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The Quantified Traveler: Using personal travel data to promote sustainable transport behavior

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Abstract

With the advent of ubiquitous mobile sensing and self-tracking groups, travel demand researchers have a unique opportunity to combine these two developments to improve the state of the art of travel diary collection. While the use of mobile phones and the inference of travel diaries from GPS and sensor data allows for lower-cost, longer surveys, we show how the self-tracking movement can be leveraged to interest people in participating over a longer period of time. By compiling personalized feedback and statistics on participants' travel habits during the survey, we can provide the participants with direct value in exchange for their data collection effort. Moreover, the feedback can be used to provide statistics that influence people's awareness of the footprint of their transportation choices and their attitudes, with the goal of moving them toward more sustainable transportation behavior.

We describe an experiment that we conducted with a small sample in which this approach was implemented. The participants allowed us to track their travel behavior over the course of two weeks, and they were given access to a website they were presented with their trip history, statistics and peer comparisons. By means of an attitudinal survey that we asked the participants to fill out before and after the tracking period, we determined that this led to a measurable change in people's awareness of their transportation footprint and to a positive shift in their attitudes toward sustainable transportation.

1 INTRODUCTION

In this paper, we present an approach to collecting travel survey data that, for the first time, will provide participant with immediate value in return for their participation by leveraging the ideas behind the increasingly popular self-tracking movement. Combined with travel survey data collection on mobile phones, this could not only motivate study participants to participate in longer-term surveys, but also provide a potential powerful policy tool when it comes to moving people out of their cars to more sustainable modes of transportation.

1.1 Addressing a pressing challenge

Many cities are dealing with the consequences of increasing demand for automobile transportation: congestion, high levels of emissions of air pollutants and greenhouse gases and public health problems, in addition to the socioeconomic consequences. Management of this demand is a challenging task, and it relies on the agencies' ability to accurately predict future demand, suggest viable improvements and shift the demand away from the automobile to more sustainable transportation modes like walking, biking and transit. Unfortunately, efforts to shift demand often suffer from the difficulty of communicating the responsibility of each and every car user, and "traditional" demand management tools, such as congestion pricing, gas taxes and regulations on car use are not popular and are generally tough to implement without considerable resistance. Furthermore, the development of more accurate prediction models to evaluate policies and demand management strategies is constrained by the costs and difficulties associated with conducting surveys, which makes long-term, broad travel diary surveys difficult.

1.2 The self-tracking movement as a solution

We suggest a methodology for tracking travel behavior, collecting travel demand data for and feeding back information with the goal of inducing behavioral change that leverages a new movement called the "Quantified Self" [1]. Recently, the increasing abundance of low-cost sensing devices, 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 groups of individuals interested in self-tracking; those collecting personal informatics and metrics about their own sleep patterns, fitness levels, reactions to various medication, personal finance, time usage and productivity or social interactions, and much more. The "Quantified Self" movement is a loosely organized yet very prominent group that promotes self-tracking and self-knowledge. One its core ideas is that tracking and quantifying one's behavior and calculating personal metrics allows people to better understand their own habits and routines, and lets them improve their quality of life by making changes. In recent years, more and more products have become commercially available that help people collect these data. 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. In this paper, we present an application that collects data on people's travel behavior and feeds back personalized information on the impacts of their behavior via a website with the goal of raising awareness and attitudes towards sustainable transportation. Ultimately, this methodology can be further developed to deliver messages aimed at influencing travel behavior and choices. We discuss how the data collected in this fashion can also be used for travel demand modeling, and how the self-tracking movement can be leveraged for collecting long-term, broad datasets.

1.3 Organization of this paper

The paper is organized as follows: First, section 2 presents previous research on the different areas that underlie our research. Section 4 then describes how the combination of mobile data collection, public interest in self-tracking and behavioral feedback has created a new opportunity to improve the current state of research. In section 4, we describe an experiment we designed to demonstrate how this can be implemented in practice, and the results of our experiment are shown in section 5. Finally, section 6 contains conclusions and directions for further research.

