University of California Transportation Center
UCTC-FR-2013-06

Quantified Traveler:
Travel Feedback Meets the Cloud to Change Behavior

Jerald Jariyasunant, University of California, Berkeley;
Maya Abou-Zeid, American University of Beirut;
Andre Carrel, Venkatesan Ekambaram, David Gaker, Raja Sengupta, and
Joan L. Walker, University of California, Berkeley
September 2013
Note: this paper supercedes UCTC-FR-2012-12, The Quantified Traveler: Changing transport behavior with personalized travel data feedback

Quantified Traveler:
Travel Feedback Meets the Cloud
to Change Behavior

Revised August, 2013

Jerald Jariyasunant[1], Maya Abou-Zeid[2], Andre Carrel[1], Venkatesan Ekambaram[3], David Gaker[1], Raja Sengupta[*,1], Joan L. Walker[*,4]

* Corresponding Authors (rajasengupta@berkeley.edu, joanwalker@berkeley.edu)

[1] Department of Civil and Environmental Engineering, University of California, Berkeley
[2] Department of Civil and Environmental Engineering, American University of Beirut
[3] Department of Electrical Engineering and Computer Science, University of California, Berkeley
[4] Department of Civil and Environmental Engineering and Center for Global Metropolitan Studies, University of California, Berkeley

Abstract

We describe the design and evaluation of a system named Quantified Traveler (QT). QT is a *Computational Travel Feedback System*. Travel Feedback is an established programmatic method whereby travelers record travel in diaries, and meet with a counselor who guides her to alternate mode or trip decisions that are more sustainable or otherwise beneficial to society, while still meeting the subject's mobility needs. QT is a computation surrogate for the counselor. Since counselor costs can limit the size of travel feedback programs, a system such as QT at the low costs of cloud computing, could dramatically increase scale, and thereby sustainable travel. QT uses an app on the phone to collect travel data, a server in the cloud to process it into travel diaries and then a personalized carbon, exercise, time, and cost footprint. The subject is able to see all of this information on the web. We evaluate with 135 subjects to learn if subjects let us use their personal phones and data-plans to build travel diaries, whether they actually use the website to look at their travel information, whether the design creates pro-environmental shifts in psychological variables measured by entry and exit surveys, and finally whether the revealed travel behavior records reduced driving. Before and after statistical analysis and the results from a structural equation model suggest that the results are a qualified success.

1. INTRODUCTION

This paper describes the development, application, and analysis of a system, in the mobile cloud, named Quantified Traveler (QT). QT is a *Computational Travel Feedback System*. Travel Feedback is an established programmatic method to change traveler mode choice or trip choice. In a typical travel feedback program, a traveler meets with a counselor who helps her to alternative mode or trip choices that ease loads on the transportation system while satisfying her mobility needs. This research explores whether the successes of travel feedback programs can be replicated without the travel counselor. Our surrogate is a computational system in the mobile cloud. Subjects stream location and movement data into the cloud via personal smartphones. Data Analytics on our server transform the raw data into trip diaries (lists of trips with timing, activity locations, route and mode) and personalized travel footprints, meaning the time, money, calories, and CO2 spent traveling. The end product of the analytics is piped into a set of visualization tools executed on a webpage. The subject uses her browser to view the data in various ways, including making social comparisons. Travel feedback programs have a record of success (see section 2). The counselor is an important component of program costs. If a computational surrogate were to persuade like a counselor, travel feedback programs would become deployable at big data scales. This is the motivation for this research.

The research contributions are

1 How to build a computational travel feedback system including visualization tools, footprint calculators, the signal processing and machine learning algorithms required to transform GPS, WiFi, accelerometer, and cell tower data into travel diaries (Section 3),

2 A 3-week, 135-subject evaluation producing 21-day automated travel diaries, an entry and exit survey measuring psychological variables, and a statistical analysis of the diaries recording significant pro-environmental shifts in psychological variables and a significant reduction in driving (Section 4),

3 A structural equation model validating consistency of the behavior change with the causal relationships posited by the Theory of Planned Behavior and quantifying the impact of the feedback (Section 5).

Travelers make trip choices, mode choices, route choices, and departure time choices. Information services are known to have an impact on route and departure time choice (see for example [1]). However, these services, such as maps or real-time traffic information, have no comparable impact on mode or trip choice. These choices seem to be rooted in lifestyle or activity choices [2], making them psychologically more complex, fundamental, and harder to change. Travel Feedback Programs [3] and Personalized Travel Planning [4] are the singular counterpoints. In many cases, they successfully change mode or trip choice by information alone, albeit through person-to-person dialog, instead of a Google maps style automated information system. QT is a new kind of information system targeting the mode and trip decision. It applies signal processing and machine learning to big data in order to replicate some of the behavior change psychology used by counselors, specifically the Theory of Planned Behavior [5]), in an information system.

Without counselor or direct subject-to-subject interaction, QT attempts to reproduce the post-treatment mileage reductions in driving observed in these studies. A researcher sends an email with instructions to recruited subjects, and thereafter the system is completely automated. Thus, it enjoys lower costs and potential economies of scale in comparison to the classical travel feedback studies. Quantified Traveler's disadvantage of course, is also the absence of human interaction, leading to the scientific challenge or research objective. We know people can persuade people to change behavior. Can computational systems persuade people? This paper suggests the answer is a qualified yes and therefore worthy of further work on both design and evaluation.

The remainder of this paper is organized as follows. Section 2 reviews main lessons from prior behavior change work including examples of behavior change trials in transportation, the use of technology driven applications, and behavior change models, and places the current study and its contributions in context. Section 3 presents the design of the Quantified Traveler system including the overall architecture and the website interface for providing feedback. Section 4 presents a descriptive analysis of the experiment, and Section 5 presents the structural equation model of behavior change. Section 6 concludes with a summary of the main findings and a discussion of the limitations and extensions of the study.

2. THE LITERATURE

QT aims to collect information about travel and feed it back to the traveler to change mode or trip choice behavior. We find three relevant bodies of literature. First, travel feedback programs have the same aim as QT; they provide a measure of how much change might be possible, and a range of design ideas. Second, there are now computational feedback systems built to encourage healthy or pro-environmental behaviors. Some have clever techniques reaching the mind of the subject. Finally, all of this social engineering rests on deeper theory in psychology, and here we review the theory underpinning QT.

Travel Feedback Programs aim to influence mode or trip choice behavior with information and psychological factors. There are various styles of Travel Feedback Programs, but common to all programs are: subjects receive feedforward information (i.e. directions for using alternative modes) as well as feedback information (e.g.. environmental impact such as the amount of CO_2 emitted, the amount of exercise while traveling or the public health benefits) and fill out travel diaries. Researchers in Japan have conducted many such programs [6]. Travelers recorded travel in diaries using paper and pen. They were often given feedback during face-to-face contact with a "travel coach". The results show measurable shifts away from automobile use and toward more sustainable modes of transportation. Taniguchi et al. [3] have documented 31 such studies in Japan with post-treatment reductions in the miles driven ranging between 6 and 27% in 23 of the studies. The largest of these involved 1500 subjects. Individualized marketing has also succeeded in changing travel behavior towards more pro-environmental modes of transportation. Rose and Ampt [7] document two studies in Sydney with 47 people and another in Adelaide with 96 households. The post-treatment driving mileage reductions are similar. Cairns et al. [4] report 5% reductions in post-treatment driving mileage due to Personalized Travel Planning treatments tried in the United Kingdom. Thus, we conclude that people can persuade people. The computational travel feedback research objective is to learn if computational systems can persuade people. QT could also be used by a travel feedback counselor to replace just the pen and paper diary.

Travel feedback programs use counselors but computational systems have been built for other kinds of behavior change. 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 that have incorporated self-tracking and behavior change into their products: Zeo -tracks sleep patterns (www.myzeo.com/sleep), Fitbit -fitness levels (www.fitbit.com), RunKeeper -jogs and runs (www.runkeeper.com), CureTogether -reactions to various medication (www.curetogether.com), Mint -personal finance (www.mint.com), RescueTime -time usage and productivity (www.rescuetime.com). Like QT, all of these record behavior and feed it back to the user. This industry, with products enabling people to collect data on their activity and adapt their behavior more intelligently than they would without these augmentations, calls itself the Quantified Self (see http://quantifiedself.com/).

