Smartphone-Based Survey for Real-Time and Retrospective Happiness Related to Travel and Activities

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Understanding and incorporating measures of travel and activity well-being in transportation research are critical for the design and evaluation of policies. In recent years, several efforts have been made to quantify travelers’ subjective well-being by using a self-reported state of happiness during participation in various activities or travel patterns. The inadequacies of these conventional survey methods in collecting uninterrupted and comprehensive information have restricted the number of such studies. In this study, a smartphone-based sensing platform was adapted to collect mobility information and measure happiness. Two surveys were conducted with respondents from five continents. Real-time and retrospective happiness measures are compared and explained. Results indicate that different cognitive biases affect the levels of happiness reported by the individuals. In comparison with staying at home, performing work and education activities tends to result in lower levels of happiness, while performing other activities tends to result in higher levels of happiness. Activity duration has a significant effect on real-time happiness but is less significant for retrospective happiness.

Understanding and modeling subjective well-being have been expanding areas of transportation research during the past decade. It has been argued that mobility is the result of people’s desire to conduct activities to satisfy needs and thus to maintain or enhance well-being (1, 2). A number of efforts have been made to measure well-being during travel and the conduct of activities. The measures used to capture activity and travel well-being can be categorized into two classes, one measuring the subjective well-being associated with activities and travel and the other the well-being derived from the capabilities (i.e., travel potentials) of the travelers. Subjective well-being measures usually take the form of self-reports, in which people evaluate their current or anticipated activity or travel well-being from their own perspectives (3). That is the approach followed in this study and in most of the transportation literature. For example, Ettema et al. (4) developed a scale for measuring satisfaction with travel, Ory and Mokhtarian (5) measured travel liking, Duarte et al. (6) measured happiness with work and leisure trips, Ravulaparthi et al. (7) studied the relationship between subjective well-being and mobility in elders, and Abou-Zeid and Ben-Akiva (1) and Bergstad et al. (8) measured happiness or affect associated with activities. In contrast, the capabilities approach (9) attempts to measure the well-being derived from the feasible alternative combinations of functionings that the person can achieve.

Advances in communication technology have opened up the potential for exploring innovative survey methods. Smartphones enabled with GPS, the Global System for Mobile Communications (GSM), wireless fidelity (Wi-Fi), and accelerometers have been used in the collection of activity–travel diaries of individuals with limited intervention from the survey participants. One recent example is work done in the San Francisco Bay Area (California), where Jariyasunt et al. (10) recorded travel diaries of 135 participants for 3 weeks. The collected data were converted into participants’ travel footprints (i.e., travel time, travel cost, amount of carbon dioxide emission, and amount of calories burned by each participant). The objective of that study was to explore the possibility of influencing people’s awareness, attitudes, and behavior to encourage them to engage in more sustainable transport behavior by feeding the data collected about their trips back to them and by providing them with the travel footprints of their peer group. Similar efforts to collect detailed information about the activities and travel of participants have been undertaken in Singapore (11).

The lack of research endeavors that capture travel and activity well-being by using the recent advances in survey methods has motivated the work described in this paper. A novel smartphone-based travel survey to measure activity and travel happiness is proposed. Data concerning activity locations were collected through the use of smartphones enabled with GPS, GSM, Wi-Fi, and an accelerometer, and the raw data were used to generate the activity diaries of individuals (including trip origin, destination, start and end time, and mode). The data were then made available through a web interface, where individuals could verify their trip and activity information and answer questions about their satisfaction with particular activities. Currently, no feedback is provided to the participants.

Two types of happiness measures were obtained for a random sample of activities for each participant: a real-time happiness measure while the individuals were performing their activities and a retrospective happiness measure, which was provided by the individuals when they verified their activity diaries online. An attempt is made

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to compare these two measures and to explain them as a function of activity, contextual, and sociodemographic characteristics. Most of the subjective well-being measures in the transportation literature have been collected retrospectively. In a later stage of the study, these happiness measurements will be incorporated into transportation and mobility models to enhance their capabilities.

