# Using Mobile Apps to Measure Spatial Travel-Behavior Changes of Carsharing Users


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**Abstract**

Positioning technologies in commercially-available mobile phones have matured significantly over the last five years, offering new opportunities to collect high resolution spatial travel behavior data for transportation research and operations. This paper discusses the use of a global positioning system mobile phone application, TRAC-IT, to collect travel behavior data of carsharing users as part of a variable pricing experiment. A random sample of 30 participants carried a mobile phone with TRAC-IT installed, resulting in over 4 million GPS data points that provided precise geographic and spatio-temporal information. These data informed an analysis of the participants' geographic footprint by estimating a set of standard-distance ellipses of carsharing and non-carsharing modes. Spatial analysis results show that carsharing users have a much smaller activity space (0.5 square miles) than individuals not using carsharing over the same period (7.8 square miles). The activity space of carsharing users contracts while using carsharing as a mode of transport (0.2 square miles for carsharing versus 0.5 square miles for other modes). This may be because carsharing users do not have access to a private vehicle and, therefore, rely on carsharing to conduct out-of-home required trips for maintenance activities, such as grocery shopping.



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## INTRODUCTION

The last decade has seen tremendous advances in telecommunications technologies. Positioning technologies for mobile phones have been at the forefront of this advancement. The development of location-determination capabilities in the U.S. was largely triggered by the Federal Communication Commission's E911 mandate, which requires cellular carriers to be able to locate emergency callers to a certain accuracy. The demands of current commercial services such as real-time navigation and social location (e.g., Facebook Places, Foursquare) have sustained the advancement of positioning technologies, with advanced precision, accuracy, and availability in adverse wireless environments, such as urban canyons and indoor locations.

Modern positioning technologies in mobile devices provide new opportunities to transportation researchers and practitioners for studying the movement of people across many different modes of transportation. Data from mobile devices can help inform the design, deployment, and analysis of new types of transportation modes, such as carsharing. Carsharing is an increasingly popular membership based service that provides access to a fleet of vehicles rented on a short-term basis with 24 hours a day and seven days a week (24/7) access. The rental cost typically covers gas, maintenance and insurance. Members reserve a car online or by phone, access the vehicle with an electronic key card to drive it and, then, return it to the same location. Carsharing can substitute for car ownership or provide employees access to vehicles for business use or personal errands during the day to avoid driving to work [1].

Past research has found that carsharing customers increase their use of carpooling, bicycling and walking, though the impact on transit use shows a slight overall decline [2]. A study of North American carsharing organizations demonstrates how the impact of carsharing on transit depends upon users' travel preferences [3]. As energy price uncertainty increases, carsharing is poised to grow in the near future [4]. However, the geographic characteristics of carsharing user travel behavior, both for carsharing and non-carsharing modes, have not been previously studied.

This paper presents the use of a global positioning system (GPS)-enabled mobile phone application, TRAC-IT, during a research study that collected travel behavior data for carsharing users in context of variable pricing [5] . GPS data from TRAC-IT was used to assess changes in spatial characteristics of user behavior for carsharing and non-carsharing modes. The following sections of the paper discuss the implementation of the carsharing program in Tampa, Florida, analysis of non-spatial carsharing data, the TRAC-IT mobile app travel behavior data collection tool and process, and the results of the spatial data analysis.

## IMPLEMENTING THE CARSHARING PROGRAM

The carsharing program was launched at the campus of the University of South Florida (USF) in Tampa, Florida, on July 23, 2009. The program started with a fleet of four hybrid vehicles available to students, faculty, and staff. Initially, the vehicle mix included three Toyota Prius and one hybrid Ford Escape. During the course of the project, the vehicle mix was changed to meet users' preferences, and carsharing technology challenges. Vehicles were located in parking lots in proximity of residence halls and the student center.

The first phase of the project focused on building awareness of carsharing on campus and adding new members. Marketing efforts focused on new student orientations, student groups, promotions at student events/gatherings and articles/advertisements within the official student newspaper. The carsharing vendor provided staff to make presentations at new student orientations to educate incoming students and their parents and inform them of available transportation options within the campus. These efforts helped membership grow steadily with nearly 50 active members per carsharing vehicle by June, 2011.

Throughout the project, rentals increased with membership, totaling 2,103 rentals through the end of September, 2011 (FIGURE 1), exhibiting seasonal fluctuation corresponding to the university fall (August through December), spring (January-April), and summer (May-July) schedules.

