NEW TECHNOLOGIES TO ASSESS BICYCLE SAFETY

FINAL REPORT

SOUTHEASTERN TRANSPORTATION CENTER

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### Abstract

Upsurge in bicycling should be complemented by safe bicycle infrastructures, which could be achieved by assessing their behavior on the road. New technologies are changing the way cyclists and planners interface with the infrastructures and data. Hence, the research team used data from the Bike share program in Phoenix, AZ, and from newly developed application I Bike KNX for Knoxville. Both of these data targeted two different categories of bicyclists. Bike share trip data was analyzed from Nov 2014 to May 2015, resulting 9101 trips. Majority (85.3%) of users were casual users contributing for greater proportion (62.9%) of travel miles. Registered subscribers made high number of shorter trips. The results from route choice model showed that they were sensitive to travel distance, number of left turns, AADT, proportion of one way roads and number of crash per mile. Similarly, for trip data of 680 trips from 89 users obtained from I Bike KNX users, one way riding behavior was ascertained for eight of the highly travelled road segments. It was found that commuter and school trips were responsible for high proportion of wrong way riding rather when compared with exercise trips.
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EXECUTIVE SUMMARY

In the present context of augmented preference towards sustainable mode of transportation, use of bicycle as the alternative mode of transportation has become the most important solution. To include bicycling in daily travel modes, provision of well-connected bicycle infrastructures is a must. Planners and engineers should be aware of the better consequences delivered by modal shift from auto to bicycles, and should design the transportation facilities that will allow convenient travel for all the modes. Installing new bicycle network seems to be one of the touted means to increase cycling among people, although there are many other factors influencing it. The decisions on bicycle route planning should be driven by the analysis of bicyclists’ behavior. What are the decisions made by cyclists in road and why are they making those decisions are the key questions that could be answered in order to assess the right facilities in right locations.

Advent of new data collection technologies have been assisting transportation-research community to collect qualitative data. GPS is one of the useful technologies that had been used for determining the exact location of user at any time. Although the use of low-cost GPS devices has made route choice analysis more precise, it suffers from self-selection bias or low penetration rates. Independent GPS units could be used for tracking bicyclists to assess their behavior at various segments of the road and intersections. The data obtained from the Grid Bikeshare --being operated in Phoenix, AZ-- uses GPS units installed in the bikes. On contrary to the independent GPS device, in-built GPS in the smartphones has made the data collection task even easier. Use of smartphone applications allows users to track their trips in addition to providing valuable data for research. We had deployed the smartphone application “I Bike KNX” for Knoxville, TN, which allowed the users to record and submit their trips. To sum up, we are using GPS technology using two different methods to collect revealed preference data from different study population.

The data collected from Bikeshare users from Phoenix is used to determine the route choice model. Bike share scheme is operating with most of the stations located in Downtown of
Phoenix. Understanding bicyclist’s route choice is a difficult problem given the many factors that influence attractiveness of different routes. Bikeshare, with instrumented bikes, allows for better assessment of revealed route preference of a large sub-population of cyclists. The users of this bikeshare scheme are limited to those users participating in bikeshare program either as a casual subscribers or a registered subscribers. The analysis for this dataset is limited strictly to descriptive results and route choice model results. On the other hand, the data obtained from the smartphone application “I Bike KNX” is used to determine the wrong direction riding behavior for the different categories of trip purpose for some of the high volume road segments. Wrong direction riding is not a safe behavior, and this behavior depends on the user’s experience, perception towards road safety, trip purpose and several others.

In this paper, we used GPS data obtained from 9101 trips made by bikeshare users from Grid Bikeshare in Phoenix, Arizona during a timeframe of November 2015. This unique bikeshare system allows for route specific modeling, is operated in a way that allows non-station origins and destinations, and operates on a grid street network; all enabling unique route choice analysis. The raw GPS data obtained from bikeshare was cleaned to get rid of erroneous points and possible recreational trips. This data was then matched to the road network using Network Analyst and model builder within ArcGIS. The performed analysis fell under two general subjects, facility usage assessment and route choice behavior. The results were compared between two classes of bikeshare users, registered subscribers and casual subscribers. Registered subscribers made shorter trips including roads with low volume and low speed limit, and preferred bike specific infrastructure. To assess route choice, we created two alternative routes, the “shortest” and “bike friendly” routes, compared to the chosen route. A Path Size Logit Model was used as to model route choice. Riders were very sensitive to travel distance, with little deviation from the shortest path to utilize more bike-friendly infrastructure. Left turns imposed higher disutility compared to right turns for both users. The proportion of one way segments, AADT and length of trip have negative influence on route choice and number of signalized intersections have positive influence on selecting route.
Similarly, GPS data of 680 trips collected from 89 users were obtained from the I Bike KNX users. Distribution of trip purpose over number of trips and total miles travelled was obtained as simple descriptive statistics. Wrong direction riding behavior was determined for eight of the highly travelled segments. Among all the considered street segments, commute trips and school trips have high proportion of wrong direction riding among all the trip purposes. By this we can answer what are the segments prone to wrong way riding and what kind of trips are more into this behavior. Wrong direction riding could shorten the trip length and could get the riders rid of crossings in many cases. But, at the same time this behavior is dangerous too. This could be extended to large number of street segments to figure out the problem areas could be determined to reduce this behavior for safe bicycling in the city. Furthermore, this data can also be used for the comparison and evaluation of any interventions employed in the street networks. For instance, if two-way bike lanes is introduced in the segment with high proportion of wrong direction riding behavior, this behavior could be determined before and after the addition of two-way bike lanes to evaluate the efficacy of the intervention.
DESCRIPTION OF PROBLEM

Introduction
With growing popularity of bicycle infrastructures of bicycle transportation in recent years in the USA, new focus is placed on planning and designing facilities to safely accommodate those users in the transportation network as well as on developing appropriate policies related to the safe use of the mode. Furthermore, the number of injuries and fatalities among those users underscores the need for better understanding of the risks to cyclists each year. In 2010, there were 618 fatalities and 52,000 injuries reported for cyclists in the USA [1], and an estimated 515,000 emergency room visits due to bicycle-related injuries [2]. Cycling represents approximately 1% of the mode share yet 2% of the reported injuries and fatalities. For comparison, 256 fatalities and 854 injuries were reported in 2010 at railroad grade crossing [3]. These numbers highlight the over-representation of bicycle users in crash data and a growing research need to investigate cyclist exposure and risk during travel. Many past studies have used records of cyclist fatalities and injuries to assess safety for the mode and for certain facilities. However, the limited number of observations and large spatial diversity between observations makes this type of assessment difficult. Little is known about rider behavior and the various trips, and certain behaviors during those trips, provide a method for assessing the safety of the mode and the user. Furthermore, there is a need to establish a methodology for assessing these behaviors with regard to user safety.