MEASURING HAPPINESS

Several countries have acknowledged the importance of the use of subjective well-being measures of their nation as an indicator of social progress. For example, the Kingdom of Bhutan conducts a yearly survey to calculate a happiness index, called gross national happiness, which is used as an indicator of the quality of life for the people of Bhutan (12). The French and British governments have acknowledged the incorporation of measurements of well-being and happiness in policy making since 2009 and 2010, respectively (13). An example of subjective well-being measurement is the day reconstruction method developed by Kahneman et al., in which respondents are asked to report the extent to which they experienced certain feelings for every activity they conducted during the preceding day on a 7-point scale (14). A similar approach was followed by Archer et al., who measured several well-being indicators (such as happiness, stress, and sadness) and studied their impact on activity–travel patterns (15).

Attempts have also been made to measure the subjective well-being of travelers. For example, Duarte et al. measured travel happiness with work and leisure trips by asking questions such as, “How happy do you feel by using your current mode of transport to make a work related trip?” (6). Abou-Zeid and Ben-Akiva proposed a measure to capture well-being derived from the entire activity pattern of an individual by using the following question: “Thinking about yesterday, how satisfied were you overall with the way you traveled, the places you went to (including staying at home), and the things you did at these places?” with a 7-point scale ranging from “very dissatisfied” to “very satisfied” (1). Other studies have analyzed the relationship between satisfaction and decisions over time. A similar approach was followed by Ettema et al., who designed scales that include affective and cognitive components related to travel and combined them with scales related to daily mood and overall daily satisfaction (4). Abou-Zeid and Ben-Akiva (16) and Said et al. (17) incorporated satisfaction indicators in a mode switching model, while Carrion et al. (18) studied the impact of well-being and satisfaction indicators in the activity pattern model in Denver, Colorado. These studies demonstrated gains in model efficiency with the addition of happiness measures as indicators of utility.

Studies focusing on the change in happiness (or other well-being indicators) over time are less abundant and in general have only appeared recently. Abou-Zeid et al. compared car commute satisfaction for car users measured retrospectively under routine commuting conditions and car commute satisfaction measured after trying public transportation for a few days and found differences between the two measures (19). Carrel et al. studied the effect of public transport satisfaction over time (20). Bailey et al. studied the change of happiness and other indicators (such as comfort, anxiety, and boredom) over time in the context of public transport (21). Borjian et al. used structural equations to model measures of happiness for commuters (22).

With regard to survey methods, smartphones have not yet been fully exploited in measuring well-being indicators (such as happiness and satisfaction). Traditional methods rely on paper-based surveys, and happiness measures for different time periods (e.g., before activity, real-time during activity, and retrospective after activity) are difficult to obtain from such surveys. Ma et al. developed a smartphone platform for measuring mood on three levels: displeasure, tiredness, and tenseness (23). Fan et al. (24) developed a smartphone-based experience survey to measure satisfaction and overall happiness of travelers on the basis of the satisfaction with travel scale (25).

Comparison and analysis of real-time and retrospective happiness measures have been insufficiently explored to date and are key elements of this study. The general framework is presented in Figure 1, which shows a general decision-making process (16). On the basis of the attributes of the alternatives (and their own preferences), individuals construct a latent decision utility and use it to choose an alternative. After the decision has been made (in this context, once the individual is traveling or performing an activity), there is a moment utility, which refers to the real-time experience of an alternative that is not observable by the analyst but an indicator of which can be obtained in the form of a real-time happiness measure. Once time has passed, the individual has a remembered utility, which refers to an individual’s retrospective assessment of alternatives, an indicator of which can be obtained through a retrospective happiness measure. The decision utility, moment utility, and remembered utility might differ, and therefore real-time and retrospective happiness measures might not be the same.