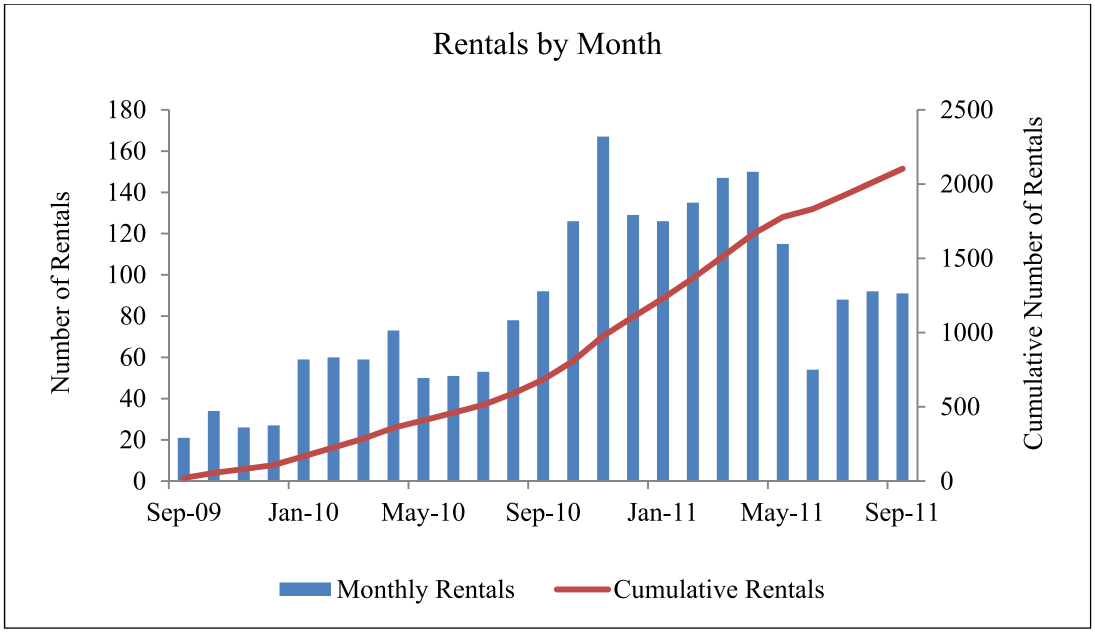


**FIGURE 1 Carsharing Rentals**

## CARSHARING USAGE PATTERNS

A monthly reporting system from the carsharing vendor was established to extract various non-spatial performance data related to carsharing rentals. The monthly rental report provided detailed information on date and time for rental reservation and use, vehicle type and location, hourly cost, total rental cost, total rental time and mileage. The data showed that carsharing rentals gradually increased over the course of the week with usage peaking on weekends (FIGURE 2). During the week, the vast majority of carsharing trips occurred in the off-peak periods, rather than during traditional rush hour periods (FIGURE 3 and FIGURE 4). A peak is reached at 6 p.m., coinciding with the start of the discounted evening rental rate. Later in the program, the start of evening rental discount was delayed to 8 p.m. to avoid overlapping with the end of the evening traffic peak period.