Two very active fields in which HCI researchers have developed self-tracking applications using Smartphones and demonstrated their effectiveness as a behavior change technique are Health/Fitness [8, 9, 10, 11, 12] and Energy Conservation/Eco-Feedback Technology [13, 14, 15, 16]. Health and fitness researchers have embedded goal-setting and feedback in apps and websites that help people maintain healthy lifestyles. One of the most notable applications was Ubifit [17], which automatically detected the physical activity levels of a subject wearing a custom device and also provided feedback to subjects. 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 subject could understand their data at a glance. A notable application in the area of eco-feedback technology, and one developed to influence transportation behaviors, is Ubigreen [15]. It involves the display of visual icons on a smartphone that reflect the effect of one's travel behavior on the environment. It was found that the visual feedback increased awareness and consideration of the effects of travel on the environment. The study also showed some potential for behavior change to sustainable modes of transportation. We take a step forward by providing more quantitative feedback such as carbon footprint numbers, enabling social comparisons on these numbers, and directly measuring the real travel in our evaluation.

The QT design is based on the Theory of Planned Behavior (TPB) [18; referenced in the context of sustainable behavior change in 19]. The TPB postulates that intention is the immediate antecedent of behavior, and is influenced by attitude, subjective norm, and perceived behavioral control. 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 [20, 21, 22]. QT focused particularly on changing awareness to change behavior. Bamberg et al. [22] found evidence that awareness of environmental problems associated with car use affects attitudes, perceived behavioral control, and subjective norms (related to expectations of others) related to pro-environmental transportation behavior. And Nordlund and Garvill [23] found that problem awareness related to the environmental consequences of car use influence personal norm (as moral obligation) towards reducing car use. Our data strongly exhibits the correlation between awareness and behavior change. We do find a weakly significant correlation between awareness and attitude. We do not find the correlations observed by Bamberg, or Nordlund and Garvill.

While various studies have modeled travel behavior based on the TPB or a variant of it (e.g. including only attitude or other psychological constructs) using path analysis or discrete choice models (e.g. [24, 25, 26, 27, 28, 29]), most of these studies have relied on either stated preferences surveys or on revealed behavior measured at one point in time, and feedback mechanisms and social comparison processes are not generally represented in these models. Beyond the contributions related to the overall QT system and experiment, a modeling contribution of this work is to model behavior change in a revealed travel experimental context, i.e., by using an app on a smartphone to log travel continuously for 3 weeks, and using the logs for a feedback treatment mechanism.

3. THE QUANTIFIED TRAVELER SYSTEM

QT has the architecture in Figure 1. Each subject is required to carry a smartphone with a QT app installed. GPS, accelerometer, WiFi, and cell tower data from the smartphone flows into a server in the cloud. There, machine learning and signal processing algorithms in the cloud process the data into travel diaries. Each subject has an account on the server and can pull up a daily diary like the one in Figure 5, by clicking a date using the calendar panel on the left. The page shows all trips for the day. A trip is an origin address, destination address, start time, end time, route, distance, and mode. Mode options include car, walk, bike, bus, light rail, and heavy rail. The subject can correct mode and the system learns from the correction and the data. Third party services in the backend include Google Maps for route and travel time matching, and GTFS for bus and rail route matching. Jariyasunant et al. [33, 34] discuss this diary component of QT, contributing to the literature on smartphone and GPS logger based travel diary systems. Here, we focus our description on the human or behavioral components of QT.

The raw trip information is augmented in a number of ways in order to provide meaningful feedback to the subjects. For each trip, the addresses of the trip origins and destinations, distance traveled, and time spent traveling are generated. Furthermore, based on the mode of the trip, the amount of CO_2 emitted during a trip, the calories expended during a trip and the approximate costs of a trip are calculated by multiplying the distance traveled with mode-specific factors for emissions, calories burned and average costs. The factors and references used for these calculations are shown in Table 1.

This information is provided to each subject on a website, which provides a number of ways of viewing the travel data. The QT user feedback design targets awareness as a first step to behavior change. The design also embodies social comparisons, which are theorized to cause changes in attitude, leading in turn to behavior change. Specifically, the website consists of four pages, as shown in Figures 2 -5. The subject first sees the "summary" page in Figure 2, which presents an overview of her aggregate travel data and a brief explanation. The main statistics on the summary page are the average daily emissions (kg of CO2), calories burned, cost ($), and travel time (minutes). The spider plot shows the statistic for the subject in relation to average statistics from groups she can compare herself to: the average American, the average resident of the San Francisco Bay Area, and the average of other subjects in the study. In this page, our goals are to deliver an aggregate summary of one's travel such that the subject can quickly glance at the page and understand her travel behavior within the context of a social reference point and also to understand that her travel expends the four resources (time, money, emissions, calories). From there, she can access three pages. The “Breakdown” (Figure 3) and “Timelines” (Figure 4) pages provide further details on the statistics presented in the summary page. The “Breakdowns” page focuses on describing the subject by her average mode split, while the “Timelines” page shows how the subject’s daily average travel statistics vary day by day. The trips page, termed “Tripography” (Figure 5) allows the subject to peruse the trips logged by the system as described earlier.

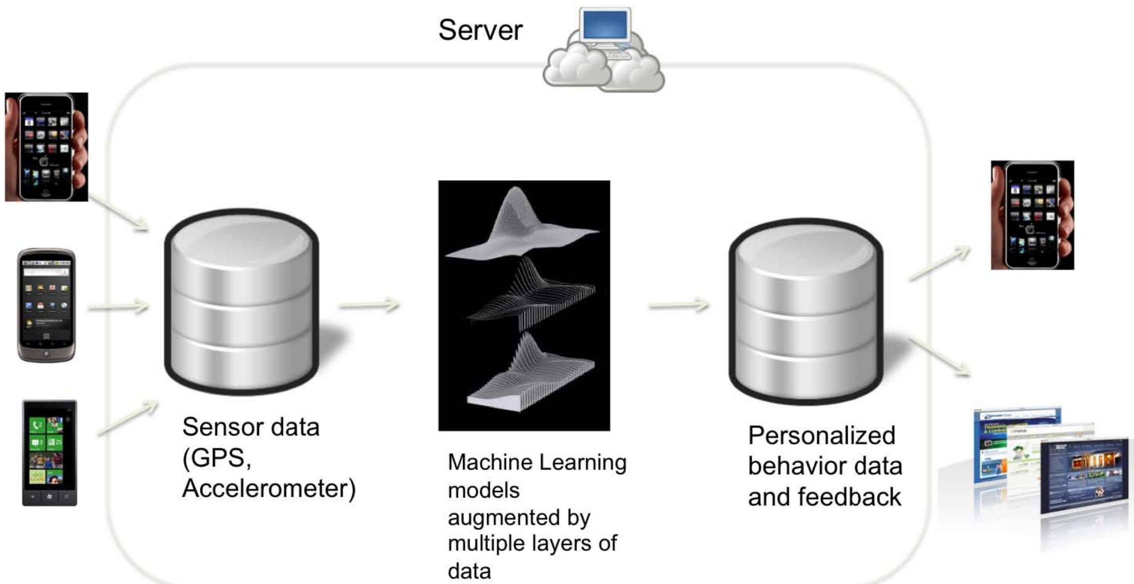

Figure 1: System architecture diagram

Table 1: Methodology for calculating trip footprint

Mode	CO_2	Calories	Costs
Walking	0	Used a calories calculator which adjusts calories burned by walking speed [30], assuming a 150-lb person.	0
Biking	0	Same as above.	0
Driving	Used a CO_2 calculator for driving [31].	0	58.6 cents/mile [32].
Train	Averaged to 39g/mile [31].	0	Appropriate costs for taking BART or Caltrain as specified by the respective transit agencies.
Bus	Averaged to 25g/mile [31].	0	Same as above.