2 PREVIOUS RESEARCH

The methodology we propose makes use of smartphones to collect traveler data which is then used for behavioral feedback via a web interface. Although travel data collection via GPS rather than paper-and-pen surveys is a rather new technique, it has been employed to various degrees by some research groups. This section reviews previous research in mobile data collection as well as research on behavioral feedback, which forms the basis for our work with self-tracking.

2.1 Traditional data collection methods

Data from travel surveys are used to understand individual travel behavior and to estimate travel demand and land-use models which in turn inform long-range planning decisions, infrastructure investments and policy-making. The problem is that traditional paper-and-pen household travel surveys, where participants are required to record their travel manually on survey forms, are expensive and rarely capture people's long-term behavior, which is linked to their lifestyles [2, 3]. Therefore, these surveys are typically only carried out with small sample sizes, at intervals of $10 - 15$ years and covering $1 - 2$ days of travel. With these comparatively small amounts of data, models are derived for 20 to 25 year forecasts, making strong assumptions to cover for the lack of long-term data. As an example, the San Francisco Bay Area Travel Survey (BATS) was last conducted in 2000 and only covers two days per study participant in 15,000 households, but it is used for long-range transportation planning in the entire Bay Area (which has a population of nearly 7.5 million) with a time horizon of up to 25 years. Researchers have long recognized that this style of data collection does not provide as much value as travel diaries over longer survey periods [4]. A few long-term panel surveys, such as the Mobidrive survey [5], have been able to provide researchers with very valuable insights into human travel behavior, as evidenced by the large body of literature that has made use of these datasets.

2.2 Gathering travel behavior data with GPS

Transportation researchers have recognized that new technologies may provide a solution to this problem [6] and are gradually moving toward the use of GPS and mobile phone positioning technologies for tracking individual travel behavior without loss of data [7, 8]. Some of these projects were conducted within the framework of traditional household survey designs, where travelers were still required to operate the phone or data collection device and to interact with applications by filling in data about their origin, destination, and travel mode [9, 10, 11]. There have also been several research groups that have worked on inferring additional information from the mobile phone sensors and from contextual information, including groups at the Swiss Federal Institute of Technology [12], the MIT Media Lab [13] and Ehime University [9]. The problem of inferring modes of transportation from GPS data has received attention regarding both real-time detection [14, 15] as well as through post-processing of the data [16, 17]. Constant location monitoring technologies have been developed to minimize the battery usage of smartphones, for example by [18, 19, 20]. These ideas have contributed to our travel behavior research and formed the basis of our smartphone application and travel mode determination system (Described in a separate paper: [21]).

Despite the slow adoption to this point, mobile technology has the potential to revolutionize data collection in travel demand modeling and to open up new ways for researchers to interact with participants. Smartphone data collection is less inconvenient to the users than paper surveys and requires less participation on their part, and the marginal cost of deployment is small, which puts long-term and more frequent surveys within reach of many agencies and researchers. Furthermore, web-enabled smartphones allow researchers to track many aspects of participants' behavior at a fine level of detail that were difficult to capture so far, such as their interaction with real-time transit or traffic information.

Ideally, in terms of scale and automation, the travel demand modeling community will be able to follow the traffic modeling community, which has leveraged distributed sensing technology to gather larger, richer datasets, making the leap from costly, sparse data collection to cheap, continuous sensing. The California Highway Performance Monitoring System (PeMS) is an example of an innovative sensor network to measure traffic [22] that not only included the collection of data, but also the analytics which provided information such as the speed of vehicles at points on the highway and travel times between destinations. Recently, the traffic modeling community has also begun collecting data via built-in GPS sensors in vehicles or even mobile phones [23].

2.3 The effectiveness of personalized feedback

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. Feedback has been shown to be a highly effective behavior change technique in many fields, most notably in health and fitness applications [24, 25], and eco-feedback technologies [26]. In transportation, an application called "Ubigreen" showed that feedback on smartphones had high potential for behavior change to sustainable modes of transportation [27].

It can also be assumed that if personalized feedback leads to a behavioral change, it is likely that the person is much happier with the decision than if the change had been imposed through harsh policies or pricing strategies. There have previously been several small-scale travel behavior feedback programs conducted by researchers in Japan [28]; 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. While these successes are very encouraging, the applicability of this approach on a broader level is problematic due to the high labor costs. Using smartphones for data collection provides an opportunity to partially or fully automate many of the tasks involved in the travel feedback programs, which in turn permits their wider application.

