University of California Transportation Center
UCTC-FR-2012-12

The Quantified Traveler: Changing transport behavior with personalized travel data feedback

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UC Berkeley
May 2012

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May 21, 2012

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Abstract

Experiments using smartphones to influence behavior have been growing rapidly in many fields, especially in health and fitness research, and studies on eco-feedback technologies. In these studies, users are first tracked to understand their baseline behaviors, then measured continuously while they receive feedback about their actions. In transportation, studies using smartphones to change behavior have been limited due to the difficulty in even tracking users in the first place. Collecting data from smartphones in a battery efficient manner is a large research problem, and behavior change studies depend on being able to track travel behaviors. We developed an automated travel diary system which efficiently and unobtrusively collected travel data using smartphones and ran an experiment to evaluate how people's awareness of their transportation behavior, attitudes towards sustainable transportation, intentions to change behavior, and measured travel behavior changed. For three weeks, 135 participants used an application on their iPhone or Android smartphone which unobstrusively tracked their location and sent data to a server which processed their data into trips and attributes related to their trips, such as time spent traveling, amount of money spent for transportation, amount of CO2 emitted, and calories burned during travel. Learning from prior work in eco-feedback studies and behavior change studies about health and fitness, a webpage was designed in which participants received feedback on their travel data along with trends and comparisons with various peer groups. Using surveys administered before and after the experiment, we measured a statistically significant change in partcipants' awareness of statistics related to their travel behavior, and an intention to drive less and walk more amongst the "mainly-driving" group of the study population. In addition, a significant decrease in the amount of driving and increase in the amount of walking was measured. However, in a regression analysis, we were not able to find statistically significant covariates explaining what types of people and travelers were more likely to shift.

1 BEHAVIOR CHANGE OPPORTUNITY IN TRANSPORTATION

There exists a large body of work dealing the with the modeling of transportation behavior and also attempting to influence travel behavior, and we believe there is a new opportunity to advance the body of research even further because of recent advances in technology over the past few years. In this paper, we present a system and experiment which are designed to collect statistics on study participants' travel footprint (emissions, calories burned, time and costs) and to feed back that information in a personalized, informative way. The goal is to explore the possibility of influencing people's awareness, attitudes and potentially behavior, and to encourage them to engage in more sustainable transportation behavior. This study is informed by previous research in the area of behavior change that has shown some success; in particular, personalized feedback programs that have been able to achieve certain changes in behavior. However, given recent developments in mobile technology and behavioral economics, we believe it is time to revisit this issue. In what follows, we first present the four major technological trends have given rise to advances in psychology and human computer interaction which has lead to a growth in academic research involving new methods of behavior change.

1. **Persuasive Technology.** Persuasive technology is broadly defined as technology that is designed to change attitudes or behaviors of the users through persuasion and social influence [1]. This technology focuses on the design, research, and analysis of interactive computing products created for the purpose of changing people's behaviors. Although behavior change methods have been used by psychologists for years, only in the past few years have these techniques been implemented on computing devices, delivering information in an automated manner.

2. **Proliferation of Smartphones.** Smartphone usage has been growing at a rapid rate since 2007. Smartphones offer more advanced computing ability, with features such as touch screens, cameras, GPS, and accelerometers, which have been used by human computer interaction designers to implement persuasive technology.

3. **The Quantified Self.** The concept of the Quantified Self describes applications which enable the process of recording behavior, processing the data collected, and feeding it back to the individual or group so that they can better understand the patterns of their activity and eventually adapt their behavior more intelligently than they would without these augmentations. As smartphone usage has increased, the launch of applications on smartphones has increased to track and study many features of people's daily lives (i.e. fitness, mood, spending habits)[2].

4. **Accessible Transportation Data.** Since 2007, hundreds of transit agencies have released their schedule and route configuration data in a popular format called GTFS[3]. Many of those agencies have also made available real-time positions and of buses and released open Application Programming Interfaces (APIs). Mapping data, thanks to Google Maps, Open Street Map, USGS and other providers have allowed for develop-

ers to enhance transportation datasets to deliver innovative routing applications for ordinary citizens.

The first three trends have already lead to new research in the fields of health and fitness, as well as environmental conservation. This paper describes how we have taken advantage of these four trends to develop and evaluate a system which influences users' awareness about their travel behavior, intentions to take sustainable modes of transportation, and actual behavior. We developed an automated travel diary system which used smartphones to collect location and other sensor data and sent data to a server which processed the raw data into trips and attributes of each trip, including travel mode, travel time, cost, and CO_2 emissions among other statistics. The technical details of the infrastructure and algorithms are discussed in Jariyasunant[4]. Using this smartphone travel diary system, we ran a three-week experiment with 135 participants, in which they were presented a webpage which gave users feedback on their personal travel statistics and comparisons to various peer groups. Section 2 describes related work in behavior change and persuasive technology in non-transportation fields, which influenced the design of our feedback system. Section 3 describes the smartphone travel diary system in more detail, only recently made possible due to advancements in smartphone technology and accessible transportation data. Our experiment, called the Quantified Traveler, along with the evaluation of the experiment and changes in users' awareness, attitudes, intentions, and behaviors are outlined in Section 4. We recognize that this work is just the first step in a long process to influence travel mode choice, and ideas for future work are presented in Section 5.