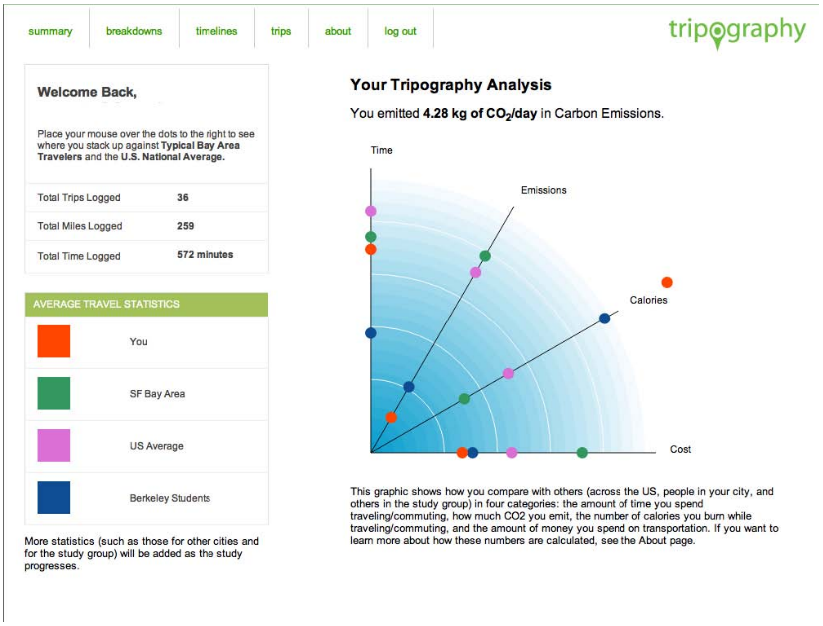

Figure 2: The summary page

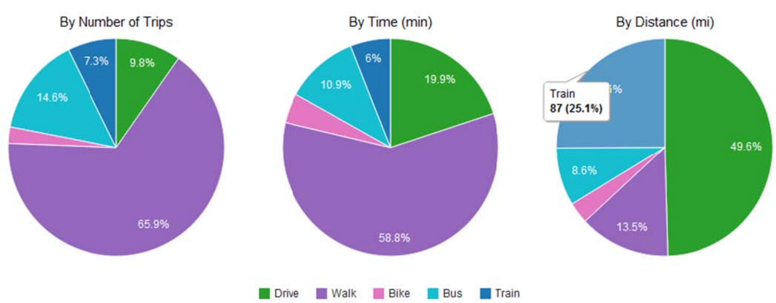

Figure 3: The breakdowns page

Figure 4: The timelines page

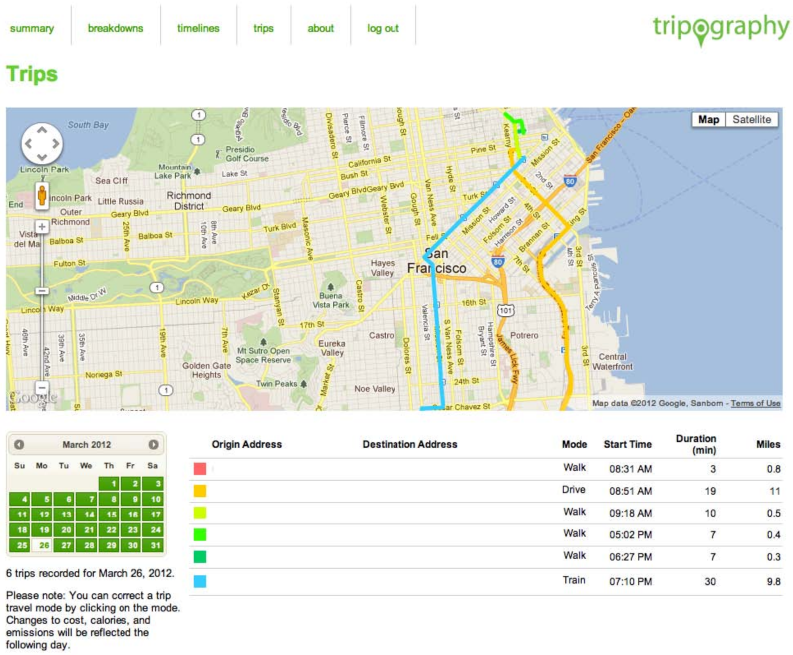

Figure 5: The trips page (addresses are blanked out in this figure)

4. EVALUATION

To evaluate the effectiveness of the system, we designed and conducted an experiment in the San Francisco Bay area with 135 subjects. The subjects 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. The XLab maintains a computer laboratory for conducting human-subject experiments and a subject pool of over 2500 members, all of whom are UC Berkeley affiliates and most are undergraduate students. Xlab staff handles the recruiting and requires that subjects receive a participation fee. We paid $15 for 1 hour of subject time, which we estimated as the time required to install the QT App, fill our the entry/exit surveys, and view the QT website. Our evaluation goals of were to understand:

- if low-battery consumption, long-term data collection can be used to collect travel diaries.
- whether the provision of personalized traveler feedback and a direct engagement of subjects via a website can change subjects' awareness of the impacts of their transportation choices, their attitudes toward sustainable modes of transportation, and their travel behavior.

We evaluate the effectiveness of the computational feedback program by measures of usability and usefulness (whether people kept the app running, whether they visited the website, and responses to survey questions on usefulness), behavior change at the aggregate level (of both travel captured by app and psychological responses from the surveys), and a structural equation model of behavior change at the disaggregate level to investigate the causal factors of behavior change.

In this section we report on the details of the experiment and all results with the exception of the structural equation model, which is presented in the next section.

4.1 Description of the Experiment

The three-week experiment ran from March 18 to April 7, 2012. We utilized the infrastructure described in Section 3 for collecting travel data via the subjects' smartphones and combined this with a pre-and post-experiment survey. The pre-experiment survey contained questions about subjects' awareness of the impacts of their transportation choices, their attitudes toward sustainable modes of transportation, and other psychological variables. This was followed by a three-week period in which the subjects were tracked. During the first week, subjects received no feedback information until the seventh day, when they were sent a link to a website on which they could view their trip history and a set of personalized statistics related to their travel patterns (explained in section 3). Following this, the students went on a spring break; however, the trips recorded during spring break (including the weekend leading into spring break and the weekend at the end of spring break) were not used in the personal travel feedback system to avoid atypical travel patterns during spring break. We also took this into account in our data cleaning process and removed observations that appeared to either leave early (Friday or earlier) for or return late (Monday or later) from spring break. After the break, subjects received another email reminder to log into the site and view their data. At the end of the three weeks, subjects were asked to fill out the post-experiment survey that contained the same questions as the pre-experiment version, but with additional questions asking them for feedback on the website.

4.1.1 Survey Design

The survey was designed to measure factors that contribute to behavior change. The questions are formulated based on the Theory of Planned Behavior and on travel surveys used by the transportation community [35, 36, 37, 38]. Statements were presented to subjects, including questions on awareness, self-efficacy and goal setting, norms, attitudes, perceived behavioral control, and intention (see Table 2). Respondents answered on seven-point Likert Scales between disagreement and agreement. The awareness questions were related to the subjects' level of knowledge of the impacts of their own travel behavior, such as the amount of CO_2 emitted by their daily transportation habits, the number of calories burned while traveling, the amount of time spent traveling and the amount of money spent on transportation. In the questions regarding norms, respondents were asked how they perceived the behavior and attitudes of their friends and family with respect to sustainable transportation. The questions on attitudes involved statements about the role and benefits of sustainable transportation and the value of reducing CO_2 emissions caused by transportation. Perceived control and self-efficacy were measured through subjects' willingness and perceived ability to set goals to change travel behavior, as well as their willingness to use sustainable transportation modes as a means of burning calories. In addition we asked a set of intention questions regarding their intended mode use both in absolute terms and relative to current use.

4.2 Data pre-processing

135 people participated in the experiment. 118 answered both the pre- and post-survey. The dataset was further cleaned beyond these 118 by removing observations where (i)

trips reported in the pre-treatment or post-treatment weeks were not associated with a transportation mode (that is, not inferred by the computational system and not entered by the subject), (ii) large unrealistic differences in the average daily distance traveled in the pre-treatment vs. post-treatment weeks were found (on the order of 50 km/day or more), (iii) a very small number of trips (less than 5) were logged in the pre-treatment or post-treatment weeks, (iv) subjects left early for or returned late from spring break, or (v) the travel time or cost per day was inconsistent with the recorded distance. The cleaned dataset consists of 78 observations, which are used for the data analysis regarding behavior change.

4.3 Demographics and basic summary statistics

Of the 135 total subjects, 82% were students and 18% staff and 27% were male and 73% female. All subjects owned smartphones; 61% were iPhones and 39% Android phones. 118 subjects completed both the pre- and post-surveys. Of these 118, 94% were between 17 and 29 years old, 39% drove at least once per week, 14% biked at least once per week, 87% used transit at least once per week and 91% had a transit pass (note the students can receive a free bus pass). After data cleaning and the removal of outliers (as described in section 4.2), we had 78 complete and clean responses. For these 78 subjects, a total of 4143 trips using 5 different modes (walking, biking, taking the bus, taking the train, and driving) were logged, covering 20,160 km of travel or an average of 258 kilometers per subject.

