Smartphone-based survey for real-time and retrospective happiness related to travel and activities

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ABSTRACT

Understanding and incorporating measures of travel and activity well-being in transportation research is critical for the design and evaluation of policies. In recent years, several efforts have been made to quantify travellers' subjective well-being using self-reported state of happiness while participating in various activities or travel patterns. The limitations of these conventional survey methods to collect uninterrupted and comprehensive information have restricted the number of such studies. In this study, we adapt a smartphone-based sensing platform to collect mobility information and measure happiness. Two surveys were conducted with respondents from five continents. We compare and explain real-time and retrospective happiness measures. Results show that different cognitive biases affect the levels of happiness provided by the individuals. Compared to 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 on retrospective happiness.

Keywords: Happiness, Well-Being, Activity, Travel, Smartphone Data.

1.- INTRODUCTION

Understanding and modelling subjective well-being has been an expanding area of research among transportation researchers during the last decade. It has been well argued that mobility is the result of people's desire of conducting activities, in order to satisfy several needs so as to maintain or enhance well-being [1, 2]. A number of efforts have been made so far to measure well-being, when travelling and conducting activities. The measures used to capture activity and travel well-being can be categorized into two classes, depending on whether they measure (i) the subjective well-being associated with activities and travel, or (ii) the well-being derived from the capabilities (i.e. travel potentials) of the travellers. Subjective well-being measures usually take the form of self-reports where people evaluate their current or anticipated activity or travel well-being from their own perspectives [3]. This is the approach followed in this study and in most of the transportation literature such as Ettema *et al*. [4] who developed a scale for measuring satisfaction with travel; Ory and Mokhtarian [5] who measured travel liking; Duarte *et al.* [6] who measured happiness with work and leisure trips; Ravulaparthy *et al*. [7] who studied the relationship between subjective well-being and mobility in elders, and others who measured happiness or affect associated with activities such as Abou-Zeid and Ben-Akiva [1] and Bergstad *et al.* [8]. The capabilities approach [9], on other hand, attempts to measure the well-being derived from the feasible alternative combinations of functionings which the person can achieve.

Recently, advances in communication technology have opened up the potential for exploring innovative survey methods. Smartphones enabled with GPS, GSM, Wi-Fi and accelerometers have been employed in the collection of activity travel diaries of individuals with limited intervention from the survey participant. One recent example of travel data collection using smart phones is the work done in the San Francisco Bay area, where Jariyasunant *et al*. [10] recorded travel diaries of 135 participants for three weeks using their smartphones with limited intervention from the participants. These collected data have then been converted into participants' travel footprints (i.e. travel time, travel cost, amount of emission (CO_2) and amount of calories burnt by each participant). The objective of that study, the Quantified Traveler, was to explore the possibility of influencing people's awareness, attitudes and behavior and to encourage them to engage in more sustainable transport behavior by feeding back to them the data collected about their trips and also by providing them the comparison of the travel footprints of their peer group. Similar data collection efforts have been employed in Singapore [11] to collect detailed information about the activities and travel of the participants.

The motivation of our proposed research stems from the lack of research endeavors in capturing the travel and activity well-being using the recent advancements of survey methods. We propose a novel smartphone-based travel survey to measure activity and travel happiness. We collect data about activity locations using smartphones enabled with GPS, GSM, Wi-Fi and accelerometer; and with this raw data we generate the activity diaries of the individual (which include the trip origin, destination, start and end time, and mode). This data is then made available to the individual through a web interface where the individual can verify his/her trips and activities information, and also answer other questions about his/her satisfaction with particular activities. Currently, no feedback is provided to the participants.

Two types of happiness measures are obtained for a random sample of activities for each participant: a real-time happiness measure, while the individuals are performing their activities, and a retrospective happiness measure, provided by the individuals when verifying their activity diaries online. We seek to compare these two measures, and to explain them as a function of activity, contextual and socio-demographic characteristics. Most of the subjective well-being measures in the transportation literature have been collected retrospectively. In a later stage of the study, we plan to incorporate these happiness measurements in transportation and mobility models, to enhance their capabilities.

The remainder of the study is organized as follows. In Section 2 we present the methodological framework for measuring happiness; in Section 3 we present the technical framework of the smartphone-based travel survey, in Section 4 we describe the survey conducted and compare real-time and retrospective happiness measures, in Section 5 we present the modelling approach for explaining the happiness measures, and finally in Section 6 we present the main conclusions of the study.

