each group. Standard deviations are presented in parenthesis.

Table 1. Descriptive Statistics of the Survey Respondents

	N	%	Bicyclist (%)	Non-Bicyclist (%)
All Respondents	677	100	12.6	87.4
University Affiliation				
Faculty	237	35.0	16.9	83.1
Staff	306	45.2	5.2	94.8
Graduate Student	93	13.7	20.4	79.6
Undergraduate Student	41	6.1	24.4	75.6
Gender				
Male	281	41.5	19.2	80.8
Female	396	58.5	7.8	92.2
Commute Distance				
Less than a mile	36	5.3	33.3	66.7
1 to 5 miles	236	34.9	24.6	75.4
6 to 10 miles	159	23.5	6.3	93.7
More than 10 miles	246	36.3	3.3	96.7
Age				
Under 25	102	15.1	19.6	80.4
26 - 30	83	12.3	9.6	90.4
31 - 35	86	12.7	15.1	84.9
36 - 40	66	9.7	9.1	90.9
41 - 45	60	8.9	20.0	80.0
46 - 50	60	8.9	8.3	91.7
Over 50	220	32.5	9.5	90.5
Flexibility in Arrival Times				
Not flexible at all	97	14.3	8.2	91.8
Rarely flexible	114	16.8	5.3	94.7
Somewhat flexible	382	56.4	13.1	86.9
Very flexible	84	12.4	25.0	75.0
Residential Self-Selection				
Strongly disagree	191	28.2	2.6	97.4
Disagree	260	38.4	5.4	94.6
Neither disagree nor agree	95	14.0	7.4	92.6
Agree	80	11.8	35.0	65.0
Strongly agree	51	7.5	60.8	39.2

Table 2. Neighborhood and Environmental Factors Affecting Individuals' Bicycling Decisions by University Affiliation and Gender

Factor	Faculty	Staff	Under-graduate Students	Graduate / Professional Students	Male	Female
Commuting by car is safer than riding a bicycle.	**4.08** (1.0)	**4.18** (1.0)	**3.83** (1.0)	**3.91** (1.0)	**4.01** (1.0)	**4.16** (1.0)
Bicycling is impractical for me because I need to carry things or transport others.	**3.60** (1.3)	**3.82** (1.2)	3.47 (1.3)	3.45 (1.2)	3.38 (1.2)	**3.90** (1.2)
I would choose to ride a bike if there were more bike routes to and from campus.	3.06 (1.3)	2.77 (1.3)	3.13 (1.3)	3.75 (1.2)	3.16 (1.3)	2.89 (1.3)
I would choose to ride a bike if there were options for renting or borrowing bicycles.	2.44 (1.1)	2.33 (1.1)	2.57 (1.1)	3.05 (1.2)	2.50 (1.1)	2.43 (1.1)
I would choose to ride a bike if there were more indoor or covered places to store bikes on campus.	2.75 (1.2)	2.66 (1.2)	3.00 (1.1)	3.29 (1.3)	2.93 (1.3)	2.66 (1.2)
There are no bicycle lanes or routes near enough for me to ride.	3.55 (1.3)	**3.82** (1.2)	3.47 (1.2)	3.41 (1.3)	**3.52** (1.3)	**3.75** (1.2)
I would have to take detours from the most direct route in order to use bike paths, bike lanes or streets more suited for bicycles.	**3.79** (1.1)	**3.81** (1.1)	3.43 (1.2)	3.67 (1.1)	**3.69** (1.1)	**3.82** (1.1)
The roadway conditions (markings, signals, width, and lighting) on some streets make the route unsafe for bicyclists on my commute route.	**4.01** (1.1)	**4.01** (1.0)	**3.70** (1.1)	**3.96** (1.0)	**3.81** (1.1)	**4.10** (1.0)
I would not leave my bicycle outside my residence because it might be stolen.	3.44 (1.2)	3.29 (1.3)	**3.67** (1.3)	**3.76** (1.1)	3.37 (1.3)	3.46 (1.3)
There is so much traffic along the street I live on that it would be difficult or unpleasant to bicycle in my neighborhood.	2.74 (1.2)	2.93 (1.3)	3.35 (1.2)	3.23 (1.2)	2.77 (1.2)	2.99 (1.3)
My bicycle might be stolen even if properly secured.	**3.65** (0.9)	3.63 (0.9)	**3.80** (1.1)	**3.88** (1.0)	**3.64** (1.0)	3.70 (0.9)
There are off-street bicycle trails or paved paths in or near my neighborhood that are easy to access.	3.18 (1.4)	3.04 (1.3)	2.96 (1.3)	2.95 (1.2)	3.12 (1.4)	3.06 (1.3)
Bicycling conditions were a factor in choosing where I live.	2.45 (1.3)	2.09 (1.1)	1.89 (0.9)	2.21 (1.2)	2.34 (1.2)	2.18 (1.1)
There is a bus stop within a reasonable bicycling distance from my residential location.	3.25 (1.4)	3.01 (1.4)	**3.74** (1.1)	**3.80** (1.3)	3.32 (1.4)	3.13 (1.4)
There are bike lanes in my neighborhood that are easy to access.	2.68 (1.3)	2.47 (1.2)	2.33 (1.1)	2.61 (1.1)	2.68 (1.3)	2.47 (1.2)
Where I currently live is a good neighborhood for riding a bicycle.	3.40 (1.2)	3.15 (1.3)	2.70 (1.2)	3.07 (1.1)	3.38 (1.2)	3.12 (1.2)

Note: Values indicate the average of the 5 Likert-scaled responses to each statement. The top five most popular factors are in bold. Standard deviations are presented in parenthesis.

Graduate students report stronger willingness to ride a bike if '*there were more bike routes to and from campus*' (3.75), *'if there were options for renting or borrowing bicycles'* (3.05), and '*if there were more indoor or covered places to store bikes on campus'* (3.29), as compared to other groups (faculty, staff, and undergraduate students).

In evaluation of neighborhood conditions for bicycling, faculty members generally have positive attitudes, and they gave higher points to the statement, '*bicycling conditions were a factor in choosing where I live*'. Undergraduate students reported the lowest satisfaction towards bicycle-related neighborhood environments.

Overall, faculty and staff members tend to rate bicycling as an inconvenient mode in terms of safety, travel, and time management as compared to undergraduate and graduate students. For example, faculty and staff members are more likely to agree with the statement '*would have to take detours from the most direct route in order to use bike paths, bike lanes or streets more suited for bicycles*'.

Both males and females tend to agree with the statement, '*commuting by car is safer than riding a bike*'. This is consistent with the fact that they similarly strongly agreed with the statement, '*the roadway conditions (markings, signals, width, and lighting) on some streets make the route unsafe for bicyclists on my commute route*' (3.81 and 4.10, respectively). Meanwhile, males present a more positive evaluation of their neighborhood environments. They are more likely to agree with statements such as '*where I currently live is a good neighborhood for riding a bicycle (3.38),' 'there are bike lanes in my neighborhood that are easier to access (2.68)*', and '*there is a bus stop within a reasonable bicycling distance from my residential location (3.32)'* as compared to females (3.12, 2.47, and 3.13, respectively).

Both male and female members strongly agreed with the statement "*I would have to take detours from the most direct route in order to use bike paths, bike lanes or streets more suited for bicycles*" while females are slightly more likely to do so (3.69 and 3.82, apiece).

Table 3 shows that both novice and intermediate cyclists strongly agree with the statements '*commuting by car is safer than cycling*' (4.29 and 3.93) and '*the roadway conditions are unsafe for bicyclists on commute routes'* (4.25 and 3.98) more than advanced cyclists (3.54 and 3.59, respectively). They feel that '*there are no bicycle lanes near enough for them'* (3.81 and 3.61) and they *'would have to take detours from the most direct routes to campus for safer bike paths*' (3.97 and 3.86) more than advanced cyclists (3.11 and 3.52, respectively). Therefore, we conclude that perceived levels of difficulty in bicycling appear to be higher for novice and intermediate cyclists as compared to advanced cyclists.

Table 3. Neighborhood and Environmental Factors Affecting Individuals' Decision to Bike by Bicycling Level

Factor	Advanced	Intermediate	Novice
Commuting by car is safer than riding a bicycle.	3.54 (1.1)	**3.93 (1.0)**	**4.29 (0.9)**
Bicycling is impractical for me because I need to carry things or transport others.	2.82 (1.3)	3.43 (1.2)	**3.91 (1.1)**
I would choose to ride a bike if there were more bike routes to and from campus.	3.59 (1.3)	3.53 (1.2)	3.12 (1.3)
I would choose to ride a bike if there were options for renting or borrowing bicycles.	2.62 (1.3)	2.61 (1.1)	2.48 (1.1)
I would choose to ride a bike if there were more indoor or covered places to store bikes on campus.	3.31 (1.3)	3.11 (1.2)	2.85 (1.2)
There are no bicycle lanes or routes near enough for me to ride.	3.11 (1.4)	**3.61 (1.3)**	**3.82 (1.2)**
I would have to take detours from the most direct route in order to use bike paths, bike lanes or streets more suited for bicycles.	3.52 (1.3)	**3.86 (1.0)**	**3.97 (1.1)**
The roadway conditions (markings, signals, width, and lighting) on some streets make the route unsafe for bicyclists on my commute route.	3.59 (1.3)	**3.98 (1.0)**	**4.25 (0.9)**
I would not leave my bicycle outside my residence because it might be stolen.	**3.68 (1.3)**	3.47 (1.3)	3.36 (1.3)
There is so much traffic along the street I live on that it would be difficult or unpleasant to bicycle in my neighborhood.	2.37 (1.1)	2.81 (1.2)	2.96 (1.3)
My bicycle might be stolen even if properly secured.	**3.70 (1.0)**	**3.76** (0.9)	3.70 (1.0)
There are off-street bicycle trails or paved paths in or near my neighborhood that are easy to access.	**3.63 (1.3)**	3.28 (1.4)	3.10 (1.4)
Bicycling conditions were a factor in choosing where I live.	3.19 (1.3)	2.56 (1.2)	2.16 (1.0)
There is a bus stop within a reasonable bicycling distance from my residential location.	**3.71 (1.3)**	3.45 (1.3)	3.19 (1.4)
There are bike lanes in my neighborhood that are easy to access.	3.16 (1.3)	2.51 (1.2)	2.59 (1.3)
Where I currently live is a good neighborhood for riding a bicycle.	**3.77 (1.2)**	3.35 (1.2)	3.28 (1.2)

Note: Values indicate the average of the 5 Likert-scaled responses to each statement. The top five most popular factors are in bold. Standard deviations are presented in parenthesis.

Table 4 shows how personal attitudes towards bicycling-related factors vary across bicyclists and non-bicyclists. Since we have a large number of attitudinal questions, we classify these questions into 10 groups of similar questions that are closely related to one another and name each accordingly.

To compare group means, we used Mann-Whitney U test, which is the alternative test to the independent sample t-test. The Mann-Whitney U test is used when the data are ordinal and it is hard to assume that a variable follows the normal distribution.

The test results indicate that non-bicycling commuters and bicycling commuters significantly differ in many aspects. On average, commuter cyclists most strongly agreed with the statements related to '*perceived additional benefits of bicycling*', including reducing environmental impacts, enjoying health benefits, and saving money. Non-bicyclists also recognized these benefits as being considerable, but not at the level that cyclists did.

Notably, '*conditional willingness to use bicycles*' seems to be the most discriminating attitudinal group of statements, followed by '*negative images towards bicyclists on the street*' and '*bicycle-friendliness of neighborhoods*'. Most of the commuter cyclists agreed that they would ride a bicycle more frequently if bicycle-related facilities are to be improved, such as more bike trails, covered bike storage places, and bike sharing facilities. On the contrary, non-cyclists' responses demonstrate that they are rather insensitive to facilities or infrastructure improvements. Non-bicyclists are more likely to perceive cyclists riding on the street as being careless.

Bicyclists are more likely to report positive values on '*bicycle-friendliness of neighborhoods*'. The significant difference across bicyclists and non-bicyclists may allow for several interpretations. Bicyclists may choose to live in more bicycle friendly neighborhoods or, they may have more favorable ratings of their environments in general when it comes to bicycling. Table 4 also reports that bicyclists are more likely to agree with the statement '*Bicycling conditions were a factor in choosing where I live'*.

Regarding deterrents, non-commuter cyclists reported higher levels of agreements to the statements under '*sensitivity to safety in mode choice*' and '*perceived obstacles to bicycling on routes*'. Non-bicyclists are sensitive to safety and weather issues more than bicyclists, but bicyclists think of these conditions as important factors as well. The gap between two groups is not as critical as in other significant components.

Table 4. Comparison of Personal Attitudes and Residential Self-Selection

Means of Attitudes for Each Group	Bicycling Commuters		Non-Bicycling Commuters	
	Mean	Std. Dev	Mean	Std. Dev
Conditional Willingness to Use Bicycles	**3.80**	**1.20**	**2.70**	**1.18**
I would choose to ride a bike if there were more indoor or covered places to store bikes on campus.				
I would choose to ride a bike if there were more bike routes to and from campus.				
I would choose to ride a bike if there were options for renting or borrowing bicycles.				
Biking can sometimes be easier for me than driving.				
I try to ride a bike to help improve air quality.				
Bicycle-Friendliness of Neighborhoods	**3.61**	**1.19**	**2.97**	**1.27**
Where I now live is a good neighborhood for bicycling.				
There are off-street bicycle trails or paved paths in or near my neighborhood that are easy to access.				
There are bike lanes easy to access in my neighborhood.				
There is so much traffic along the street I live on that it would be unpleasant to bicycle in my neighborhood.				
Sensitivity to Safety in Mode Choice	**3.38**	**1.19**	**3.88**	**1.15**
Safety in traffic is an important factor.				
Safety from crime is an important factor.				
Extreme weather conditions are important factors.				
Perceived Obstacles to Bicycling on Routes	**3.31**	**1.37**	**3.81**	**1.10**
The roadway conditions on some streets make the route unsafe for bicyclists on my commute route.				
I would have to take detours from the most direct route in order to use bike paths or bike lanes.				
There are no bicycle lanes or routes near enough for me to ride.				
Perceived Additional Benefits of Bicycling	**4.67**	**0.56**	**4.06**	**0.96**
Biking reduces environmental impacts.				
Biking benefits health and fitness.				
Biking gives me the opportunity to save money.				
Negative Images towards Bicyclists on the Street	**2.66**	**1.06**	**3.31**	**1.09**
Bicyclists do not care about drivers on the road.				
Bicyclists do not care about pedestrians on the street.				
Availability of Bicycle Racks	2.95	1.21	3.09	0.85
Bicycle racks are easy to find.				
There are enough parking racks for bicycles.				

Table 5. Comparison of Personal Attitudes and Residential Self-Selection *(Continued)*

Means of Attitudes for Each Group	Bicycling Commuters		Non-Bicycling Commuters	
	Mean	Std. Dev	Mean	Std. Dev
Concerns about Theft	3.68	1.11	3.59	1.10
I would not leave my bicycle outside my residence because it might be stolen.				
My bicycle might be stolen even if properly secured.				
Familiarity with Bicycle-Related Services	2.65	1.15	2.70	1.02
I can find a place to help repair my bicycle if needed.				
When needed, I can find a convenient place to shower and change clothing after bicycling.				
The Degree of Residential Self-Selection	**3.78**	**1.27**	**2.11**	**1.05**
Bicycling conditions were a factor in choosing where I live				

Note: Values indicate the average of the 5 Likert-scaled responses to each group of statements and its standard deviations. Group means in bold indicate that differences between groups are statistically significant at the 95% (p-value<0.05) level using Mann-Whitney U Test.

c. Implications

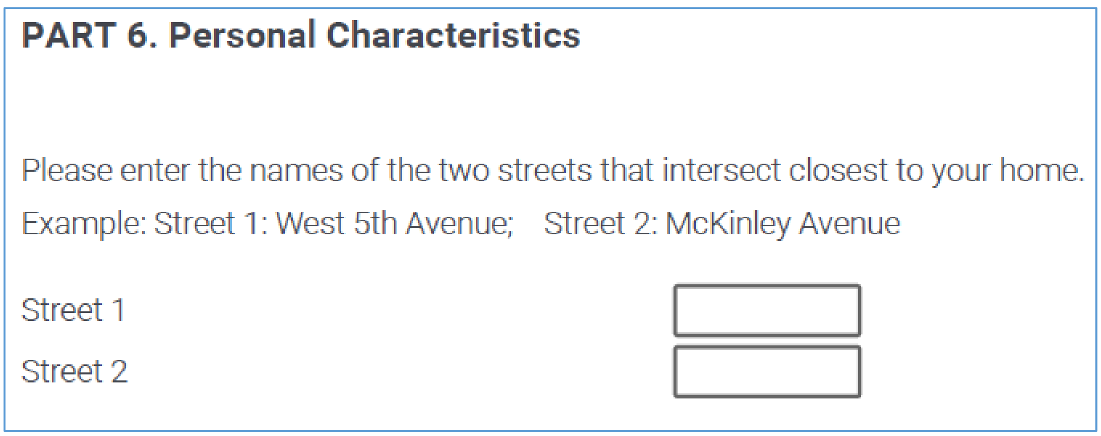
The 2015 Campus Travel Pattern Survey features a variety of survey questions that measure attitudes and perceptions of university members towards bicycling. The analyses reveal that most of the bicyclists live within 1 to 5 miles from campus. Investing in separate bicycle facilities or improved ones is found to be important to encourage bicycling especially for novice bicyclists who account for a significant portion. Promoting safety on bicycle routes, more bicycle lanes, and separating bike riders from auto traffic may increase the number of bike commuters. Separate bicycle facilities should follow the shortest routes (as much as possible) to keep commute times and distances at a minimum.