4.4 Usability and usefulness of the system

We collected a number of data points regarding the usability and usefulness of the system. While some of the subjects did not fill out the requested pre- and/or post-survey, travel data were collected for a duration of 3 weeks for all 135 subjects. No subject stopped or uninstalled the application due to battery drainage or other inconvenience. In this sense, the evaluation showed QT able to collect long-term data from subjects. We expended considerable effort in optimizing the energy consumption-data accuracy trade-off to achieve this objective, because users top using the average application quickly. According to Pinch Media, long-term users are generally only 1% of total downloads[1]. The accuracy of QT's long-term travel diaries is described in [33] and [34].

The subjects used and interacted with the website, logging in on average 4.1 times during the final week of the experiment to view their travel data. As described in Section 3, study subjects were able to correct the mode for any trip if the system incorrectly inferred it; overall, 13.5% of trips were corrected by the subjects and this rate stayed approximately constant across the first and the final week suggesting that there was not a significant lapse of engagement.

The post-experiment survey contained an additional set of questions regarding the subjects' evaluation of the website. The questions asked (all on a 7 point Likert scale with 1 disagree and 7 agree) and a summery of the responses are as follows:

[1] http://www.techcrunch.com/2009/02/19/pinch-media-data-shows-the-average-shelf-life-of-an-iphone-app-is-less-than-30-days

- I enjoyed taking a look at my dashboard/statistics/trip history page and getting a summary of my travel — Mean = 5.4, Std Dev = 1.2
- In the future, this web page is something I would consider using. — Mean = 5.9, Std Dev = 1.0
- If I were to set a goal to change my travel behavior (be greener, reduce cost, travel less), I consider this web page helpful. — Mean = 5.1, Std Dev = 1.3
- This web page was easy to use. — Mean = 5.3, Std Dev = 1.1

On average there was positive feedback on the website and the subjects liked the presentation of their trip data. Subjects were also asked which webpage they liked the most, and there was a strong preference for the summary and travel diary pages: 39% most liked the travel diary pages (Figure 5), 38% most liked the summary page (Figure 2), 15% most liked the breakdown page (Figure 3), and 7% most liked the timeline page (Figure 4).

4.5 Survey results on psychological variables

The survey results on the psychological variables are summarized in Table 2. The numbers are derived from the answers to the Likert-scale questions on a scale from 1 to 7. For all the questions except some related to intention (at the bottom of Table 2), 1 indicated "strongly disagree" and 7 indicated "strongly agree" with 4 indicating a neutral response (neither agree nor disagree). The intention questions regarding absolute use by mode were on a scale from 1 "Never" to 7 "4 or more times per week", and the relative use by mode was on a scale from 1 "Much less than now" to 7 "Much more than now". The average and standard deviation of the survey responses are reported for both the pre-experiment survey and the post-experiment survey. The differences between the pre- and post- means are also reported along with a p-value testing the null hypothesis that the pre- and post- responses are the same. An asterisk denotes a significant change between pre- and post- (** at 95% confidence and * at 90% confidence). The final column highlights whether any significant change is in the direction of more sustainable behavior (denoted with a "+") or less sustainable behavior (denoted with a "-"), and the survey questions are sorted on this column within each category. The sample size for all statistics is N = 78 (our cleaned dataset).

To get a general sense of the sample, we examine the baseline (pre-experiment) survey. There was a lot of variation in responses and here we simply focus on the mean response for each Likert question, focusing on average responses that leaned toward the lower end of the scale (average less than 3.5) or leaned toward the upper end of the scale (average greater than 4.5). The subjects, on average, had mixed responses to attitudinal questions regarding the environment. On the one hand, they responded positively to questions related to their personal travel such as setting a goal to reduce their carbon footprint (Q39), being willing to pay more for clean vehicles to improve air quality (Q32), and valuing the benefits to society when they use sustainable modes (Q34). They also responded positively to some societal level questions such as everybody together should change their travel to reduce fuel use (Q23). And they responded positively to science questions, generally agreeing that vehicles that burn fossil fuels emit greenhouse gases (Q24) and greenhouse gases cause environmental problems (Q22). However, they responded more negatively (in terms of sustainable orientation) in that they don't feel

Table 2: Psychological and intention survey questions and summary of responses

Category	Q#	Question	Average Likert Response: Pre	Average Likert Response: Post	Comparison: Difference	Comparison: p-value	Change vis-à-vis Sustainability
Awareness	1	I know how much CO2 I emit from transportation.	2.67	4.00	1.33	0.00 **	+
	2	I know how much CO2 the average person in the UC Berkeley community emits from transportation.	2.13	3.91	1.78	0.00 **	+
	3	I know how many calories I burn while commuting/traveling.	2.90	4.00	1.10	0.00 **	+
	4	I know how much money I spend on commuting/traveling per year.	4.40	4.31	-0.09	0.67	
	5	I know how much time I spend commuting/traveling per year.	3.87	4.13	0.26	0.24	
Norms	6	My friends and family believe that it is positive to do one's daily travel by: Bike	5.27	4.82	-0.45	0.02 **	-
	7	My friends and family believe that it is positive to do one's daily travel by: Driving	3.54	3.32	-0.22	0.28	
	8	My friends and family believe that it is positive to do one's daily travel by: Carpooling	5.15	5.17	0.01	0.94	
	9	My friends and family believe that it is positive to do one's daily travel by: Public Transit	5.28	5.14	-0.14	0.41	
	10	My friends and family believe that it is positive to do one's daily travel by: Walk	5.85	5.55	-0.29	0.11	
	11	My friends and family think I should do my daily travel by: Driving	4.12	3.99	-0.13	0.44	
	12	My friends and family think I should do my daily travel by: Carpooling	3.77	3.95	0.18	0.32	
	13	My friends and family think I should do my daily travel by: Public transit	5.12	4.95	-0.17	0.29	
	14	My friends and family think I should do my daily travel by: Bike	4.44	4.18	-0.26	0.16	
	15	My friends and family think I should do my daily travel by: Walk	5.32	5.54	0.22	0.22	
Attitudes	16	Regardless of cost, I choose the fastest way to travel	4.29	3.96	-0.33	0.06 *	+
	17	I don't see why it is necessary to engage in sustainable behavior in transportation.	5.69	5.46	-0.23	0.07 *	+
	18	We should raise the price of gasoline to reduce congestion and air pollution.	3.46	3.77	0.31	0.06 *	+
	19	I feel guilty if I don't take sustainable modes of transportation.	3.03	3.32	0.29	0.06 *	+
	20	Using sustainable modes of transportation is beneficial to my health.	5.18	5.44	0.26	0.02 **	+
	21	I value the health benefits of using sustainable modes of transportation.	5.15	5.38	0.23	0.10 *	+
	22	Greenhouse gases cause environmental problems such as global warming.	6.23	6.04	-0.19	0.01 **	-
	23	Everybody together should reduce the amount of fuel burned by their transportation behavior.	5.71	5.50	-0.21	0.09 *	-
	24	Vehicles that burn fossil fuels emit greenhouse gases.	6.08	5.90	-0.18	0.11	
	25	I like driving	3.17	3.32	0.15	0.35	
	26	I like carpooling	4.56	4.64	0.08	0.59	
	27	I like taking transit	4.47	4.68	0.21	0.22	
	28	I like riding a bike	4.22	4.28	0.06	0.64	
	29	I like walking	5.45	5.62	0.17	0.20	
	30	It is important for me to take non-auto modes of transportation.	3.74	3.85	0.10	0.54	
	31	If I used more sustainable methods of transportation, the effects would be so small that it would not matter	4.59	4.56	-0.03	0.89	
	32	To improve air quality, I am willing to pay a little more to use an electric or other clean-fuel vehicles	4.71	4.83	0.13	0.36	
	33	Biking/taking transit/carpooling makes me feel good about myself.	4.53	4.69	0.17	0.36	
	34	I value the benefits to society when I take sustainable modes of transportation.	4.77	4.99	0.22	0.17	
	35	I wouldn't change my transportation behavior if it were only for the benefit of the environment.	4.08	4.09	0.01	0.95	
	36	I am not particularly interested in the calories I burn while traveling.	4.29	4.35	0.05	0.80	
	37	It is important to me to exercise regularly.	5.63	5.46	-0.17	0.15	
Goal setting & Self-efficacy	38	I can get exercise when traveling.	5.17	5.55	0.38	0.03 **	+
	39	I would consider setting a goal to reduce my carbon footprint.	4.55	4.50	-0.05	0.69	
	40	If it would save time, I would change my mode of travel.	5.63	5.54	-0.09	0.47	
	41	I would change my transportation behavior if I knew whether it really benefits my health.	5.01	5.10	0.09	0.60	
Perceived Behavioral Control	42	There are many constraints and limitations that keep me from changing my transportation behavior.	2.92	2.64	-0.28	0.07 *	+
	43	For me, it would be easy to do my daily travel by: Driving	4.09	4.21	0.12	0.56	
	44	For me, it would be easy to do my daily travel by: Carpooling	3.38	3.38	0.00	1.00	
	45	For me, it would be easy to do my daily travel by: Public Transit	5.15	4.83	-0.32	0.12	
	46	For me, it would be easy to do my daily travel by: Bike	4.27	4.05	-0.22	0.30	
	47	For me, it would be easy to do my daily travel by: Walk	5.55	5.38	-0.17	0.36	
Intention	48	Over the next few months, how often do you intend to: Drive	4.65	4.35	-0.31	0.10 *	+
	49	Over the next few months, how often do you intend to use: Bike	1.99	2.24	0.26	0.04 **	+
	50	Over the next few months, and compared to what you do now, how often do you intend to use: Walk	4.28	4.68	0.40	0.02 **	+
	51	Over the next few months, how often do you intend to use: Carpooling	3.15	3.06	-0.09	0.59	
	52	Over the next few months, how often do you intend to use: Public Transit	5.44	5.23	-0.21	0.18	
	53	Over the next few months, how often do you intend to use: Walk	6.72	6.56	-0.15	0.32	
	54	Over the next few months, and compared to what you do now, how often do you intend to use: Driving	3.83	3.81	-0.03	0.88	
	55	Over the next few months, and compared to what you do now, how often do you intend to use: Carpooling	3.87	3.68	-0.19	0.28	
	56	Over the next few months, and compared to what you do now, how often do you intend to use: Public Transit	4.24	4.06	-0.18	0.24	
	57	Over the next few months, and compared to what you do now, how often do you intend to use: Bike	3.88	3.68	-0.21	0.20	
	58	I am certain that I am going to change my transportation behavior for the benefit of the environment.	3.99	4.00	0.01	0.93	