2 LESSONS FROM PRIOR BEHAVIOR CHANGE WORK

In this section, we review prior work which allowed us to develop and design the system, website, and surveys. The first step was to learn about the successes of prior behavior change studies in transportation, which have been ran for the past 20 years. These studies were successful, but had many difficulties, with room for improvement thanks to modern smartphone technology. The design of the system and implementation of the behavior change techniques was also influenced by other studies non-transportation persuasive technology experiments, while the design of the surveys were influenced by models of behavior change from the psychology literature. Based on this prior work, our contribution to the literature is the design and evaluation of an updated version of a Travel Feedback Program using smartphones and web technology.

2.1 Behavior Change in Transportation

There is a large body of work in Travel Feedback Programs, which aim to influence mode choice behavior with information and psychological factors. There are various styles of Travel Feedback Programs, but common to all programs are: users receive feedforward information (i.e. directions for using alternative modes) as well as feedback information (i.e. amount of CO2 emitted) which is gathered from program participants filling out travel diaries. There have previously been several small-scale travel behavior feedback programs conducted by researchers in Japan [5]; in those experiments, the feedback was based on paper-and-pen surveys, and participants were often given feedback during face-to-face contact with a "travel coach". It could be shown that through travel feedback programs, measurable and lasting shifts away from automobile use and toward more sustainable modes of transportation could be achieved. Individualized marketing has also succeeded in changing travel behavior towards more pro-environmental modes of transportation [6].

Although Travel Feedback Programs have been shown to be successful in inducing a mode shift away from auto usage, the implementation of these programs is not scalable. Manually entering information in travel diaries is a time consuming process. Using smartphones for data collection provides an opportunity to partially or fully automate many of the tasks involved in the travel feedback programs, and do things that was previously not technically feasible. There is an opportunity to leverage the lessons learned from HCI researchers in the design of automated tools on the web and smartphones to motivate behavior change, starting with the integration of open transportation data into persuasive technology programs.

2.2 The Quantified Self : Self tracking to change behavior

The concept of the Quantified Self describes applications which enable the process of recording behavior, processing the data collected, and feeding it back to the individual or group so that they can better understand the patterns of their activity and eventually adapt their behavior more intelligently than they would without these augmentations. Recently, the increasing abundance of low-cost sensing devices(including smartphones), coupled with the use of social networks, mobile devices and web-based applications for many different aspects of daily life (e.g., banking) has led to an abundance of detailed data becoming available to end-users. This has given rise to many companies which have incorporated self-tracking and behavior change into their products: Zeo - tracks sleep patterns, Fitbit - fitness levels, RunKeeper - jogs and runs, CureTogether - reactions to various medication, Mint - personal finance, RescueTime - time usage and productivity.

The Quantified Self website and regular meeting groups across the country have become active forums where people exchange ideas, experiences and findings about themselves. While there have been significant advances in self-tracking applications for health and fitness, there has been a relative lack of work on quantifying one's travel behavior.

2.2.1 Self-tracking potential in transportation

The maturity of GPS tracking technology and the surge in self-tracking interest present a new and powerful opportunity to collect traveler data by combining these two areas. In our system, smartphone technology is used to collect data through continuous, unobtrusive sensing with minimal effort required from the traveler. With large amounts of individual travel behavior data, the research community can also model behavior and manage demand by getting a better understanding of how and why people travel.

There are also considerable benefits to introducing self-tracking in transportation: Many of the costs are not paid when the trip is made, but are hidden in infrequently paid items such as car insurance fees or the price of a season parking pass. Emissions are not routinely measured and quantified, and since travel is an induced activity that is conducted for the purpose of another desired activity (e.g., shopping), many travelers may not be making a conscious, informed decision about how much time they want to spend traveling, or how many calories they want to burn when traveling. However, transportation decisions have a large impact on people's lives. For instance, the average Californian household spends around 15% of total income on transportation [7, 8], and the average Californian spends 26.5 minutes per day commuting; this adds up to more than 110 hours per year - almost as much as a typical worker's yearly vacation[9]. If people were to track their own travel patterns and attempted to reduce travel time or costs, for example, this could also benefit society as a whole as it may catalyze a reduction in vehicle miles traveled or a shift to more sustainable modes of transportation. Raising awareness of negative impacts of transportation on the environment and public health can be considered a policy tool in its own right to reduce the overall footprint of the transportation sector. The introduction of automated self-tracking devices presents a new, powerful method to present every traveler with personalized information on their specific contributions.