2.- MEASURING HAPPINESS

Several countries in the world 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 (GNH) which is used as an indicator for the quality of life for the people of Bhutan [12]. The French and British governments have also acknowledged the incorporation of measurements of well-being and happiness in policy making since 2009 and 2010, respectively [13]. An example of measuring subjective well-being is the day reconstruction method developed by Kahneman *et al*. [14], where 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. A similar approach is followed by Archer *et al*. [15], who measured several well-being indicators (such as happiness, stress and sadness) and studied their impact on activity-travel patterns.

Attempts have also been made in the field of travel well-being research to measure the subjective well-being of travellers. For example, Duarte *et al*. [6] 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?” Abou-Zeid and Ben-Akiva [1] proposed a measure to capture well-being derived from the entire activity pattern of an individual using the question “Thinking about yesterday, how satisfied were you overall with the way you travelled, 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”. Other studies have analyzed the relationship between satisfaction and decisions over time. A similar approach is followed by Ettema *et al*. [4], 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. Abou-Zeid and Ben-Akiva [16] and Said *et al*. [17] incorporate satisfaction indicators in a mode switching model, while Carrion *et al*. [18] study the impact of well-being and satisfaction indicators in the activity pattern model in Denver. These studies demonstrated gains in model efficiency with the addition of happiness measures as indicators of utility.

Studies that focus on the change in happiness (or other well-being indicators) over time are less abundant, and in general quite recent. Abou-Zeid *et al*. [19] compare car commute satisfaction for car users measured retrospectively under routine commuting conditions and car commute satisfaction after trying public transportation for a few days and find differences between the two measures. Carrel *et al*. [20] study the effect of public transport satisfaction over time. Ogunbekun *et al*. [21] study the change of happiness and other indicators (such as comfort, anxiety, and boredom) over time in the context of public transport. Borjian *et al*. [22] use structural equations to model different measures of happiness for commuters.

In terms of survey methods, the usage of smartphone to measure well-being indicators (such as happiness and satisfaction) has not yet been fully exploited. Traditional methods rely on paper-based surveys, from which it is hard to obtain happiness measures on different time periods (e.g. before activity, on real-time during activity and retrospective after activity). Ma *et al*. [23] develop a smartphone platform to measure mood, on three levels: displeasure, tiredness and tensity. Fan *et al*. [24] develop a smartphone-based experience survey to measure satisfaction and overall happiness of travellers, based on the Satisfaction with Travel Scales [25].

The comparison and analysis of real-time and retrospective happiness measures, something that has not been sufficiently explored yet, is a key element in this study. The general framework is presented in Figure 1, which shows a general decision making process [16]. Based on the attributes of the alternatives (and their own preferences), individuals construct a latent Decision Utility, based on which they choose an alternative. After the decision has been made (in our context, once the individual is travelling or performing an activity), there is a Moment Utility which refers to the real-time experience of an alternative but that is not observable by the analyst, but of which we can obtain an indicator 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, of which we can obtain an indicator through a Retrospective Happiness measure. It is important to take into account that the Decision Utility, Moment Utility and Remembered Utility might differ, and therefore real-time and retrospective happiness measures might not be the same.