There are number of factors that can influence a cyclist’s behavior during trips. A study in Portland, OR, used GPS to observe cyclists’ behaviors on utilitarian trips and estimate a route choice model, finding a number of factors influencing route choice decisions [4]. Among those that have also bearing on user safety are turn frequency, the presence and type of traffic control devices, traffic volumes, and bicycle-specific infrastructures. A different study used GPS data collected from smartphone devices in California to analyze route choice decisions and found a strong preference for routes with bike lanes in addition to the other factors affecting the route choice [5]. The influence of cycling in mixed traffic conditions, without separate bicycle facilities, is less for bicycle users with more riding
experience [6]. A stated preference study of cyclists’ route choice in Texas also identifies on-street parking as an important factor in route choice decisions [7]. The presence of on-street parking and the amount of separation between parking and bicycle facilities are other factors that influence cycling safety [8]. Other aspects of the transportation network can have negative impact on the safety of bicycle users. The street patterns on a selected route have impact on user safety. For instance, compared to other street patterns, a disconnected network design (loops and cul-de-sacs) increases the probability of an injury but reduces the probability of fatality and property-damage-only in an event of a crash [9].

**Literature Review**

Bicycle use has grown in most North American and European cities in the past decades. A 46% upsurge in bicycle commuting has been seen in the United States from 2005 to 2013 [10]. This increase could be attributed to the growing concerns and subsequent efforts by the public to overcome the lack of physical activity, increased auto dependency resulting degraded air quality, and congestion that results in environmental, social and economic costs. Moreover, bicycling investment could result in health care cost savings (B/C ratio 3.8) and fuel savings (B/C ratio 1.2), which are direct benefits of a gain in physical activity and emission-free transportation [11] in addition to increase in commute mode share [12].

Increased cycling has also increased the emphasis on safety. With 726 bicyclist fatalities in the U.S. in 2013, there is growing concern for bicycle safety among planners and engineers. These fatalities represents 2.3% of the all traffic fatalities, however, only about 1% of the trips are made by bicycle [13]. Furthermore, total bicyclist fatalities are increasing with a 19% rise in number of cyclists killed in 2013, compared to 2010 [14]. Increased cycling activities call for better infrastructure planning to improve safety.

In 2009, about 41 percent of the total trips in the USA were three miles or less, of which 67 percent of trips were made on cars, 27 percent by walk and 2.2 percent by bikes [13]. Similarly, 42 percent of trips shorter than 1 mile were made on cars, 51 percent were by walk and 3.3 percent by bike, and others by transit. This provides opportunities for modal
shift towards bicycling. There are, in general, two stages that should be considered for the successful modal shift towards bicycling. First is inducing the people to bicycling, and second is motivating the current bicyclists to continue bicycling. A good understanding of these could assist planners to efficiently allocate limited funds to improve or add bicycle facilities to enhance safe bicycle riding and increase ridership as well. Traffic congestion is found to be one major reason for most people to avoid bicycling, which was followed by fast moving traffic, distracted drivers and lack of bicycle-specific infrastructure respectively [15].

Numerous studies explore causes of safety and risk of cyclists. However, recent studies have focused on behavior of cyclists and route choice, particularly in the context of safety. Using bicycle specific infrastructure, choosing the roads with less exposure to traffic, and preferring routes having fewer traffic signals could be proxy to the desire to have safe ride. The results also have implications in terms of providing valuable information on making informed decisions to attract the potential cyclist by understanding their preferences.

In the course of understanding the riding behavior of cyclists, several efforts have been made to determine route choice behavior. Two main approaches to explain route choice behavior of cyclists hinge on either stated preference (SP) data [7, 16, 17] or revealed preference (RP) data [18, 19]. Most of these studies have focused on presence of various bike-specific infrastructure, route attributes, individual characteristics, land use and so on. There are numerous studies that use SP surveys because of the ease in collecting data, which is free from extraneous observations, and is simple to model. Typical SP surveys will allow the participants to rate different type of facilities and choose among different routes, or some SP surveys also might allow the people to recall the path they have followed from their memories and complete the information required by the surveys. Most of these studies attempt to model behavioral intent and are inflicted by the possibility that responses might be biased from their actual behavior [20]. Recent development of low-cost GPS has made accurate collection of the actual routes possible. Some studies collect data through GPS installed in the bike of the participants [21], whereas some studies make use of the smartphone applications [18, 19] to collect data. In addition to reduced burden on the
participants to remember the route, it is low-cost and effective to map the route and collect data on attributes of specific links.

Previous route choice models, either based on SP or RP, have agreed on most of the factors that influence the choice of the route for bicyclists, like distance, safety, turn frequency, road slope, intersection control, traffic volumes, land use and scenic beauty along the route [5, 7, 18-20]. This behavior is contrary to the drivers of vehicle, who generally chose routes based on distance and duration of travel alone. In general, travel time and suitability of the route with high quality bicycle facilities remain two major objectives while selecting a route [22]. Of all route attributes, provision of facilities dedicated to cycling have been portrayed as factor that induces new cyclists, in addition to encouraging existing cyclists [7, 23]. Some studies found bike lane are superior to all other bike facilities, from a user perspective [5], while others found off-street bike facilities were valued more than other bike facilities. Different from most of the studies, another study found length and width of the bike lane had positive effect on choosing the route [24]. That study found that the longer the length of the bike facility, the higher the deviation from shortest route to use them. Furthermore, proximity to bicycle facilities was found to be vital factor that induces use of bicycle infrastructure.