2.3 Recent Examples of Technology Designed for Behavior Change

Many researchers recognized the potential of implementing many of the behavior change techniques into computer technologies, including providing personalized feedback on actions measured with smartphones. Two very active fields in which Human Computer Interaction researchers have built and evaluated applications are in Health/Fitness and Energy Conservation/Eco-Feedback Technology. Studies using these applications have shown that feedback is a powerful behavior change technique in health and fitness applications [10, ?], and eco-feedback technologies [11].

Health and fitness researchers have tried using goal-setting and feedback to design applications that help people maintain healthy lifestyles. One of the most notable applications was Ubifit[12], which automatically detected the physical activity levels of a user wearing a custom device, and also provided feedback to users. One of the notable features of Ubifit was the simplicity of the feedback: the person's cell phone background changed depending on the amount of physical activity, such that a user could understand their data at a glance. Ubifit is one example of numerous applications which have evaluated the effects of Goal-Setting and Feedback in monitoring fitness[13, 14, 15]. There are also numerous examples of applications of eco-feedback technology, which have been designed to change behavior[16, 17, 11] and successfully shown that feedback has an effect to conserve energy. While transportation plays a role in potentially reducing one's environmental impact on the earth, only one behavioral HCI study has been conducted to influence transportation behaviors[18] and showed a high potential for behavior change to sustainable modes of transportation.

2.4 Understanding Behavior Models to Measure Aspects of Change

While the goal of a system may be to design behavior, it is just as important to measure the factors which contribute to behavior change.

The Theory of Planned Behavior showed that behavior was influenced by attitudes, normative beliefs[19], a person's level of self-efficacy[20] and a person's past experiences,

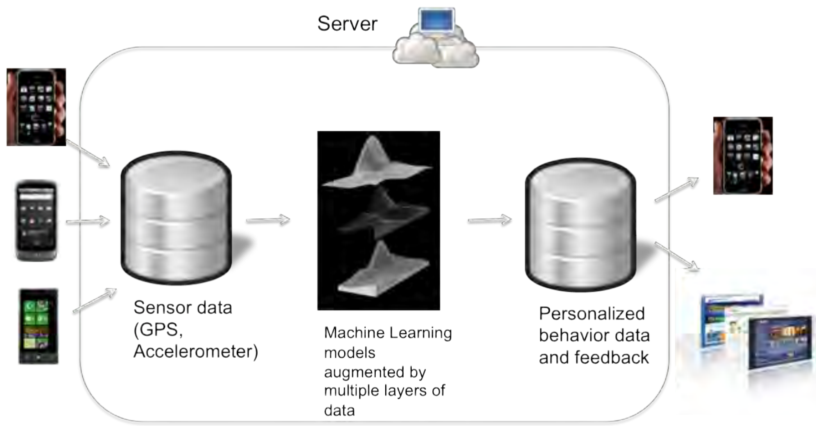

Figure 1: System Architecture Diagram. The components of the system consist of mobile phones, trip determination algorithms running on a server, and web tools to view and correct trips.

social persuasion and emotional states[21]. Later models based on the TPB expanded the influences on one's behavior to habits, environmental constraints, knowledge and skills to perform behaviors, and moral obligations[22, 23, 24]. Thus, our system was designed to surveys were designed to capture these influences.

Other behavior change models such as the TransTheoretical Model, which used people's attitudes and levels of self-efficacy to classify people in to different stages of change[25]. This model is notable because it recognizes that behavior change techniques have different effects on people in different stages of change. While education and information may be the most effective technique in influencing someone at the very early stages of change, goal-setting may be a better technique for one attempting to maintain a changed behavior.

While acting "green" has been a popular movement for a while, in transportation most people are not actively attempting to change their modes of transportation or distance traveled. Therefore, the feedback website was designed as a educational and information page, and an attempt was made to measure a change in education by surveying if one's "awareness" of their emissions, calories burned, and other factors changed.

3 THE QUANTIFIED TRAVELER SYSTEM

We built an automated travel feedback system based on the work of prior researchers and new technology using smartphones. The system consists of many parts, from smartphones to collect data efficiently without draining the battery, server infrastructure to receive data and handle large loads of data requests, algorithms to process data into trips and attributes, and a carefully designed website which presented a large amount of data to users in a concise graphical manner. The first three parts are briefly described in this section, with further described in Jariyasunant[4] while the website is described here.