3 AN OPPORTUNITY TO IMPROVE THE STATE OF THE ART

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. To do this, mobile technology can be 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 move on to more challenging problems of modeling behavior and managing demand to get a better understanding of how and why people travel.

Since this data collection depends on the participation of individual smartphone owners, an important question is how to get people interested in joining and remaining active in a data collection effort. Barring the incentive of financial compensation, the Quantified Self movement presents an excellent opportunity for this since the travel data can also be of value to the individuals collecting them. A lot of the attention of the self-tracking movement has been focused on personal health and on financial activity monitoring. These applications generally take the perspective of presenting the users with the effect of all of their daily decisions on one particular domain, e.g., on their budget. When it comes to decisions that affect multiple areas of someone's life (e.g., both health and money), this does not necessarily afford a complete picture that shows all the tradeoffs involved. Transportation is an excellent example of this: Mode choice, route choice and destination choice decisions are made on a very frequent basis, and every one of these decisions has an impact in terms of time and money consumption, calories burned when traveling there and the environmental impact. By taking a decision-centric perspective and by showing the effect of transportation decisions on all the areas mentioned above, it is possible for the user to see the tradeoffs and correlations between positive or negative effects of their travel behavior. For example, biking may be beneficial to somebody's health and environmental footprint and cost less than using a car, but these benefits come at the cost of increases in travel time. There has so far been one application that tracked transportation behavior, UbiGreen, which quantified users' travel-related emissions with the goal of affecting travel behavior [27]. However, this application was only focused on emissions and did not track any of the other effects of transportation

In general, 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 [29], 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 [30].

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. However, since the contributions of a single person are often lost in aggregate numbers, the introduction of automated self-tracking devices presents a new, powerful method to present every traveler with personalized information on their specific contributions.

4 A FIELD EXPERIMENT USING SMARTPHONES

In Summer 2011, we designed and conducted an experiment in the San Francisco Bay area with a small set of participants. This two-week experiment utilized a prototype infrastructure for collecting traveler data via smartphones, and its goals 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 attitudes 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.

4.1 Experimental design

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 average Americans and San Francisco Bay Area residents. 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.

Our sample was a convenient sample of 28 young individuals, mostly from the city of San Francisco, who responded to an online posting advertising our study. 8 males and 20 females volunteered to participate, all of which were employed and were regular commuters. Of these, 10 used a variety of phones on the Android platform (version 2.0 or higher) while 18 used an iPhone 4. Participants used their own smartphones for the duration of the study; a tracking application which collected GPS traces was sent to the them to install on their own phones before the commencement of the study, and the data were broadcasted to servers owned by the university. 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 two-week period in which users tracked themselves with the app. On the fifth day, they were sent a link to a website on which they could view their trip history and a set of personalized statistics and scores (explained in section 4.5) related to their travel patterns. Users then received periodic email reminders to log into the site and view their scores. At the end of the two 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 Feedback website

Every participant was given access to a website on which they could view their individual trip history and their scores. Specifically, the website consisted of four pages, as shown in figure 1. After logging onto the website, participants were first presented with the “Dashboard”, a page presenting an overview of their