Analyses on the Shortest Path to Campus

a. Data & Methodology

i. <u>Sample Collection</u>

Among the 1,574 participants who participated in the 2015 Campus Transportation Survey, 1,189 participants provided information on where they live. The respondents were asked to report the names of the two streets that intersect closest to their homes (Figure 1). The survey results reveal that most bicyclists live within 5 miles from campus. Therefore, we assumed this distance to be a bikable distance in this context, and created shortest paths for bicycle commute for all respondents living within 5 miles from campus. This resulted in 584 respondents for mapping.



PART 6. Personal Characteristics

Please enter the names of the two streets that intersect closest to your home.
Example: Street 1: West 5th Avenue; Street 2: McKinley Avenue

Street 1

Street 2

Figure 1. The Survey Question on Street Intersections

ii. Data Preparation

Data cleaning and creating a valid network

Observations with missing values, uncorrectable typos and unrelated answers were deleted from the sample. Centerlines Shape Data which shows all roads and streets lines for Greater Franklin County provided by the Mid-Ohio Regional Planning Commission (MORPC), named 'Location Based Response System (LBRS)', is used as the network dataset for mapping. The network data could not be used as they were, because bicyclists cannot ride on all roads (i.e. highways). By using the attribute information on speed limits, those roads with speed limits more than 35 mph were selected and excluded while creating the links and nodes for the final network dataset. We demonstrate the difference between two networks later on by comparing these maps. To create links and nodes on the network before the shortest path analysis, ArcGIS function 'Feature Vertices to Points' was used with a selection of both-ends as an option. This function generates two nodes at the vertical points of each link and assigns random numbers to newly created nodes. Two nodes at the end of a link have the same link ID which they are connected to. This function assigns two ID numbers to each node because nodes are connected to two different links at the same time (Figure 2). Thus, after endowing spatial coordinates to every node, we exported the attribute table for further manipulation.

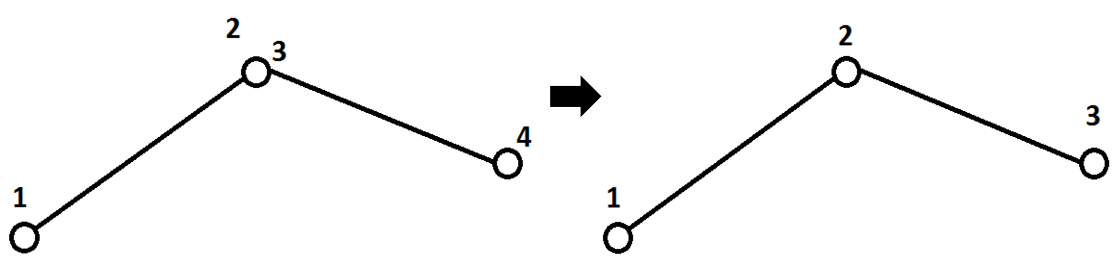


Figure 2. Cleaning Duplicate Nodes

The results file contains data on link ID, starting node ID, ending node ID, speed limit and link length (as impedance).

iii. Geocoding Process and Conversion to GIS

Geocoding converts an address to a set of latitude and longitude values for spatial reference. ArcGIS ver. 10.2.2 provides functions for these types of geocoding tasks. However, since our data set is not in an ordinary address format we used another tool for this step. Our data provide information on the closest intersection. We converted these intersections into corresponding coordinates using '*Batch Geocoding*' (http://www.findlatitudeandlongitude.com/batch-geocode). If one enters a vector of values with spatial references (addresses or coordinates) as inputs and clicks the button 'geocode', *Batch Geocoding* converts these into other forms of spatial references (Figure 3). Following this, we checked for outliers and errors, and plotted the coordinates created by *Batch Geocoding* on the map (Figure 4). Finally, we refined the list of individual coordinates and prepared them to be imported into GIS (Figure 5).

We used ArcMap ver.10.2.2, to import the refined data set of coordinates. The result file is a point layer on ArcMap (Figure 6). The green point at the center of the map is the location of the Thompson Library of the Ohio State University. The procedure followed for importing excel coordinates into ArcGIS is well outlined in ESRI's technical article '*How To: import XY data tables to ArcMap and convert the data to a shapefile*' (ESRI, 2016).

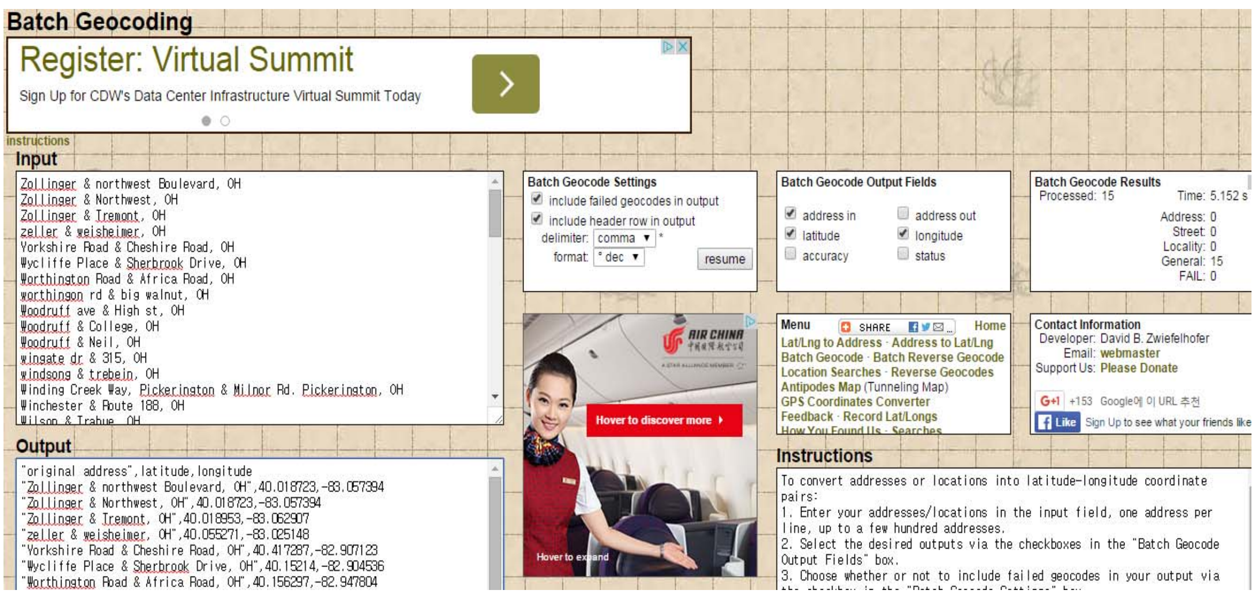


Figure 3. The Snapshot of the Batch Geocoding Website

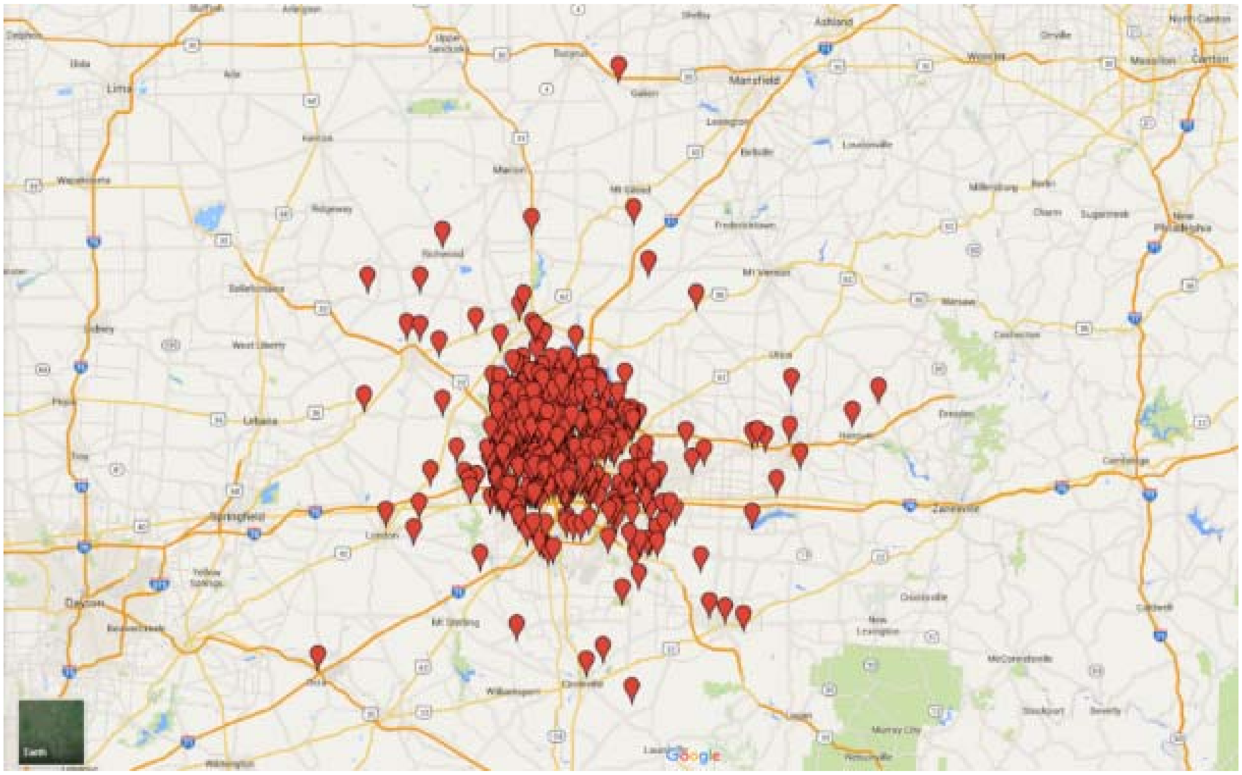


Figure 4. Plotting Residential Locations on Google MyMaps

Please enter the names of	&	Please enter the names of t	Intersection	Address	No.	Corrected Address	latitude	longitude
Zollinger	&	northwest Boulevard	Zollinger & northwest Boulev	Zollinger & northwest Boulevard, OH	1	Zollinger & northwest Boulevard, OH	40.018723	-83.057394
Zollinger	&	Northwest	Zollinger & Northwest	Zollinger & Northwest, OH	2	Zollinger & Northwest, OH	40.018723	-83.057394
Zollinger	&	Tremont	Zollinger & Tremont	Zollinger & Tremont, OH	3	Zollinger & Tremont, OH	40.018953	-83.062907
zeller	&	weisheimer	zeller & weisheimer	zeller & weisheimer, OH	4	zeller & weisheimer, OH	40.055271	-83.025148
Yorkshire Road	&	Cheshire Road	Yorkshire Road & Cheshire R	Yorkshire Road & Cheshire Road, OH	5	Yorkshire Road & Cheshire Road, OH	39.998741	-83.067459
Wycliffe Place	&	Sherbrook Drive	Wycliffe Place & Sherbrook D	Wycliffe Place & Sherbrook Drive, OH	6	Wycliffe Place & Sherbrook Drive, OH	40.15214	-82.904536
Worthington Road	&	Africa Road	Worthington Road & Africa R	Worthington Road & Africa Road, OH	7	Worthington Road & Africa Road, OH	40.156297	-82.947804
worthingon rd	&	big walnut	worthingon rd & big walnut	worthingon rd & big walnut, OH	8	worthingon rd & big walnut, OH	40.182495	-82.925445
Woodruff ave	&	High st	Woodruff ave & High st	Woodruff ave & High st, OH	9	Woodruff ave & High st, OH	40.003725	-83.008787
Woodruff	&	College	Woodruff & College	Woodruff & College, OH	10	Woodruff & College, OH	40.00384	-83.01094
Woodruff	&	Neil	Woodruff & Neil	Woodruff & Neil, OH	11	Woodruff & Neil, OH	39.961176	-82.998794
wingate dr	&	315	wingate dr & 315	wingate dr & 315, OH	12	wingate dr & 315, OH	40.18067	-83.049004
windsong	&	trebein	windsong & trebein	windsong & trebein, OH	13	windsong & trebein, OH	39.961176	-82.998794
Winding Creek Way, Pic	&	Milnor Rd., Pickerington	Winding Creek Way, Pickerin	Winding Creek Way, Pickerington & Mil	14	Winding Creek Way, Pickerington & Milno	39.91626	-82.746635
Winchester	&	Route 188	Winchester & Route 188	Winchester & Route 188, OH	15	Winchester & Route 188, OH	39.640169	-82.896455
Wilson	&	Trabue	Wilson & Trabue	Wilson & Trabue, OH	16	Wilson & Trabue, OH	39.98752	-83.107468
Wilson	&	Cypress Creek	Wilson & Cypress Creek	Wilson & Cypress Creek, OH	17	Wilson & Cypress Creek, OH	39.993982	-83.112479
Wilber Ave	&	Neil Ave	Wilber Ave & Neil Ave	Wilber Ave & Neil Ave, OH	18	Wilber Ave & Neil Ave, OH	39.979459	-83.011516
Whittier	&	Jager	Whittier & Jager	Whittier & Jager, OH	19	Whittier & Jager, OH	39.944568	-82.989994
Wexford Woods Dr	&	Tullymore Dr	Wexford Woods Dr & Tullym	Wexford Woods Dr & Tullymore Dr, OH	20	Wexford Woods Dr & Tullymore Dr, OH	40.113055	-83.163188
Wetmore Rd	&	High St	Wetmore Rd & High St	Wetmore Rd & High St, OH	21	Wetmore Rd & High St, OH	40.058813	-83.019689
Westwood Ave	&	W 5th Ave	Westwood Ave & W 5th Ave	Westwood Ave & W 5th Ave, OH	22	Westwood Ave & W 5th Ave, OH	39.989128	-83.052782
Westwood	&	Olentangy Blvd	Westwood & Olentangy Blvd	Westwood & Olentangy Blvd, OH	23	Westwood & Olentangy Blvd, OH	40.047522	-83.027787
Westpoint	&	Prarie	Westpoint & Prarie	Westpoint & Prarie, OH	24	Westpoint & Prarie, OH	39.962929	-83.231335

Figure 5. The Table Showing Geocoding Results

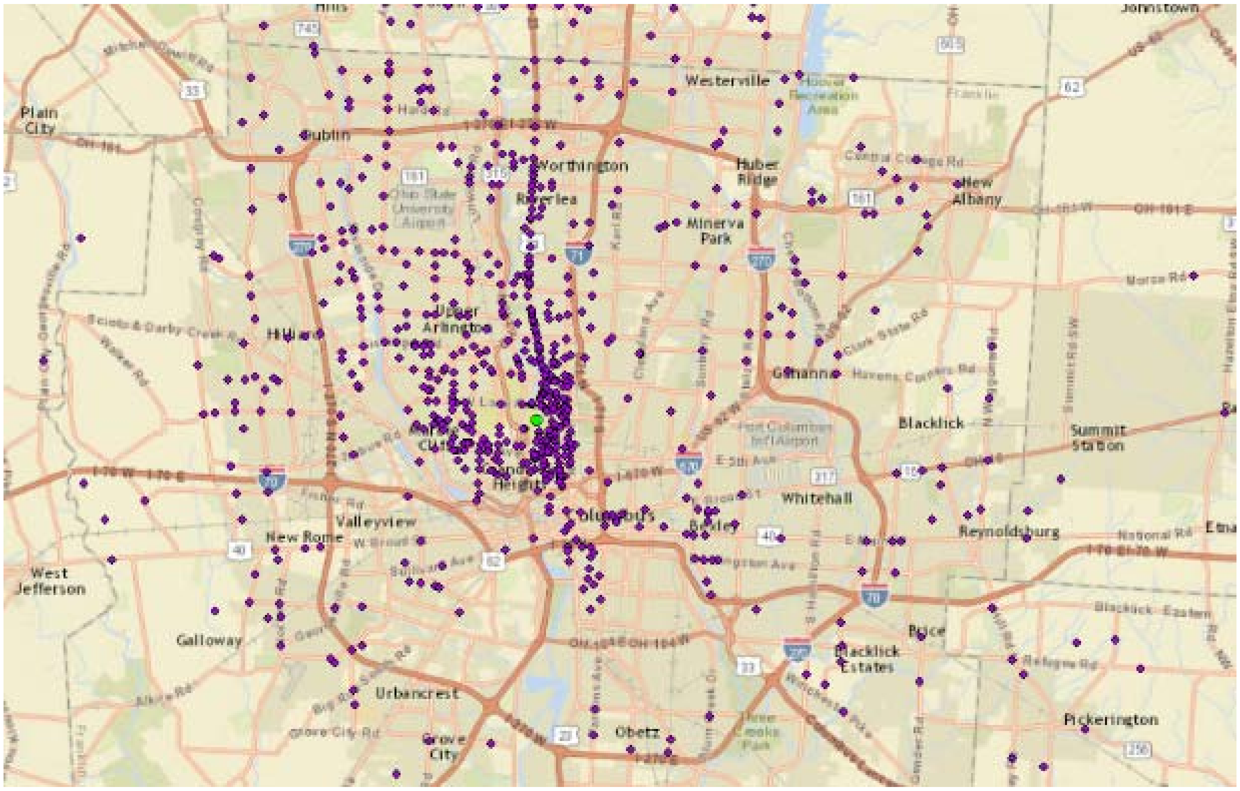


Figure 6. Point Mapping on ArcMap

iv. Shortest Routes Algorithm

The purpose of these analyses is to create shortest distance routes for potential bicycle trips with individuals' residences as origins and central campus as the destination. By employing Dijkstar's algorithm and Python programming, we computed impedances and shortest times from every origin point. Dijkstar's algorithm works with inputs of link ID, starting node ID, ending node ID, and impedance value of each link. The preparation of these values were discussed in the Data Preparation section. The Python code file can be downloaded from the Python open source website (http://pypi.python.org/pypi/Dijkstar/2.2).

b. Results

i. Potential Use of Shortest Paths to Campus

We assigned the corresponding volumes of potential trips to each link. We categorized trip volumes into 5 classes (i.e., 1 to 10 trips, 11 to 50 trips, 51 to 100 trips, 101 to 200 trips, and 201 to 584 trips) to give different width to each class so that frequently used links would appear thicker on the map (Figures 7 and 8). Blue-colored circles in Figure 7 represent 1, 3, and 5-mile buffer areas. Circles in Figure 8 represent 1 and 3-mile buffer areas.