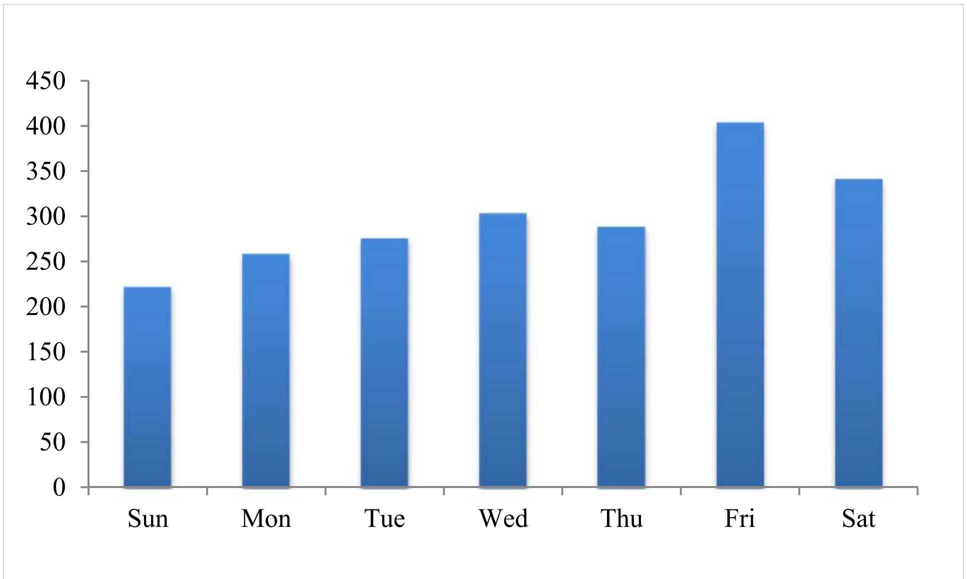


**FIGURE 2 Carsharing Use by Day of Week**

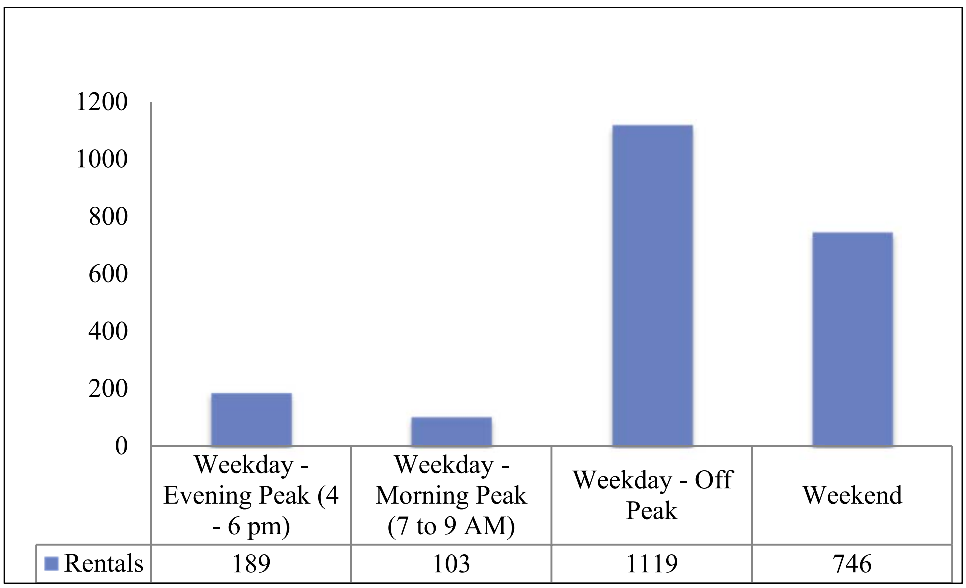


**FIGURE 3 Carsharing Use by Peak and Off-Peak Periods**

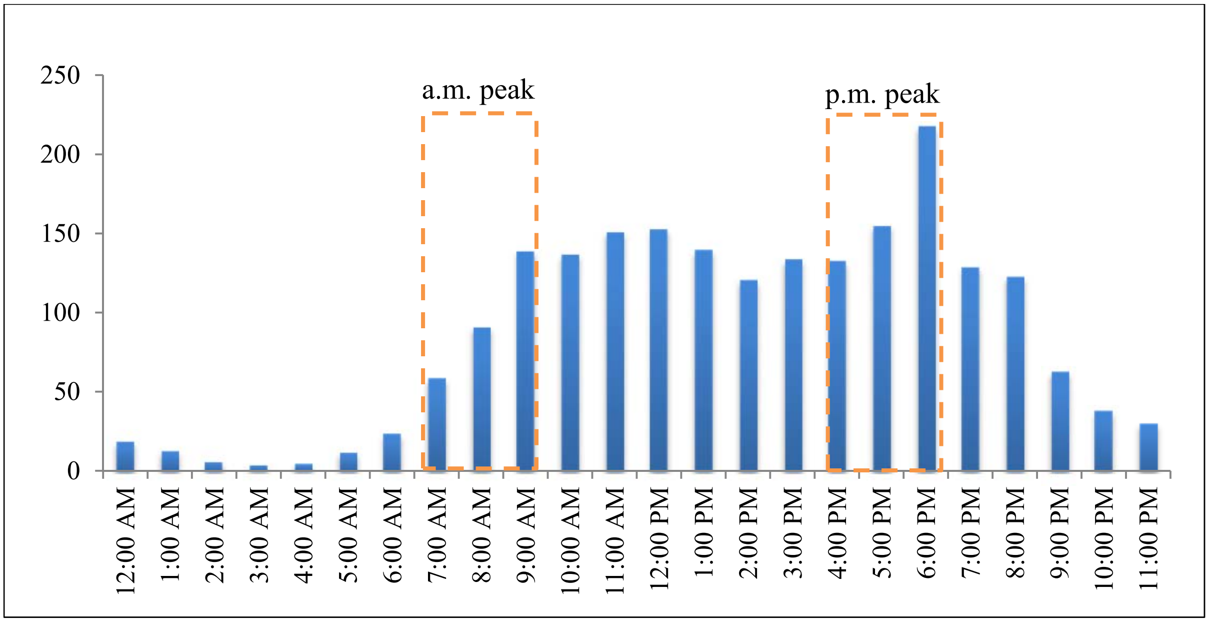


**FIGURE 4 Numbers of Rentals by Start Time**

## SPATIAL TRAVEL BEHAVIOR DATA COLLECTION

While the data discussed in the previous section provides an idea of when carsharing rentals were occurring, the spatial and temporal characteristics of the travel behavior of the users while they were using the carsharing vehicles remained unknown. Additionally, the use of non-carsharing modes (e.g., transit, bicycle, walk, carpool) by carsharing members was also unknown.

To collect high-resolution spatial and temporal travel behavior data for carsharing and non-carsharing modes for participants, the study used GPS-enabled mobile phones with the TRAC-IT mobile application. TRAC-IT is a Java Micro Edition mobile application for GPS-enabled cell phones developed by the National Center for Transit Research at the University of South Florida [6, 7]. TRAC-IT collects GPS data points for all major transport modes (e.g., transit, bike, walk, carsharing) and provides passive real-time monitoring without requiring real-time interaction from the participant. TRAC-IT uses several patented and patent pending algorithms to minimize the impact of data collection on mobile phone battery life and minimize the amount of data sent over the cellular network [7-13] Every morning, the TRAC-IT system generates an email to each participant containing a link to their travel behavior data from the previous day to be viewed in Google Earth. The participant is asked to reply to this email after reviewing their time-lapse GPS data to provide additional details for each trip, including mode of transportation, trip purpose, and vehicle occupancy. This email response from the participant is then catalogued by the TRAC-IT system and associated with their GPS data in the TRAC-IT database.

Figure 5 describes the TRAC-IT software architecture, detailing the interactions between the various system components. The TRAC-IT Database Toolkit desktop application assists in server management, data processing and analysis, and communication with participants via email. The toolkit runs as an automated service on the TRAC-IT server, but administrators and analysts can also run versions of this same software on their desktop computer to export data manually from the database or perform other processing. A distinct advantage of the TRAC-IT application over other GPS tracking devices is its ability to collect and transmit GPS data in real-time. This allows distinguishing users who actively contribute to the survey data collection and users who have technical difficulties or fail to carry the phone. The TRAC-IT Database Toolkit monitors the system and sends automated alert emails to the participants and administrators if no data are received from a user after a certain elapsed time (e.g., 24 hours).