Planners require good quality bicycling data, unbiased by self-selection, which can be used for understanding the behavior of cyclists. These are complemented by new methods of real time data collection using dedicated GPS devices or smartphones, which have facilitated researchers and practitioners with new techniques to assess the route choice and behavior of cyclists on the road. Nowadays, some cyclists are using smartphone applications such as Strava, MapMyRide, CycleMaps or other fitness capturing applications to record and track their data in order to encourage physical activity and health [25]. However, those data sources are not usually accessible to planners. Leveraging this technology, some cities are utilizing GPS data collection techniques from open source applications like Cycle Tracks [5]. These data collection techniques utilizes built-in GPS capabilities of smartphones, which provides high quality revealed data at a reduced cost compared to stated preference surveys.
The collected data is directly sent to remote servers without any requirement to go to field to retrieve the data. There are several applications that are being used by the cities of US, like Cycle Tracks (San Francisco, Calif.), Cycle Atlanta (Atlanta, Georgia), CyclePhilly (Philadelphia, Penn.), My ResoVelo (Montreal, Quebec), and I Bike KNX (Knoxville, Tenn.). The data from these apps can inform transportation planning in these cities and allows for disaggregate analysis. Nevertheless, one of the challenges with app-based data collection is that users have to opt-in and use the application for every trip.

In the last decade, bicycle-sharing system have gained popularity in many North American cities along with the other major cities in the world. There are more than 500,000 bicycles under bike-sharing scheme in more than 500 cities of 49 countries[26]. This bike-sharing scheme allows individuals to use a bicycle for a short period between fixed bike share stations. Some, like Grid Bikeshare in Phoenix, Ariz., have facilitated the use of public racks as the bike stations too. Availability of bike share is meant for efficient short distance travel, thus solving the “first/last mile problem” by connecting to other modes or providing urban circulation. Furthermore, increase in the bikeshare trips is supposed to be including individuals other than bikeshare users to cycle, which will eventually increase total bicycle trips in a city. Although it is thought to be beneficial in reducing car use and increasing bicycle trips, some results suggest that bikeshare replaces mostly walk trips and bicycle trips rather than car trips [27, 28]. In addition to expanding docking stations and making convenient use of bikeshare scheme, high substitution of car trips could be obtained by making the travel time of bikeshare trips competitive to that of car trip by employing efficient routing system or by improving bicycle amenities[29]. Bikeshare systems are ripe for developing new data streams to understand bicycling behavior in cities. Several recent studies have mined bikeshare data to understand flows between stations and identify differences in user types[30]. Bikeshare users are generally classified as subscription or registered subscribers (frequent users who subscribe to a membership that usually includes unlimited use for the duration of the membership) and casual subscribers (occasional users who pay for service as they use it, often travelers or tourists). Unlike the casual subscribers,
who primarily make recreational trips, commuting is the main purpose for registered subscribers [31].

Most of the previous literature on bikeshare users focus on the demographics of users [32], or station or system performance [30, 33]. Recent bikeshare systems have included vehicle tracking telematics onboard the bicycle, which allows for finer level of analysis, i.e., vehicle level of analysis instead of station level of analysis. This has opened a new opportunity to investigate route choice, particularly as it relates to safety and comfort, of an entire sub-population of bicyclists, bikeshare users. This subpopulation is an important group because it constitutes a large portion of urban cyclists and represents an important part of the travel trip, generally short urban center trips. To the author’s knowledge, there is no study based on the real time GPS data of bicyclists in bikeshare systems. Although there are many route choice models trying to describe the regular bicyclists’ trip patterns, understanding the decision pattern of the bikeshare users is an important aspect of the route choice question.

This study relies on data from one of the first GPS-enabled bikeshare systems in North America, the Grid Bikeshare system in Phoenix, Ariz. This system is unique because it relies on Social Bicycles’ (SoBi) onboard telematics, it utilizes a more flexible station and pricing protocol (e.g., users are not required to return bikes to stations), and it is deployed in a city with a grid street network that provides many possible route choices. We investigate and model bikeshare riders’ route choice and identify factors that influence that choice, using GPS tracks for each trip, and GIS based analysis for alternative routes, similar to other studies, but with a more robust dataset and user type. The rest of the paper presents the methodology that describes the data and modeling approach, the results of the model, and conclusions and recommendations.

**Research Objective:**
New technologies are changing the way cyclists and planners interface with infrastructures and data. Bike share is transforming cycling use and behavior in many cities. Some of these systems are instrumented to assess behavior. Ubiquitous smartphone use also allows effective
New technologies to assess bicycle safety

and low cost data collection. Using new sources of data, the research proposed here will study route choice and behaviors of users with regard to safety during trips. The objective of this work is to establish a methodology for using these data sources to assess safety for cycling as a mode and for the decisions made during cycling. This will be based on characteristics of the route chosen such as traffic volumes, speed limits, and the presence and type of bicycle facilities on the route. The assessment will also consider observed user behaviors during that trip including travel speed on different facilities, stopping behavior at intersections, and others.

The data sources used in this study include two distinct groups of bicycle users. First, we will assess bikeshare users, who are likely more casual urban cyclists [27]. Next, we will observe behavior of other cyclists who use a smartphone app to record their trips providing the opportunity to compare differences in behavior between those groups. This analysis could provide insight into the behavioral differences between different groups of bicycle users, which could affect policies and future planning regarding the safety of these groups. The methodology established through this research will serve as a platform for the potential creation of tools to assess route and user safety. Furthermore, this research could serve as a basis for user education about bicycle transportation safety.