78 observations
** significant change at 95% confidence
* significant change at 90% confidence
+ significant change that is in the desired direction vis-à-vis sustainability
- significant change that is in the wrong direction vis-à-vis sustainability

guilty for not using sustainable modes (Q19), they think any changes their behavior will be too small to make a difference in the environment (Q31), and they don't see why it's necessary to engage in sustainable travel behavior (Q17). Further, they objected to the policy of raising the price of gas to reduce congestion and air pollution (Q18).

They were much more uniformly positive on the health questions. They would change their travel behavior if they knew it would impact their health (Q41), they value the health benefits of using sustainable modes (Q21), they think using sustainable modes is beneficial to their health (Q20), they think it is important to exercise regularly (Q37), and they think they can get exercise when traveling (Q38).

They were also fairly uniformly positive to sustainable modes of travel. They don't like driving (Q25), they do like walking (Q29), biking/taking transit/carpooling makes them feel good about themselves (Q33), it would be easy for them to do their daily travel by public transit (Q45) and walking (Q47), Further, their friends and family are pro sustainable modes: public transit (Q9 and Q13), carpooling (Q8), biking (Q6), and walking (Q10 and Q15). However, they do feel there are many constraints and limitations that keep them from changing their transport behavior (Q42).

The responses to the questions regarding awareness of CO_2 emitted and calories burned from travel were amongst the most extreme answers, indicating subjects had little knowledge of these values (Q1, Q2, and Q3). They seemed to have a better handle on cost (Q4) and time spent (Q3), but still responding relatively neutrally to these knowledge questions.

The intention questions regarding changes in travel mode split over the next few months indicate a slightly positive intention to walk (Q50) and take public transit (Q56) more and a slightly negative intention to drive (Q54), carpool (Q55) and bike (Q57) more. However, the average responses on all were fairly close to the neutral (no change) value of 4.

So given our sample of people with mixed views on the environment, pro health views, little knowledge on travel resources expended, openness to sustainable modes, friends and family who are pro sustainable modes, but having constraints on being able to change their travel and stating no intention to change their travel, the question is how the QT experiment impacted them? For this we first turn to the comparison of the pre- and post-survey results, the post-experiment results are also summarized in Table 2. Many of the questions saw no significant shift in responses. However, there was significant shift in a subset of questions within each of our general categories, and most of these shifts were in the direction of increased sustainability. The awareness category saw the most obvious positive shift. This is not surprising since the information system most directly targeted awareness. While the information provided on time (Q5) and cost (Q4) spent traveling did not shift awareness, the information on calories (Q3) and CO_2 (Q1 and Q2) did seem to be novel to the respondents.

The least impacted categories were social norms, goal setting, self-efficacy, and perceived behavioral control. However, the significant and positive change in the behavioral control question regarding the "many constraints and limitations that keep me from changing my transportation behavior" (Q42) represents an important shift necessary for more sustainable travel. As does the increased feeling that "I can get exercise when traveling" (Q38).

There were numerous attitudes questions and many of these changed for the positive. There was a positive shift on the policy question regarding raising the price of gas to reduce congestion and pollution (Q18). There were also positive shifts regarding personal sustainable behavior, such as feeling it is more important to engage in sustainable travel behavior (Q17) and feeling guilty for not using sustainable modes (Q19). Even though the group started out very pro-health, two health attitudes increased even more: using sustainable modes is beneficial to health (Q20) and valuing the health benefits of using sustainable modes (Q21). However, the two most general questions regarding societal issues of sustainability saw a move in the wrong direction. These questions were “Greenhouse gases cause environmental problems such as global warming” (Q22) and “Everybody together should reduce the amount of fuel burned by their transportation behavior” (Q23). This is in contrast to the positive shifts that were mostly related to the subject’s personal behavior. This response is interesting and the reason is not clear. It could be a reaction to the clearly environmentalist push of the experiment. It could also be related to the fact that these were amongst the most extreme (and very positive) responses in the pre survey so in a sense there was not a lot of room for improvement.

Finally, the intention to change their travel behavior in the future towards using more sustainable transportation modes also saw positive shifts away from driving (Q48) and towards biking (Q49) and walking (Q50).

Perhaps the most interesting outcome of the pre- and post-survey analysis is that this fairly simple experiment that mostly involved reporting back to people on their resources spent traveling (time, cost, CO_2, and calories) was able to see significant behavioral shifts, overwhelmingly in the desired direction, in a large number of questions across a range of behavioral categories.

4.6 Measured behavior change

Beyond the survey questions, the smartphone tracking allowed us to measure a realized behavior shift between the first and last week. Our analysis of their travel behavior did show a shift in mode usage away from driving and towards walking and biking. Table 3 shows the difference in average travel distances by mode. Most importantly, we observed a statistically significant decrease in the average distance traveled by driving (p-value <0.01), with the average reduction being 38 kilometers or 32% lower than the first week. When looking at the full sample, we did not observe a corresponding statistically significant increase in walk/bike or transit. However, once we segment the group by driving frequency, we begin to see shifts in walking and biking. We define frequent drivers as those who self-reported in the pre-survey that they drive on two or more days per week ($N = 15$), and infrequent drivers (including non-drivers) as those who self-reported that they drive on fewer than two days per week ($N = 63$). As can be seen in Table 3, the frequent drivers shift more than the infrequent drivers. The frequent drivers drove on average 120 fewer kilometers the final week of the experiment (relative to the first), a reduction of 38% (p-value <0.01). The infrequent drivers drove 20 fewer kilometers the last week, a reduction of 27% (p-value 0.09). Neither group significantly changed their distance traveled by transit. However, the statistics on frequent drivers suggest (albeit with a somewhat high p-value of 0.17) that they walked on average 5 km more the final week, an increase of 42% over the first week.

To better understand what factors drove the behavioral changes and to what degree they were related to the travel feedback system, we developed and estimated a behavior change model, which is presented in the next section.