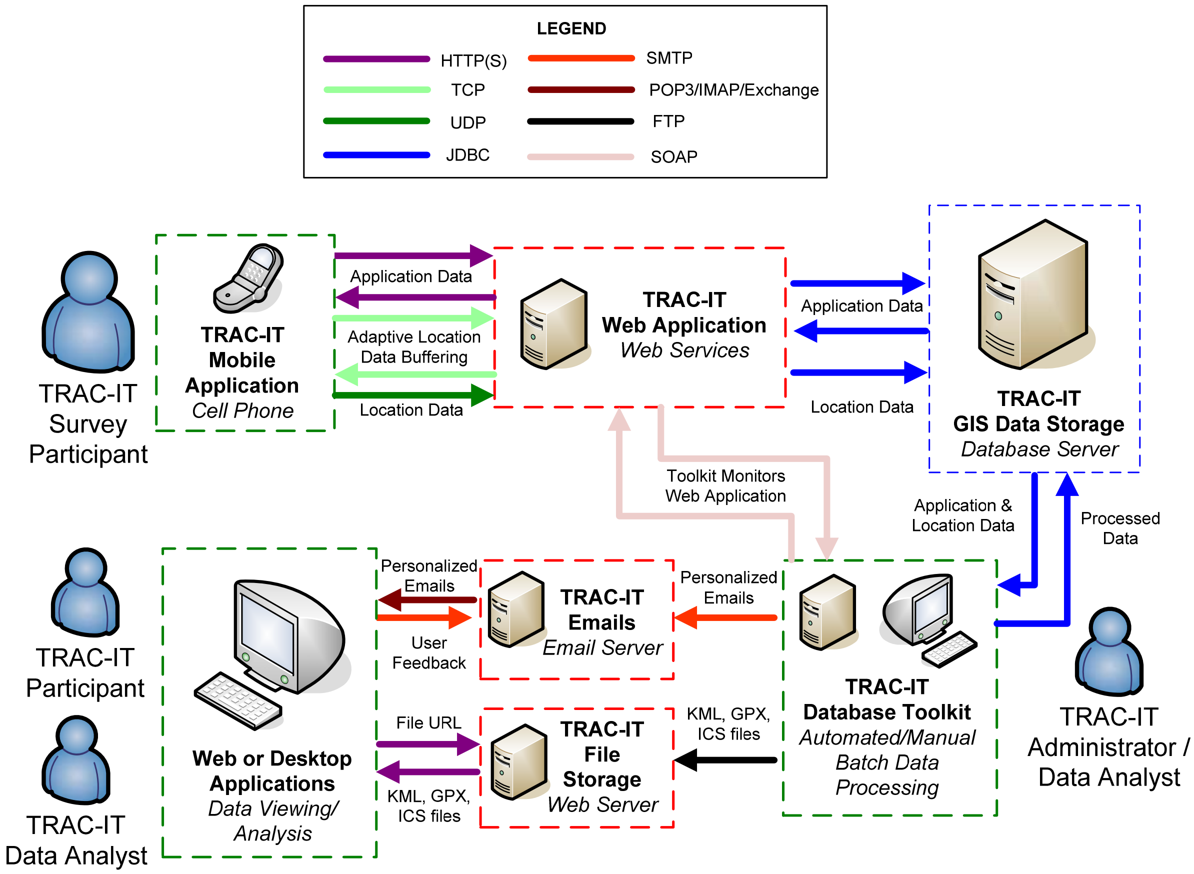


**FIGURE 5 TRAC-IT System Architecture**

## GPS Data Collection using TRAC-IT

Based on the weekly usage analysis, it was observed that rental frequency varied significantly among carsharing members, necessitating an extended period of data collection to observe vehicle usage. After an initial field test of the app, a sample of 30 individuals was selected for a nine-week survey from February through May, 2011. Each participant was given a low-cost GPS-enabled phone (Sanyo Pro 200 on Sprint) with a pre-installed copy of the TRAC-IT software. Participants were given an incentive consisting of a $25 debit gift card for each week they carried the cell phone, and a bonus $25 gift card issued at the completion of a 3-week survey period.

Throughout the survey, TRAC-IT sent daily email reminders to participants with a link to the previous day's trips displayed in Google Earth. In the email reminder, participants were asked to provide a brief description of the purposes and modes of transportation of their trips. Participants were asked to charge cell phones nightly and were given a wall charger and a second charger that doubled as a wall charger and car charger. A car charger was also left in the glove box of the carsharing rental cars.

From February 10 until April 29, 2011, TRAC-IT collected 1,857 sessions from 30 users (over 60 sessions on average per user) for a total of 4,023,917 GPS data points. TRAC-IT collected an average of 40 days of travel behavior data per participant, with approximately 1,195 total survey person days. Lost data during this period due to technology failures were minimal, as the TRAC-IT Web Application server up-time during this period was over 99 percent.

**Trip Segmentation – GPS Data Post-processing**

Before this GPS data can be analyzed, it must be transformed into actual trip patterns through a process called trip segmentation. When segmenting trips from GPS data, we use the concept of points-of-interest (POIs) and trips. We define a POI as a location where the user performed an activity, and a trip is defined as the travel behavior between two POIs. Figure 6 shows the relationship between POIs and trips, with temporally-ordered GPS data connecting POIs to trips.

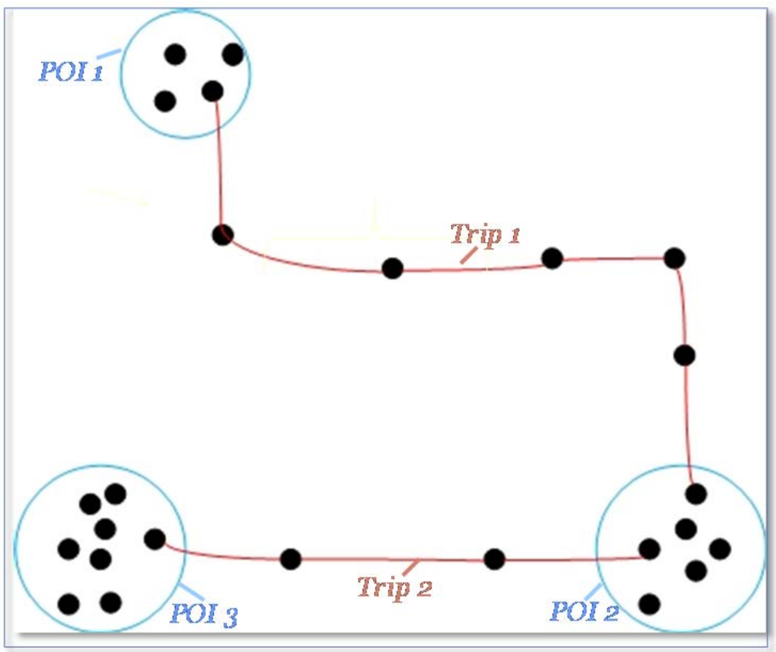


**FIGURE 6 - Points-of-interest (POIs)**

We categorize trip segmentation into two types: manual (i.e., performed by data analysts using software tools) and automated (i.e., performed by algorithms in software). Manual trip segmentation was utilized to post-process the collected GPS data for this research project. Automatic trip segmentation is in an early experimental stage, and was tested using the collected GPS data. We discuss manual trip segmentation below, and automated trip segmentation in the Future Work section of this paper.