**Data Sources and Study Areas:**

**Bike Share users:**

The data used in this study was collected from two different sources. The first is probe data collected directly from the bikeshare system “Grid Bike Share” in Phoenix, AZ. The Grid Bikeshare system was installed in Fall 2014 and includes ~500 bikes and 39 stations (or hubs). The stations cover an area that is approximately 2.5 km East to West and 8 km North to South, covering downtown Phoenix. The system is also in the process of expanding to Tempe and Mesa. Although the system relies heavily on stations, users can also park bikes away from stations for a small fee. The target population for the study was all cyclists who either register monthly/annually for the bike share or are casual users pay a marginal fee for
renting a bike. Our study area have grid network patterns on most of the area, and bicycle lane comprises large proportion (more than 50%) of bicycle facilities on the grid network [Figure 1].

I Bike KNX App. Users:
The second data source is collected for other bicycle users, usually regular cyclists, from the smartphone application “I Bike KNX” deployed for Knoxville, Tennessee. This app Attracts a more diverse user base than bikeshare users, capturing casual, exercise, leisure, and utilitarian trip types. I Bike KNX is modified by the research team for the use in Knoxville, TN, area and modeled after the Cycle Atlanta smartphone application, which was also rebranded from the Cycle Tracks application used in San Francisco, California. This application, when used while riding bikes, tracks the trip information using built-in GPS of smartphones. The screenshots of various phases while recording trip are included in Appendix. Moreover, it allows user to view the trip summary like, trip miles, trip duration, route, etc. Besides, Knoxville has lot of Greenways followed by signed route, bike lane and sharrow respectively (Figure 2).
Use of smartphone application I Bike KNX in this study is very similar to the GPS travel survey, which allows user to fill out personal information like cycling frequency, income, age, home ZIP, work ZIP and email address in the smartphone application. This, however, is not mandatory and confidential too. Before submitting each trip, user can specify purpose of a trip (commute, exercise, shopping, etc.). Similar to providing personal information, recording and submitting the trips is voluntary too. The data was collected through the voluntary participation of the bicycle users, i.e. without providing any incentives for using the application. The use of bicycle application was publicized by the use of various methods: distributing the flyers around the campus (library, student housing, downtown), or attaching them to the handlebars of the parked bicycles, and parking racks that have large inflow and outflow of bicycles.
APPROACH AND METHODOLOGY

Route choice behavior was modeled through the data collected from the Grid Bike Share users. The data collected from Grid Bike Share are the raw GPS data whose accuracy depends upon several factors like quality of GPS receiver unit, position of the satellites while recording the data and the characteristics of the landscape in which the GPS device is being used. Our majority of study area being in a high-rise urban environment (Phoenix downtown) increases the chances of inaccurate data collection. For these reasons, the data collected was prepared for the analysis to avoid getting false results and interpretation afterwards.

Data Cleaning:
For each trip, data were collected using GPS devices. GPS data logging frequency varied but their sub-minute resolution allowed reasonable route assignment. Raw GPS data obtained were cleaned for further analysis in order to prevent any incorrect interpretation from the results of the study. The GPS data includes errors, which could be associated with urban canyons, unavailability of satellites, quality of GPS unit, and others. In addition to removing the “error points”, another main objective of the data cleaning is to remove all the possible recreational trips. With high number of trips made on weekends [Figure 6], it becomes necessary to remove possible recreational trips. This was done for the current scope of analysis because bicycle trips for recreational purposes are very different from the utilitarian trips. For instance, recreational cyclists might be using longer route including bicycle specific facilities without apparent destinations. Also, many recreational trips returned to the origin, or included loops, making route assignment and identification of alternate routes challenging at best. The following are the basic criteria for the data cleaning process.

1. Trips with following criteria were removed
   a. Travel Time < 1 min
   b. Travel Time > 90 minutes
   c. Travel distance < 0.02 miles
   d. Travel distance > 10 miles
e. Average velocity <1.5 mph
f. Average velocity > 25 mph
g. Trips having fewer than 10 GPS points

2. Trips based on the origin and destination and shortest distance were removed to eliminate circuitous tours that were not likely destined for a specific place.
   a. Trip distance > 3× O-D “as the crow flies” distance
   b. Trip distance > 2.5× shortest possible travel distance between the O-D pair
   These numbers were assigned based on the assumption that any person will not make the trip such that it is more than three times the O-D-“as the crow flies”-distance or more than 2.5 times the shortest possible travel distance between O-D pair.

3. Certain GPS points very close others were removed to reduce the volume of data required for analyses. A point that was at a distance of less than 10 feet from both the preceding and succeeding points was deleted.

Map matching
The raw GPS coordinates available from the bikeshare users were matched (or “snapped”) to the street segments in order to identify all the links that were traversed during the trip. Although map matching allows one to determine the street segments used by the cyclists, it is difficult to estimate the path with high accuracy. Key reasons behind this are the inaccuracy of the data points and the use of the sidewalks, parking lots and alleys, which are not represented as the separate features in the map. The available methods for the map matching are geometric map matching, topological map matching and advanced map matching. The method used for this study to match the GPS points is obtained from the study by (25), which uses the ArcGIS model for predicting the actual path of the bicyclists. The Arc Catalog’s Model used by this study was based on an algorithm developed by Dalumpines and Scott (26). This algorithm successfully implements geometric and topological map matching procedure with the help of network functions in ArcGIS.
Generation of Choice Sets

Alternative routes for the pair of origin and destination were created using the Network Analyst extension in ArcGIS10.1. Initially, three alternative routes were generated. First, the chosen path was identified based on the GPS data. Next, the next-shortest path (excluding the chosen path) was identified based on the algorithm available in ArcGIS Network Analyst, that tries to minimize the total length of the route. Third, the path that has high preference for street segments with bicycle facilities and medium preference for residential streets was identified.