Table 3: Average travel distances by mode

Participant type	Distance traveled (kilometers)	First week		Last week		Comparison	
		Mean	Std Dev	Mean	Std Dev	Difference	p-value
All participants (N = 78)	Drive	119.9	154.6	80.7	111.7	-39.2	<0.01
	Walk/bike	14.4	11.2	15.2	11.1	0.8	0.54
	Transit	14.5	28.5	13.8	25.6	-0.7	0.72
Frequent drivers (N = 15)	Drive	317.0	211.1	197.0	162.2	-120.0	<0.01
	Walk/bike	12.2	9.0	17.3	14.1	5.1	0.17
	Transit	3.4	13.1	2.5	6.3	-0.9	0.66
Infrequent drivers (N = 63)	Drive	73.0	89.4	53.0	74.2	-20.0	0.09
	Walk/bike	14.9	11.7	14.7	10.3	-0.2	0.90
	Transit	17.2	30.5	16.5	27.7	-0.7	0.78

5. MODEL

In this section we evaluate, through modeling, the impact of feedback about travel time, emissions, cost, and calories and peer influences on behavioral modification in the experiment while explicitly representing the psychological process driving this change in behavior. The behavioral measure is the change in the distance traveled by car and by non-motorized modes (walk and bike) from the pre-treatment week (first week) to the post-treatment week (the last break). The aggregate data analysis showed that the post-treatment distance driven decreased significantly compared to the pre-treatment distance driven, while the distance traveled by non-motorized modes increased although not significantly. We wish to investigate the psychological mechanisms driving these changes: which of the psychological variables affect the changes in distance traveled (e.g. attitudes towards sustainable travel behavior, perceived norms of others' behavior and expectations, etc.) and how these psychological variables are in turn influenced by awareness of the impacts of one's travel behavior and comparison to others. As described earlier, the model structure is based on the theory of planned behavior extended to include a representation of feedback. We present below the model framework followed by the estimation results.

The underlying behavior represented in this experiment is likely extremely complex, with a number of latent explanatory variables. To this end, we asked in our survey a large number of psychometric questions to get at a range of latent constructs. However, in developing the econometric model to represent this behavior, we are limited by our relatively small sample. Therefore, the model that follows is necessarily a subset of the complete behavioral relationships. For example, intention and behavioral control were not included in the final model as they did not produce meaningful results. Our process in model development was to look for the psychometric indicators and attitudes that best explained the resulting behavior. We kept in the model only those indicators that proved relevant via statistical tests. The model presented below was selected considering the reasonableness of all model coefficient signs, the overall goodness of fit, and the statistical significance of the major causal paths.

5.1 Model framework

The model framework is a structural equation model with relationships as shown in Figure 6. In this figure, latent variables are shown in ellipses and observed variables are shown in rectangles. Solid straight arrows represent causal (behavioral) relationships, dashed arrows represent measurement relationships, and curved arrows represent correlations between variables. The measures of behavioral change we wish to explain are the change in distance driven and the change in walk/bike distance (defined as distance in km traveled in the post-treatment week minus distance in km traveled in the pre-treatment week, divided by 100), which are correlated, and are modeled as a function of change in attitude towards the environmental impact of travel, change in subjective norms, and socio-economic variables including whether the subject is a driver, whether he/she is a student, and the number of logins to the experiment website after the first week of the experiment (as an indicator of the frequency of viewing the feedback information). Positive values of changes in attitude and norms indicate more positive attitude towards the environmental impact of travel and stronger subjective norms related to traveling by sustainable modes. The feedback mechanism consists of (i) presentation of information about one's travel impacts, which changes the level of awareness of these impacts, and (ii) presentation of statistics about the travel impacts of peers, which results in a social comparison process. The change in awareness influences the change in attitude and the change in norms, and the peer influence[2] effect contributes to the change in attitude. Each of the psychological constructs was measured pre-and post-experiment through a number of questions in the survey (Table 2). Therefore, the change in a given psychological construct has as indicators the change in the responses to the corresponding survey questions from pre-to post-treatment. We specifically use those measures/questions from the survey that changed significantly from pre-to post-treatment, and which when included in the model, resulted in intuitive model coefficients. Three indicators are used to measure attitude, three to measure awareness, and two to measure norms.

5.2 Estimation results

The model was estimated using the maximum likelihood method using the SEM package [39] in R with all equations estimated in deviations form (from the mean) except the equations pertaining to change in distance driven and change in distance walk/bike where intercept terms were also estimated. The estimation results are shown in Table 4 and Figure 6. We discuss the main findings with respect to the influence of

[2] The peer influence variable is defined as the average of 4 deviations of an individual's time, emissions, cost, and calories from the averages of time, emissions, cost, and calories across all study subjects. These 4deviations are expressed in time units by applying certain factors to the emissions, cost, and calories deviations based on the visual representation of these dimensions on the website (e.g., the mid-point of the time axis represents 56 minutes and the mid-point of the cost axis represents $10, so we convert cost into time units by multiplying cost by 56/10). A positive value of the peer influence variable corresponds to a positive deviation, i.e. whereby a subject's travel impact is larger than the mean (unfavorable comparison to others), while a negative value indicates a smaller travel impact (favorable comparison to others).

feedback on attitudes and norms and the main determinants of behavior change.

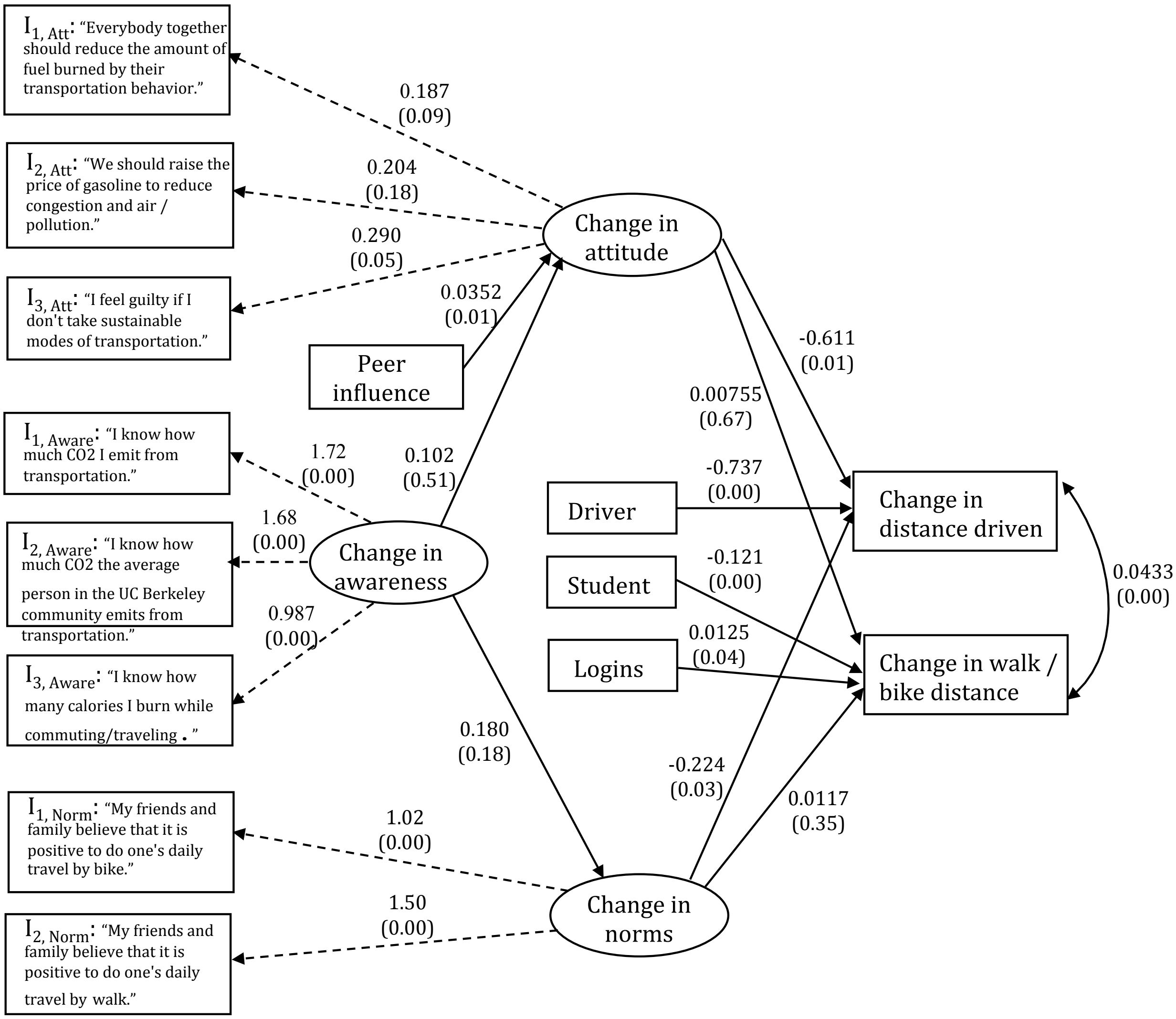

Figure 6: Model framework with parameter estimates
(p-values in parentheses; intercept terms and variances are not shown on the figure)