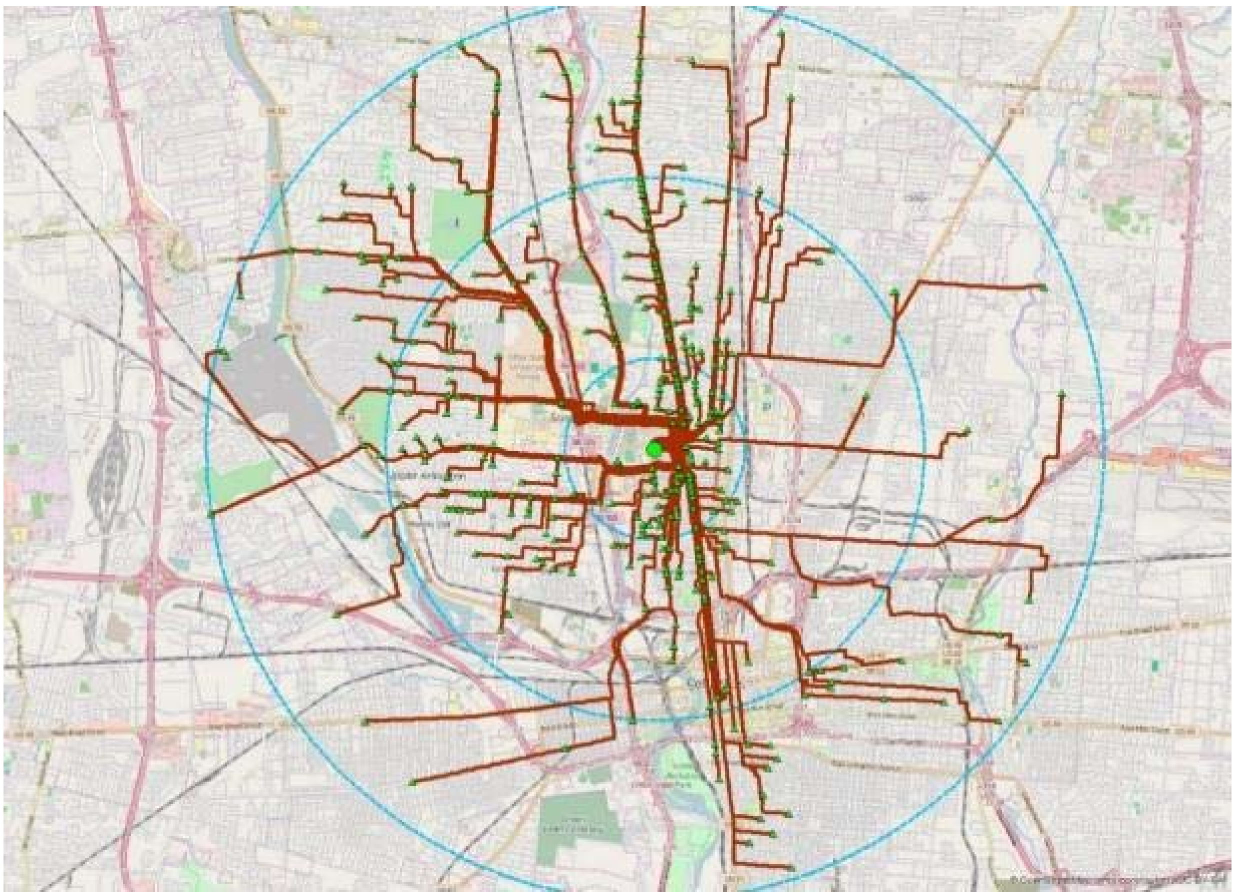


Figure 7. Shortest Routes from the Origin Points within 1, 3, and 5 Miles of Campus

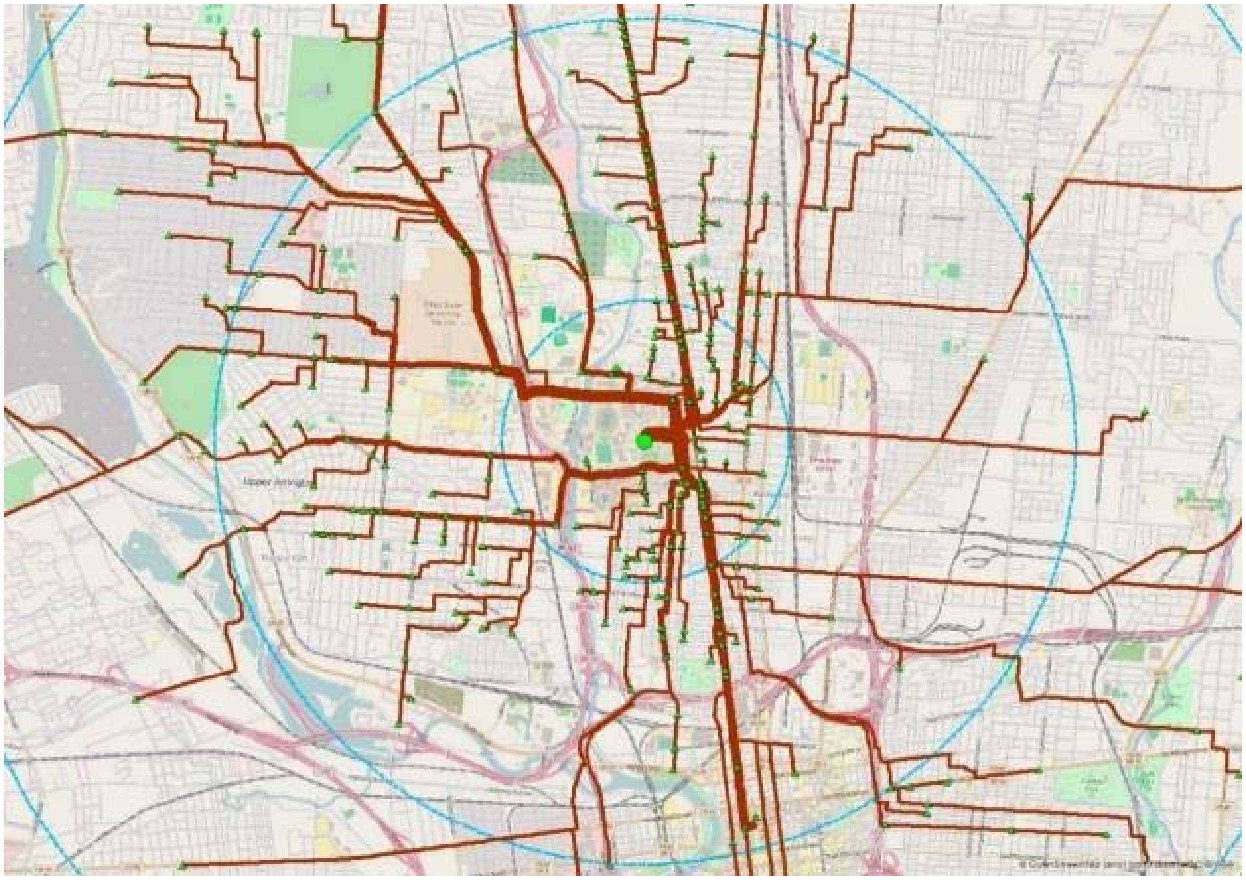


Figure 8. Shortest Routes from the Origin Points within 1 and 3 Miles of Campus

Analyses on Bicycle Level of Service (BLOS)

a. Data & Methodology

i. <u>Data</u>

We obtained the data on Bicycle Level of Service (BLOS) at the street link level from MORPC. The map below (Figure 9) shows the streets in central Ohio categorized by their bicycle level of service values based on MORPC's classifications (https://apps.morpc.org/bikemap/).

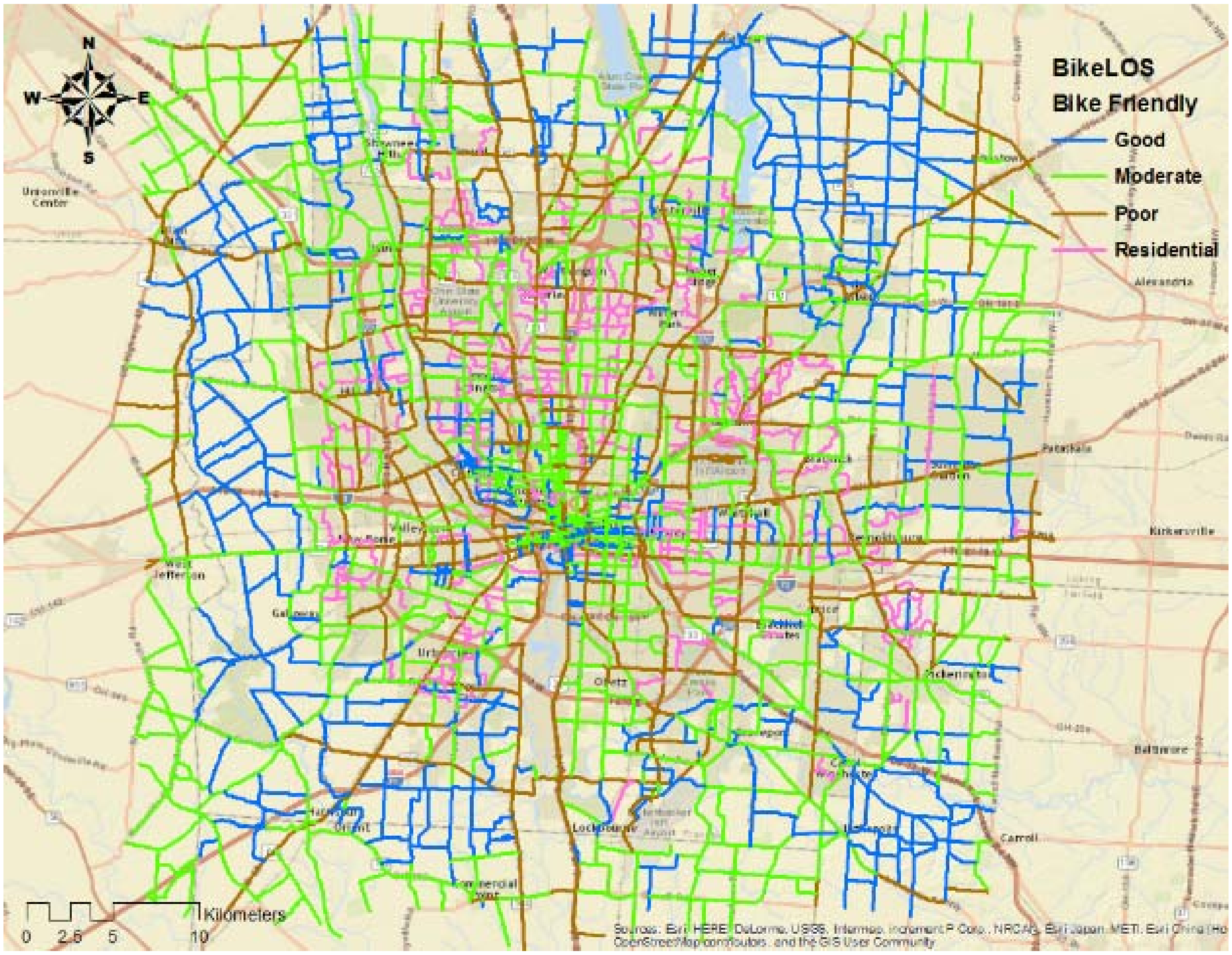


Figure 9. Distribution of Streets with Different Bicycle Level of Service (BLOS)
(Source: Mid-Ohio Regional Planning Commission)

ii. Methods

We use the 'Intersect' option of the 'Overlay' function of ArcGIS, a fundamental spatial exploratory tool, which enables users to compare information or attributes of different source data that are from the same location by overlaying two layers. Detailed information on this function can be found at: http://resources.esri.com/help/9.3/arcgisdesktop/com/gp_toolref/geoprocessing/overlay_analysis.htm

b. Results

i. Comparison of BLOS values with Potential Bicycle Trip Demands

Since the input dataset, here the BLOS dataset, does not include all the streets, some street segments did not receive BLOS values during the intersect process. The map below exhibits all the shortest distance paths with four different BLOS values (Figure 10).

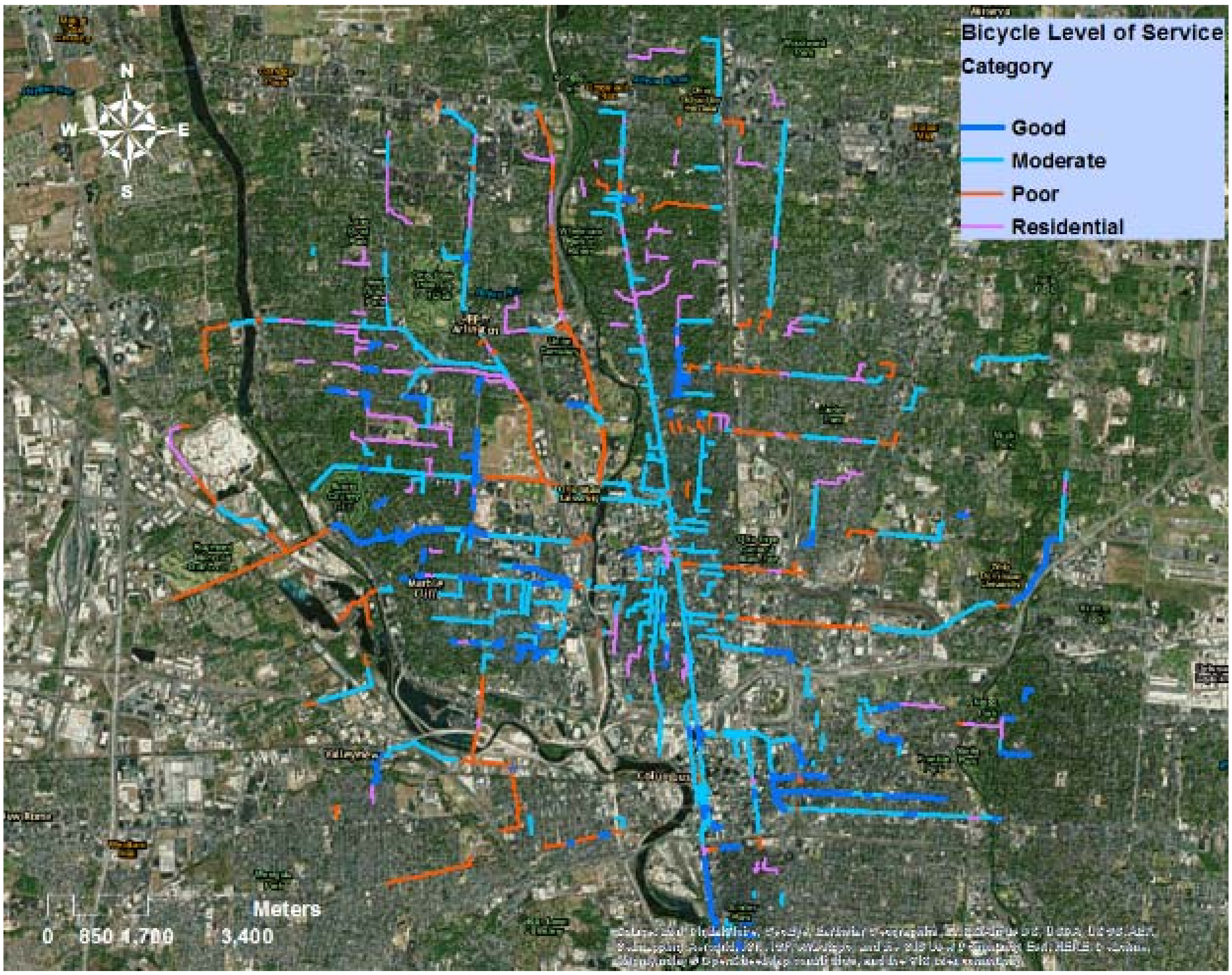


Figure 10. Bicycle Level of Service (BLOS) Values and Shortest Paths

We calculated some basic statistics to understand whether there is any pattern in the distribution of BLOS values (Tables 5 and 6). According to the results shown in Table 6, we find that most of the potential bicycle trips are on road segments with ‘moderate’ BLOS.