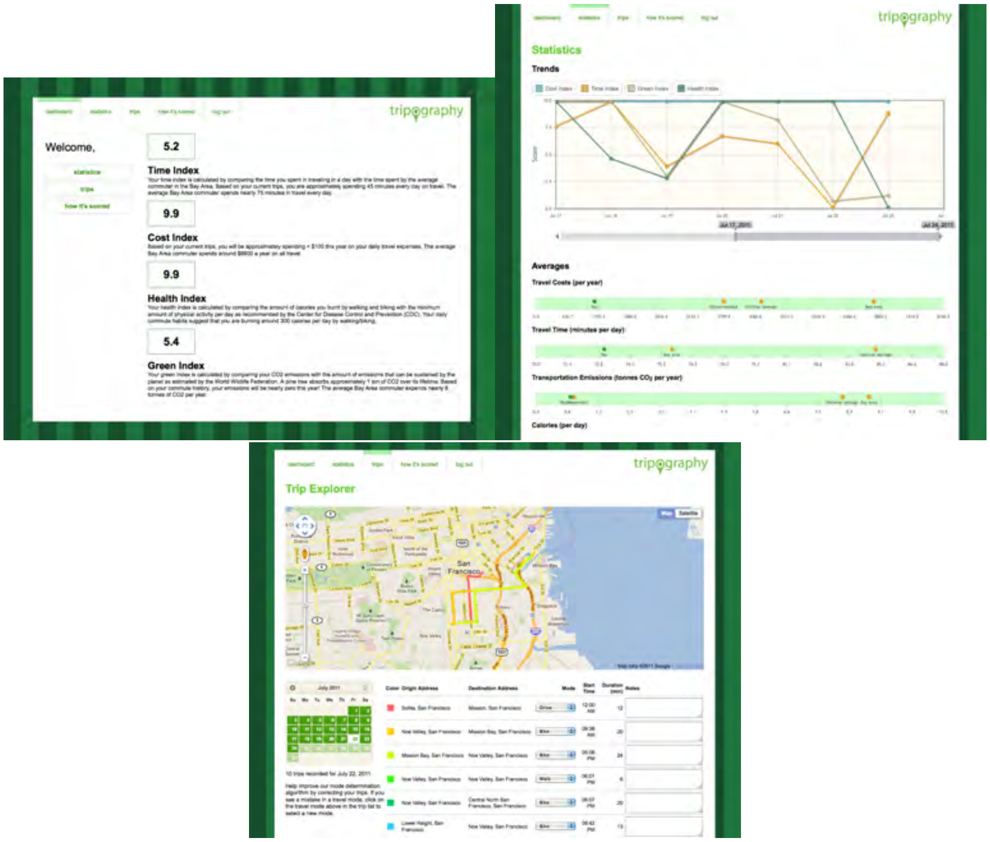

Figure 1: Screenshots of the Website: Top left - A person's summary of their travel using scores. Top right - A person's raw statistics compared to local and national averages. Bottom - History of trips made, shown on a map.

aggregate scores and a brief explanation. From there, the user could access three pages: One that explained the scoring methodology, one with the detailed daily history of scores and one with the trip history (termed "Tripography"). On the tripography page, the user could view all past trips by day together with information on the inferred origin, destination and travel mode. The daily score history page presented the user with two items: A line graph showing the four scores calculated for every day on which data were available and four visual comparisons showing, respectively, the person's emissions, calories burned, time spent and money spent on transportation in comparison to the averages in the San Francisco Bay Area and the United States, as well as recommended values where available (e.g., recommended amount of daily exercise). The latter graphs were not shown as scores but rather in the actual units (calories, etc.).

4.3 System architecture

The design of the data collection system is shown in figure 2. 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 periodic job reads the raw data, processes them to infer trip origin and destination and applies travel mode determination models to determine whether the participant was biking, walking, in a car (though carpooling cannot be automatically detected) or using transit [21]. This also makes use of information from third party sources such as public transit data which are stored on the server. 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