The purpose of collecting happiness indicators can be twofold: on the one hand, happiness measures can be seen as a direct quantification of satisfaction in terms of service quality. For this purpose, happiness, along with other well-being measures, can be monitored by operators and authorities to improve the level of service provided. On the other hand, these indicators can be used to model behavior. Happiness can be seen as an indicator of utility and therefore can be used to help in understanding decisions (in any context). In the context of transportation, different measures of happiness can help

![FIGURE 1 General framework for measuring happiness and its relationship to utility (16).](image-url)
in understanding different decisions. General satisfaction or retrospective happiness could be linked to pretrip decisions (such as mode or time of day), while real-time happiness could be linked to en route decisions (such as changing paths). Although real-time measures can be more objective (they are not affected by external events and are less prone to cognitive biases), they might not provide information concerning future behavior. It has been shown that remembered utility (and therefore retrospective happiness) is determined by selected moments of the actual experience (26–28). Those moments tend to be the “peak” and “end” of the experience (peak–end rule), while the length of the experience usually does not affect its retrospective evaluation (duration neglect). People also tend to repeat choices that are remembered as less unpleasant or more pleasant (29); in this way, remembered utility affects decision utility. Therefore, different measures provide different valuable information.

FUTURE MOBILITY SENSING

Future Mobility Sensing (FMS) is a smartphone-based travel survey system that leverages increasingly pervasive smartphone ownership, advanced sensing technologies, and machine learning techniques to automate travel surveys. It consists of three separate but interconnected components: the smartphone app that collects the sensing data, the server that includes the database as well as the data processing and learning algorithms, and the web interface that users access to view and verify the processed data and answer additional questions to supplement the verified data. Figure 2 shows the three components and the data flows among them.

Smartphone App

The smartphone app, available for both Android and iOS platforms, collects data from a multitude of the phone’s sensors, including GPS, GSM, accelerometer, and Wi-Fi. The app runs in the background and collects sensor data silently without user intervention. The intent was to minimize the app’s influence on participants during their normal daily activities. In addition, the application is designed to be lightweight (in terms of memory use), easy to use, and energy efficient. Various approaches are used to minimize battery consumption, a major concern for location-based applications. The sensor data collected on the phone are transferred to the backend server through either the cellular network or Wi-Fi, according to the user’s preference.

Backend Server

Raw data collected via the app are uploaded to a database, where a series of algorithms are used to process the data and make inferences about stops, travel modes, and nontravel activities. To minimize the user’s interaction burden, the backend algorithms translate raw data into trips and activities. The first round of stop detection is based on location and point-of-interest data. GSM, Wi-Fi, and accelerometer information are used to merge stops that would otherwise be interpreted as distinct stops. Travel modes are detected on the basis of GPS and accelerometer features, as well as public transit location information. Short-duration stops that are unimportant from a data validation standpoint (such as stops in traffic) are deleted for purposes of presentation in the web interface. Travel destinations (e.g., home, work, shopping, drop-off) are also inferred on the basis of previous validations by the user, point-of-interest data, and other contextual information.

Web Interface

The web interface provides a platform that enables users to review and verify their processed data in the form of a daily timeline or activity diary (Figure 3). Verification involves filling in missing information and amending incorrectly inferred data about modes of travel used for particular trips and specific activities engaged in at inferred stop locations (destinations). The verified data are uploaded, and the algorithms learn from the user validations to make better inferences subsequently. The website is flexibly designed to enable supplementary data collection, such as information pertaining to a specific trip (e.g., how many people the user traveled with or what, if any, fee was paid for parking), during the activity diary verification stage.

The FMS system was field-tested in Singapore in conjunction with the Singapore Land Transport Authority’s Household Interview...
Travel Survey (HITS) between October 2012 and September 2013. More than 1,500 HITS respondents also participated in the FMS demonstration project, and comparison between their HITS and FMS data indicates that FMS can deliver a substantially richer, higher-resolution, and larger travel and activity data set (30).