Table 6. The Sum of Street Segment Lengths for Each BLOS Value

Bicycle Level of Service	Sum of Segment Lengths (in meters)	%
Good	28,085.29	11.0
Moderate	95,942.59	37.7
Poor	42,473.62	16.7
Residential	39,593.97	15.5
(unknown)	48,698.77	19.1
Total	254,794.24	100.0

Table 7. Cross-Tabular Analysis of BLOS and Potential Bicycle Trips per Segment

	The Number and Share (%) of Trip Segments					
Potential Bicycle Trips	Good	Moderate	Poor	Residential	Unknown	Total
1 ~ 10	295 (12.7)	825 (35.5)	436 (18.8)	308 (13.3)	459 (19.8)	2323 (100.0)
11 ~ 50	36 (10.4)	183 (52.7)	54 (15.6)	28 (8.1)	46 (13.3)	347 (100.0)
50 ~ 100	9 (9.2)	65 (66.3)	18 (18.4)	5 (5.1)	1 (1.0)	98 (100.0)
101 ~ 200	0 (0.0)	64 (76.2)	10 (11.9)	7 (8.3)	3 (3.6)	84 (100.0)
201 ~ 584	0 (0.0)	0 (0.0)	0 (0.0)	1 (16.7)	5 (83.3)	6 (100.0)
Total	340 (11.9)	1137 (39.8)	518 (18.1)	349 (12.2)	514 (18.0)	2858 (100.0)

ii. <u>Heavily used road segments versus BLOS: Matched?</u>

We find that the most heavily used road segments (or the ones that would attract the most trips based on the shortest path algorithm) have “moderate” or “residential” BLOS based on MORPC’s classifications. We did not include the top two heavily used road segments here because they do not have assigned BLOS values. The table below (Table 7) displays third, fourth, and fifth most heavily used road segments, their BLOS classifications and expected trips. Since the current definition of ‘moderate’ service is too broad to determine any specific service level, more detailed categories are needed in future studies.

Table 8. The Three Most Frequently Used Road Segments

Rank	Road Segment	Expected Trips	Bicycle Level of Service	Location
3	On College Road	280	4 (Residential)	
4	On College Road	178	4 (Residential)	
5	On Annie and John Glenn Avenue	160	2 (Moderate)	

Looking closer at the data, we find that potential riders would face various levels of BLOS on their routes to campus if they were to follow the shortest paths. Here we look at two bicyclists who live in Upper Arlington (refer to the two red circles in Figure 11). We take a few snapshots of some locations along their predicted shortest routes. Blue lines denote 'Moderate', light-green lines 'Poor', dark-green lines 'Good' and pink lines 'Residential' BLOS.

The cyclist who starts from location *Upper Arlington 1* will usually ride on streets which have 'moderate' and 'poor' BLOS. The other cyclist who starts from Upper Arlington 2 would start with 'Good' BLOS but then will have to ride through 'poor' and 'moderate' BLOS segments.

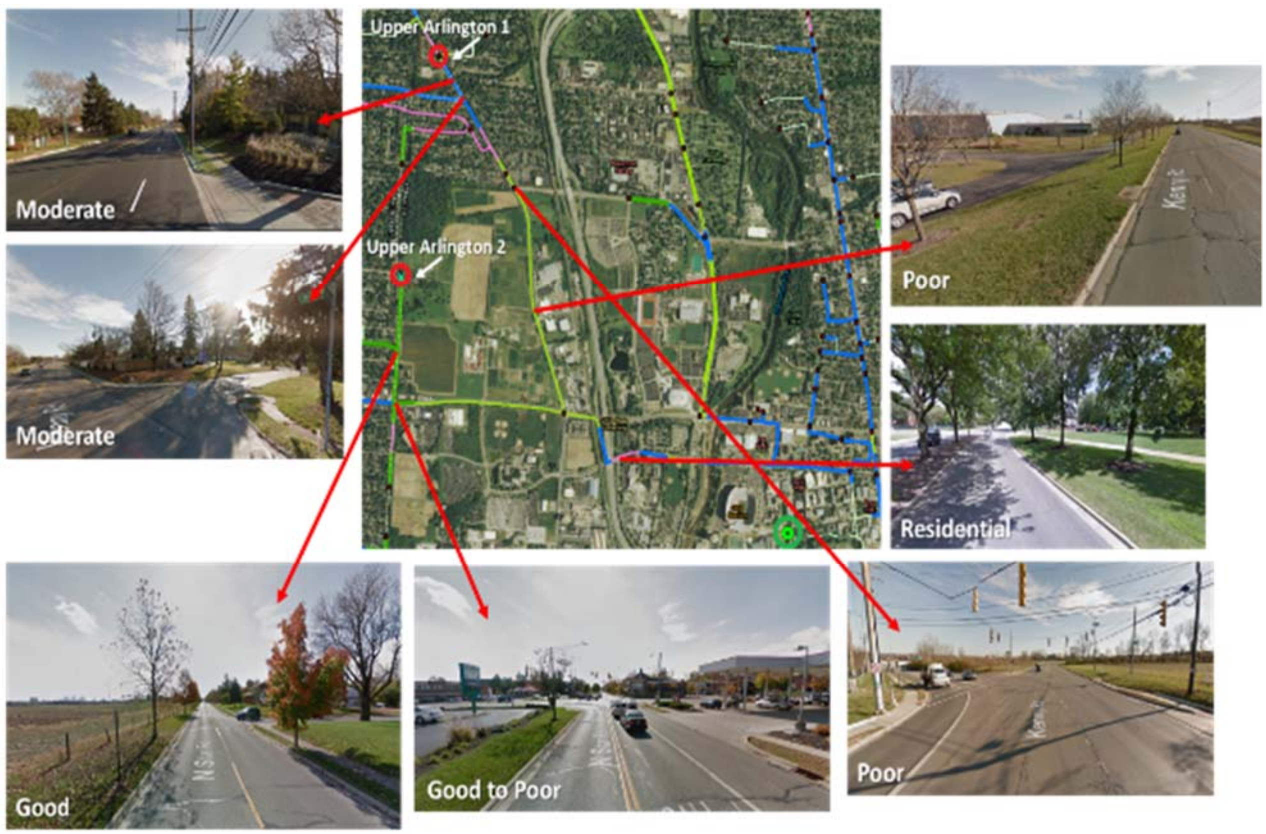


Figure 11. Snapshots of Some Locations along the Shortest Paths

Discussions

This section of the report analyzed the 2015 OSU Campus Travel Pattern Survey data combined with data from MORPC (Mid-Ohio Regional Planning Commission) to draw out bicycling-related implications. First, we examined the bicycling behavior, attitudes and perceptions of university members and demonstrated different behaviors and attitudes across bicyclists, potential bicyclists and non-bicyclists. Then we mapped the shortest routes of respondents living within 5 miles from campus and examined the BLOS levels of these routes.

Potential bicyclists as well as current bicycle commuters rated bicycle lanes and separated facilities as important factors that would encourage more bicycle trips. Most respondents agreed with the statement that roadway conditions (e.g. markings, signals, width, and lighting) on some streets make the route unsafe for bicyclists. Survey respondents rated the influence of extreme weather conditions as considerable, but room for increased bicycle ridership through policy measures and infrastructure improvements was also comparable.

We analyzed the shortest routes of the potential bicyclists and identified the BLOS of these routes. We found that most bicyclists would have to ride through segments with various service levels if they were to follow the shortest routes. We found that most road segments with considerable potential bicycle trips would fall into the “moderate” BLOS category.

PART 2.

Tracking Bicyclists' Route Choices Using Smartphone GPS

Introduction

Bicycling is an effective way to enhance urban vitality and mitigate the negative environmental and health effects of our long and continued dependence on motorized vehicle travel. One promising way to encourage bicycling is to understand the attributes of the built environment conducive to bicycling-related choices in order to provide a well-planned bicycle infrastructure reflecting riders' needs.

Existing studies that rely on traditional surveys (e.g. mail or email surveys) use shortest distance paths as proxies for the actually chosen path to analyze environmental attributes preferred by bicyclists. There is a high probability that the actual route is not correctly represented. Cyclists do not necessarily constrain their rides to shortest routes, which are not always comfortable to ride on, and may have significant physical barriers, such as slopes and high vehicular traffic. GIS-based shortest path routes can be misleading for behavioral modelling.

To avoid the arbitrary assumption of bicyclists' routes and analyze route choice behaviors more accurately, a small number of studies have used GPS-based route tracking techniques. An individual's smartphone constitutes valuable infrastructure for researchers to explore travel behavior. A large number of people in U.S. and other developed countries now possess smartphones – The smartphone ownership rate in U.S exceeded 80% in 2016[3]. Every smartphone has a built-in GPS signal device that can be used to track and record the owner's geographic locations real-time as well as navigate the shortest time path to a destination. Many of the GPS-enabled applications and built-in programs of smartphones are free to download. If a research team seeks to conduct a survey using GPS signals, they do not need to consider any extra cost to purchase, distribute and deliver survey-assisting devices to survey participants thanks to this ubiquitous device. The developers of the applications often provide part of the collected data at one's request at a given price, and the survey would require no extra effort for researchers to develop an independent application and secure a data storage server for a particular survey. Smartphones are also mobile. Participants do not have to pay extra attention not to forget to carry a survey device with them, and an application can be turned on rather quickly for GPS tracking whenever they begin and finish their trips. Therefore, smartphone-GPS-surveys can be promising options for travel behavior research.

In this part of the project report we describe the following tasks:

i. Collection of the GPS data on bicycle trips (origin, destination, purpose and route);
ii. Cleaning and matching the GPS points to the complete network;

[3] https://www.comscore.com/Insights/Blog/US-Smartphone-Penetration-Surpassed-80-Percent-in-2016 (Accessed in August 1, 2017)

iii. Developing maps illustrating the collected data;
iv. Comparing the chosen routes with the shortest routes;
v. Specifying future research plans with these data

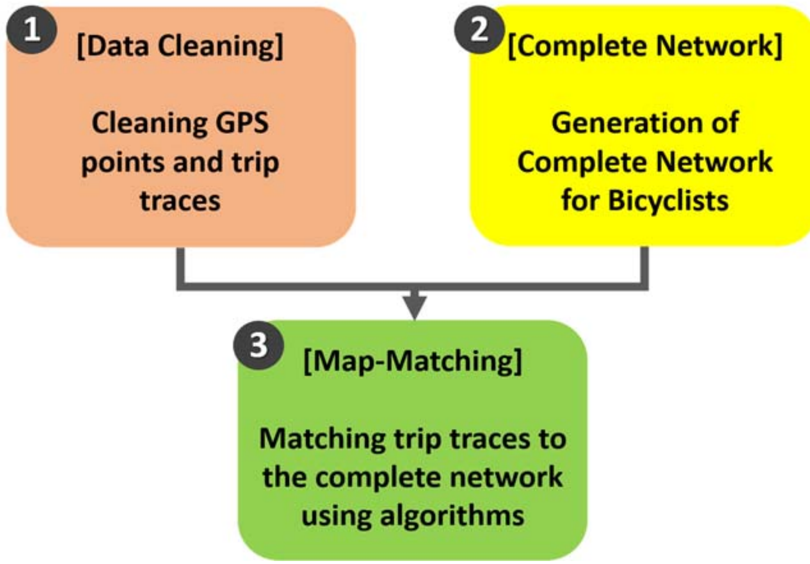


Figure 12. Work Flow of GPS Data Processing and Preparation before Analysis

Figure 12 presents the work flow of GPS data preprocessing that we conducted before route analyses. We collected and used bicycle GPS data in an effort to analyze bicycle route preferences and their associations with facility types. Data were collected through smartphone GPS in central Columbus from September through the end of November, 2016. We recruited study participants from The Ohio State University through email invitations, fliers, and advertisement on campus buses.

Data Collection

a. CycleTracks™ Smartphone Application

The origins, destinations, and routes of bicycle trips and basic personal information of participants were collected through a smartphone application: CycleTracks™. This app is developed by SFCTA (San Francisco County Transit Authority) to collect data on users' bicycle trip routes and times and display maps of their rides using smartphone GPS signals. The official website (http://www.sfcta.org/modeling-and-travel-forecasting/cycletracks-iphone-and-android) provides more information in detail. Our data collection took place from August 21, 2016 until December 1, 2016, for about two and a half months.

Respondents were asked to download a smartphone application, CycleTracks™. The individuals recorded their bicycle trips by turning the app on and off at the beginning and end of each bicycle trip. We provided the address of our survey promotion website in the survey invitation emails and postcards, where detailed step-by-step instructions were described with screenshots of the application (u.osu.edu/cycletracks) (Appendix 1, 2, and 3).

b. Recruiting Participants

We used three recruitment techniques: 1) mass email distribution, 2) survey promotion through an official website created for this study, and 3) distribution of postcards on the campus area and campus shuttles for more visibility. Under the permission of the Office of Chief Information Office, we sent mass emails twice to OSU faculty, staff and students. The survey invitation emails were sent to 23,116 people with university affiliations from August, 22, 2016 to August, 24, 2016 (Undergraduate students (8,500) + Graduate students (1,500) + Staff & Faculty (10,000) + those who allowed additional contacts for follow-up research through other studies (3,116)). The content of the invitation email, survey promotion website, and postcards are attached as Appendices 2, 3, and 4, respectively.

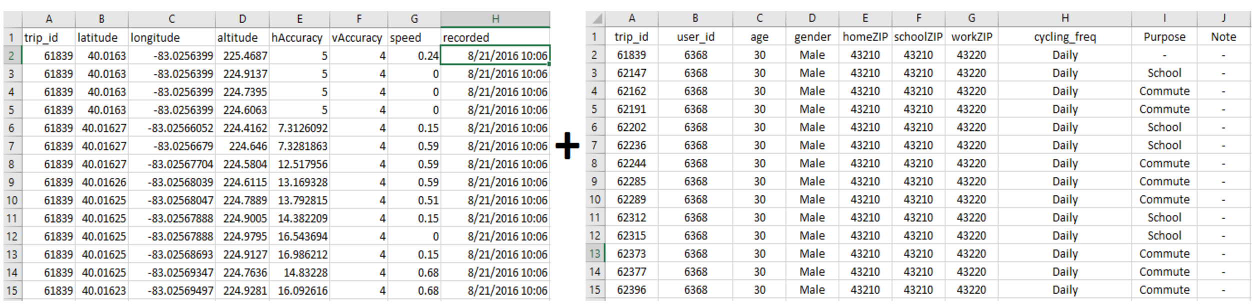
We were able to collect GPS points of a total of 1,584 bicycle trips. With a high resolution network reconstructed by the authors to include all possible links available for cycling, GPS traces were matched to the network links using ArcGIS custom routines, as suggested by Dalumpines and Scott (2011). After a series of data screening and cleaning steps, in addition to the removal of identical routes generated by the same rider, 452 utilitarian trips by 76 cyclists were available for our analysis.

Data Preparation

a. Importing the data

The GPS points contributed by the bicyclists who used CycleTracks application during their rides were accessed through the SFCTA online database with a user ID and password offered by SFCTA (Figure 13). We downloaded the data in CSV file format (Figure 14). The downloaded data file contains two sheets, one for the GPS points, and the other for user information.