*Manual Trip Segmentation*

During the survey period, participants received a daily-automated email from the TRAC-IT system about their previous day of travel, which included a link to see their GPS travel data viewable in Google Earth (FIGURE 7). Google Earth provides a sophisticated view of the GPS data, including a time-lapse feature that allows the users "playing" their travel for the day and seeing their movements on a map. Researchers requested each participant to review these data, and then reply to each of the automated emails with a written description of their trip for the day, including location names, modes of transportation, and trip purpose. TRAC-IT saved this reply email for further analysis. If the phone did not move from a single location over the period of one day, or if no data were received from the phone (i.e., the phone was powered off), then the TRAC-IT system sent an automated email to remind the participant turn the phone on and carry it with them.

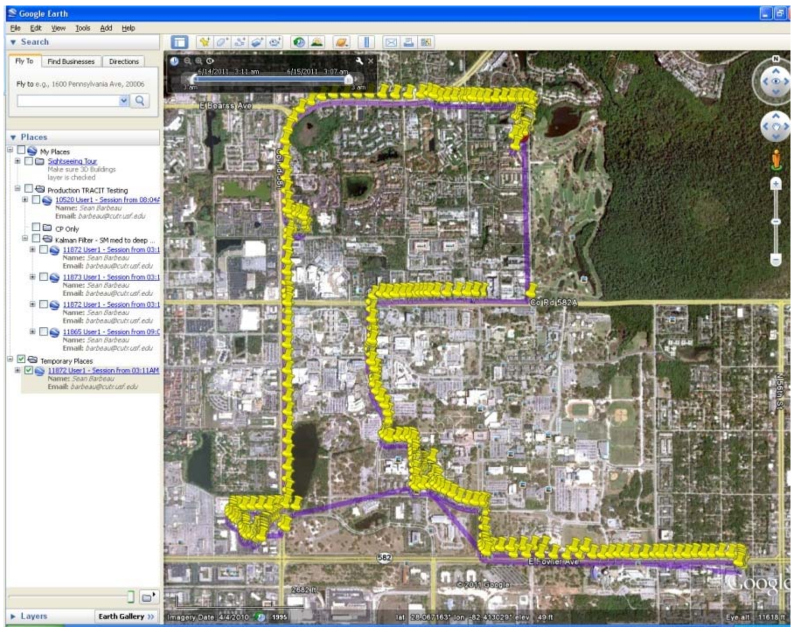

**FIGURE 7 Example of a Daily email link viewed in Google earth**

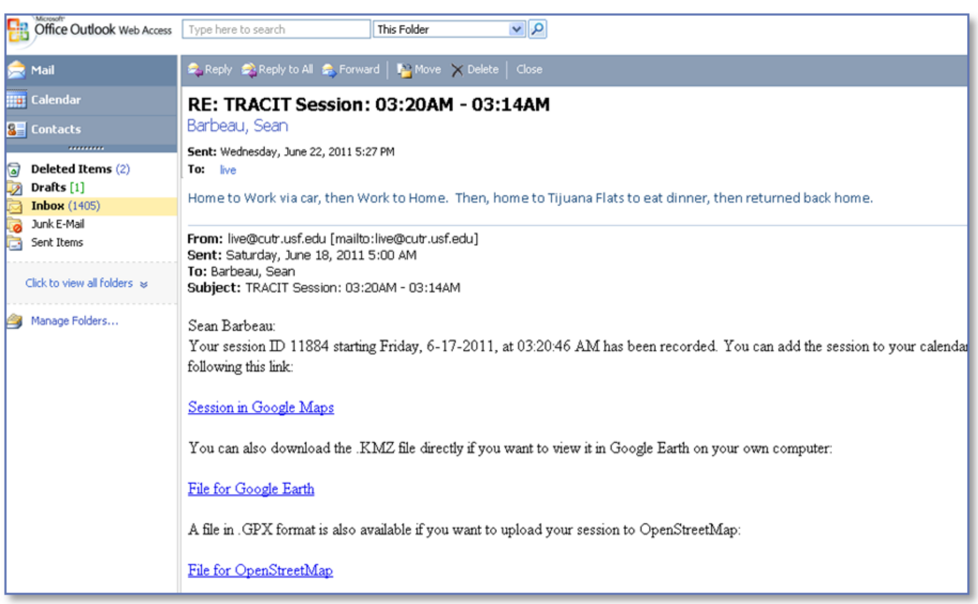

**FIGURE 8 Example showing a user's written feedback description of a trip**

At the end of the survey period, each data analyst manually segmented the trip data after retrieving all reply emails from a participant. The analyst proceeded to read each email from the participant, and simultaneously view the data in Google Earth by clicking on the generated Google Earth link. The analyst reviewed the locations where the user appeared to stop and cross-referenced this data with the written description from the participant's email. Database management tools (e.g., SQL Server Management Studio, pgAdmin for PostGIS) and specialized database queries were used to enter identifiers for the GPS points that defined the start and end points of trips, to manually segment the raw GPS data into discrete trips and insert this trip information, along with the origin and destination points-of-interest, into the database. If the participant provided written descriptions of the points-of-interest or trips (e.g., location description = "Home", Trip Purpose = "Go to Work"), this information was attached to the POIs and trips in the database. If the user did not explicitly state the purpose or mode for a trip, but the analyst reasonably inferred this information from the context of the email, then this information was added to the database along with a flag indicating that the assessment was based on an analyst's assumption.

Once all emails from survey participants were processed, the analysts proceeded to process any remaining sessions for which the participant did not provide written feedback. The analysts referenced a spreadsheet with links to Google Earth files for each session to visualize and analyze the data, following the approach used when the participants provided feedback. This provides data for start and end trip times as well as latitude and longitude for the points-of-interest, but no extra descriptions for the locations or trips were available if the participant did not provide this information via email.

After all data were manually processed, the TRAC-IT system post-processed the trips and automatically determined additional information that would have been time-consuming to determine manually. For example, the total distance for each trip was calculated automatically based on the GPS data assigned to each trip via the manual trip segmentation process. The total distance covered for each daily session, as well as the total area covered by the participant's travel, was also calculated using custom software and spatial queries. Software also automatically cross-referenced the log of carsharing rentals using the TRACIT user ID and Carsharing user ID, and labeled any trips in the TRAC-IT database by a user that matched the starting and ending time of that user's carsharing rental with the mode of "carshare."