Discrete Route Choice Model

Discrete route choice model is used as a main modelling technique for predicting route choice of the bike share users (11; 16; 18). These approaches empirically model and analyze the decision maker’s preferences among a set of alternatives available to them. The Multinomial Logit (MNL) model is the simplest among the family of logit models, for which the probability of choosing the alternative \(i\) among the alternatives available in the choice set \(C_n\) is given by

\[
P(i \mid C_n) = \frac{\exp(V_{in})}{\sum_{j \in C_n} \exp(V_{jn})}
\]

Where, \(C_n\) is the choice set of alternatives, \(i\) is the chosen alternative, \(j\) is any alternative within \(C_n\), \(V_{in}\) and \(V_{jn}\) are the utility of the alternative \(i\) and \(j\).

The Independence of Irrelevant Alternatives (IIA) property of the MNL model suggests that the alternatives should be mutually exclusive, i.e. the alternative routes should not have overlapping routes. If this is property is not considered, MNL will overestimate the overlapping paths. Hence, a correction is introduced in the model in the form of a Path Size (PS) factor given by following equation (27).

\[
PS_{in} = \sum_{a \in A} \frac{1}{L_a} \frac{1}{\sum_{j \in C_n} (\frac{L_j}{l_j})^{\gamma} \delta_{a,j}}
\]
Where, $l_a$ is the length of link $a$, $L_i$ is the length of the alternative $i$, $\Gamma_i$ is the set of the links of alternative $i$, $\delta_{aj} = 1$ if $j$ includes the link $a$, 0 otherwise, and $\gamma$ = long-path correction factor, which is considered 0 in our case. For this study, due to the few number of alternatives, there are not any very long alternatives in our choice set $C_n$. Hence the above equation will be reduced to the basic Path Size Logit (PSL) model (28). After the correction factor of PSL, the resulting probability that the alternative $i$ is chosen from choice set $C_n$ is given by

$$P(i | C_n) = \frac{\exp(V_{in} + \ln (PS_{in}))}{\sum_{j \in Cn} \exp(V_{jn} + \ln (PS_{jn}))}$$

Where $PS_{in}$ will have values between 0 and 1, and hence, the $\ln(PS_{in})$ is always negative. This implies that the utility decreases when there is more overlap between the alternatives, as we are introducing the penalty for the route by introducing the path size factor. All the models were estimated through the freely available software Easy Logit Modeler. The new form of the deterministic part of the utility function will be:

$$U_n = \beta x_n + \beta_{PS} \times \ln \text{(path size)}$$

Where, $x_n$ is the vector of attributes of the route and $\beta$ is the estimated coefficient.

**Distance trade-off calculation**

To aid in interpretation, we can estimate marginal rates of substitution between distance and other explanatory variables. The distance trade-off for a unit change in attributes can be determined after estimating the utility coefficients of the attributes from following equation for the non-unit changes:

$$Equivalent \% \Delta \text{distance} = \left( \exp \left( \Delta \text{attribute} \times \frac{\beta_{attributes}}{\beta_{\ln(distance)}} \right) - 1 \right) \times 100$$

Where $\beta$ is the coefficient of the attributes of the path estimated from the model.
FINDINGS AND CONCLUSIONS

Grid Bike Share Dataset

Descriptive Results
The registered subscribers comprise approximately 15 percent of the 1866 users but account for 37.0 percent of the total 10476 miles travelled. The results summarized in Figure 4 show a high proportion of the number of trips made by the registered subscribers. After cleaning the data (i.e., removing recreational tours and erroneous GPS points), the final dataset was reduced to 9101 observations of which 43.5 percent of the trips were made by registered subscribers and 56.5 percent of the trips made by casual [Figure 4].

![Figure 3 Distribution of registered and casual subscribers](image)

Once the raw data was cleaned, processed data was matched to the base road network and final map was obtained illustrating the number of trips for the segments. Location of bikeshare and volume of the bicycle trips are illustrated in Figure 3. There is high number of bicycle trips along the Central Ave and 1st Ave, both of these roads connect to the downtown Phoenix. Similarly, density of the bikeshare stations around downtown is high too. Most of
the roads around the central downtown have high volume as compared to the outer roads of
the downtown Phoenix.

![Map of bikeshare trips](image)

*Figure 4 Number of bikeshare trips for portion of Downtown Phoenix*

Figure 5 shows that trips by casual users increase steadily from the morning and peak
at 5pm, and then drop off into the night. However, trips by registered users peak at 8 a.m., 12
p.m. and 5 p.m. Figure 6 shows that most of the casual trips are made during weekend, with number of weekend trips being approximately equal for the weekdays. The variation in daily activity for registered users is nominal.

Figure 5 Time of the day variation for percentage of trips for registered and casual users

Figure 6 Day of the week variation of number of trips for registered and casual users
The trip behavior of the two user groups differed. The mean distance of the trips for registered and casual users were 1.0 (std dev: 0.64) and 1.3 (std dev: 0.95) miles, respectively; and similarly, the mean duration of the trip was 9.5 (std dev: 7.2) and 14.5 (std. dev: 11.7) minutes, respectively. Registered subscribers were making high percentage (69%) of trips less than 10 minutes if travel time. In contrast, 55% of casual user’s trips are more than 10 minutes. Similarly, only 2% of the registered user’s trips and 10% of the casual user’s trips have travel time greater than 30 minutes. The trips made by registered subscribers, however, are generally made on lower volume and lower speed streets (Figure 7, 8, and 9) implying familiarity with alternative routes on the network.