REAL-TIME AND RETROSPECTIVE HAPPINESS SURVEY

The FMS platform was provided with additional functionality to conduct a happiness survey. First, the mobile app was modified to collect real-time responses to the happiness survey from the survey participants. In an initial stage, for conducting a pilot survey, the happiness survey was activated for each participant every day at a randomly selected time between 9:00 and 21:00. The starting time of the questions was later modified for a second pilot survey, so they can be activated earlier than 9:00 if the app detects movement. The app notifies the participant whenever the survey is activated. The participants can then respond to the survey and report their happiness level and the current activity (Figure 4) at any time after survey activation until the next one becomes available on the next day. For the pilot survey, happiness was measured with a 5-point scale (Figure 4a). Since the results for the first pilot survey had answers concentrated toward neutral levels, for the second survey a change was made to a 7-point scale (Figure 4b). The responses to the survey along with the time stamp of when the responses were reported are both recorded in the back end.

Another issue corrected after analysis of the results of the first pilot survey was the wording of the real-time happiness question. Initially, the question was simply, “How happy are you with your current activity?” Since the respondent could delay the answer, there was no guarantee that the answer provided was related to the activity conducted when the question was activated or to the activity conducted when the question was answered. This could generate a mismatch between the activities for which happiness measures are available in real time and in retrospect. Therefore, in the second survey, the question, if it was not answered within 30 min, was changed to, “How happy were you with your activity XXX hours ago?” This change eliminates the potential selection bias that may occur if participants themselves choose the activities or times for which they want to report their happiness level.

In the second stage of the study, the participant was presented with a happiness question in the activity diary along with the activity for which he or she answered the real-time question (Figure 5). The participants were required to verify and confirm the activity details and report their retrospective happiness level.

As mentioned, two surveys were conducted with the FMS platform. The first pilot survey helped in improving and making changes to the second survey. The total sample size consisted of 737 real-time happiness measures for various activities. For 147 of those activities, retrospective happiness measures were provided by the FMS.
FIGURE 4  FMS on-phone real-time happiness pilot survey: (a) pilot survey, 5-level happiness; (b) second survey, 7-level happiness; and (c) activity question.

FIGURE 5  FMS activity diary interface to collect retrospective happiness-level responses.
users when they verified their daily activity schedules online. The surveys gathered data from users in Chile, China, Denmark, Hong Kong, Lebanon, Macau, Malaysia, Philippines, Singapore, South Korea, Sri Lanka, Tanzania, Thailand, the United Kingdom, and the United States.

Table 1 gives the responses to the real-time happiness measures by activity type. For analysis and modeling purposes, five main activity categories were defined. Most of the responses tend to be concentrated in the “neutral” and “happy” levels, regardless of the activity performed. Work and education activities tend to be associated with lower happiness levels than the rest of the activities, including traveling (which is the only activity that might not provide direct benefit). These results follow the trend of other studies, such as that of Kahneman et al., who found that working and commuting were among the least enjoyed activities (14). A potential selection bias comes from the fact that respondents can choose a time of their convenience to answer the real-time happiness question, and therefore work and home activities can be overrepresented in comparison with other activities such as traveling (for example, drivers should not be able to answer the question while they are traveling, but instead when they perform their next activity). The latter issue applies to the first pilot study but not the second. Furthermore, the longer duration of the work and home activities compared with other activities increases their probabilities of being randomly sampled for the happiness question.

The comparison between real-time and retrospective happiness measures for the first pilot survey is shown in Table 2, and the same comparison for the second survey is shown in Table 3. This comparison was made by using the sample of activities for which both retrospective and real-time happiness measures were reported by the respondents. The values in the diagonal are the number of activity episodes for which the respondents provided the same happiness levels in real time and retrospectively (47% of the instances in the first pilot survey, 25% in the second survey). The upper-right cells in green indicate higher happiness levels in retrospect than in real time (29% of the instances in the first pilot survey, 43% in the second survey), and the lower-left cells in pink indicate higher happiness in real time than in retrospect (24% of the instances in the pilot survey, 32% in the second survey). As expected, the 7-level happiness responses have a higher dispersion, but the general trends are the same in the two surveys. People tend to be consistent in the happiness levels they provide. In the first pilot survey the difference between real-time and retrospective happiness was higher than one level in only seven cases (11%). In the second survey there were 24 such cases (29%), and the difference between real-time and retrospective happiness was higher than two levels in only six of those cases (7%). The retrospective levels of happiness tend to concentrate in stable (i.e., more neutral) levels as time passes, which may be explained by a hedonic treadmill effect (31, 32), although