5.2.1 Effect of Feedback on Attitudes and Norms

Change in awareness due to the information provided after the treatment has a positive but insignificant effect on change in attitudes and norms. That is, as an individual becomes more aware of his/her travel impacts (time, cost, emissions, and calories), the individual's attitude towards sustainable travel behavior becomes more positive, and would tend to think more strongly that others have high expectations from the individual for engaging in environmentally friendly behavior. Peer influence seems to play a significant role in changing attitudes towards sustainable travel. The coefficient of the peer influence variable is positive, indicating that subjects who overall compare favorably to others in terms of the 4 impacts measured (time, cost, emissions, and calories), i.e. have a negative value of the deviation from the mean across subjects, develop more negative attitudes towards environmentally friendly transportation behavior, while those who fare worse than others on time, cost, emissions, and calories (and thus have a positive value of the deviation from the mean) change their attitudes

Table 4: Estimation results for the behavioral change model.

Model component and variable	Parameter estimate	Standard error	p-value	
Structural Model of Change in Attitude				
Change in Awareness	0.102	0.154	0.51	
Peer Influence	0.0352	0.0141	0.01	**
Structural Model of Change in Norm				
Change in Awareness	0.180	0.134	0.18	
Structural Model with Change in Distance Driven (in km/100) as Dependent Variable				
Intercept	-0.250	0.102	0.01	**
Change in Attitude	-0.611	0.226	0.01	**
Change in Norm	-0.224	0.104	0.03	**
Driver Dummy	-0.737	0.220	0.00	**
Variance of Error Term	0.322	0.278	0.25	
Structural Model with Change in Distance Walk/Bike (in km/100) as Dependent Variable				
Intercept	0.0587	0.0375	0.12	
Change in Attitude	0.00755	0.01750	0.67	
Change in Norm	0.0117	0.0125	0.35	
Student Dummy	-0.121	0.031	0.00	**
Number of Logins	0.0125	0.0062	0.04	**
Variance of Error Term	0.0113	0.0018	0.00	**
Covariance of Error Terms of Change in Distance Driven and Change in Distance Walk/Bike	0.0433	0.0145	0.00	**
Measurement Model of Change in Attitude (with Normalization of Variance of Change in Attitude to 1)				
I1,Att: Factor loading	0.187	0.112	0.09	*
I1,Att: Variance	1.04	0.17	0.00	**
I2,Att: Factor loading	0.204	0.153	0.18	
I2,Att: Variance	1.98	0.32	0.00	**
I3,Att: Factor loading	0.29	0.15	0.05	**
I3,Att: Variance	1.76	0.29	0.00	**
Measurement Model of Change in Awareness (with Normalization of Variance of Change in Awareness to 1)				
I1,Aware: Factor loading	1.72	0.24	0.00	**
I1,Aware: Variance	1.31	0.55	0.02	**
I2,Aware: Factor loading	1.68	0.23	0.00	**
I2,Aware: Variance	1.07	0.51	0.04	**
I3,Aware: Factor loading	0.987	0.221	0.00	**
I3,Aware: Variance	2.73	0.47	0.00	**
Measurement Model of Change in Norm (with Normalization of Variance of Change in Norm to 1)				
I1,Norm: Factor loading	1.02	0.24	0.00	**
I1,Norm: Variance	1.64	0.45	0.00	**
I2,Norm: Factor loading	1.50	0.30	0.00	**
I2,Norm: Variance	0.199	0.796	0.80	

78 observations
Final log-likelihood = -120.738
BIC = 195.43
** significant change at 95% confidence
* significant change at 90% confidence

towards more sustainable travel behavior. This "magnet" effect whereby peer influences tend to pull an individual closer to the mean of a comparison group is significant and consistent with similar findings in the context of energy consumption for instance [40].

5.2.2 Behavior Change

A positive change in the attitude towards environmentally friendly transportation behavior and in subjective norms related to this behavior is found to be associated with less driving in the post-treatment week, and these effects are significant. At the same time, these positive changes lead to an increase in the distance traveled on foot or by bike in the post-treatment week although this influence is not significant. Overall, there is a significant decrease in driving in the post-treatment week, as indicated by the negative and significant intercept term. Subjects who were regular drivers pre-treatment (if the pre-treatment reported frequency of driving per week is 2+ days/week) were also more likely to reduce their amount of driving in the post-treatment week. On the other hand, the increase in walking/biking in the post-treatment week is non-significant, and being a student is likely to decrease non-motorized travel in the post-treatment week, while a higher frequency of logins to the website significantly increases the amount of walk/bike distance in the post-treatment week.

To summarize, the main significant influences in the process of behavioral change observed in the experiment arise from the effect of peer influences on attitudes, which together with norms, trigger a change in distance driven.

5.2.3 Measurement Model

The indicators of the latent variables have the expected positive association with the corresponding latent variables. Most variance terms of the measurement errors are significant. The covariance of the error terms of the change in distance driven and change in distance walked/biked is positive and significant.

6. CONCLUSIONS AND FUTURE WORK

This paper has described the design of an automated smartphone travel diary system, which along with a web interface to view trips, collects location data from participants and processes them into trips with the aim of influencing awareness, attitudes, and sustainable travel behaviors. Using the automated diary system, an experiment has been conducted with 135 subjects and showed how feedback on one's travel history and peer influence can significantly affect one's awareness of their impact on the environment, attitudes towards sustainable transportation, intention to change behavior, and actual behavior change. The average weekly distance driven decreased an average of 39 km, amounting to a 33% reduction in driving miles. Frequent drivers showed greater reductions in driving both in terms of magnitude (120 km) and percentage (37%). Frequent drivers also showed an average increase in walking of 5 km (42% higher than pre treatment), albeit this had a lower statistical significance. A structural equation model explains the change in distance driven and distance walked/biked as a function of the changes in attitudes and norms, which in turn are driven by peer influences and the change in awareness as a result of the feedback. We found shifts in attitudes and norms to significantly impact changes in distances driving. The model shows the more frequent the interaction with the website, the greater the increase in the amount of walking/biking.

There are a number of limitations of the study that could be addressed in the future. First, studies with at least a few hundred subjects are required. A larger subject pool would enable inclusion of a control group, as has been done for some travel feedback studies [41], whereby subjects would not be given feedback on the impacts of their travel behavior or how they compare to their peers. Control group data would help account for seasonality effects and potential self-selection bias in the analysis. Second, our evaluation lasted only 3 weeks in duration. Since many travel feedback programs collect travel diaries for only a few days, ours is an improvement in longitudinal depth. Nevertheless, we believe short-term temporary behavior changes are easier to achieve than the longer-term sustained shifts meaningful to the transportation sector, and so the next step is expanding the study from 3 weeks to a longer duration.

Our primary research goal has been to explore the viability of replicating the success of travel feedback programs with computational surrogates for counselors, thereby lowering costs and improving scalability. We consider this work only a first step towards this goal and the use of technology to persuade individuals to more sustainable transportation modes. Of the many psychological levers for behavior change, QT uses only awareness and social comparison. For example, it does nothing with goal setting, norms, self-efficacy, personalized travel advice, or the performance of alternative modes, all of which are part of the intellectual repertoire of the human counselor QT purports to replace. The statistically significant reduction in driving, change in awareness, and the coefficients of the structural equation model, make QT an encouraging first step, but QT is obviously a very primitive travel counselor. Can a deeper engagement with mobile computing, machine learning, and data mining bring computational feedback systems close to the travel feedback programs created by the travel demand management community? Embedding the intellectual and emotional sophistication of a human counselor in a computation travel feedback system by leveraging advances in mobile computing to nudge people towards sustainable modes of transportation is a great research endeavor.

ACKNOWLEDGEMENTS

This research has been funded in part by the University of California Transportation Center (UCTC), the National Science Foundation (NSF), a UC CITRIS Seed Grant, the UC Berkeley Vice Chancellor for Research, and the UC Berkeley XLab. 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.