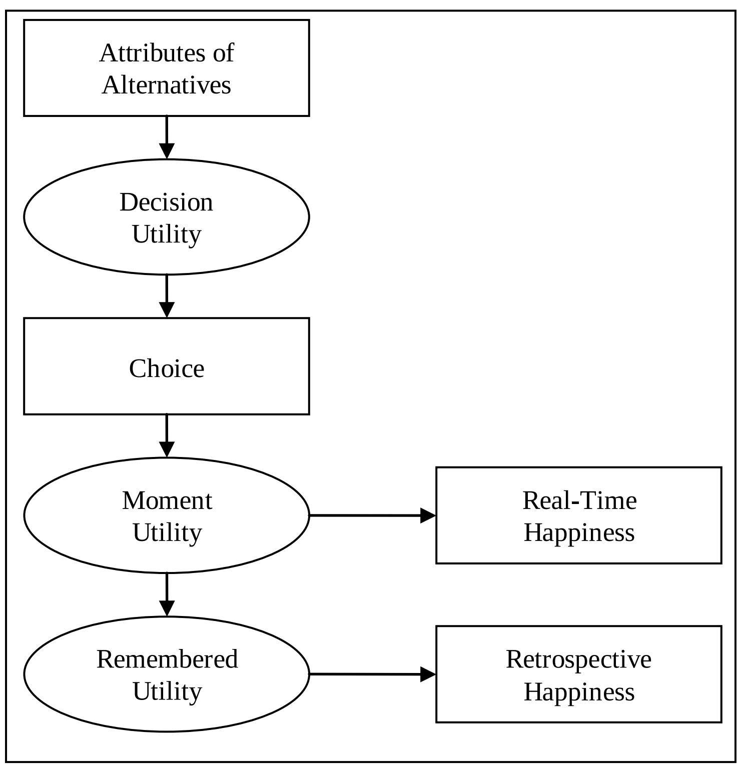


FIGURE 1 General Framework for Measuring Happiness and Its Relationship to Utility (Adapted from Abou-Zeid and Ben-Akiva [16])

The purpose of collecting happiness indicators can be twosome: on one hand, happiness measures can be seen as direct quantification of satisfaction in terms of service quality. For this purpose, happiness, along other well-being measures, can be monitored by operators and authorities, in order to improve the level of service provided. On the other hand, these indicators can be used to model behaviour. Happiness can be seen as an indicator of utility, and therefore be used to further understand decisions (in any context). In the context of transportation, different measures of happiness can help understand different decisions; general satisfaction or retrospective happiness could be linked to pre-trip decisions (like mode or time of day), while real-time happiness could be linked to en-route decisions (like 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 regarding future behaviour. 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 which are remembered as less unpleasant or more pleasant [29]; this way remembered utility affects the decision utility. Therefore, different measures provide different valuable information.

3.- 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 inter-connected, 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.

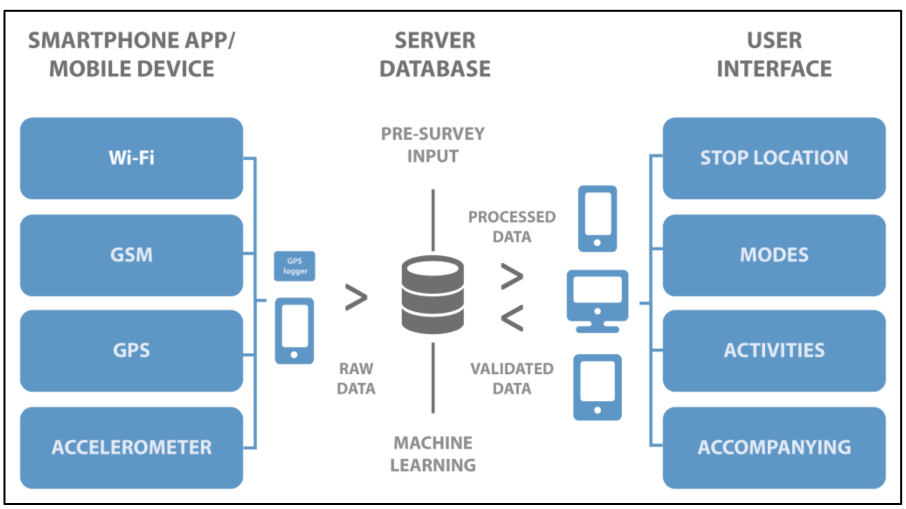


FIGURE 2 FMS Overview

3.1- Smartphone App

The smartphone app, available for both Android and iOS platforms, collects data from a multitude of the phones' sensors, including GPS, GSM, accelerometer, and WiFi. The app runs in the background of the phone, silently collecting sensor data without user intervention. We aim 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, using various approaches to minimize battery consumption, a major concern for location-based applications. The sensor data collected on the phone are transferred to the back-end server through either the cellular network or WiFi, based on the user's preference.

3.2- 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 non-travel 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 made based on location and point-of-interest (POI) data. GSM, WiFi and accelerometer information are used to merge stops that would otherwise be interpreted as distinct stops. Travel modes are detected based on 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 the purposes of presentation in the web interface. Travel destinations (e.g., home, work, shopping, drop-off) are also inferred based on previous validations by the user, POI data, and other contextual information.

3.3- 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 subsequently make better inferences. 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 Singapore Land Transport Authority's (LTA's) Household Interview Travel Survey (HITS) between October 2012 and September 2013. More than 1500 HITS respondents also participated in FMS demonstration project, and comparison between their HITS and FMS data reveals that FMS can deliver substantially richer, higher resolution and larger travel and activity dataset [30].