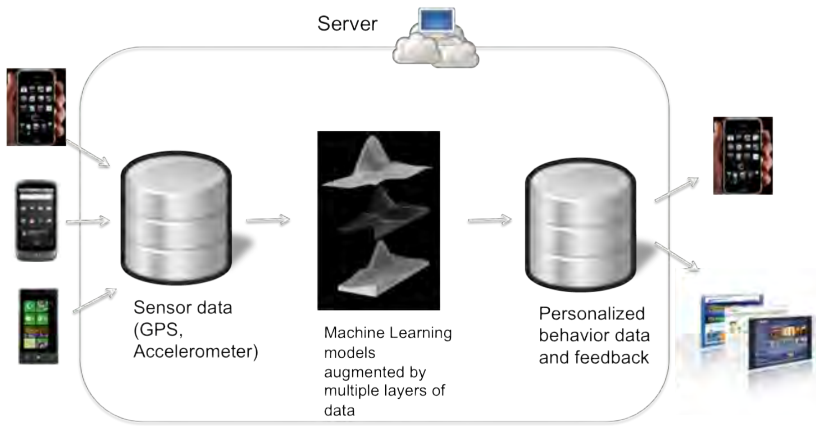

Figure 2: System Architecture and Flow of Data

Mode	CO_2	Calories	Costs
Walking	0	Used a calories calculator which adjusts calories burned by walking speed [31], assuming a 150lb person.	0
Biking	0	Same as above.	0
Driving	Used a CO_2 calculator which adjusted emissions by driving speed [32].	0	58.6 cents / mile [33].
Train	Averaged to 39g / mile [32].	0	Appropriate costs for taking BART or Caltrain as specified by the respective transit agencies.
Bus	Averaged to 25g / mile [32].	0	Same as above.

Table 1: Methodology for calculating trip footprint

methodology for computing the last three of these items is detailed in table 1.

4.4 Attitudinal survey

The survey consisted of 34 statements which participants agreed or disagreed with on a seven-point Likert Scale. Seven 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 CO_2 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, 25 questions were asked about attitudes, levels of self-efficacy, and perceived norms about sustainable travel behavior. Two questions were asked about 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 held strong pro-environmental attitudes (M = 5.24, SD = 1.33; on a scale from 1 to 7 where 7 corresponds to the strongest pro-environmental attitudes) and believed that they engaged in more sustainable travel behavior than the average person in the San Francisco Bay Area (M = 4.2, SD = 1.0). However, the results of the survey also showed that the participants were unaware of how "green" they actually were (M = 2.9, SD = 1.0; 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

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

environmental effects of using different transportation modes, and that this was a group that was generally motivated to engage in sustainable behavior.

4.5 Feedback and scoring methodology

As part of the study, individuals were to be provided with feedback on their travel patterns, including environmental and financial footprint, calories burned and time spent traveling. For instance, the choice to use a car is often based on the time savings with that mode of transportation, but if a person can also view the environmental, financial and health consequences of that decision, it may become more apparent to the person that there is a tradeoff involved, and that the lower travel time comes at the expense of several other valuable resources. In order to provide participants with feedback, a format had to be chosen that was easy to understand but also allowed users to quickly see changes and to assess how they were doing compared to benchmarks. The benchmarks included recommended values (e.g., for health and emissions) as well as average values (e.g., for time and money expenditure).

Since a feedback system that presented only "raw" numbers, such as actual emissions in kgs/year or calories per day was not considered to convey the comparative aspect sufficiently, a scoring system was devised, where every participant's performance in terms of emissions, calories burned, money and time spent traveling was rated on a scale from 0 to 10, where 10 was best. This methodology emulates the approach taken by service like the "Good Guide" [34]. The functions that mapped a person's actual performance to a score were linear with the exception of greenhouse gas emissions, which will be explained in more detail below:

- The score for calories burned was linearly increasing between 0 and 156 calories/day (10.0 after that) such that a person received a score of 5.0 for the minimum amount of exercise recommended by the CDC [35]
- The score for travel time was linearly decreasing between 30min and 120min of travel per day based on the average commute time of San Francisco Bay Area residents [30]
- The score for travel costs was linearly decreasing between 15% and 28% of total income spent on transportation. Below 15%, a score of 10.0 applied [36].
- The score for emissions was nonlinear to account for the fact that there were likely to be two clusters, one corresponding to an auto-oriented lifestyle and the other to a non-auto-oriented lifestyle [37]. To increase distinction among individuals within those clusters, an exponential function was devised that set the score of 10.0 at zero emissions and the score of 5.0 at 1 tonne/year of CO_2 emissions. The latter value corresponds to approximately 25% (typically the share of transportation of an individual's greenhouse gas emissions [38]) of 3.8 tonnes/year, which has been calculated by the World Wildlife Federation [39] to be the amount of yearly greenhouse gas emissions per person that the planet can sustain.

For every participant in the experiment, these four scores were calculated for every day on which they had collected data, as well as on an aggregate basis for their entire trip history throughout the experiment. Scores were updated daily.