Figure 13. The Screenshot of the Main Page



trip_id	latitude	longitude	altitude	hAccuracy	vAccuracy	speed	recorded
61839	40.0163	-83.0256399	225.4687	5	4	0.24	8/21/2016 10:06
61839	40.0163	-83.0256399	224.9137	5	4	0	8/21/2016 10:06
61839	40.0163	-83.0256399	224.7395	5	4	0	8/21/2016 10:06
61839	40.0163	-83.0256399	224.6063	5	4	0	8/21/2016 10:06
61839	40.01627	-83.02566052	224.4162	7.3126092	4	0.15	8/21/2016 10:06
61839	40.01627	-83.0256679	224.646	7.3281863	4	0.59	8/21/2016 10:06
61839	40.01627	-83.02567704	224.5804	12.517956	4	0.59	8/21/2016 10:06
61839	40.01626	-83.02568039	224.6115	13.169328	4	0.59	8/21/2016 10:06
61839	40.01625	-83.02568047	224.7889	13.792815	4	0.51	8/21/2016 10:06
61839	40.01625	-83.02567888	224.9005	14.382209	4	0.15	8/21/2016 10:06
61839	40.01625	-83.02567888	224.9795	16.543694	4	0	8/21/2016 10:06
61839	40.01625	-83.02568693	224.9127	16.986212	4	0.15	8/21/2016 10:06
61839	40.01625	-83.02569347	224.7636	14.83228	4	0.68	8/21/2016 10:06
61839	40.01623	-83.02569497	224.9281	16.092616	4	0.68	8/21/2016 10:06

+

trip_id	user_id	age	gender	homeZIP	schoolZIP	workZIP	cycling_freq	Purpose	Note
61839	6368	30	Male	43210	43210	43220	Daily	-	-
62147	6368	30	Male	43210	43210	43220	Daily	School	-
62162	6368	30	Male	43210	43210	43220	Daily	Commute	-
62191	6368	30	Male	43210	43210	43220	Daily	Commute	-
62202	6368	30	Male	43210	43210	43220	Daily	School	-
62236	6368	30	Male	43210	43210	43220	Daily	School	-
62244	6368	30	Male	43210	43210	43220	Daily	Commute	-
62285	6368	30	Male	43210	43210	43220	Daily	Commute	-
62289	6368	30	Male	43210	43210	43220	Daily	Commute	-
62312	6368	30	Male	43210	43210	43220	Daily	School	-
62315	6368	30	Male	43210	43210	43220	Daily	School	-
62373	6368	30	Male	43210	43210	43220	Daily	Commute	-
62377	6368	30	Male	43210	43210	43220	Daily	Commute	-
62396	6368	30	Male	43210	43210	43220	Daily	Commute	-

Figure 14. The Structure of the Raw GPS Point Dataset

In the dataset, Trip_ID is assigned to each trip trace and User_ID is assigned to a unique participant. 'hAccuracy' (i.e. horizontal accuracy) indicates the error range of a given GPS point in meters by a horizontal radius size around coordinates and 'vAccuracy' (i.e. vertical accuracy) indicates the vertical error range of a given GPS point. These two accuracy measures are used to filter out those GPS points with low positioning precisions. Speed is reported in meters per second. The number of bicycle trips collected during the period is 1,584 contributed by 81 participants (Table 8).

Table 9. Descriptive Information of the Collected Trips and Bicyclists

Information	Category	The Number of Bicyclists	%
Gender	Male	42	51.9%
	Female	17	21.0%
	Unknown	22	27.2%
	Total	81	100%
Age	18 – 25	22	27.2%
	26 – 35	17	21.0%
	36 – 45	6	7.4%
	46 – 55	8	9.9%
	55 +	5	6.2%
	Unknown	22	27.2%
	Total	81	100%
Cycling Frequency	Daily	35	43.2%
	Several times per week	21	25.9%
	Several times per month	3	3.7%
	Less than a month	0	0.0%
	Unknown	22	27.2%
	Total	81	100%
Purpose	Commute	921	58.1%
	School	254	16.0%
	Work-related	172	10.9%
	Errand	20	1.3%
	Shopping	5	0.3%
	Social	9	0.6%
	Exercise	20	1.3%
	Other	3	0.2%
	Unknown	180	11.4%
	Total	1584	100%

Figures 15, 16, and 17 show the GPS points and traces collected in Central Ohio and the immediate areas of The Ohio State University. With a closer look, one can identify problems related to outliers (Figure 18).

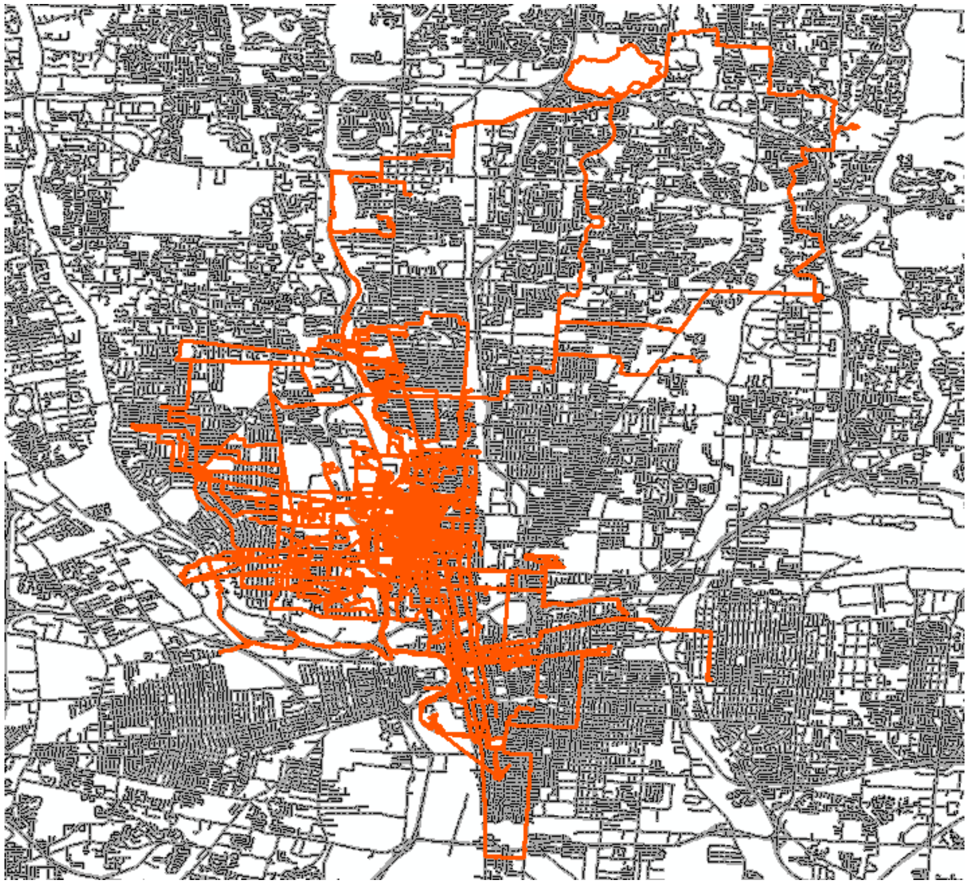


Figure 15. An Excerpt Map of Raw GIS Traces in Central Ohio (1)

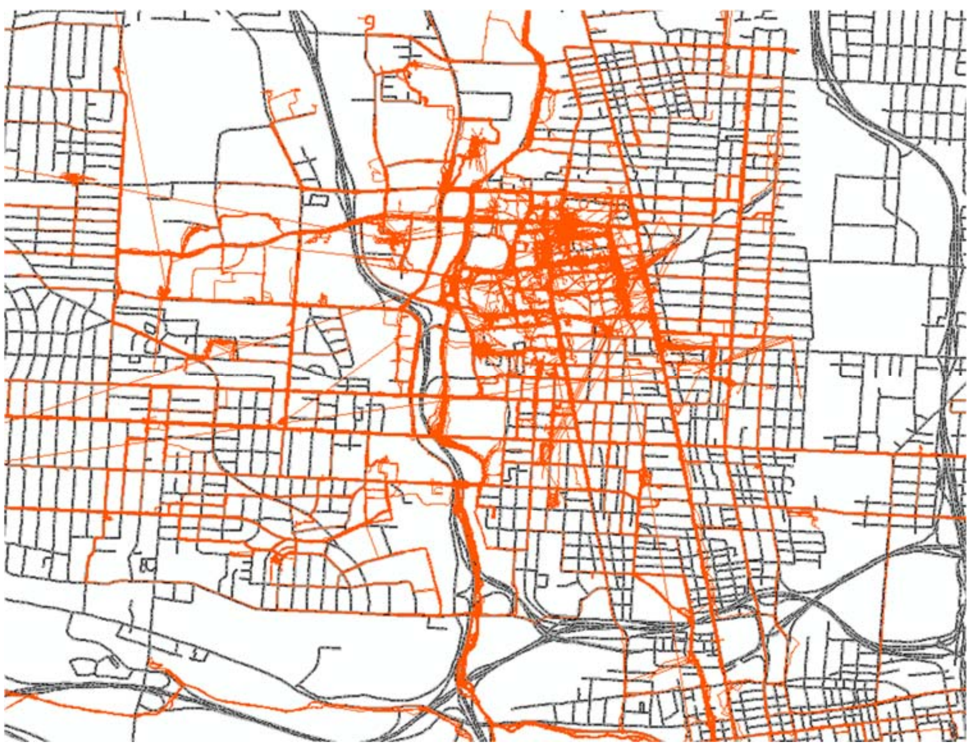


Figure 16. An Excerpt Map of Raw GIS Traces in Central Ohio (2)

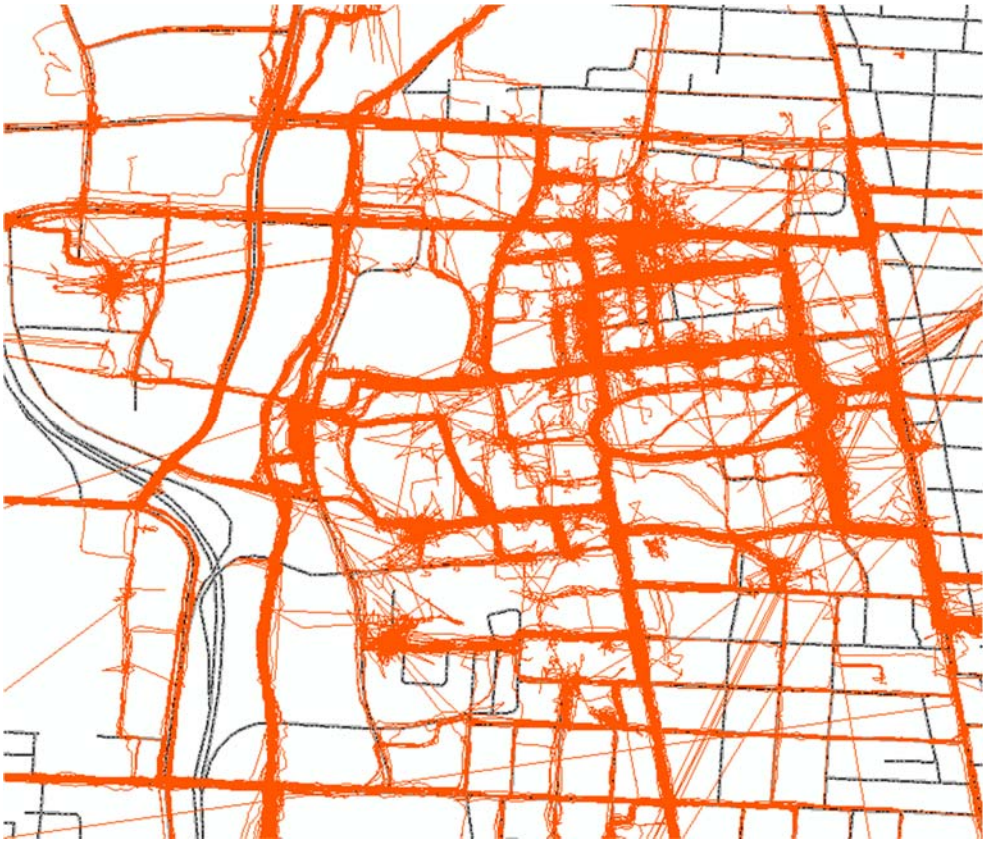


Figure 17. An Excerpt Map of Raw GIS Traces in Central Ohio (3)

Figure 18. An Excerpt Map of Raw GIS Traces at the OSU Campus

Processing the collected bicycle GPS data involves three crucial components as follows:

a) Cleaning the data of errors: removing outlier signals, signal noises, interruptions of signal reception, or very short traces
b) Creating a complete bicycling network: a new network should include the street network as well as other links bicyclists may use, e.g., park trails, parking lots, small passages
c) Matching GPS points to the complete network links: collected GPS points should be matched onto correct network links

b. Cleaning the data

Data cleaning is implemented at the GPS point level, not at the trace level. To capture defective or irrelevant points, we calculated several values using the GPS coordinates. These are (a) distance traveled since last captured point (meter), (b) change in time (sec), (c) speed (meter per sec) (Figure 19).

I1015 =(ACOS(COS(RADIANS(90-B1014))*COS(RADIANS(90-B1015))+SIN(RADIANS(90-B1014))*SIN(RADIANS(90-B1015))*COS(RADIANS(C1014-C1015)))*6371)*1000

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	trip_id	latitude	longitude	altitude	hAccuracy	vAccuracy	speed	recorded	distm_diff	time_diff	timesec_diff	speed_meterpersec			
1005	62355	40.009971	-83.066416	254.394688	5	3	4.69	9/12/2016 9:04	4.559860	0:00:01	1.0000	4.5598601			
1006	62355	40.00997	-83.066358	254.404026	5	3	5.24	9/12/2016 9:04	4.988396	0:00:01	1.0000	4.9883960			
1007	62355	40.009968	-83.066313	253.908787	5	3	6.06	9/12/2016 9:04	3.850443	0:00:01	1.0000	3.8504427			
1008	62355	40.009968	-83.066311	253.877171	5	3	6.07	9/12/2016 9:04	0.134259	0:00:01	1.0000	0.1342588			
1009	62355	40.009961	-83.066146	253.982151	5	3	6.49	9/12/2016 9:04	14.106759	0:00:01	1.0000	14.1067592			
1010	62355	40.009958	-83.066071	254.048252	5	3	5.94	9/12/2016 9:04	6.438825	0:00:01	1.0000	6.4388252			
1011	62355	40.009955	-83.066002	253.871861	5	3	5.88	9/12/2016 9:04	5.844499	0:00:01	1.0000	5.8444995			
1012	62355	40.009952	-83.065933	253.821629	5	3	5.82	9/12/2016 9:04	5.895933	0:00:01	1.0000	5.8959330			
1013	62355	40.00995	-83.065877	253.742405	5	3	5.79	9/12/2016 9:04	4.796817	0:00:01	1.0000	4.7968167			
1014	62355	40.009947	-83.065809	253.717747	5	3	5.54	9/12/2016 9:04	5.760625	0:00:01	1.0000	5.7606251			
1015	62355	40.002704	-83.027325	223.031174	65	10	-1	9/12/2016 9:18	3375.290	0:13:40	820.0000	4.1162076			
1016	62355	40.002704	-83.027325	223.031174	65	10	-1	9/12/2016 9:18	0.000000	0:00:01	1.0000	0.0000000			
1017	62355	40.002479	-83.027274	223.928879	65	10	-1	9/12/2016 9:18	25.380948	0:00:02	2.0000	12.6904740			
1018	62355	40.002492	-83.027227	225.350555	65	10	-1	9/12/2016 9:18	4.192229	0:00:06	6.0000	0.6987049			
1019	62355	40.002653	-83.027165	226.705795	65	10	-1	9/12/2016 9:18	18.619908	0:00:06	6.0000	3.1033179			
1020	62355	40.002681	-83.027159	227.447403	65	10	-1	9/12/2016 9:18	3.206790	0:00:05	5.0000	0.6413580			
1021	62355	40.002778	-83.027104	227.447403	92.1239236	10	-1	9/12/2016 9:18	11.781161	0:00:09	9.0000	1.3090179			

Figure 19. Calculation of Differences in Time and Distance between GPS Points

Some of the GPS points were removed if at least one of the following conditions applied:

a) Either horizontal or vertical accuracy values (measured in meters) were greater than 65 meters (this is a typical value we get when a GPS locator is not operating properly)
b) original GPS speed indicator is equal to -1
c) the distance from last captured point is greater 200 m or time difference is greater than 1800 seconds (30 minutes)
d) the calculated speed was greater than 30 mph (13.5 meter per second) or less than 2 mph (0.9 meter per second)

Once these points were removed, the new column data showing changes between the points were recalculated. Based on these cleaned data, a trip was split into multiple trips if there was more than three minutes or more than 1,000-ft (305 m) between points in order to account for trip chaining. Finally, trips with fewer than five collected points were removed from the dataset. Before plotting the cleaned dataset into ArcGIS, we assigned 'ObjectID' to each point to make the inspection easier. The maps illustrating the GPS traces before and after these processes are shown in Figures 20 and 21.

The number of all commute trips were 1,327 (commute 901, school 254, work-related 172). After data cleaning, this number reduced to 1,294 with 76 bicyclists. Using the 'Delete Identical' built-in function in ArcGIS, we removed those duplicate polylines whose geometries are identical to one another with a geometric tolerance set to be up to 20m.