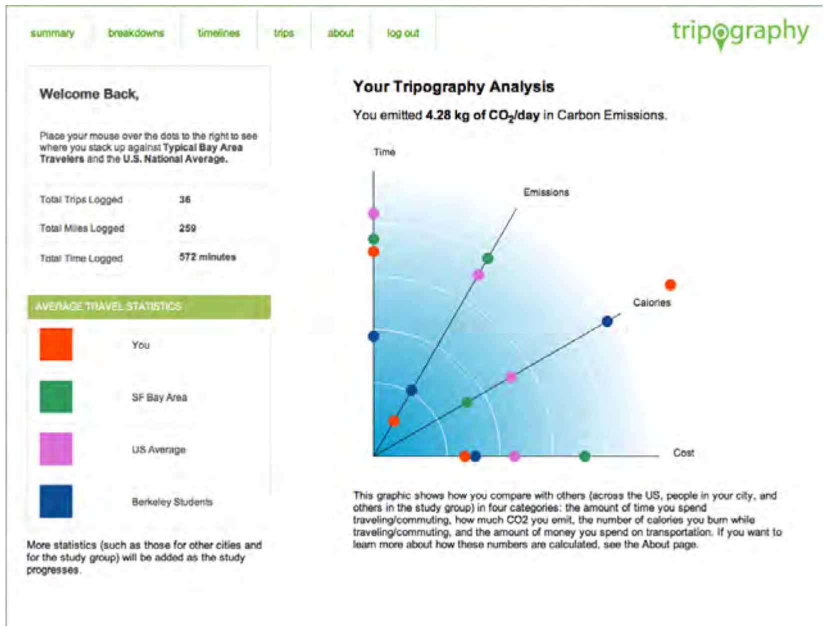

Figure 2: The summary page, which shows a person's travel stats and comparisons with peer groups.

3.1 Architecture and Data-flow

The design of the data collection and feedback system is shown in Figure 1. It consists of three components: the tracking application on smartphones, the server architecture to handle incoming location data and handle data requests, and the analytics software to transform the raw data into trips made and meaningful statistics and information about those trips. The applications running on the participants' phones collect raw sensor data and upload it to a cloud-based server which saves it to the database. A nightly job reads the raw data, processes them to infer trip origin, destination, start time, end time, route and travel mode[4]. Trips are further augmented with data such as addresses/neighborhoods of trips made, distance traveled, time spent traveling, CO_2 emitted, calories expended and travel costs. The methodology for computing the last three of these items is detailed in Table 1.

As described by Jariyasunant[4], the trip determination system consists of a smartphone application that runs on Android phones and iPhones, in a battery efficient manner. A person who travels 2 hours a day experiences on average 33 hours of typical usage (including texting, talking o the phone, browsing the web, and using apps). The application runs in the phones' background and periodically uploads location data to a server which runs a trip determination algorithms to generate trips and statistics to be shown on the website.

3.2 Website Design

Users of the data collection system are given access to a website on which they can view their individual travel behavior data in different ways. Specifically, the website consists of four pages, as shown in Figures 2 - 5. After logging onto the website, participants are first presented with a “summary”page, which presents an overview of their aggregate travel

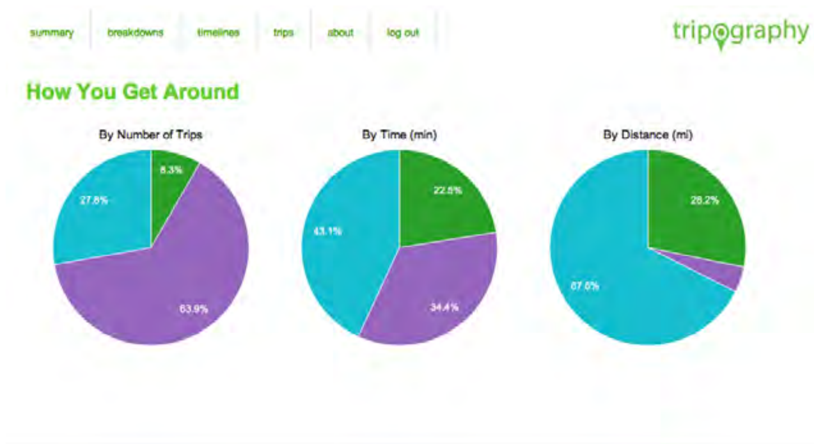

Figure 3: The breakdowns page, which shows mode split by trips made and distance traveled.

Figure 4: The timelines page, which shows a person's change in travel time/emissions/calories/cost over time.

data and a brief explanation. The main metrics which are shown to the user are emissions, calories burned, cost, and travel time, for their own data and a set of groups they can compare themselves to, the average America, the average resident of the San Francisco Bay Area, and the average of other people in the study. In this page, our goal was to deliver a summary of one's travel history such that a person could quickly glance at the page and immediately understand their data and trends. From there, users can access three pages: One that explains the scoring methodology, one with the detailed daily history of scores and one with the trip history (termed "Tripography"). The "Breakdown" and "Timelines" page provide more detail from the summary page and present the information in a different manner. The "Breakdowns" page focuses on describing a person by his mode split, while the "Timelines" page shows how a person's travel statistics change over various periods of time.