| Activity       | Very Unhappy | Unhappy | Slightly Unhappy | Neutral | Slightly Happy | Happy | Very Happy | Total |
|----------------|--------------|---------|------------------|---------|----------------|-------|------------|-------|
| First Pilot Survey | 5            | 8       | —                | 22      | —              | 21    | 5          | 61    |
| Education      | —            | 5       | —                | 5       | —              | 2     | 2          | 14    |
| Home           | —            | 4       | —                | 20      | —              | 21    | 8          | 53    |
| Traveling      | 1            | —       | —                | 3       | —              | 7     | 1          | 12    |
| Other          | —            | 1       | —                | 15      | —              | 17    | 16         | 49    |
| Total          | 6            | 18      | —                | 65      | —              | 68    | 32         | 189   |

Second Survey

| Activity       | Very Unhappy | Unhappy | Slightly Unhappy | Neutral | Slightly Happy | Happy | Very Happy | Total |
|----------------|--------------|---------|------------------|---------|----------------|-------|------------|-------|
| Work           | 2            | 15      | 22               | 48      | 45             | 24    | 9          | 165   |
| Education      | —            | 10      | 15               | 24      | 22             | 11    | 10         | 92    |
| Home           | 2            | 5       | 10               | 31      | 40             | 35    | 16         | 139   |
| Traveling      | 3            | 1       | 3                | 10      | 12             | 6     | 3          | 38    |
| Other          | —            | 6       | 10               | 23      | 17             | 29    | 29         | 114   |
| Total          | 7            | 37      | 60               | 136     | 136            | 105   | 67         | 548   |

Note: — = no responses in these categories were obtained.

| Real-Time Happiness | Retrospective Happiness | Percentage of Total |
|---------------------|-------------------------|---------------------|
| Very unhappy        | 1                       | —                   | 2                   | —                   | —                   | 5                   |
| Unhappy             | —                       | 2                   | 6                   | —                   | —                   | 12                  |
| Neutral             | —                       | 1                   | 16                  | 6                   | 2                   | 38                  |
| Happy               | —                       | —                   | 10                  | 9                   | 3                   | 33                  |
| Very happy          | 1                       | —                   | 2                   | 2                   | 3                   | 12                  |
| Percentage of total | 3                       | 5                   | 55                  | 26                  | 12                  |                     |

Note: — = no responses in these categories were obtained.
extreme levels (i.e., very unhappy and very happy) appear to remain over time. The hedonic treadmill effect relates to the human tendency of quickly returning to relatively stable levels of happiness (i.e., centered on neutral in this case) despite experiencing major positive or negative events. Another explanation for the differences in the two happiness measures could be that in real time people evaluate a particular instance of the activity, while in retrospect they may evaluate the overall activity or certain specific moments (peak–end rule).

**UNDERSTANDING HAPPINESS**

To understand the relationship between happiness measures (both in real time and retrospectively) and activities, an ordinal logit model was estimated. On the basis of this approach, the latent happiness experienced by individual \( n \) during activity \( a \) \((h_{an})\) is a function of socioeconomic characteristics \((S_a)\) and activity attributes \((A_{an})\), according to Equation 1, in which \( \eta_{an} \) is a random error. The relationship between the latent happiness and the explanatory variables is assumed to be linear.

\[
h_{an} = h_{an}(S_a, A_{an}) + \eta_{an} \tag{1}
\]

The observed measure of happiness \( d_{an} \) (which could be either real-time or retrospective) is indicated by a set of thresholds \( \tau_x \), depending on the value of the latent happiness, according to Equation 2. For the data collected in the first pilot survey, with a 5-point happiness scale, the thresholds related to “slightly unhappy” and “slightly happy” do not apply.