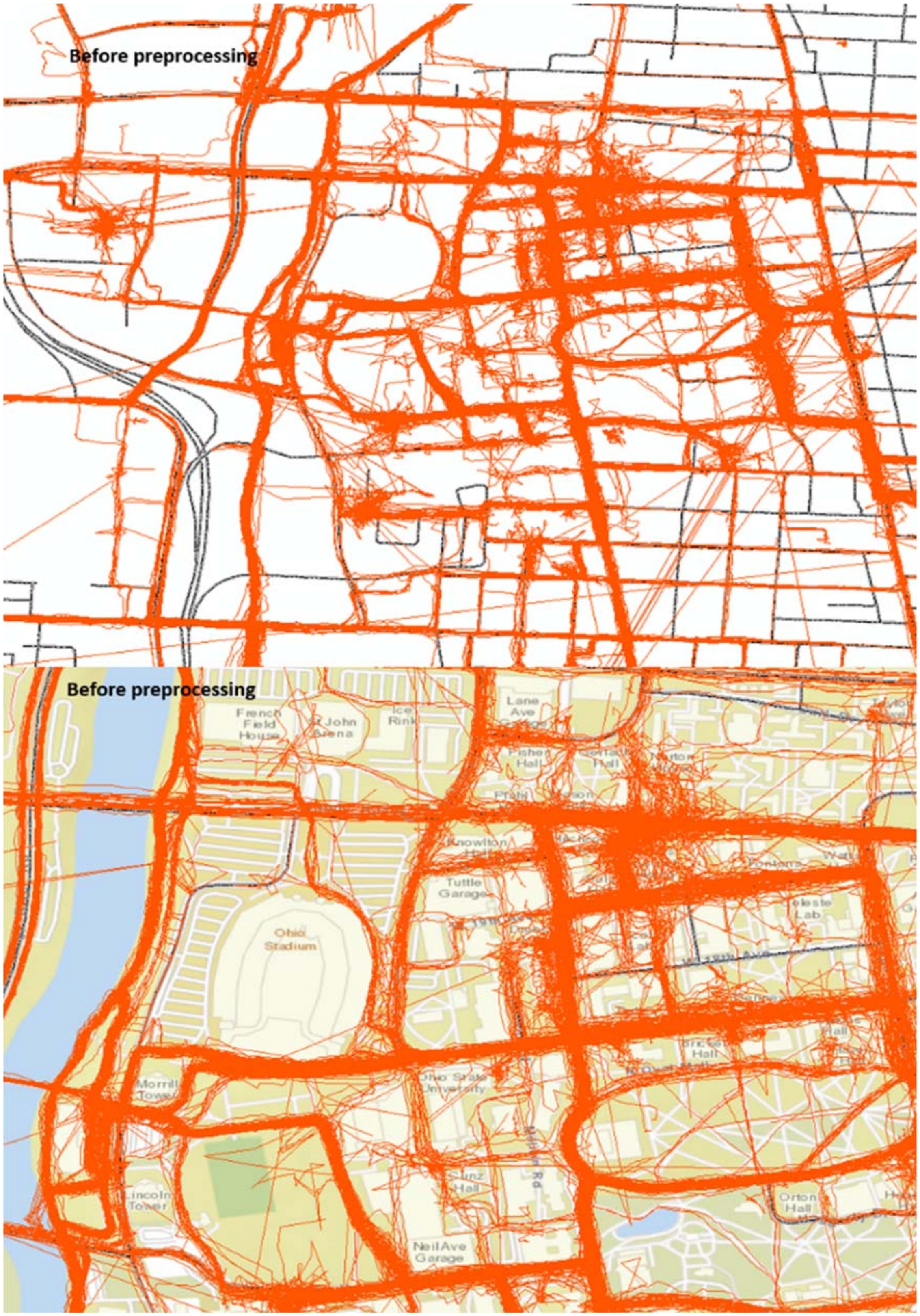


Figure 20. The Maps before Preprocessing

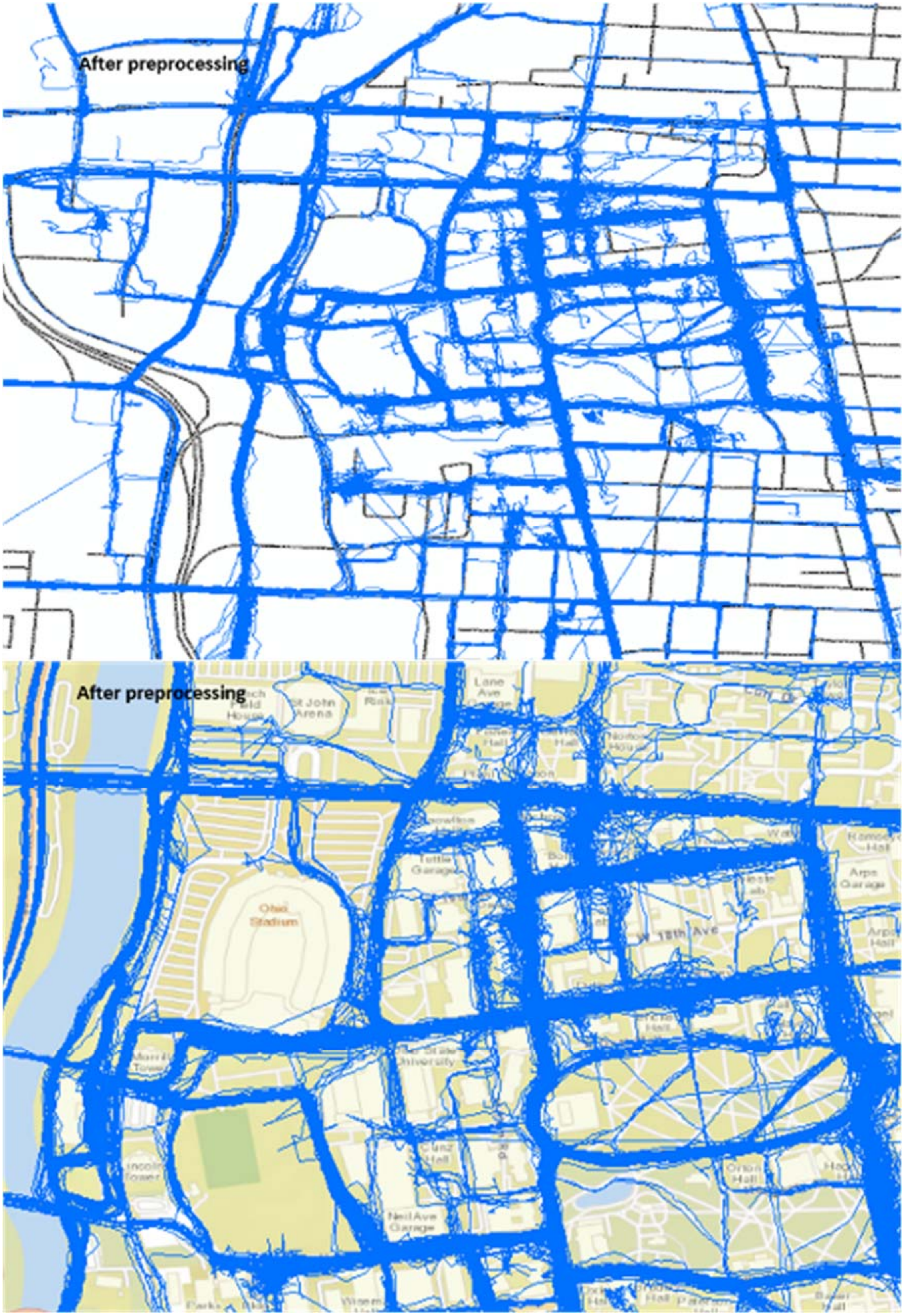


Figure 21. The Resulting Maps after Preprocessing

Removing part of the GPS points at origins and destinations was necessary to correct the unrealistic segments of a route trace (Figure 22). Some bicyclists forgot to turn off the application that recorded their GPS signals at their destinations. Even after they got off their bicycles, their applications were still in operation and the GPS points at that moment were shown on the map at the top of the buildings or other features on which it was not possible to ride. At origins, bicyclists' GPS applications took some time to normally and precisely locate the users' geographic locations and thus points were often randomly scattered (Figure 23). Therefore, removing 20-30 points recorded at origins and destinations helped reduce the noise in GPS points shown in maps, without critically affecting the overall traces (Figure 24). We used ArcPy module to assign numbers to GPS points in ascending and descending orders of record time. Then we deleted the first and last 30 points. Following this, those points plotted on top of buildings were removed using the ArcGIS Editor tool.

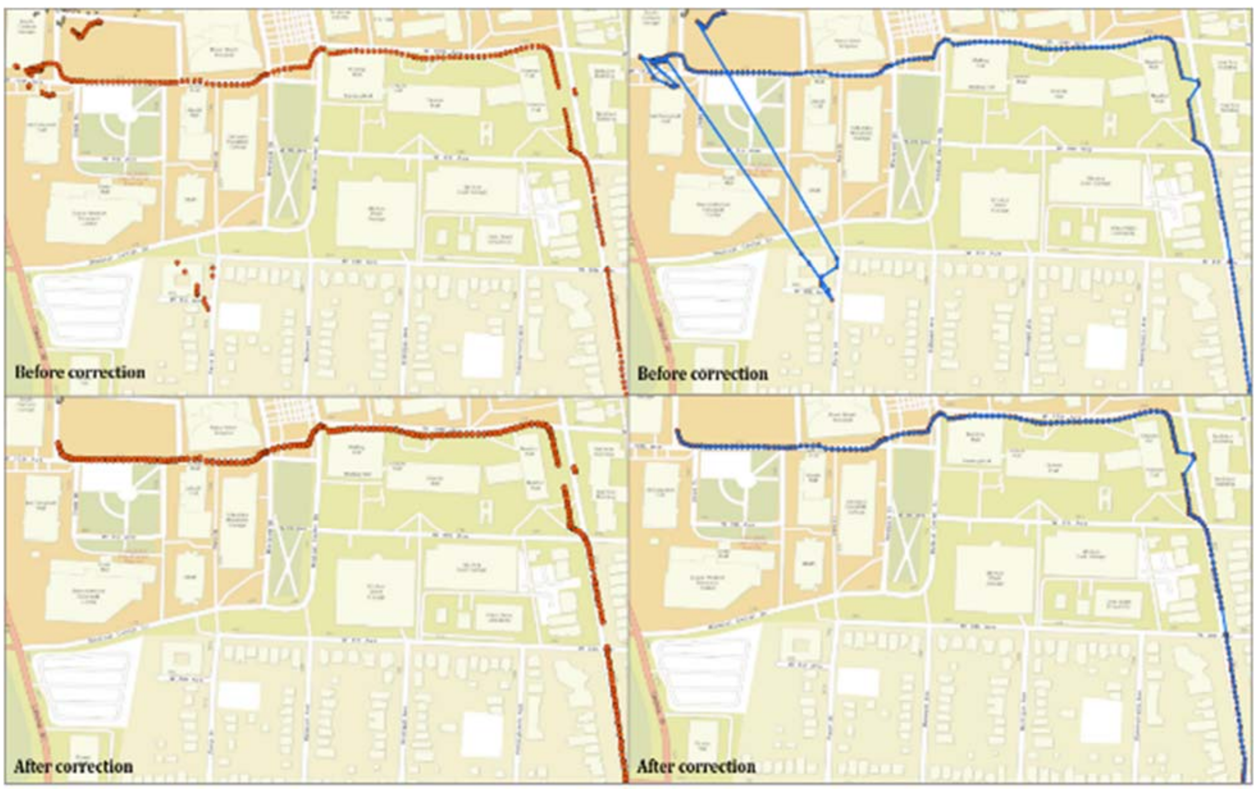


Figure 22. Removal of Several Outlying Points at Origins and Destinations for Trace Rectification

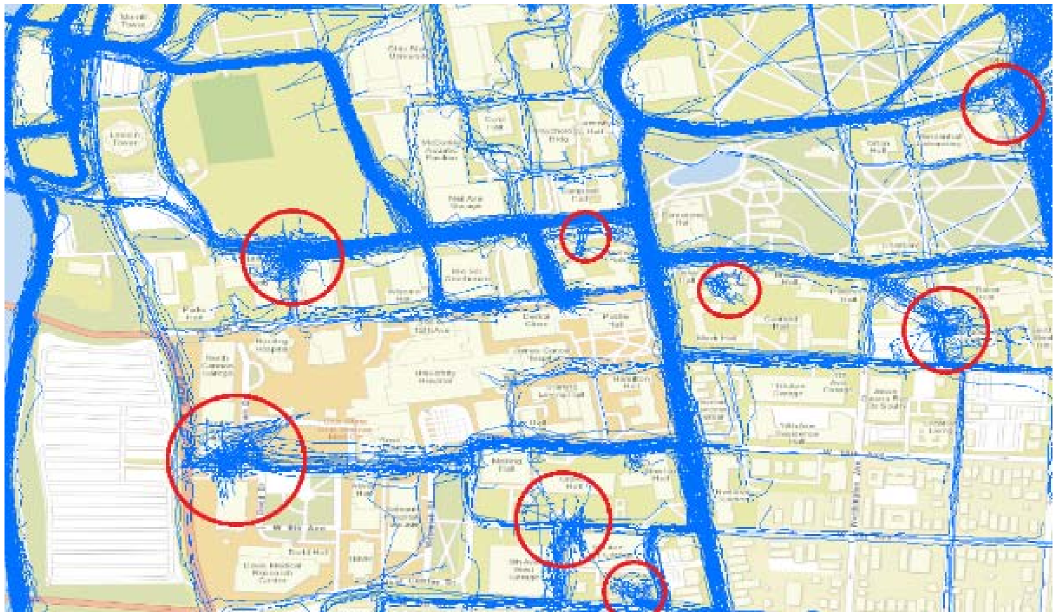


Figure 23. Unstable GPS Signals Resulting in Scattered Geocoded Points

The following map (Figure 24) shows the screen shots of the final bicycle GPS traces after a series of data cleaning processes described above.

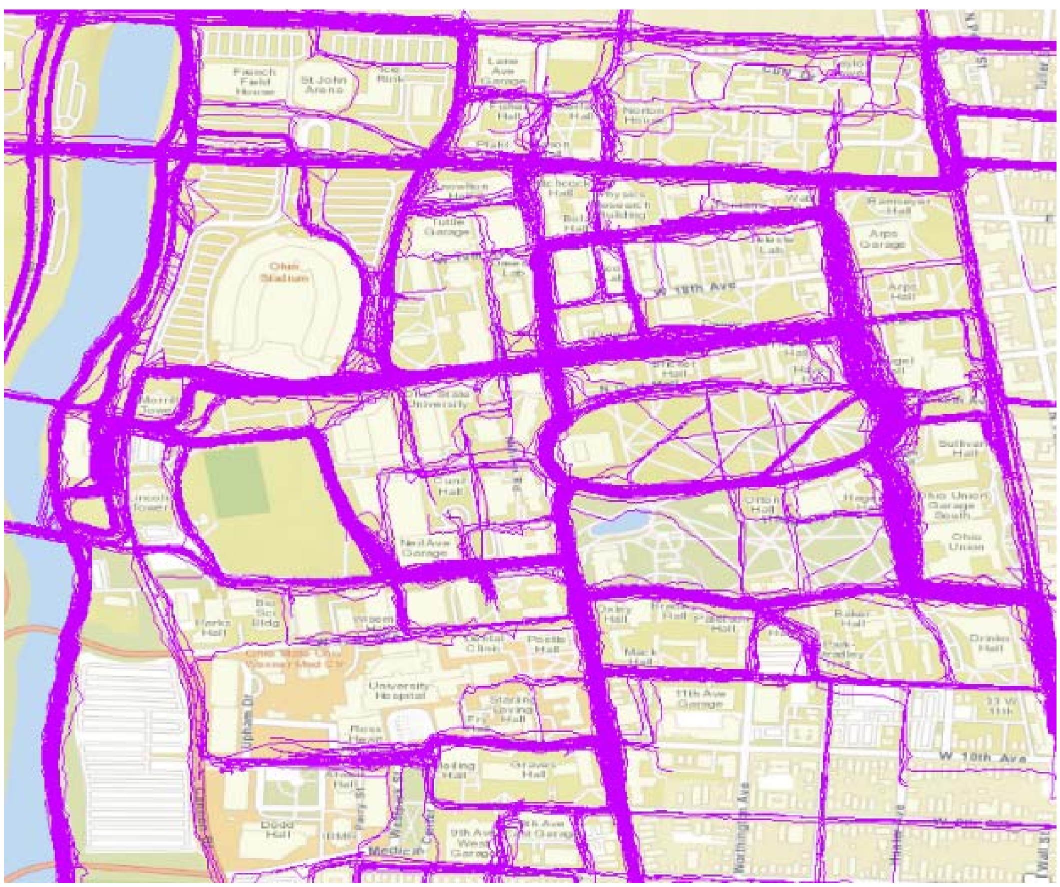


Figure 24. GPS Traces on the Google Base Map after Data Cleaning (N= 1,408)

c. Matching the GPS traces to the Network

We combined the network datasets from multiple sources into one consistent, connected network to match the resulting GPS traces. Table 9 presents several network data sources available for the Central Ohio region. Zhou and Golledge (2006) and Hudson (2012) noted that, compared to the rapid development of GPS and other positioning technology, map accuracy is relatively lagging behind, requiring a long-term and energy-intensive task. The maps have not been extended to represent the details of streets and particular types of facilities such as bike paths and sidewalks. Having said that, Open Street Map provides a quite solid and detailed map based on which researchers can begin constructing their own network data. It includes park trails, parking lot passages, and pedestrian walkways, saving researchers time and energy needed to manually add unrepresented links to the network.