The "Trips" page shows a history of one's trips on a map by calendar day, and also allows users to correct the travel mode of any incorrectly predicted trips. Changes entered into

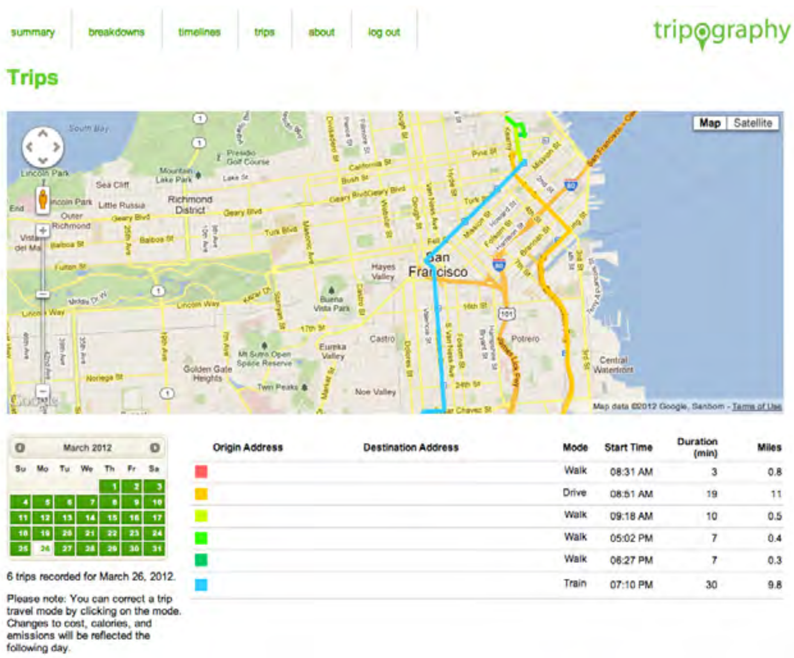

Figure 5: The trips page, which shows all trips for a calendar day on a map. The addresses are blanked out in this figure.

the system also update the travel statistics shown on the various feedback pages to give the most accurate view of the user's travel behavior data.

4 EVALUATION

To evaluate the effectiveness of the system, we designed and conducted an experiment in the San Francisco Bay area with 135 participants. The participants were recruited from the subject pool of the UC Berkeley XLab (the "Experimental Social Science Laboratory"), which is run by the Haas School of Business. This is a computer laboratory for conducting human-subject experiments. The lab maintains a subject pool of over 2500 members, all of whom are UC Berkeley affiliates and most are undergraduate students. Xlab administration handles the recruiting and requires that researchers provide subjects with participation fees of around $15/hour.

For recruitment, we reached out to both students and staff at UC Berkeley. In total, 111 students and 24 members of staff participated in the experiment, of which 37 were male and 98 female. All participants owned smartphones; 82 were iPhones and 53 Android phones. Of the 135 participants, 121 completed the two surveys that were given (see below). These surveys showed that 106 (94%) were between 17 and 29 years old. Of those 113 participants, 44 had access to an automobile, 17 regularly biked, 101 regularly used transit and 103 had a transit pass.

This three-week experiment ran from March 18 to April 7, 2012. We utilized the infrastructure described in Section 3 for collecting traveler data via smartphones, and the goals

Mode	CO_2	Calories	Costs
Walking	0	Used a calories calculator which adjusts calories burned by walking speed [26], assuming a 150lb person.	0
Biking	0	Same as above.	0
Driving	Used a CO_2 calculator for driving [27].	0	58.6 cents / mile [28].
Train	Averaged to 39g/mile [27].	0	Appropriate costs for taking BART or Caltrain as specified by the respective transit agencies.
Bus	Averaged to 25g/mile [27].	0	Same as above.

Table 1: Methodology for calculating trip footprint

of the experiment were twofold: first, it was intended to demonstrate how the Quantified Self movement can be leveraged by the travel demand modeling community for data collection, with a positive outcome for both sides. Second, as stated above, the experiment was designed to investigate whether a data collection effort that includes elements of traveler feedback and a direct engagement of subjects via a website can lead to a change in behavior toward more sustainable modes of transportation. If that proved to be possible, it would provide evidence of the viability of automated, web-based traveler feedback on a large scale for use as a policy tool to promote more sustainable transportation.

We chose to focus on studying the effect of feedback and peer influences on (1) attitudes towards sustainable travel and (2) awareness of the impacts of one's own travel behavior. The latter comprises both awareness of absolute values (e.g., amount of emissions) and an awareness of where the person stands compared to average Americans, San Francisco Bay Area residents and to their peer group, which in this case was the group of survey participants from the XLab. In addition, we were interested in using this experiment as a learning experience for the long-term research goal of using technology to persuade individuals to use more sustainable transportation modes.