**Final post-processed data set**

The manual trip segmentation process was used to post-process the GPS data collected via the TRAC-IT mobile app. The final dataset consisted of a subset of the entire TRAC-IT database, comprising 1,633 trips made by 30 sampled users, and shows that most of the trips were made by car, followed by walking, bike, bus, and carsharing (Table 1). The vast majority of the trips were related to students-specific activities, like going to school, returning home, or going to work. A relatively high percentage of participants did not report their trip purpose.

**TABLE 1 Trip Purpose: TRAC-IT Manually Segmented Sample**

| *Mode* | *Count* | *Percent* |
|---|---|---|
| *Car* | 666 | 40.8% |
| *Bicycle* | 155 | 9.5% |
| *Bus* | 132 | 8.1% |
| *Scooter* | 18 | 1.1% |
| *Walking* | 410 | 25.1% |
| *Carsharing* | 31 | 1.9% |
| *Not Reported* | 221 | 13.5% |
| *Total* | *1,633* | *100.0%* |

## SPATIAL ANALYSIS OF TRIP DISPERSION

To understand how carsharing pricing might affect the spatial characteristics of travel behavior, the analysis below compares the spatial dispersion of out-of-home activities undertaken by survey participants, differentiating between those who used the carsharing program versus those who did not during this period.

Area-based geometric measures of spatial dispersion [14] were employed to estimate the spatial extent of out-of-home activities across the urban landscape. The simplest measure is represented by the standard distance deviation (SDD) which is essentially a bivariate (i.e., showing the relationship between two variables) extension of the standard deviation of a univariate distribution. SDD measures the standard distance deviation from a mean geographic center and is computed as:

$$SDD = \sqrt{\frac{\sum(x_i-\bar{x})^2+\sum(y_i-\bar{y})^2}{n}} \tag{1}$$

where $\bar{x}$ and $\bar{y}$ represent the spatial coordinates of the mean center of out-of-home activities, and the $i$ subscript indicates the coordinates of each non-work activity. The coordinates represent longitude and latitude measurements of each activity and are reported in meters following the Universal Transverse Mercator (UTM) coordinate system.

Thus, the SDD of an individual's activity pattern is estimated as the standard deviation (in miles) of each activity location from the mean center of the complete daily activity pattern. Interpretation is relatively straightforward, with a larger standard distance indicating greater spatial dispersion of activity locations. The area of the SDD is the area of a circle with a radius equal to the standard distance. The SDD provides a summary dispersion measure that can be used to explore systematic variations of activities subject to socio-demographic, travel patterns, and patterns of land-use. To eliminate dependency from spatial outliers, another measure of dispersion, called the standard deviational ellipse (SDE) is usually employed, which uses an ellipse instead of a circle. The advantages of the SDE with respect to the SDD have been discussed in the literature [14]. In addition to control for outliers, the SDE also allows accounting for directional bias of activities with respect to their mean center. The ellipse is centered on the mean center with the major axis in the direction of maximum activity dispersion and its minor axis in the direction of minimum dispersion (See Figure 4.1). In this study, we employ the standard distance ellipse (SDE), using the formula described in Levine [15]:

$$SDE = \sqrt{\frac{\sigma_x^2 + \sigma_y^2}{2}} \quad (2)$$

where $\sigma_x$ and $\sigma_x$ represent the length of the major and minor axes of the ellipse. The SDE is centered on the mean center with the major axis in the direction of maximum activity dispersion and its minor axis in the direction of minimum dispersion (Figure 6).

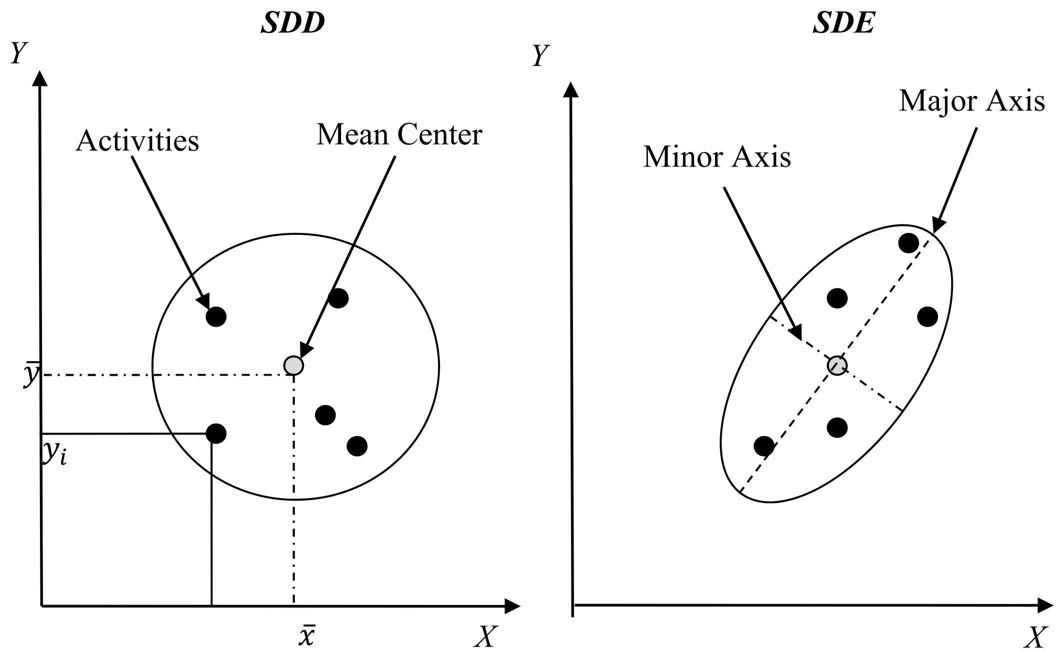


**FIGURE 9 Standard Distance Circle and Standard Distance Ellipse**

The literature provides additional activity-space measures. For example, while Buliung and Kanaroglou [16] use SDE, they also introduce an area-based geometry that defines a minimum convex polygon containing activity locations visited by a household during a reference period (i.e., the travel-survey period). The advantage of using a convex polygon is that it weights the activity space by the relevance of activities, such as their type (recreational, maintenance, etc.) and their relative frequencies. Although this metric represents an accurate geographical measurement of the activity space, Buliung and Remmel [17] show that the use of the minimum convex polygon algorithm provides similar results to SDE in terms of behavioral interpretation. Other research shows that the choice of an appropriate shape representing an individual's activity space is highly dependent on the spatial distributions and frequencies of the locations visited by the person in the given time period [18].