![Figure 7 Use of different roadway infrastructures](image)

![Figure 8 Distribution of travel distance over range of AADT](image)
Model Results

Table 1 presents results for the estimation of the final route choice model. Two models were developed, one for registered subscribers and one for casual users. Negative coefficient for log distance agrees with the well-known fact that bicyclists prefer shorter routes among available alternatives, unless there are other desirable attributes present on other alternatives. The magnitude of the coefficient suggests that registered subscribers are more sensitive to the length of selected route compared to casual users. This is likely because registered subscribers use bike share to make utilitarian trips in most of the cases, which is reinforced by Figure 4. The length of the observed path for registered users is 6.9 percent higher than shortest path compared to 8.3 percent higher for casual users also bolsters the preference of these two groups over the length of the route. Average Annual Daily Traffic (AADT) and posted speed limit for the entire route were obtained from the weighted sum of the lengths of all the links traversed by the route. AADT was scaled to a smaller value dividing by 1000 for more appropriately scaled parameter estimates. AADT was associated with negative utility for both categories of users, although it was not significant for the casual user. The risks associated while travelling along high volume roads, which affects the perceived safety of the users, is likely a major reason for the disutility towards high volume roads.

![Figure 9 Distribution of travel distance over range of posted speed limit](image)

*Figure 9 Distribution of travel distance over range of posted speed limit*
The number of turns along the route is another factor that a cyclist accounts for while choosing a route. Both registered and casual users chose routes with fewer left- and right-turns, but in a different manner as suggested from Table 1. The difference in the value of coefficient shows that cyclists, in general, have a greater aversion to left turns compared to right turns, as expected. Higher delay associated with left turns, at signalized as well as un-signalized intersections, and additional safety risk associated left turns compared to right turns could be the main reasons for disutility of this variable for both users. For each left turn, registered users would choose routes that were 3.4 percent longer and casual users chose routes that were 7.5 percent longer (Table 2). Corresponding additional percentage of route length for additional one right turn is 2.4 percent and 5.8 percent for each additional right turn. This clarifies the comparison between left and right turns on the route made by casual and registered users.

Table 1 Estimation of Utility Coefficients

<table>
<thead>
<tr>
<th>Variable</th>
<th>Registered Subscribers</th>
<th>Casual Subscribers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est. coeff.</td>
<td>t-Stat</td>
</tr>
<tr>
<td>ln(length of trip (mile))</td>
<td>-3.8825</td>
<td>-16.85</td>
</tr>
<tr>
<td>AADT/1000</td>
<td>-0.0429</td>
<td>-5.28</td>
</tr>
<tr>
<td>Posted speed limit (mph)</td>
<td>0.562</td>
<td>11.88</td>
</tr>
<tr>
<td>Number of crash per mile</td>
<td>-0.0033</td>
<td>-1.67</td>
</tr>
<tr>
<td>Proportion of one way roads</td>
<td>-1.3509</td>
<td>-8.66</td>
</tr>
<tr>
<td>Number of left turns per mile</td>
<td>-0.1286</td>
<td>-7.45</td>
</tr>
<tr>
<td>Number of right turns per mile</td>
<td>-0.0922</td>
<td>-5.27</td>
</tr>
<tr>
<td>Number of signalized intersection/ mile</td>
<td>0.0264</td>
<td>2.55</td>
</tr>
<tr>
<td>ln(PS)</td>
<td>0.9823</td>
<td>20.83</td>
</tr>
</tbody>
</table>

Number of observations: 3958, 5143
Log Likelihood at Zero: -4348.31, -5650.163
Log Likelihood at Convergence: -3088.19, -4441.285
Rho-square: 0.2898, 0.214
The number of reported crashes along the route is a negative factor for route choice. However, the negative effect is not significant for both user groups. Crashes are not only based on roadway characteristics, but also affected by the behavioral patterns of cyclists. Hence, cyclists neither choose a route based on crash likelihood, nor are their safety perceptions always consistent with known (measured) safety outcomes. The negative utility captured by the number of crashes per mile in the model could be from the crashes due to roadway characteristics such as high traffic, poor roadway conditions and so on. The natural logarithm of the Path Size is positive which is consistent with the theory. Also, including this variable improved the model fit significantly.

Table 2 Distance value (%) for unit change in attribute

<table>
<thead>
<tr>
<th>Variable</th>
<th>Distance trade-off (% dist.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Registered Subscribers</td>
</tr>
<tr>
<td>Proportion of one way roads</td>
<td>41.62</td>
</tr>
<tr>
<td>Number of crash per mile</td>
<td>0.09</td>
</tr>
<tr>
<td>Number of left turns per mile</td>
<td>3.37</td>
</tr>
<tr>
<td>Number of right turns per mile</td>
<td>2.40</td>
</tr>
<tr>
<td>Number of signalized intersection/ mile</td>
<td>-0.68</td>
</tr>
</tbody>
</table>

Higher speed of the vehicle is positively correlated with the severity of the accidents involving bicyclists. In addition, cyclists generally choose roads to avoid segments with high speed limits. However, the posted speed limit for the road segments in this study is a positive factor for route choice as per our model. A possible explanation for this counterintuitive result could be the short travel distance made by the users, making non-recreational trips. Riders are not willing to deviate from high-speed roadways for short utilitarian trips. Alternatively, lower-speed alternatives are too costly otherwise in terms of additional distance, extra travel time, and so on. This could also be a specification problem and a weakness of our model, given that one of our alternative routes included in the choice model is the often non-chosen neighborhood streets and bikeways. Although Grid Bike Share
utilizes dockless system, the majority of the trips were made from either start or end of the bike share stations, and most of these busy stations are around a street with high speed limits. Similarly, cyclists tend to choose routes with more signalized intersections. This could be because they tend to ride on main arterials, but it could also be an indication that they tend to avoid routes that require them to cross un-signalized (e.g., midblock) minor street crossings.

**Dataset from I Bike KNX bike application**

**Preliminary results**
Major challenge with app-based data collection is that users have to opt-in and use the application for every trip. As the application was in the first phase, the data collection was not significant high although the number of trips collected was satisfactory. The trips having insufficient number of coordinates (less than 30), having transit as one of the mode during trip, and trips outside the bound of the study area of Knoxville were removed from the analysis. These conditions were imposed to remove short trips, to remove complexity in analysis due to bicycle trips using transit along the trip, and due to irrelevancy of the trip data outside the study area respectively.