4.1 Experimental Design

At the beginning of the study, the participants were asked to fill out a survey about their awareness of transportation impacts and their attitudes toward sustainable modes of transportation. This was followed by a three-week period in which the users were tracked. During the first week, participants received no feedback information until the seventh day, when they

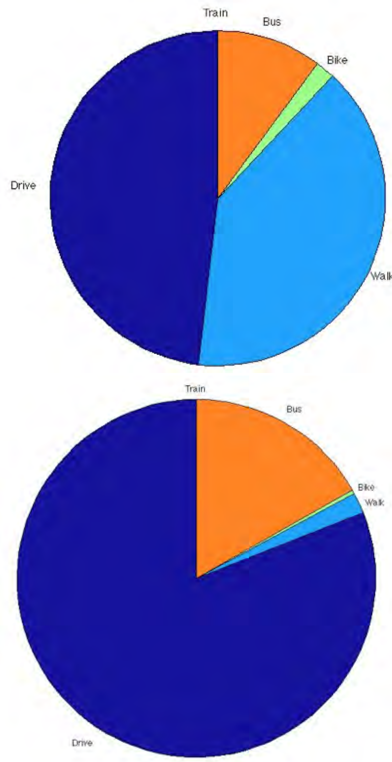

Figure 6: Mode Split of all trips recorded in 3-week period. Top: Mode Split measured by number of trips made. Bottom: Mode Split measured by distance traveled.

were sent a link to a website on which they could view their trip history and a set of personalized statistics (explained in section 3.2) related to their travel patterns. Following this, the students went on a spring break, in which trips were recorded, but the data shown in users' "summary" page did not reflect the trips during spring break. Users then received another email reminder to log into the site and view their data. On average, the participants logged in 4.1 times during the final week of the experiment. At the end of the three weeks, participants were asked to fill out a survey that contained the same questions as the first one, but with an added section asking them for feedback on the website. The following sections describe the components of the experiment in detail.

4.2 Recorded Activity

During the three-week study we recorded a total of 8607 trips and 115,169 miles of travel across 6 different modes: walking, biking, taking the bus, taking the train, and driving. Plane trips are included in the amount of miles logged but ignored in the calculation of trip statistics. The breakdown of the usage of modes is shown in Figure 6. As described in Section 3.2, study participants corrected their trips on the website if the system incorrectly predicted their travel mode. Out of the 8607 trips, 13.5% of trips were corrected.

4.3 Measuring Attitudes

The field study provided valuable information with respect to both of its goals. The surveys showed that there was a potential for increasing participants' awareness of their transportation carbon footprint via the personalized statistics, trends, and trips shown on the website.

4.3.1 *Survey Questions and Baseline Results*

The design of the survey was based on measuring factors contributing to behavior change as identified by the Integrated Behavior Model: Experiential attitudes, Instrumental attitudes, Injunctive Norms, Descriptive Norms, Perceived Control, Self-Efficacy, and Moral Obligation for public transit, biking, driving, and walking attitudes on a 7-point Likert scale. These questions were based on common travel surveys used by the transportation community[29], and categorized into the various components of the behavior model.

The survey consisted of 55 statements which participants agreed or disagreed with on a seven-point Likert Scale. 11 of these questions were asked about the participant's level of awareness of their own travel behavior. This included questions about their knowledge of the amount of CO2 emitted by their daily transportation habits, the number of calories burned by traveling, their amount of time spent traveling, and the amount of money they spent on transportation. Based on ideas from the theory of planned behavior, 3 questions were asked about participants' willingness to set goals to change travel behavior. Sample questions for these various categories of questions are listed in table 2. The baseline (pre-experiment) survey showed that participants responded positively to questions asking about their environmental sentiments (M = 4.73, SD = 1.73; on a scale from 1 to 7 where 7 corresponds to the strongest pro-environmental attitudes), but on average, they slightly disagreed with the statement that they engaged in more sustainable travel behavior than the average person at UC Berkeley (M = 3.22, SD = 1.40). Furthermore, participants responded positively to statements about health, exercise and the possibility of burning calories while traveling (M = 5.09, SD = 1.45). The results of the survey also showed that the participants were not very aware of how "green" they actually were (M = 4.41, SD = 1.69; 1 corresponding to completely unaware, 7 corresponding to very aware). In particular, the participants didn't know the amount of CO_2 they emitted, the amount of CO_2 emitted by the average person in San Francisco, nor the magnitude of the impact of their emissions. This showed that there was an opportunity for education on the environmental effects of using different transportation modes, and that this was a group that was generally motivated to engage in sustainable behavior.

Due to the heterogeneous nature of the participant pool (students and staff), we further decomposed the group by their self-reported planned mode use during the months following the experiment. Specifically, we created the following three groups, based on their planned auto use:

- People who were planning to use a car once a month or less (including never): Non-drivers (55 observations)
- People planning to use a car between once a month and once a week: Multimodal travelers (29 observations)

Category	Sample Question
Awareness	I know how much CO_2 I emit from my daily transportation.
Self-Efficacy	I can get exercise when traveling.
Perceived Norms	My friends actually engage in sustainable transportation behavior (carpooling/biking/walking/taking public transit)
Setting Goals	I would consider setting a goal to reduce my carbon footprint.
Attitudes on Sustainable Behavior	I value the benefits to society when I take sustainable modes of transportation.