Table 10. Network Data Sources

Institution	Name	Coverage	Attributes
Open Street Map (www.openstreetmap.org)	**GeoFabrik**	**Ohio**	**Contains potential pathways for bicyclists,** Road class (motorway, residential, etc), One-way, Locations of traffic signals
US Census TIGER/Line System	All Streets	Franklin, OH	None (but detailed network)
MORPC (Mid-Ohio Regional Planning Commission)	Bikeways	Central Ohio	Path-type, Class, Route-type,
MORPC (Mid-Ohio Regional Planning Commission)	Bike Level of Service (BLOS) Network	Central Ohio	Lanes, Speed, One-way, Bike-friendliness
State Government of Ohio - Ohio Geographically Referenced Information Program (OGRIP)	LBRS (location based response system) street centerlines	Central Ohio	# of Lanes, Speed, One-way, Road class

After manually inspecting the accuracy and completeness of the resulting network data, we used ArcGIS ModelBuilder module to develop a map-matching algorithm. The algorithm was developed by Dalumpines and Scott (2011). This algorithm requires the unique feature of ModelBuilder, ‘Iterate Field Values’ to iteratively process multiple bike traces with different origins and destinations and polyline barriers. It also requires the standard Network Analyst™ extension license to be implemented. The way this algorithm works is that it finds the shortest path between a pair of origin and destination points within a bounded area, which is the 30 or 40 meter buffer area of a polyline connecting the set of GPS points of a trip.

The success rate of this map-matching task was 89.1%. This rate is around the average success rate reported in previous studies (Dalumpines and Scott, 2011; Hudson et al. 2012). After we matched all routes to the network, it became evident that some of these routes were identical and traveled by the same bicyclist, therefore should be merged into a single route. If one path overlapped with another path within a twenty meter error range at the origin or destination, the two paths were considered to be the same path. After removing these identical routes, we ended up with a total of 452 unique routes made by 76 unique bicyclists. The following map presents the final map of the collected GPS traces cleaned and matched to the complete street network for bicyclists (Figure 25).

In addition to the map representing the actually chosen routes of the participants, we created a separate map showing the shortest distance routes between the origins and destinations (Figure 26).

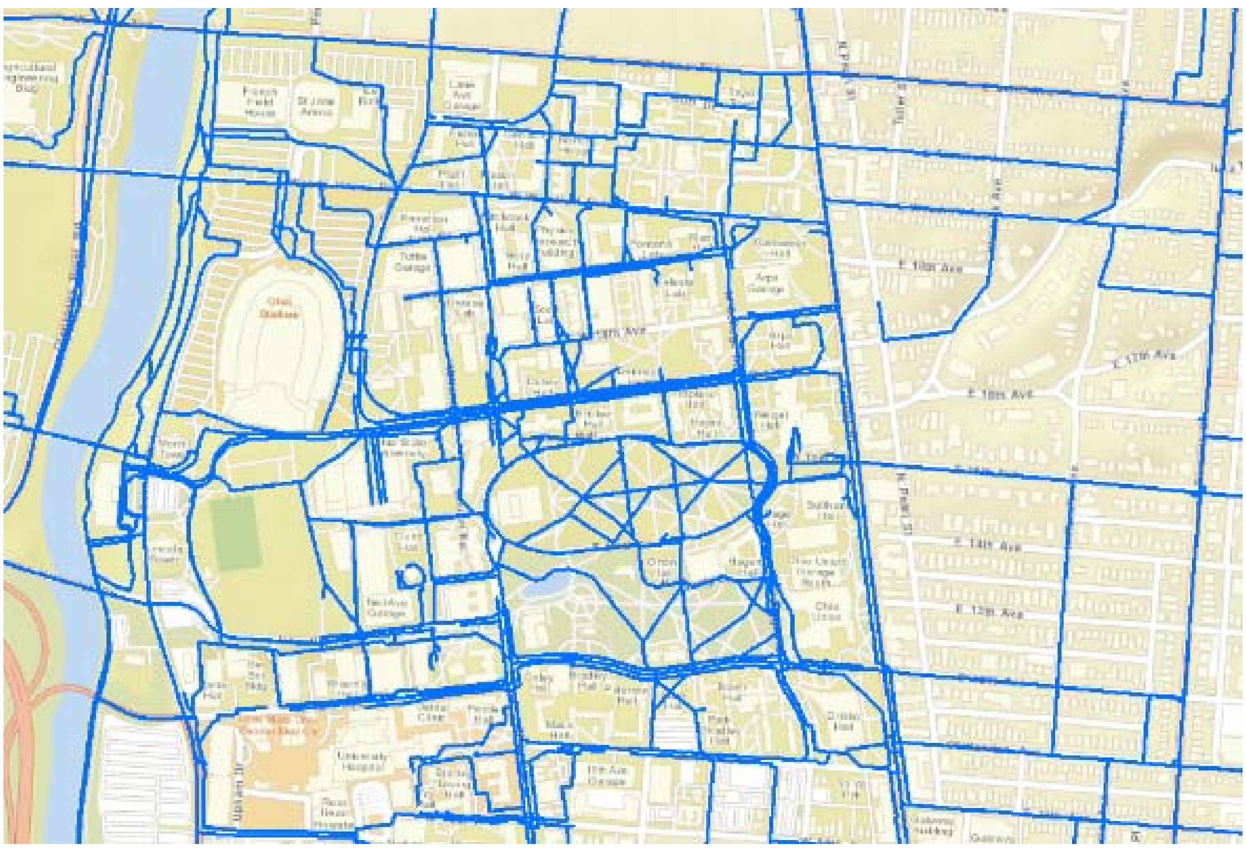


Figure 25. The Map of the Actually Chosen Routes Matched to the Network Map (N = 452)

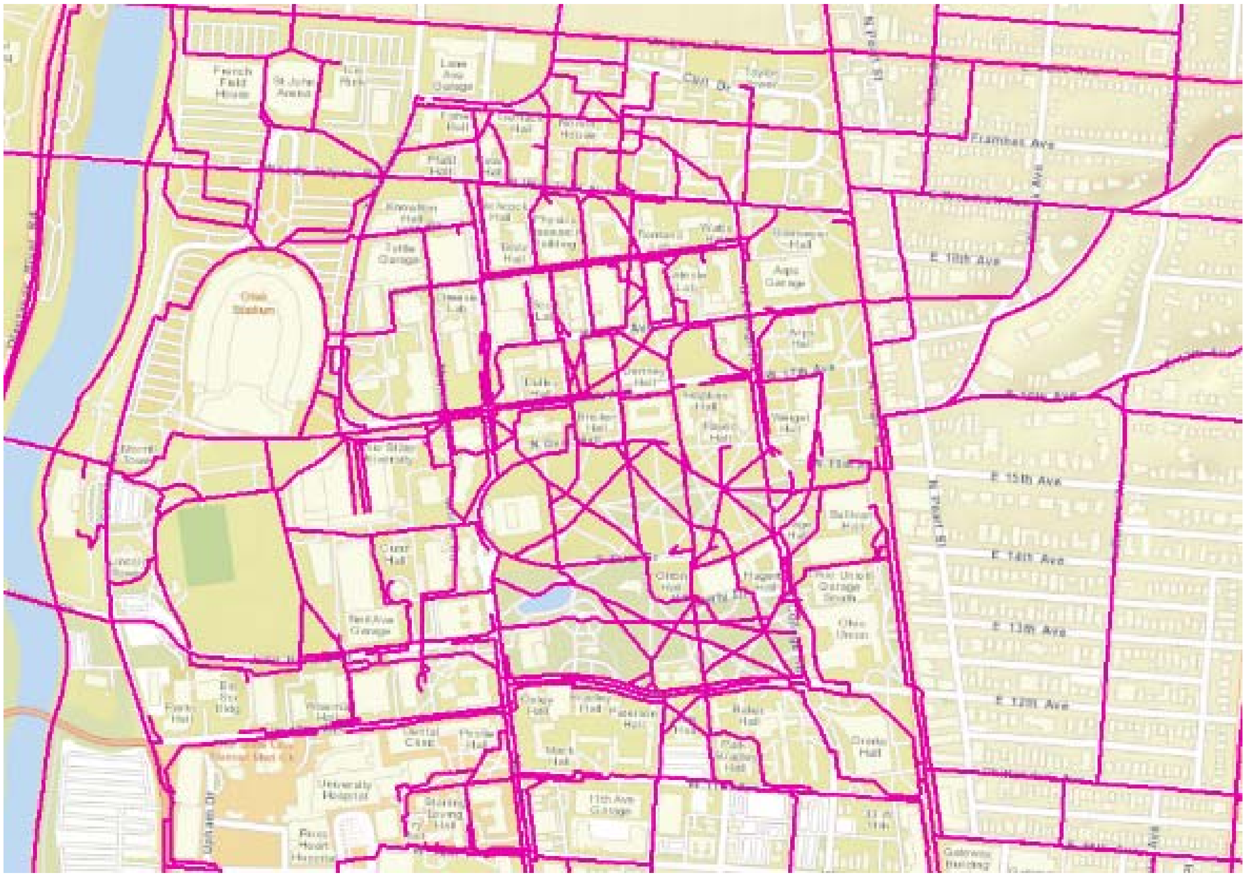


Figure 26. The Map of the Shortest Routes for Comparison (N = 452)

d. Frequently used network segments

The Actually Chosen Routes (trip frequency ≥ 20)	The Shortest Routes (trip frequency ≥ 20)

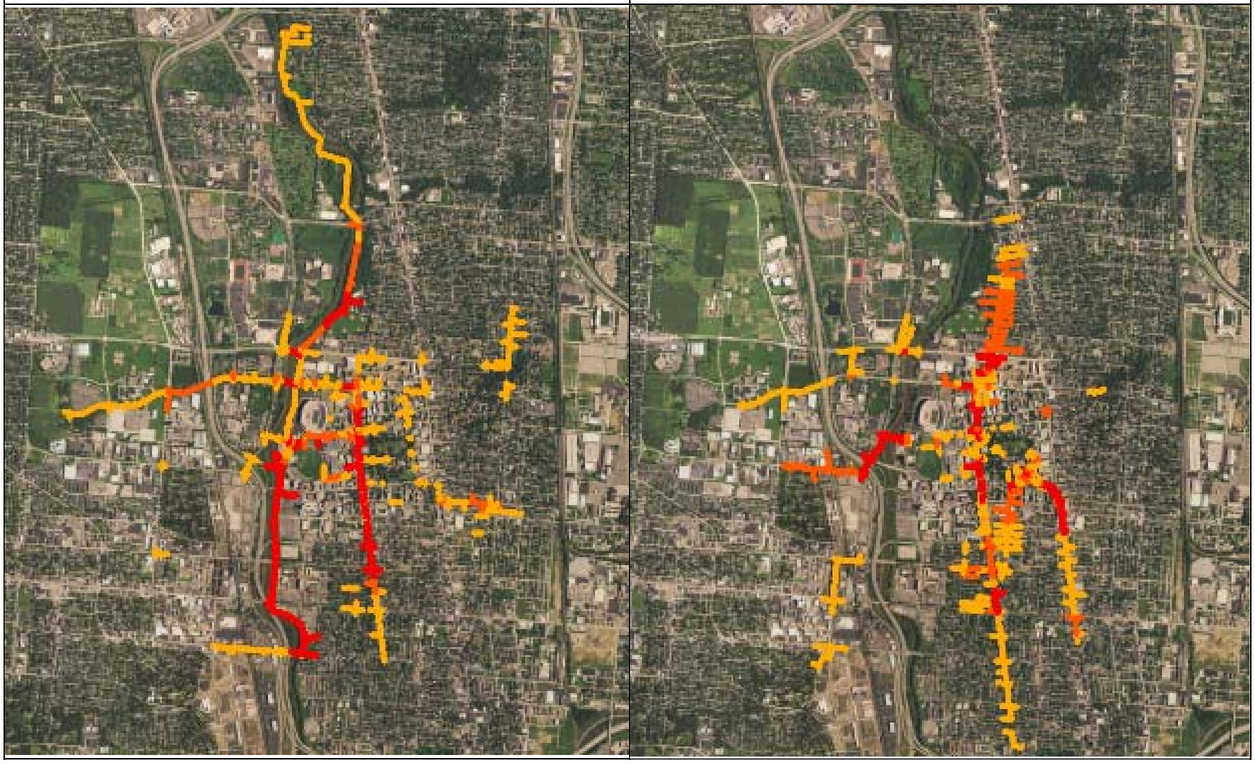


Figure 27. Comparison of the Most Frequently Used Routes (Chosen and Shortest Paths)
(Yellow: 20≤ n <30, Orange: 30≤ n <40, Red: 40≤ n <82)

Figure 27 shows the most frequently used street segments among the chosen routes and the shortest routes. The two maps look quite different. They suggest that different segments were actually preferred by the bicyclists, unlike those expected by the shortest path algorithm. As Table 10 presents, many of the participant bicyclists used pedestrian walkways near the central university library (i.e. Thompson Library) and those segments along Neil Avenue, where many university buildings and facilities are located. Many of the participant bicyclists also preferred the exclusive bicycle trails, for example Olentangy Trail, which is close to the campus area. Except for the segments within the campus area, the segments with higher levels of bikeability were favored by the bicyclists. Based on these data we anticipate that the characteristics of the chosen routes differ from those of the shortest routes.

Table 11. The Five Most Frequently Used Link Segments by the OSU Participants

Rank 1	Location	Neil Avenue & Neil Drive
	Trip Frequency	78 ~ 81
	Bicycle Level of Service	Good
	Satellite View	
Rank 2	Location	John H Herrick Dr & Cannon Dr & Olentangy Trail
	Trip Frequency	66 ~ 77
	Bicycle Level of Service	Poor
	Satellite View	
Rank 3	Location	Olentangy Trail
	Trip Frequency	58 ~ 65
	Bicycle Level of Service	Good (Exclusive Bicycle Trail)
	Satellite View	

Table 12. The Five Most Frequently Used Link Segments by the OSU Participants *(Continued)*

Rank 4	Location	Neil Avenue & W 8th Ave
	Trip Frequency	52 ~ 57
	Bicycle Level of Service	Moderate
	Satellite View	
Rank 5	Location	Olentangy Trail
	Trip Frequency	46 - 51
	Bicycle Level of Service	Good (Exclusive Bicycle Trail)
	Satellite View	

Future Plans

a. Research Questions

To analyze bicyclists' route choice behaviors more accurately, a small number of studies have employed revealed preference surveys on commute routes using GPS-based route tracking applications. These studies identify physical, functional, and operational characteristics of chosen and alternative routes as factors associated with route choices (Broach, Dill & Gliebe, 2012; Gim & Ko, 2016; Hood, Sall & Charlton, 2011; Howard & Burns, 2011; Menghini et al. 2010; Sener, Eluru & Bhat, 2009; Zhu & Levinson, 2015; Zimmermann, Mai & Frejinger, 2017). It is commonly found that, even if cyclists favor off-street bike paths and bike lanes, their sensitivity to trip length turns out to be stronger than their sensitivity to shared use, especially in the case of commute trips (Broach, Dill & Gliebe, 2012; Hood, Sall & Charlton, 2011; Menghini et al. 2010; Sener, Eluru & Bhat, 2009). The influence of route gradient and its variations are significant, though small (Hood, Sall & Charlton, 2011; Zimmermann, Mai & Frejinger, 2017). While the results of traffic volume, speed limits and the number of lanes vary from study to study, signalized turns and stop signs appear to have significant impacts (Broach, Dill & Gliebe, 2012; Sener, Eluru & Bhat, 2009).

Despite the significance of the road and traffic conditions, there is a lack of consideration on the environmental characteristics of bicycle routes, such as surrounding land-use/cover patterns and streetscape. These environmental indicators are important because riders seek diverse utilities, such as health and recreation, even during utilitarian trips. Surrounding land-uses are also associated with average daily traffic and pedestrian volumes, which affect bicycling conditions (Morency et al., 2012). Information on the effects of the built-environment can inform decision makers on where to invest in and how to design bicycle facilities. Existing studies on walking behavior of urban residents find significant relationships between street network walkability and walking distance and route choices (Sarkar et al. 2015; Tribby et al. 2016). Tribby et al. (2016) find that a higher number of offices, on-street parking and graffiti increases the propensity of riding along whereas retail stores/restaurants, industrial land-use and pedestrian safety infrastructure decrease this propensity. While research on the relationship between streetscape design elements and propensity to walk is active, there has been few studies that examine the relationship between land-use patterns, streetscape, and bicycling route preferences.