Results of mean comparison tests of SDD and SDE by user type reported in Table 2 confirm that carsharing users have a much smaller activity space (0.5 square miles) than all other sample individuals (7.8 miles). This might be because carsharing users do not have access to a private vehicle and, therefore, rely on carsharing to conduct out-of-home required trips for maintenance activities, such as shopping or other errands. Table 2 also shows that the activity space of carsharing users contracts while using carsharing as a mode of transport. This result is counterintuitive, since individuals might reach locations that are not available by other means of transport by relying on carsharing. This finding is confirmed by measuring the size of the activity space by using SDD rather than SDE. The SDD is more sensitive to the presence of outliers or trips that are longer than usual, while the SDE reduces the outlier effect, while accounting for spatial-directional bias (trips made to the same location with more frequency). The fact that the size of the SDE gets smaller when carsharing users rely on carsharing indicates that they tend to make the same trip type to the same location when using this mode, thus determining a SDE with an elongated ellipse, as shown in Figure 6. This is consistent with the assumption that carsharing is used to conduct maintenance trips (higher frequency, constant locations).

**TABLE 2 Mean Comparison of Trip Length and SDE, Carsharing vs. Non-Carsharing**

| | *Trip Length (miles)* | | | *SDE (square miles)* | | |
|---|---|---|---|---|---|---|
| *User Type* | *Average* | *Carsharing Trip* | *Non-Carsharing* | *Average* | *Carsharing Trip* | *Non-Carsharing Trip* |
| *Carsharing* | 2.6 | 8.0 | 1.7 | 0.5 | 0.2 | 0.5 |
| *Non-Carsharing* | 4.2 | - | 4.2 | 7.8 | - | 7.8 |

## FUTURE WORK

### Automated Trip Segmentation

Since the manual trip segmentation process takes a substantial amount of time and effort, an automated trip segmentation algorithm would be a significant asset to any GPS-based travel behavior data collection effort. The TRAC-IT system includes an experimentation POI detection algorithm that identifies places where users spent a significant amount of time via GPS data clusters [8]. Once POIs are identified, the trip segmentation algorithm identifies the most recent GPS data point in the starting POI, and the oldest GPS data point in the next POI, and assigns all data in between and including these two points to a new trip. Trip start and end times, trip length, trip duration and travel paths can then be derived from the GPS data contained within the POIs and segmented trips.

Errors in GPS due to the impact of various environmental factors (e.g., building structures) produce variations in position and speed, known as “GPS drift,” in proximity of the user’ location that make automated trip segmentation difficult. Early versions of the algorithm could not differentiate between certain elements of GPS noise and true POIs. Figure 10 shows a spatial histogram of automated detected POIs, with the height being determined by the number of visitations of a user to that POI. Red and orange clusters likely indicate areas of frequent traffic congestion, while green and yellow clusters likely represent true POIs. Current work is focused on improving automated trip segmentation based on the GPS data and manual trip segmentation from this research project.