Table 2: Sample questions given to participants at the beginning and end of the study

- People planning to use a car more than once a week: Drivers (29 observations)

We found that in terms of their attitudes toward environmental and health issues, there was no significant difference between the three groups.

A last set of questions was related to people's intention to change their transportation behavior in the future. On average, the study participants slightly disagreed with statements suggesting that they were going to change (M = 3.83, SD = 1.44), and there was no noticeable difference between the three mode use groups.

4.4 An increase in awareness, changes in intention, but not in pro-sustainability attitudes

We were able to measure statistically significant changes in participants' awareness of environmental, health, financial and time impacts of travel as well as their attitudes towards sustainable travel behavior. The questions in the survey were divided into 6 categories: awareness, perceived norms, goal-setting, attitudes towards sustainable behavior and towards health benefits of sustainable transportation modes. A paired t-test was run to compare the pre- and post-experiment results for each individual question. In addition, the questions were grouped together to create composite scores for the five categories. A Hotelling's T-Squared test for two multivariate independent samples with unequal covariance matrices was carried out to compare composite scores for the five categories between the pre- and post-experiment survey. The different questions in each of the categories correspond to different variables that are correlated and the T-squared test is used to see if there is a significant difference in these categories.

Example statements which showed a statistically significant ($p < 0.001$) increase in awareness of the amount of CO_2 emitted were: "I know how much CO_2 I emit from transportation" and "I know how much CO_2 the average person in my city emits from transportation". While all awareness questions (environmental, health, financial and time) showed an improvement of awareness over the study period, the change was the strongest with respect to the environmental footprint. On the other hand, even though we detected a positive shift in some

		Pre-survey		Post-survey			
Participant type	Mode	M	SD	M	SD	t stat	p-val
Drivers	Driving	4.76	1.4	3.86	1.55	5.31	0.02
	Walking	3.86	0.87	4.79	1.56	7.8	0.01
Non-drivers	Driving	3.8	1.35	3.96	1.36	0.4	0.53
	Walking	4.45	1.03	4.75	1.43	1.49	0.22
Multimodal	Driving	4.31	0.96	4.34	1.07	0.02	0.89
	Walking	4.68	1.13	4.48	1.15	0.47	0.49

Table 3: Answers to question on future mode use

of the attitude questions related to sustainable travel behavior, the overall shift in this category was statistically insignificant. An example statement (with a p-value of 0.19) was: "We should raise the price of gasoline to reduce congestion and air pollution." There was also no significant difference between the three mode use groups.

Finally, a set of questions was asked regarding people's intention to change their travel behavior in the future towards using more sustainable transportation modes. A example statement was: "I am certain that I am going to change my transportation behavior for the benefit of the environment". Overall, the average answer for this group of questions was "neither agree nor disagree", and it did not change significantly during the experiment ($p = 0.46$). However, in a related question, people were asked to indicate whether they were planning to increase or decrease their use of certain modes in the future. It was interesting to find that even though people did not state explicitly they had an intention to change, the planned mode use of drivers revealed significant shifts. Specifically, after the experiment, drivers reported that they were planning to walk more and drive less compared to what they had answered before the experiment. The exact question was "Over the next few months, and compared to what you do now, how often do you intend to use the following modes of transportation for commuting/traveling?", and the possible answers, on a scale from 1 to 7, ranged from "much less than now" to "much more than now". Answers are shown in table 3. Planned use of other modes (carsharing, biking, transit) did not change. Multimodal participants and non-drivers on the other hand did not state mode use plans after the experiment that were significantly different from those before the experiment.

While this does not mean that people were averse to change, it appears that they were unsure about how they might change in the near future, and the feedback provided during the survey did not have a statistically significant influence on that.

4.5 Classification of participants

We suspected that participants viewing their stats on the website would be influenced by whether they were above or below the average of their peer group on the four dimensions plotted (emissions, calories, money and time), and by how far from the mean they were. This led us to conduct an analysis of how the participants in our study compared to the mean of their group. Given 16 possible combinations (above or below the mean on each of the four dimensions), the study participants can technically be divided into 16 groups. However,

Group	Observations	Time	Calories burned	Emissions	Costs
1	15	+	-	+	+
2	7	+	+	+	+
3	26	-	-	-	-
4	5	+	-	-	-
5	5	+	+	-	-
6	2	-	-	+	+
7	30	-	+	-	-

Table 4: Mobility styles among the study participants; "+" = above mean, "-" = below mean.

	First week		Last week		
Mode share	M	SD	M	SD	p-val
Drive	0.63	0.35	0.55	0.36	0.08
Walk	0.19	0.26	0.27	0.29	0.03
Bike	0.03	0.10	0.03	0.08	0.99
Bus	0.14	0.23	0.14	0.21	0.83
Train	0.01	0.01	0.01	0.04	0.15

Table 5: Mode split by distance traveled, showing the significant shift from driving to walking

we found that in our population, only 7 groups were represented, and of those, only 4 were larger than 5 people. This is shown in table 4; a "+" means that the participant was above the mean in that category, whereas a "-" is below the mean.