![Figure 10 Trip Purpose of the I Bike KNX users](image)

Initially, there were 120 users who submitted 845 trips until September 15th, 2015. After removing the trips according to aforementioned criteria, there were 680 trips remaining...
collected from 89 users. Highest proportion of trips were commute trips, which was followed by exercise trips (19.7 %) and then by school trips (14.9 %) respectively (Figure 10).

![Percentage of total miles according to trip purpose](image)

*Figure 11 Percentage of total miles according to trip purpose*

Commute and exercise trips comprises more than 80 percent of the total distance travelled. Total miles for exercise trips is highest i.e. 46.6 percent despite being 19.7 percent of the total number of trips. This is due to the longer trip length of the exercise trips as compared to commute trips, which are shorter in length (Figure 11). Comparing number of social trips with total miles travelled as school trips, it can be concluded that the school trips are generally short. Similar is the case with commute trips.

**Wrong Direction Riding:**

Wrong way riding is most common behavior of cyclists and undoubtedly dangerous too. Due to the resolution of the GPS data, it is impossible to differentiate whether the cyclist is using sidewalk or not. In this report, whole road is divided into two divisions using centerline of the road, and the direction of the road is compared with the direction of the cyclists to determine the wrong direction riding of the cyclists. The following statistics is generally calculated to find out and compare the wrong direction riding behavior among trips for various trip purpose.
Every user can select the purpose of the trip before submitting the trip through the application. For each trip purpose, we will determine proportion of the users cycling in the wrong direction. We have selected eight of the road segments for this case study. The road segments are selected in such a way that if fulfils two of the following conditions:

i. The road segment should be one of the highly traversed segment of the study area.

ii. The volume of cycle trips in a segment should not be overrepresented by limited number of cyclists.

Table 3 summarizes proportion of wrong direction riding for each of the eight street segments considered for the analysis. The values are the proportion of wrong direction riding for each categories of trip purpose.

**Table 3 Wrong direction riding for the eight street segments for each purpose**

<table>
<thead>
<tr>
<th>Street</th>
<th>Commute</th>
<th>Exercise</th>
<th>Errand</th>
<th>Other</th>
<th>School</th>
<th>Shopping</th>
<th>Social</th>
<th>Work-related</th>
</tr>
</thead>
<tbody>
<tr>
<td>Henley Bridge</td>
<td>12% (2/17)</td>
<td>38% (3/8)</td>
<td>-</td>
<td>50% (1/2)</td>
<td>70% (7/10)</td>
<td>0% (0/2)</td>
<td>0% (0/3)</td>
<td>-</td>
</tr>
<tr>
<td>Clinch Ave between Henley St. and 11th St.</td>
<td>27% (6/22)</td>
<td>25% (3/12)</td>
<td>-</td>
<td>-</td>
<td>26% (9/34)</td>
<td>-</td>
<td>36% (5/14)</td>
<td>57% (4/7)</td>
</tr>
<tr>
<td>Cumberland Ave. between 16th St. and James Agee</td>
<td>45% (5/11)</td>
<td>-</td>
<td>-</td>
<td>0% (0/1)</td>
<td>6% (2/31)</td>
<td>-</td>
<td>33% (2/4)</td>
<td>100% (1/1)</td>
</tr>
<tr>
<td>Volunteer Blvd. between Cumberland Ave. and Melrose Ave.</td>
<td>38% (5/13)</td>
<td>-</td>
<td>0% (0/1)</td>
<td>0% (0/1)</td>
<td>53% (26/49)</td>
<td>-</td>
<td>13% (1/8)</td>
<td>-</td>
</tr>
<tr>
<td>Andy Holt Ave. between 20th St. and Melrose Ave.</td>
<td>16% (5/31)</td>
<td>33% (1/3)</td>
<td>0% (0/1)</td>
<td>0% (0/1)</td>
<td>29% (4/14)</td>
<td>-</td>
<td>33% (1/3)</td>
<td>0% (0/1)</td>
</tr>
<tr>
<td>Clinch Ave between Locust St. and Walnut St.</td>
<td>33% (9/27)</td>
<td>0% (0/5)</td>
<td>-</td>
<td>-</td>
<td>50% (21/42)</td>
<td>0% (0/1)</td>
<td>67% (6/9)</td>
<td>50% (1/2)</td>
</tr>
<tr>
<td>White Ave between 16th St. and James Agee St.</td>
<td>34% (5/15)</td>
<td>0% (0/1)</td>
<td>-</td>
<td>0% (0/1)</td>
<td>0% (0/18)</td>
<td>-</td>
<td>0% (0/5)</td>
<td>100% (1/1)</td>
</tr>
<tr>
<td>Gay St. between Depot Ave. and Jackson Ave.</td>
<td>31% (11/35)</td>
<td>0% (0/2)</td>
<td>-</td>
<td>50% (2/4)</td>
<td>-</td>
<td>50% (1/2)</td>
<td>31% (5/16)</td>
<td>50% (1/2)</td>
</tr>
</tbody>
</table>

**Interpreting 12% (2/17) = 2 out of 17 commute trips OR 12% of commute trips were involved in wrong way riding**
The result on the limited number of street segments suggest that commuters were mostly involved in wrong direction riding. In average 30 percent of the commuters were involved in wrong direction riding. However, trips with school as origin or destination constitutes highest proportion of wrong way riding. More than 40 percent of the school trips were involved in wrong direction riding. Less proportion of wrong way riding among exercise trips could be attributed to the desire to travel longer path without compromising comfort during the travel. In contrast, commute trips and school trips do not have different route for most of the cases. As they have to travel same route over and again, they might have been involved in the wrong way riding on the sections of those familiar route. Most cyclists follow this behavior to reduce the number of possible crossings on a small section too.