\[
d_{an} = \begin{cases} 
\text{very unhappy} & \text{if } -\infty < h_{an} \leq \tau_1, \\
\text{unhappy} & \text{if } \tau_1 < h_{an} \leq \tau_2, \\
\text{slightly unhappy} & \text{if } \tau_2 < h_{an} \leq \tau_3, \\
\text{neutral} & \text{if } \tau_3 < h_{an} \leq \tau_4, \\
\text{slightly happy} & \text{if } \tau_4 < h_{an} \leq \tau_5, \\
\text{happy} & \text{if } \tau_5 < h_{an} \leq \tau_6, \\
\text{very happy} & \text{if } \tau_6 < h_{an} < \infty
\end{cases} \tag{2}
\]

The estimated parameters, their \( t \)-values, and goodness-of-fit indicators for the model are presented in Table 4. The explanatory variables can be divided into four categories:

- Activity-specific binary variables;
- The gender of the respondent;
- Activity duration, which has a quadratic specification to capture nonlinear effects; and
- An individual-based random term to capture a potential panel effect.

The panel effect was included for two purposes: (a) to capture potential heterogeneity among the individuals (since happiness is highly subjective) and (b) to capture correlation among responses from the same individual.

Results indicate that, compared with staying at home, performance of work and education activities tends to be associated with lower levels of happiness. As expected, performance of education activities on weekends instead of weekdays is also associated with lower measures of happiness. Compared with staying at home, performance of other activities is associated with higher levels of happiness. All these effects are statistically significant at a 95% level of confidence.

Men tend to provide higher levels of happiness in real time, while women tend to provide higher levels of happiness retrospectively. Gender was the only sociodemographic variable found to have a statistically significant effect on the measures of happiness provided by the respondents.

Activity duration has a statistically significant effect on real-time happiness but not on retrospective happiness. This could relate to the duration neglect phenomenon (33), in which, in retrospect, people do not consider the duration (or overall pleasantness) of an event but only certain key moments, such as its peak and its end. In real time, longer work and education activity durations have a negative effect on happiness levels; this effect is nonlinear. In contrast, a longer duration of other activities has a positive effect on happiness levels.

Finally, the panel effect is not statistically significant. This can be interpreted in two ways: (a) there is no strong heterogeneity among the individuals (which is unexpected, since happiness tends to be highly subjective) and (b) there is no strong correlation among answers from the same individuals.

**CONCLUSIONS AND EXTENSIONS**

Real-time and retrospective happiness measures were compared and analyzed. Both measures were obtained by adapting the FMS platform through a nonintrusive smartphone-based survey. When real-time
and retrospective happiness measures were compared, two cognitive biases were observed: the peak–end rule and the hedonic treadmill effect. The extreme (i.e., peak) real-time measures of “very unhappy” and “very happy” appear to last over time, while the less extreme measures tend to more neutral levels in retrospect.

When the happiness measures provided by the respondents are modeled, a third cognitive bias appears: duration neglect. The duration of the activity affects the real-time measures (negatively for work and education activities and positively for other activities) but does not affect the retrospective measures. Clear preferences between activities are found, as well as differences depending on gender. This study could be extended to include these happiness measures in traditional transportation and mobility models (such as mode choice, route choice, activity scheduling) to enhance their explanatory and forecasting capabilities.

In the initial implementation of an on-phone happiness survey, participants can choose a time of their convenience to provide real-time happiness responses. This could introduce bias toward certain types of activities or certain happiness levels. To account for this potential selection bias, in the second survey the FMS implementation was modified so that the participant was always asked to report his or her happiness level around the time the question was triggered. A drawback of this approach is that the real-time measure could become a pseudoretrospective measure (in a shorter time frame than the proper retrospective happiness measure), a phenomenon to be studied. On the web interface, the retrospective happiness question was shown for the activity for which the real-time question was activated.