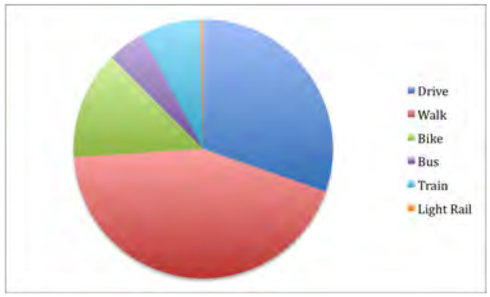

Figure 3: Mode split by number of trips made (Drive: 30.34%, Walk: 43.65%, Bike: 13.50%, Bus: 4.63%, Train: 7.49%, Light Rail: 0.39%)

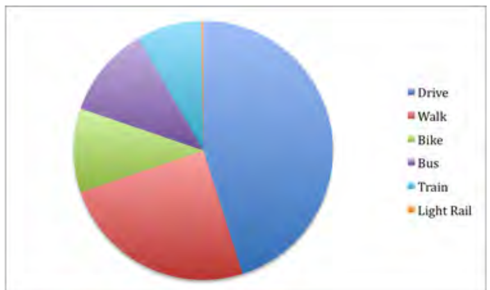

Figure 4: By total travel time (Drive: 45.11%, Walk: 24.63%, Bike: 10.49%, Bus: 11.39%, Train: 8.12%, Light Rail: 0.25%)

5 RESULTS

The field study provided valuable information with respect to both of its goals. The surveys showed that (a) there was a potential for increasing participants' awareness of their transportation carbon footprint, and that (b) the personalized statistics, trends, and trips shown on the website were successful in raising users' awareness. The feedback and social comparison measures were effective, but need to be refined in order to increase their impact - not just on attitudes, but on actual travel behavior.

5.1 Recorded activity

During the two-week study we recorded a total of 1,016 trips and 22,398 minutes of travel across 6 different modes. Unfortunately, if participants had their phone turned off, the application was not running and the system was not able to record trips, so it cannot be said that we captured the entirety of our participants' travel. The breakdown of the usage of modes is shown in figures 3 and 4. As a group, the study participants were multi-modal, with each participant using about 3 unique modes (Mean number of modes used = 3.25, standard deviation = 1.29).

5.2 An increase in awareness and pro-sustainability attitudes

The short period of the study did not allow us to measure potential changes in travel behavior, but with the survey described in section 4.4, 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 5 categories: awareness, self-efficacy, perceived norms, goal-setting, and attitudes towards sustainable behavior. 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 paired t-test was also run for each one of these five categories.

	Mean (before)	Mean (after)	Standard Deviation (before)	Standard Deviation (after)	t-statistic	p-value
Awareness	2.91	3.75	0.22	0.27	2.8210	0.0106
Perceived norms	5.64	5.60	1.17	0.98	0.2483	0.8065
Setting goals	4.14	4.36	0.90	1.05	1.0141	0.2060
Attitudes toward sustainable behavior	5.12	5.38	1.18	0.95	2.2326	0.0372

Table 3: Comparison of participants' survey answers before and after tracking and feedback

Example statements which showed a statistically significant ($p < 0.0023$) 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. An example statement which showed a statistically significant ($p < 0.013$) change in attitude toward sustainable travel behavior was: "We should raise the price of gasoline to reduce congestion and air pollution." The attitude questions cannot be broken down into environmental, health, financial and time groups since they are strongly mode-focused and therefore combine all the effects of a single mode.

5.3 Correlation between driving behavior and attitudes

The study also validated the theory that attitudes and perceived norms are correlated with observed behavior. A correlation coefficient for percentage of trips made by auto vs. attitudes on sustainable behavior and perceived norms was calculated. The result was that those who held pro-sustainable transportation behavior attitudes and believed that their friends and family also engaged in sustainable transportation had significantly lower numbers of driving trips recorded during the study (Attitudes: $R = -0.6631$, $p <= 0.001241$, $t = -3.861$, Norms: $R = -0.6306$, $p <= 0.002442$, $t = -3.542$).

5.4 Lessons learned for future experiments

To evaluate the website, the post-experiment survey contained an additional set of questions regarding the participants' evaluation of the website. They were shown screenshots of the three personalized webpages and asked to respond to four statements on a 7-point Likert Scale about each webpage. The statements were:

1. I enjoyed taking a look at my dashboard/statistics/trip history page and getting a summary of my travel

2. In the future, this web page is something I would consider using.

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.