Building upon these findings and using the cycling GPS data processed for empirical analysis, we will seek answers to the following questions.

- How much do cyclists prefer the shortest route when riding a bicycle?

- How far are cyclists willing to take detours to enjoy their preferred attributes? How much are these routes adjacent to and overlapping with the shortest routes?
- Which factors drive bicyclists to take detours? What are the differences between a chosen route and the corresponding shortest route?
- What determinants are closely associated with the decision to detour and the degree of diversion?

b. Network and Environmental Attributes

Table 11 presents the list of expected explanatory variables for the study. The explanatory variables include:

- Roadway physical characteristics and classes (e.g., grade, the number of lanes, signalized and unsignalized intersections and road hierarchy (arterial, secondary, tertiary, residential, and service roadways))
- Bicycle-related facilities (e.g., the share of bicycle trails, paths, and lanes along each route)
- Route characteristics (e.g., travel length, number of turns, trip purpose)
- Roadway functional characteristics (e.g., typical traffic estimates, speed limits)
- Surrounding land-uses and natural features (e.g., commercial, residential, offices, industrial and other land-uses, and land cover (e.g., vegetation, impervious, water and bare soil)
- Streetscape features (the amount of street trees and greenery)

To quantitatively assess the association between the explanatory variables and the degree of diversion (i.e. percentage of overlap with the shortest path), we plan to develop two different forms of models where the dependent variable will take two different forms:

i. OLS regression models where the dependent variables will be the degree of diversion measured as the percentage of overlap with the shortest route (0 ~ 100%)
ii. Ordered logit/probit models where we will assign discrete categories for different overlap levels (for instance: 0 to 25%, 25 to 50%, 50 to 75% and 75% and above)

These models will help identify the factors associated with bicyclist route choice decisions.

Table 13. The Description of Potential Explanatory Variables for Bicycle Route Choice Analysis

Category	Description
Trip related	Distance of the actually chosen route (meter)
	Distance of the shortest route (meter)
	How much longer the actual route is than the shortest (%)
	The length of an overlap between the chosen and shortest routes
	How much portion of the chosen route stay on the shortest route (%)
Land Use Zoning	% of Land for Commercial Use within a 50m buffer of a route
	% of Land for Industrial Use within a 50m buffer of a route
	% of Land for Office within a 50m buffer of a route
	% of Land for Single-Family Residence within a 50m buffer of a route
	% of Land for Multifamily Residence within a 50m buffer of a route
	% of Land for Education within a 50m buffer of a route
	% of Land for Governmental Use within a 50m buffer of a route
	% of Land for Park within a 50m buffer of a route
	Land-Use Mix Index (= 8-category land use entropy score)
Land Cover	% of Land with Green Vegetation Cover within a 50m buffer of a route
	% of Urban Impervious Cover within a 50m buffer of a route
	% of Water Surface within a 50m buffer of a route
	% of Other types (e.g. bare soil) within a 50m buffer of a route
	Land-Cover Mix Index (= 4-category land cover entropy score)
	Average Normalized Difference in Vegetation Index within a 50m buffer of a route (a range from -1 to 1) using remote sensing images
Slope	% of Route Segments where larger than 6% Up Slope
	% of Route Segments where larger than 10% Up Slope
	% of Route Segments where larger than 15% Up Slope
	% of Route Segments where larger than 20% Up Slope
	Mean Gradient (average slope, %)
	Variation in Elevation (std. dev, %)
Turns	No. of Turns along a route
	No. of Right Turns along a route
	No. of Left Turns along a route
Intersection	Average number of intersections per 100m along a route
	Average number of signalized intersections per 100m along a route
	Average number of unsignalized intersections per 100m along a route
Speed Limit	The average of posted speed limit along a route
	% of a route where posted speed limit is more than 35 mph
	% of a route where posted speed limit is more than 40 mph
	% of a route where posted speed limit is more than 45 mph
Road Hierarchy	1 = primary, 2 = secondary, 3 = tertiary, 4= collector, 5= local, 6 = local, 7 = minor street, 8 = no motorized traffic path
Lanes	Average number of road lanes along a route
Traffic	Typical traffic along a route during peak hours (Tuesdays, 8AM) collected from Google Maps traffic records (0 = no motorized traffic, 1= fast, 2= active, 3= moderate, 4=busy, 5=heavy)
Bicycle Facilities	% of a route which bicycle path exists
	% of a route where bicycle boulevard exists
	% of a route where bicycle lanes exist
	% of a route where bicycle routes exists

Concluding Remarks

There is increasing interest among colleges and universities in ways to reduce local congestion, contributions to greenhouse gases, and provide leadership in sustainable transportation. This study brings these two emerging areas together: analyzing campus transportation patterns and identifying the factors associated with bicycle trip generation and bicycle route choices using state-of-the-art data collection techniques at a large university campus, The Ohio State University (OSU). This report covered these two components and provided directions for future research.

The first part of this study uses data from the 2015 Campus Travel Pattern Survey. We explored the factors associated with individuals' bicycling choices and analyzed the shortest paths that these individuals would potentially take if they were to ride bicycles to campus. We found that potential bicyclists would encounter roads with multiple BLOSs. For instance, individuals may ride on road segments with 'moderate' or 'residential' BLOS near their neighborhoods and close to campus, but likely face 'poor' or 'moderate' road segments in between.

The second part of the study uses smart phone GPS data to analyze bicycle route preferences and their associations with facility types. The data were collect using a smart phone app *CycleTracks.* The results show that the most frequently used street segments among the chosen routes and the shortest routes are different in terms of their locations and characteristics. These suggest that riders preferred different segments as compared to those predicted by the shortest path algorithm. Following these results, we will conduct further analysis on the determinants of route choices, particularly focusing on the factors that are closely associated with the decision to detour and the degree of diversion.

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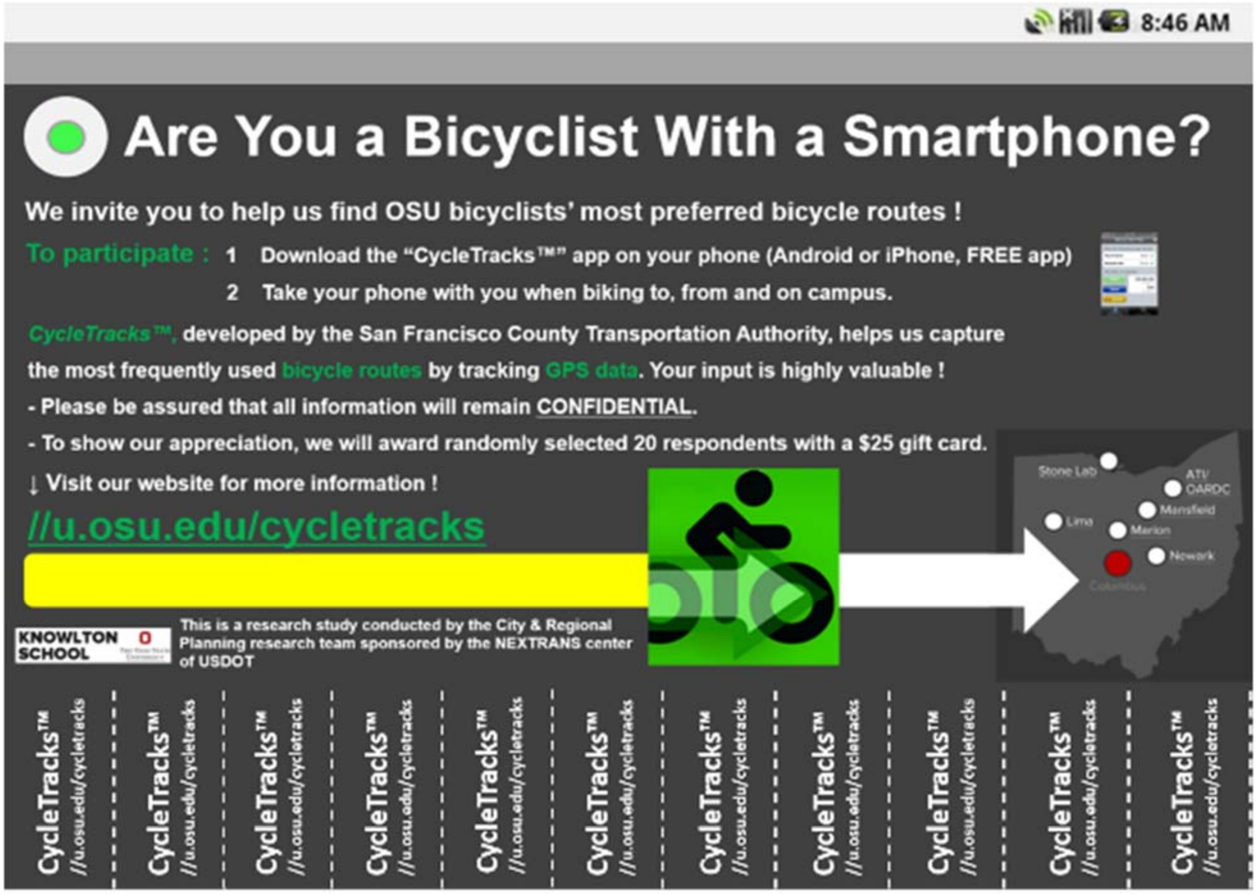
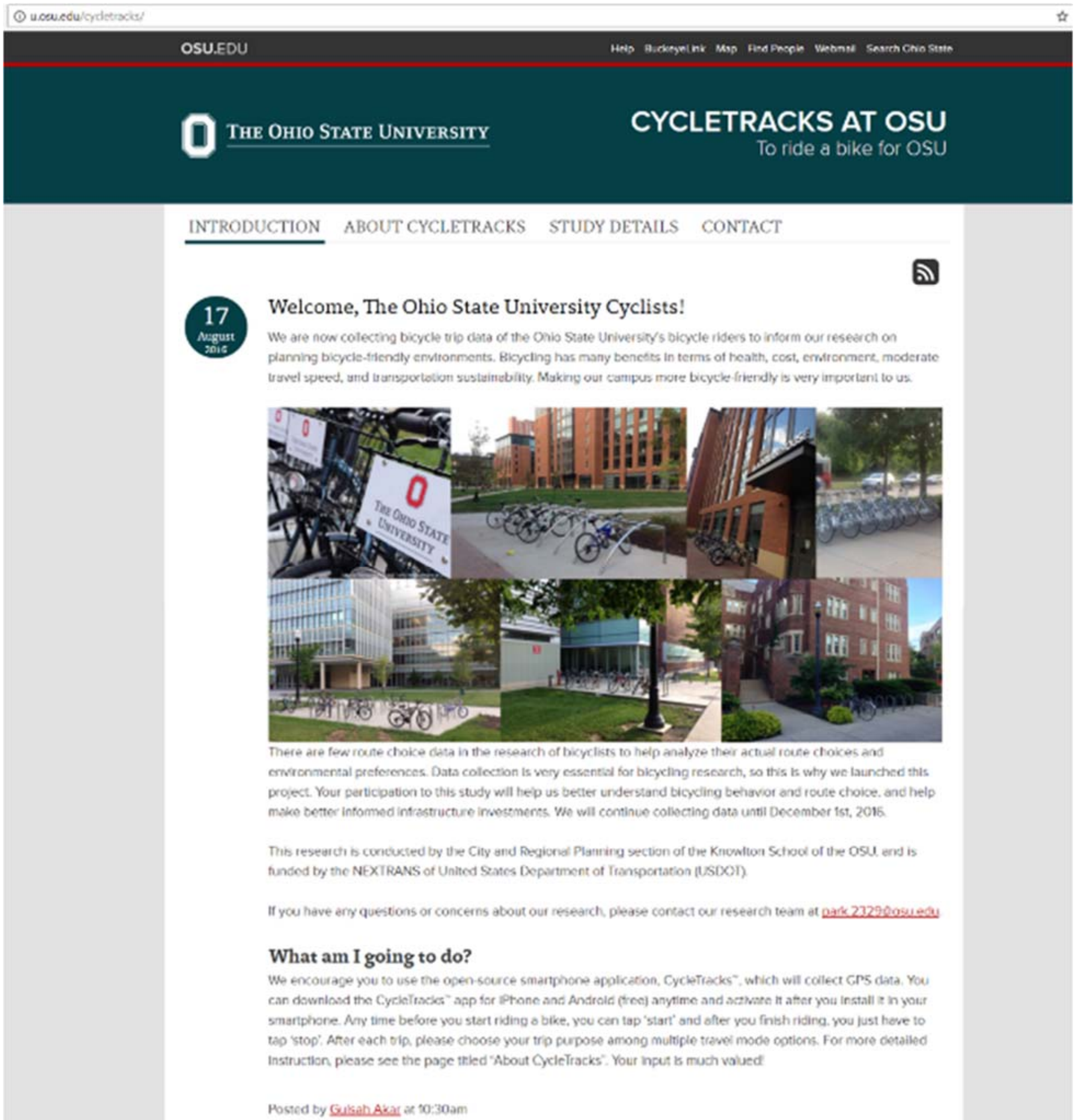
Appendix 1. Survey Fliers



Appendix 2. Survey Promotion Website



u.osu.edu/cycletracks/

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CYCLETRACKS AT OSU

To ride a bike for OSU

INTRODUCTION ABOUT CYCLETRACKS STUDY DETAILS CONTACT

17 August 2016

Welcome, The Ohio State University Cyclists!

We are now collecting bicycle trip data of the Ohio State University's bicycle riders to inform our research on planning bicycle-friendly environments. Bicycling has many benefits in terms of health, cost, environment, moderate travel speed, and transportation sustainability. Making our campus more bicycle-friendly is very important to us.

There are few route choice data in the research of bicyclists to help analyze their actual route choices and environmental preferences. Data collection is very essential for bicycling research, so this is why we launched this project. Your participation to this study will help us better understand bicycling behavior and route choice, and help make better informed infrastructure investments. We will continue collecting data until December 1st, 2016.

This research is conducted by the City and Regional Planning section of the Knowlton School of the OSU, and is funded by the NEXTRANS of United States Department of Transportation (USDOT).

If you have any questions or concerns about our research, please contact our research team at park.2329@osu.edu

What am I going to do?

We encourage you to use the open-source smartphone application, CycleTracks™, which will collect GPS data. You can download the CycleTracks™ app for iPhone and Android (free) anytime and activate it after you install it in your smartphone. Any time before you start riding a bike, you can tap 'start' and after you finish riding, you just have to tap 'stop'. After each trip, please choose your trip purpose among multiple travel mode options. For more detailed instruction, please see the page titled "About CycleTracks". Your input is much valued!

Posted by Gulsah Akar at 10:30am

Appendix 3. Survey Invitation Email

Subject: Participate in an OSU Bicycling Study Using a Smart Phone App

Hello,

We recently sent you an invitation to participate in a transportation related study conducted by a team of researchers from the City and Regional Planning Section of the Knowlton School of OSU. This is a reminder to say our data collection is still going on.

The purpose of this study is to understand university members' bicycle travel patterns to, from, and on campus using a GPS-tracking smartphone application. If you wish to participate, we ask you to download the CycleTracks™ application (iPhone and Android) and turn it on when you ride a bike. For detailed information on this app, please visit our website, http://u.osu.edu/cycletracks, or visit the CycleTracks official website, http://www.sfcta.org/modeling-and-travel-forecasting/cycletracks-iphone-and-android. We will continue collecting data until December 1st, 2016.

As a potential respondent willing to help us to further identify bicyclist travel behavior, your email address was randomly selected within the university population. There are no direct benefits to participants for being a part of this study. Your participation in this study is completely voluntary and your decision to participate will not affect your relationship with the University.

To show our appreciation, we will randomly select 20 participants to award a $25 gift card. We will be contacting around 23,000 people for this study and expect between 200 and 800 to participate. We expect the odds of being awarded a gift card to be between 1/10 and 1/40. On the first stage of starting the CycleTracks app, you will be asked if you would like to enter your email address. Be assured that you will only be contacted in the case you have won a prize.

Your input is very important to us. Every response is highly valuable to this study, and even those who have little previous experience in campus biking can help us assess university members' preference toward bicycle routes. Definitely all identifying information that you would provide will remain confidential; your responses will only be reported in aggregate form. We will work to make sure that no one sees your responses without approval. But, because we are using the Internet, there is a chance that someone could access your online responses and geographic commute data without permission. In some cases, this information could be used to identify you. This risk is minimal. Your data will be protected with a code to reduce the risk that other people can view the responses. If you choose to withdraw from the study, simply do not turn the app on and/or remove it from your phone.

Please proceed only if you are 18 years or older.

If you have any questions, please contact Yujin Park, PhD student, park.2329@osu.edu. For questions regarding your rights as a participant in this study or to discuss other study-related concerns or complaints with someone who is not part of the research team, you may contact Ms. Sandra Meadows in the Office of Responsible Research Practice at 1-800-678-6251.

Thank you in advance for your participation.

Sincerely,