In the first pilot survey, many responses were concentrated at the neutral and happy levels. Therefore, in the second survey a finer resolution for the happiness measure was adopted (with a 7-point scale instead of a 5-point scale). A continuous happiness measure is another alternative to evaluate (this can be done in FMS through providing a sliding bar instead of providing predefined happiness levels to the respondents).

The verification rate of respondents (the rate at which respondents provide retrospective happiness measures) needs to be improved. As seen in the section on the real-time and retrospective happiness survey, for most real-time happiness measures there is no matching retrospective measure (590 out of 884 cases). To increase the number of retrospective happiness answers, the FMS app will send a reminder to the participant at the end of the day to validate the activity diary; in the reminder the participant will be asked about happiness retrospectively.

The next stage of this study could focus on analyzing and modeling differences between real-time and retrospective happiness measures in terms of individual characteristics. This would help in understanding the circumstances that affect how activities are remembered by

### TABLE 4  Happiness Model Results

| Explanatory Variable | Real-Time Happiness | Retrospective Happiness |
|----------------------|---------------------|-------------------------|
|                      | Parameter | $t$-Value | Parameter | $t$-Value |
| Home activity$^a$    | 0         | Fixed     | 0         | Fixed     |
| Work activity$^a$    | -0.193    | -2.54     | -0.193    | -2.54     |
| Education activity on weekday$^a$ | -0.101 | -2.35     | -0.101    | -2.35     |
| Education activity on weekend$^a$ | -0.378 | -2.11     | -0.378    | -2.11     |
| Other activity$^a$   | 0.542     | 3.16      | 0.542     | 3.16      |
| Women                | 0         | Fixed     | 0.127     | 2.13      |
| Men                  | 0.104     | 1.90      | 0         | Fixed     |
| (Education–work activity duration) | -0.0182 | -2.75      | -0.00672  | -0.98     |
| (Education–work activity duration)$^2$ | -0.00691 | -2.87      | -0.00212  | -1.23     |
| (Other activity duration) | 0.0276 | 2.07      | 0.00340   | 1.26      |
| (Other activity duration)$^2$ | 0.00575 | 2.28      | 0.00145   | 1.20      |
| Panel effect (mean)$^a$ | 0.152  | 1.11      | 0.152     | 1.11      |
| Panel effect (standard deviation)$^a$ | 0.0201 | 0.98      | 0.0201    | 0.98      |

**First Pilot Survey Thresholds**

| Threshold Description                  | Real-Time Happiness | Retrospective Happiness |
|---------------------------------------|---------------------|-------------------------|
| Very unhappy–unhappy threshold $\tau_1$ | -3.12               | -3.78                   |
| Unhappy–neutral threshold $\tau_{5/5}$ | -1.70               | -2.21                   |
| Neutral–happy threshold $\tau_{10}$    | 0                   | Fixed                   |
| Happy–very happy threshold $\tau_4$    | 1.80                | 2.55                    |

**Second Survey Thresholds**

| Threshold Description                  | Real-Time Happiness | Retrospective Happiness |
|---------------------------------------|---------------------|-------------------------|
| Very unhappy–unhappy threshold $\tau_1$ | -2.47               | -3.21                   |
| Unhappy–slightly unhappy threshold $\tau_2$ | -1.15               | -2.04                   |
| Slightly unhappy–neutral threshold $\tau_3$ | -0.49               | -1.98                   |
| Neutral–slightly happy threshold $\tau_4$ | 0                   | Fixed                   |
| Slightly happy–happy threshold $\tau_5$ | 0.67                | 1.65                    |
| Happy–very happy threshold $\tau_6$    | 1.10                | 2.51                    |

Note: Sample size = 884; adjusted $R^2 = .221$.

$^a$The parameters for these variables were assumed to be the same for real-time and retrospective happiness.
respondents. The time between the real-time measure and the retrospective measure (which is provided by the respondents when they verify their activity diaries) could also be analyzed further and could be used in the modeling stage as an explanatory variable, since recent activities are remembered in more detail. These analyses will be included in a next stage of the study, since they require higher verification rates.

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