4. This web page was easy to use.

Participants were also encouraged to provide any general comments about each particular page. Based on the responses for all three web pages, the overall study was well received by the participants, although certain features stood out more than others. Based on the quantitative evaluations and feedback from interviews with participants, it was clear that the scoring system described in section 4.5 needed improvement. Some participants mentioned that it was unclear whether increasing or decreasing their score was desired, and they were also unclear on the exact effects their trips had on the score. However, all participants agreed that if they were to set a goal to reduce their carbon footprint, a clear summary of their trips in a refined page would be more effective than showing raw data, or a history of trips made. While the scoring system may have not been executed as well as the research team would have liked, the comparison and trends page was the best received. It was very clear to participants how they compared to local and national averages on all four items reported. In fact, participants wanted even more localized comparisons, including with other people in their neighborhoods rather than a large comparison with the overall population. We also performed tests for correlation between attitudes and levels of awareness, how much participants liked the web pages and their mode split. However, no notable correlations were found.

While we were able to measure a difference in attitudes and awareness, there was no measurable behavior change, which is not surprising given the short study period. A longer term study is planned for this. An interesting and motivating indicator that a behavior change could be induced were the answers to the question: "If I used more sustainable methods of transportation, the effect would be so small that it would not make a difference." More participants disagreed with that statement at the conclusion of the study ($p < 0.03$). This reduced one of the major concerns of the study group – that even making an attempt to change transportation mode choice through behavior change techniques such as goal-setting and feedback would be difficult. Before the end of the study, we also asked participants if they had any plans to change their travel behavior. One participant in the study mentioned that they would be purchasing a bicycle to get around. This particular participant spent over 60 minutes a day primarily taking transit and walking, and mentioned that seeing her actual time spent traveling was not what she had expected.

6 CONCLUSION AND FUTURE WORK

In this paper we described the opportunity to shift travel behavior data collection to smartphones, how the Quantified Self movement can be leveraged to improve data collection and what opportunities there are for influencing the attitudes and behavior of travelers to promote more sustainable travel behavior. The design of data collection infrastructure and of a feedback website was described, as well as the development of a feedback metric that incorporated benchmarks and was easy to communicate. The feedback metric should be seen as a flexible tool that can be adapted to the objectives of future work as a function of the user group. The following sections describe two major areas for future research.

6.1 Behavioral feedback in transportation

The experiment described here was a very simple feedback system, and a first foray into the concept of using technology to influence and persuade users to change transportation behavior. However, there exists a large number of behavior change techniques which have been successfully applied in other fields, and that can be experimentally incorporated in our system. Behavior change techniques which have been recognized and tested include: Information, Goal-Setting, Comparison, Incentives, and Feedback [40]. All of these techniques have been tested in a variety of fields and largely confirmed to have positive effects for behavior change. A logical next step for experimentation is to combine feedback with feedforward information (i.e. directions on how to travel between locations via other modes, real-time information, prompts), which is a strategy common to all successful Travel Feedback Programs. Although manual 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. Thus, there is an opportunity to leverage the lessons learned from Human Computer Interaction research in the design of automated tools on the web and smartphones to motivate behavior change.

6.2 Demand Modeling with automatically collected datasets

It was mentioned above that employing smartphones for data collection in travel demand modeling would help reduce the resources needed by agencies for data collection, allowing agencies to conduct travel diary surveys more frequently and on a wider basis. This would improve the accuracy of forecasts, and the resulting increase in availability of long-term panel data would allow researchers to incorporate more behavioral dynamics and lifestyle components into their models that have been very difficult to capture so far .

Despite these advantages, there is an important question that remains with respect to the use of discrete choice models. At present, a fundamental assumption of discrete choice modeling is that the data used for the model estimation are all correct. Yet, when using automatically collected data, there will probably always be a small fraction of the data that were misclassified or subject to a detection error. Before using automatically collected data for estimating choice models, there needs to be a coordinated research effort to develop methods and procedures with which the choice models and estimation algorithms can be adapted to deal with such data errors. Notwithstanding this hurdle, we believe that the benefits of collecting and using such data by far outweigh the potential complications caused by this issue, which is why it merits further attention.

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