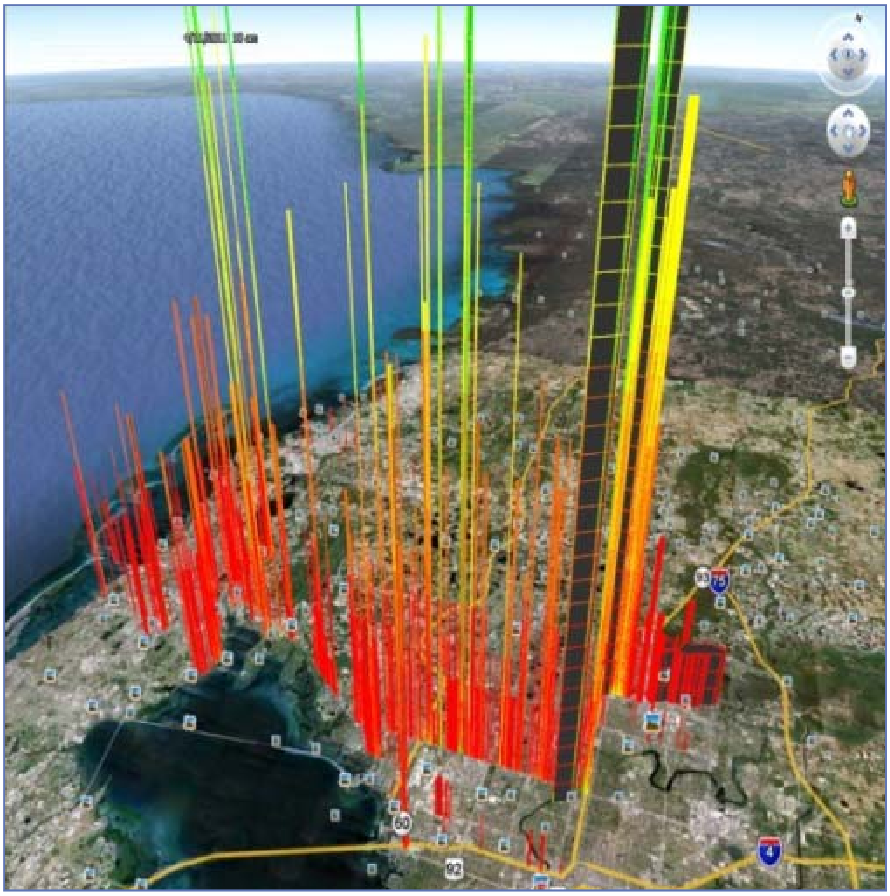

**Figure 10 Points-of-interest Histogram**

**TRAC-IT as software-only deployment**

In this study, mobile phones with the TRAC-IT app installed were distributed to survey participants instead of using the participants own phone. When deciding between a deployment of TRAC-IT on the participants' phone versus a dedicated GPS survey device, many tradeoffs must be considered. A pure software deployment of TRAC-IT to participants' own smart phones would reduce deployment costs for equipment, but would need to consider battery life issues along with the data transfer constraints on the cellular network for users with tiered, limited data plans. However, using a separate device reduces the battery life and cellular data challenges, since the only use of the device is to collect and send GPS data. Perceived and actual control over privacy by the participant is greater when a separate device other than the user's phone is used, since the user can always leave the device behind or power it down completely if they do not want to be monitored. Additionally, sampling challenges of identifying enough users with the supported smart phone platforms are eliminated if a dedicated device is used, since the low-cost cell phone can be distributed to any participant. Future research could compare the cost effectiveness of an independent smart phone application versus the provision of a separate device.

## ADDITIONAL FINDINGS

This paper focuses primarily on the spatial characteristics of participants trips based on GPS data collected with the TRAC-IT mobile app and GPS-enabled mobile phones. However, in this research study, additional analysis was performed on the non-spatial data to discover more about the impact of variable pricing strategies on participants.

## CONCLUSIONS

Modern positioning technologies in today's mobile phones provide new opportunities for studying travel behavior, including the use of new modes of transportation such as carsharing. This study examined the spatial characteristics of carsharing users in a car-centric university setting, unlike other carsharing programs housed in downtowns of major metropolitan areas with extensive transit options. To collect travel behavior data, GPS-enabled cell phones loaded with the TRAC-IT mobile app were used to follow a sample of participants to provide longitudinal information on the program's impacts, including the temporal and spatial dispersion of daily trips. Spatial analysis on the GPS data from TRAC-IT showed that carsharing users have a much smaller activity space than all other sample individuals. The analysis also showed that the activity space of carsharing users contracts while using carsharing as a mode of transport. This result might be explained by users relying on carsharing to conduct maintenance activities, such as grocery shopping and other more recurring, short-distance, trips.

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**REFERENCES**


1. Martin, E., S. Shaheen, and J. Lidicker, *Impact of Carsharing on Household Vehicle Holdings: Results from North American Shared-Use Vehicle Survey.* Transportation Research Record: Journal of the Transportation Research Board, 2010(2143): p. 150-158.
2. Millard-Ball, A., et al., *Car-Sharing: Where and How it Succeeds*, 2005, Transit Cooperative Research Program: Washington, D.C.
3. Martin, E. and S. Shaheen, *The Impact of Carsharing on Public Transit and Non-Motorized Travel: An Exploration of North American Carsharing Survey Data.* Energies, 2011(4): p. 2094-2114.
4. Shaheen, S.A., A.P. Cohen, and M.S. Chung, *North American Carsharing: 10-Year Retrospective.* Transportation Research Record: Journal of the Transportation Research Board, 2009. **2110**: p. 35-44.
5. Winters, P.L., et al., *Value Pricing Pilot Program-Variably Priced Carsharing Project*, 2012, Office of Transportation Management, HOTM, Federal Highway Administration, U.S. Department of Transportation: Washington, D.C.
6. *TRAC-IT*. Location Aware Laboratory 2012; Available from: http://www.locationaware.usf.edu/ongoing-research/projects/trac-it/.
7. Barbeau, S.J., et al., *TRAC-IT: Software Architecture Supporting Simultaneous Travel Behavior Data Collection and Real-Time Location-Based Services for GPS-Enabled Mobile Phones*, in *Transportation Research Board 88th Annual Meeting*2009: Washington, D.C.
8. Barbeau, S., N.L. Georggi, and P.L. Winters, *Dynamic Travel Information Personalized and Delivered to Your Cell Phone* 2011, National Center for Transit Research.
9. Barbeau, S.J., et al. *Dynamic Management of Real-Time Location Data on GPSEnabled Mobile Phones*. in *UBICOM 2008 International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*. 2008.
10. Barbeau, S.J., et al., *System and Method for Determining Critical Points in Location Data Generated by Location-Based Applications*, in *U.S. Patent and Trademark Office*2008.
11. Barbeau, S.J., et al., *Optimizing Performance of Location-Aware Applications Using State Machines*, in *U.S. Patent and Trademark Office*2011.
12. Barbeau, S.J., et al., *Architecture and Two-Layered Protocol for Real- Time Location-Aware Applications*, in *U.S. Patent and Trademark Office*2011.
13. Barbeau, S.J., et al., *Adaptive Location Data Buffering for Location-Aware Applications," Patent* in *U.S. Patent and Trademark Office*2011.
14. Ebdon, D., *Statistics in Geography: A Practical Approach*1977, Oxford: Blackwell Publishing.
15. Levine, N., *Spatial statistics and GIS: Software tools to quantify spatial pattern.* Journal of the American Planning Association, 1996. **62**(3): p. 381-392.
16. Buliung, R. and P. Kanaroglou, *Urban form and household activity-travel behavior.* Growth and Change, 2006. **37**: p. 174–201.
17. Buliung, R. and T.K. Remmel, *Open Source, Spatial Analysis, and Activity-Travel Behavior Research: Capabilities of the aspace Package.* Journal of Geography Systems, 2008. **10**: p. 191–216.

18. Rai, R.K., et al., *Capturing Human Activity Spaces New Geometries.* Transportation Research Record: Journal of the Transportation Research Board, 2007(2021): p. 70-80.