Which group a person falls into is related to that person's travel-related lifestyle, which we shall call mobility style. Groups 1 is worst on all four dimensions and likely represents habitual drivers. People in group 2 are quite similar to group 1, except that they burn more calories. It is likely that these are high-mileage travelers. The opposite is group 3, which is consistently below the average on all four dimensions and presumably includes low-mileage travelers, which is plausible since many participants live near campus and only travel minimally. Groups 4 and 5 might be multimodal travelers who combine transit with walking and biking, while group 6 is too small to meaningfully interpret. Finally, group 7, which is the largest group, is best on all four dimensions. This group is likely characterized by very green travel behavior, predominantly walking and biking.

4.6 Measured behavior change

Interestingly, our analyses of participants' travel behavior showed a shift in mode usage. Table 5 shows the mode split by distance traveled for the first and last survey weeks. Most importantly, we observed a significant decrease in driving and a significant increase in walking. In other words, a number of trips were shifted in the direction of lower emissions, higher calories, and lower costs. Regarding the shares of other modes, there was no significant change in the use of bikes and buses, and there was a slight, though not significant, increase in train rides (not visible in the table due to rounding).

In order to gain a better understanding of the potential influences of the feedback provided on the website, we built several linear regression models. The individuals' distance from the mean, averaged over all four dimensions, were regressed on either the participants' changes in time, emissions, costs and calories burned between the first and the last survey week or on the log-odds ratio of walking as the dependent variables. Every group described in section 4.5 was represented by an explanatory variable. Additional variables were binary variables indicating whether somebody was female and a student, as well as the number of logins to the website by that person. The goal of the regression model was to understand whether the different groups reacted differently to the presentation of the feedback, and which ones were most likely to shift their behavior. Unfortunately, the regression analysis was complicated by the strong correlation between the four feedback dimensions, and even though we had observed a significant shift from driving to walking at the aggregate level, we were not able to find statistically significant covariates explaining what types of people and travelers were more likely to shift.

4.7 Feedback about the website

To evaluate the website, the post-experiment survey contained an additional set of questions regarding the participants' evaluation of the website. They were asked to login to the website and respond to the following four statements on a 7-point Likert scale about the website.

1. I enjoyed taking a look at my dashboard/statistics/trip history page and getting a summary of my travel (M = 5.37, SD = 1.2)

2. In the future, this web page is something I would consider using. (M = 5.87, SD = 1.01)

3. If I were to set a goal to change my travel behavior (be greener, reduce cost, travel less), I consider this web page helpful. (M = 5.12, SD = 1.28)

4. This web page was easy to use. (M = 5.3, SD = 1.13)

Overall there was positive feedback on the website and the subjects liked the presentation of their trip data. In particular, they reported that they enjoyed seeing their transportation data and enjoyed seeing how they compared with their peers. Users were also asked which webpage they liked the most, and there was a strong preference for the summary and trips page: Summary: 38.46% Breakdown: 15.38% Timeline:6.84% Trips: 39.32%. On average many of them reported that they would consider using the webpage in the future and felt that it would help setting a goal to change their travel behavior.

5 CONCLUSIONS AND FUTURE WORK

This paper showed the reasoning behind the designs of an automated smartphone travel diary system and the subsequent experiment showed how feedback on one's travel history can affect one's awareness of their impact on the environment, and for some segments of the population, intentions to change behavior, and actual behavior change. In addition, we were able to show that an automated travel diary system using smartphones along with a web interface to view trips could successfully collect data from 135 participants and process location data into trips, which was used to both influence behaviors, intentions, and awareness and build a travel behavior model.

The next step is expanding the study from 3 weeks to a longer duration. A number of other variables may have contributed to the measured changes in behavior, such as the participants' mindfulness of being tracked and taking part in a study, or even a novelty effect of using a new application. The measured change in behavior is a step in the right direction, and the real test of a behavior change system is prolonged and maintained changes in travel mode usage over a much longer study period.

The experiment we ran used two behavior change strategies of feedback and comparison. This was an initial attempt into the concept of using technology to influence users' transportation behavior, and there exists a large number of other behavior change techniques which have been successfully applied in other fields that could have been experimentally incorporated in our system. Behavior change techniques which have been recognized and tested include: Information, Goal-Setting, Comparison, Incentives, and Feedback [30]. All of these techniques have been tested in a variety of fields and largely confirmed to have positive effects for behavior change. The next step involves analyzing successful experiments which have used one of these techniques and molding it to our problem of nudging people towards sustainable modes of transportation.

6 ACKNOWLEDGEMENTS

This research has been supported by grants from University of California Transportation Center (UCTC) and the National Science Foundation (NSF). Many thanks to Justin Martinez and Peter Nguyen for their work developing the website, and to Thejo Kote, Ram Jayaraman, and David Palmer for their contributions to the development of the mobile applications and server infrastructure.

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