REFERENCES

[1] Vautin, D. A., & Walker, J. L. (2011). Transportation Impacts of Information Provision & Data Collection via Smartphones. *Transportation Research Board 90th Annual Meeting* (No. 11-3500).

[2] Vij, A., Carrel, A. & Walker, J.L. (2013). Incorporating the Influence of Latent Modal Preferences on Travel Mode Choice Behavior. *Transportation Research Part A, publication forthcoming*.

[3] Taniguchi, A., Suzuki, H., & Fujii, S. (2007). Mobility management in Japan: Its development and meta-analysis of travel feedback programs. *Transportation Research Record: Journal of the Transportation Research Board*, *2021*(1), 100-109.

[4] Cairns, S., Sloman, L., Newson, C., Anable, J., Kirkbride, A., & Goodwin, P. (2004). Smarter choices-changing the way we travel.

[5] Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

[6] Fujii, S., & Taniguchi, A. (2005). Reducing family car-use by providing travel advice or requesting behavioral plans: An experimental analysis of travel feedback programs. *Transportation Research Part D: Transport and Environment*, *10*(5), 385-393.

[7] Rose, G., & Ampt, E. (2001). Travel blending: an Australian travel awareness initiative. *Transportation Research Part D: Transport and Environment*, *6*(2), 95-110.

[8] Consolvo, S., McDonald, D. W., Toscos, T., Chen, M. Y., Froehlich, J., Harrison, B., Klasnja, A. LaMarca, L. LeGrand, R. Libby, I. Smith & Landay, J. A. (2008). Activity sensing in the wild: a field trial of ubifit garden. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1797-1806). ACM.

[9] Obermair, C., Reitberger, W., Meschtscherjakov, A., Lankes, M., & Tscheligi, M. (2008). perFrames: Persuasive picture frames for proper posture. In *Persuasive Technology* (pp. 128-139). Springer, Berlin/Heidelberg.

[10] Lin, J. J., Mamykina, L., Lindtner, S., Delajoux, G., & Strub, H. B. (2006). Fish'n'Steps: Encouraging physical activity with an interactive computer game. In *UbiComp 2006: Ubiquitous Computing* (pp. 261-278). Springer, Berlin/Heidelberg.

[11] Klasnja, P., Consolvo, S., McDonald, D. W., Landay, J. A., & Pratt, W. (2009). Using mobile & personal sensing technologies to support health behavior change in everyday life: lessons learned. In *AMIA Annual Symposium Proceedings* (Vol. 2009, p. 338). American Medical Informatics Association.

[12] Fan, Y., Chen, Q., Douma, F., & Liao, C. F. (2012). Smartphone-Based Travel Experience Sampling and Behavior Intervention among Young Adults (No. CTS 12-11). Intelligent Transportation Systems Institute, Center for Transportation Studies, University of Minnesota.

[13] Holstius, D., Kembel, J., Hurst, A., Wan, P. H., & Forlizzi, J. (2004, August). Infotropism: living and robotic plants as interactive displays. In *Proceedings of the 5th conference on Designing interactive systems: processes, practices, methods, and techniques* (pp. 215-221). ACM.

[17] Mankoff, J., Matthews, D., Fussell, S. R., & Johnson, M. (2007, January). Leveraging social networks to motivate individuals to reduce their ecological footprints. In *System Sciences, 2007*. HICSS 2007. 40th Annual Hawaii International Conference on (pp. 87-87). IEEE.

[15] Froehlich, J., Dillahunt, T., Klasnja, P., Mankoff, J., Consolvo, S., Harrison, B., & Landay, J. A. (2009, April). UbiGreen: investigating a mobile tool for tracking and supporting green transportation habits. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1043-1052). ACM.

[16] Kappel, K., & Grechenig, T. (2009, April). Show-me: water consumption at a glance to promote water conservation in the shower. In *Proceedings of the 4th international conference on persuasive technology* (p. 26). ACM.

[17] Consolvo, S., Klasnja, P., McDonald, D. W., & Landay, J. A. (2009, April). Goal-setting considerations for persuasive technologies that encourage physical activity. In *Proceedings of the 4th international Conference on Persuasive Technology* (p. 8). ACM.

[18] Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention and behavior: An introduction to theory and research.

[19] Stern, P. C. (2000). New environmental theories: toward a coherent theory of environmentally significant behavior. *Journal of social issues*, 56(3), 407-424.

[20] Carver, C. S., & Scheier, M. F. (2001). On the self-regulation of behavior. Cambridge University Press.

[21] Gollwitzer, P. M. (1993). Goal achievement: The role of intentions. *European review of social psychology*, 4(1), 141-185.

[22] Bamberg, S., Hunecke, M., & Blöbaum, A. (2007). Social context, personal norms and the use of public transportation: Two field studies. *Journal of Environmental Psychology*, 27(3), 190-203.

[23] Nordlund, A. M., & Garvill, J. (2002). Value structures behind pro-environmental behavior. *Environment and Behavior*, 34(6), 740-756.

[24] Prochaska, J., DiClemente. C. (1986). Toward a comprehensive model of change. *Treating addictive behaviors: Processes of change* (86), 3-27.

[25] Chen, C. F., & Lai, W. T. (2011). The effects of rational and habitual factors on mode choice behaviors in a motorcycle-dependent region: Evidence from Taiwan. *Transport Policy,* 18(5), 711-718.

[26] Choo, S., & Mokhtarian, P. L. (2004). What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice. *Transportation Research Part A: Policy and Practice, 38*(3), 201-222.

[27] Cordoba Maquilon, J. E., Gonzalez-Calderon, C. A., & Posada Henao, J. J. (2011). The selection of a mode of urban transportation: Integrating psychological variables to discrete choice models. *Dyna*, *78*(170), 98-105.

[28] Scagnolari, S. & Maggi, R. (2010). Modelling heterogeneity in young persons night-time choices -accounting for attitude towards alcohol consumption. In *Proceedings of the 10th Swiss Transport Research Conference*, Ascona, Switzerland.

[29] Theis, G., Adler, T., Clarke, J. P., & Ben-Akiva, M. (2006). Risk aversion to short connections in airline itinerary choice. *Transportation Research Record: Journal of the Transportation Research Board*, *1951*(1), 28-36.

[30] Table of calories burned per hours. Wisconsin Department of Health Services. Last retrieved 08/01/2011. [Online]. Available: http://www.dhs.wisconsin.gov/health/physicalactivity/ToolCalcs.htm

[31] Chester, M. (2008). Life-cycle environmental inventory of passenger transportation in the United States. *PhD Thesis*, University of California, Berkeley.

[32] Your driving costs. American Automobile Association [Online]. Last retrieved 08/01/2011. Available: http://www.aaaexchange.com/

[33] Jariyasunanat, J. (2012). Overcoming battery life problems of smartphones when creating automated travel diaries. *PhD Thesis*, University of California, Berkeley.

[34] Jariyasunanat, J., Sengupta, R., & Walker, J.L. (2012). Overcoming battery life problems of smartphone when creating automated travel diaries. In *proceedings of the 13th International Conference on Travel Behavior Research*, Toronto, Canada.

[35] Schwanen, T., & Mokhtarian, P. L. (2007). Attitudes toward travel and land use and choice of residential neighborhood type: Evidence from the San Francisco bay area. *Housing Policy Debate*, *18*(1), 171-207.

[36] Montano, D. E., & Kasprzyk, D. (2008). Theory of reasoned action, theory of planned behavior, and the integrated behavioral model. *Health behavior and health education: Theory, research, and practice*, *4*, 67-95.

[37] Kunert, U., Kloas, J., & Kuhfeld, H. (2002). Design characteristics of National Travel Surveys: international comparison for 10 countries. *Transportation Research Record: Journal of the Transportation Research Board*, *1804*(1), 107-116.

[38] Stopher, P., Wilmot, C., Stecher, C., & Alsnih, R. (2003). Standards for Household Travel Surveys-Some Proposed Ideas. In *10th International Conference on Travel Behavior Research in Lucerne*.

[39] Fox, J., Nie, Z., & Byrnes, J. (2009). Sem: structural equation models. *R package version 0.9-15*.

[40] Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. *Psychological science*, *18*(5), 429-434.

[41] Taniguchi, A., Suzuki, H., & Fujii, S. (2007). Mobility management in Japan: Its development and meta-analysis of travel feedback programs. *Transportation Research Record: Journal of the Transportation Research Board*, *2021*(1), 100-109.