![Figure 12 Aggregated wrong direction riding for the eight street segments](image)

Figure 12 shows the aggregated proportion of the wrong direction behavior for each categories. While interpreting these results, we should be aware of the fact that this data only represents the eight street segments listed in Table 3. As compared to rest of the trip purposes, number of school and commute trips gives the overall picture of wrong way riding behavior as per trip purpose.
LIMITATIONS AND FUTURE RECOMMENDATIONS:

The route choice analysis was done with only two alternatives, namely “shortest route” and “bike-friendly route”. The results of this study clearly showed the preferences of bike share users in the road. Further analysis could include all the feasible routes between origin and destination to get more robust estimates. Map matching with the ArcGIS model only could match about 84% of the total trips. The limitation was that whenever two consecutive points were at larger distance, the algorithm failed to match that trip to road network. Hence, advanced map matching could be a very good option to match those trips too. The route choice model of bikeshare users are highly influenced by the locations of bikeshare stations. Therefore, the current study could be furthered by including the effect of those locations on route choice. The study suffers from several limitations. As a purely revealed preference study, we do not know anything about the actual alternative routes that are in the choice set of the users. We estimate two reasonable alternative routes. We also do not have any personally identifying information of the users, including some demographic factors, such as gender, sex, occupation, income, cycling frequency etc. that could influence route choice. As gender and different age group had found to be one of the factor in making the decisions, and also defines the perceptions on the road, these variables could have helped in determining rider’s behavior in depth. Perhaps, the preference of left turns, right turns and number of signalized intersections could be different among these groups. Or perhaps, the data from Phoenix might be overestimated by younger male populations. Hence, these information on the demographic variables could be helpful in providing clearer picture.

One of the limitation for the data obtained from the I Bike KNX users were limited number of trips. Future research will focus on utilizing significant numbers of trip from the large number of bicyclists of Knoxville to determine the wrong way riding. This could help the planning organization to determine the locations where one-way/two-way bike lanes or any other bicycle amenities are required. Similarly, crossing the road from the location without having proper crossing facility is another behavior that have major implication on road safety of bicyclists. This could be incorporated in further study too.
ACKNOWLEDGEMENTS

The authors would like to thank Southeastern Transportation Center (STC), a Federal University Transportation Center, for funding this project, and Social Bicycles for providing the GPS data from the Grid Bikeshare, in Phoenix Arizona.
REFERENCES

New technologies to assess bicycle safety

APPENDIX

The Smartphone Application “I Bike KNX”

I Bike KNX is a free application-for the users of Knoxville- with affiliated web map developed/rebranded for the research project aimed at improving bicycle safety. I Bike KNX is based off CyclePhilly, which is based off of CycleAtlanta, which is based off of CycleTracks. It is available in android and iOS version, and uses inbuilt GPS of the smartphone to track the trip of the users. This application allows user to record the trips, view the trip summary (miles, total time, etc.), view the travelled routes, and could review these saved trips later too. All the data and personal information are saved to the server of the research team, and are accessible to a limited number of personnel of the research group.

This can be compared to the GPS travel survey, which also allows user to fill out personal information like cycling frequency, income, age, home ZIP, work ZIP and email address in the smartphone application. This, however, is not mandatory/ only optional and confidential too. This information will be aggregated as de-identifiable information whenever used for the research. Before submitting each trip, user can specify purpose of a trip (commute, exercise, shopping, etc.). Similar to providing personal information, recording and submitting the trips is voluntary too.

Table 4 Data Collected from I Bike KNX application

<table>
<thead>
<tr>
<th>User Level Information</th>
<th>GPS Coordinates</th>
<th>Trip Level Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>User Id</td>
<td>Trip Id</td>
<td>Trip Id</td>
</tr>
<tr>
<td>Email</td>
<td>Latitude</td>
<td>User Id</td>
</tr>
<tr>
<td>Age</td>
<td>Longitude</td>
<td>Purpose</td>
</tr>
<tr>
<td>Gender</td>
<td>Altitude</td>
<td>Start-time of trip</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>Speed</td>
<td>End-time of trip</td>
</tr>
<tr>
<td>Income</td>
<td>hAccuracy</td>
<td>Number of coordinates</td>
</tr>
<tr>
<td>Cycling frequency</td>
<td>vAccuracy</td>
<td></td>
</tr>
<tr>
<td>Rider history</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rider type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home ZIP</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School ZIP</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work ZIP</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The collection of the data was done through the volunteer cyclists, i.e. any kind of incentives was not provided to them for using the application. The use of bicycle application was publicized by the use of various methods: distributing the flyers, as shown in Figure 13, around the campus (library, student housing, downtown), or attaching them to the handlebars of the parked bicycles, and parking racks that have large inflow and outflow of bicyclists. Sending out emails through the listserv of the bicyclists was done. Flyers were distributed on the Bike to Work Day (May 20, 2011) as well.

Figure 13 Flyer used for publicizing the app to recruit the volunteers
Using the application I Bike KNX

The application is easy to use. After first installation of the app, user have to spend few minutes to fill out personal information like gender, age, cycling frequency, income, age,
home ZIP, work ZIP and email address. This has to be done only once. However, it is not mandatory to fill out this information. User have to tap ‘Start’ to start recording the trip and tap ‘save’ to save the trip at the end. After the end of the each trip, user still have opportunity to opt out of submitting the trip.

Figure 14 is the list of almost all steps required from start to submission of the trip. Screenshot (a) and (b) are the screen for recording the personal information of the user. Screenshot (c) is the start of the application, in which tapping the “Start” button initiates the recording of the trip. At the end of the trip, user can stop and save the trip by tapping “Save” as shown in screenshot (d). Additionally, user have privilege of selecting the purpose of trip as seen on screenshot (e). Screenshot (f) shows the route that is displayed on google map at the end of the trip. All of the recorded trips can be viewed at any time. Table 3 is the list of the entire trip data collected from the each submitted trip by the user.

Figure 15 Online map of the routes of I Bike KNX users
Figure 15 is the screenshot of the online map of the routes of the I Bike KNX users, and this map can be accessed from http://cycleknox.phillipgoldfarb.com/gis-routes/. This map has the ability to show the routes according to the selected trip purpose under drop down menu under Layers situated at top right corner.