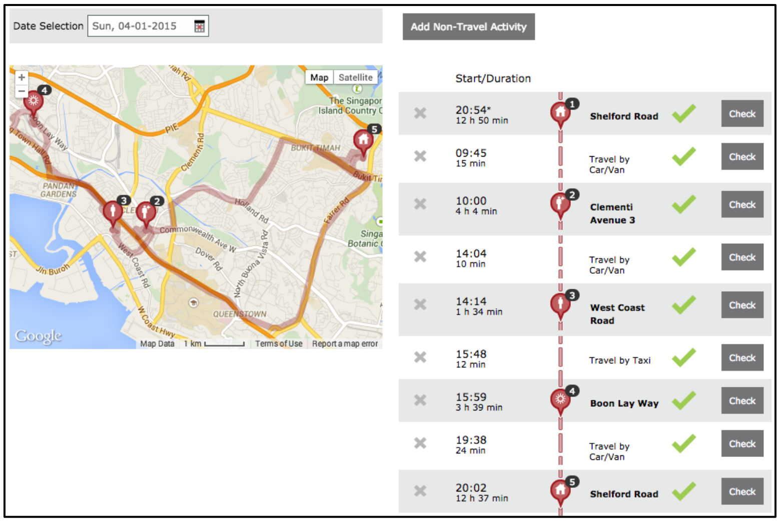


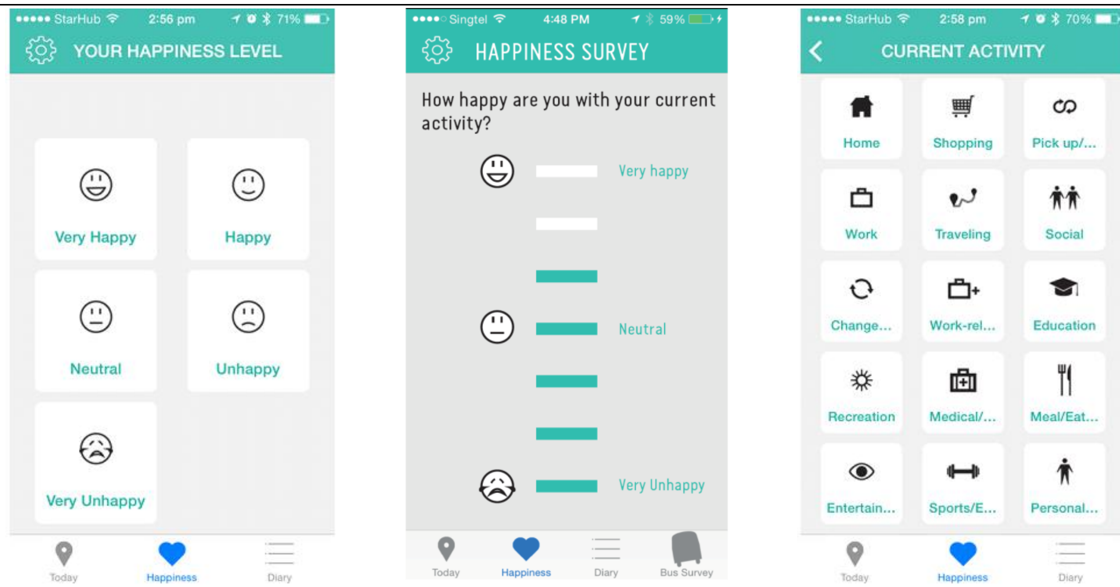
FIGURE 3 FMS Activity Diary Interface

4.- REAL TIME AND RETROSPECTIVE HAPPINESS SURVEY

The FMS platform was extended with additional functionality to conduct a happiness survey. Firstly, 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 the survey was activated until the next one becomes available on the next day. For the pilot survey, happiness was measured using a 5-point scale (Figure 4a). As the results for the first pilot survey had answers concentrated towards neutral levels, for the second survey the measurement scale was changed to a 7-point happiness question (Figure 4b). The responses to the survey along with the timestamp of when the responses were reported are both recorded in the backend.

Another issue corrected after analysing 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?*" Nevertheless, as the respondent can delay the answer, it was not guaranteed 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 we have happiness measures in real-time and in retrospect. Therefore, in the second survey the question was changed to "*How happy were you with your activity XXX hours ago?*" if it is not answered within 30 minutes. This change eliminates the potential selection bias that may occur if participants themselves chose the activities/times for which they want to report their happiness level.

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



(a) Pilot survey 5-level happiness (b) Second survey 7-level happiness (c) Activity question

FIGURE 4 FMS on-Phone Real-Time Happiness Pilot Survey

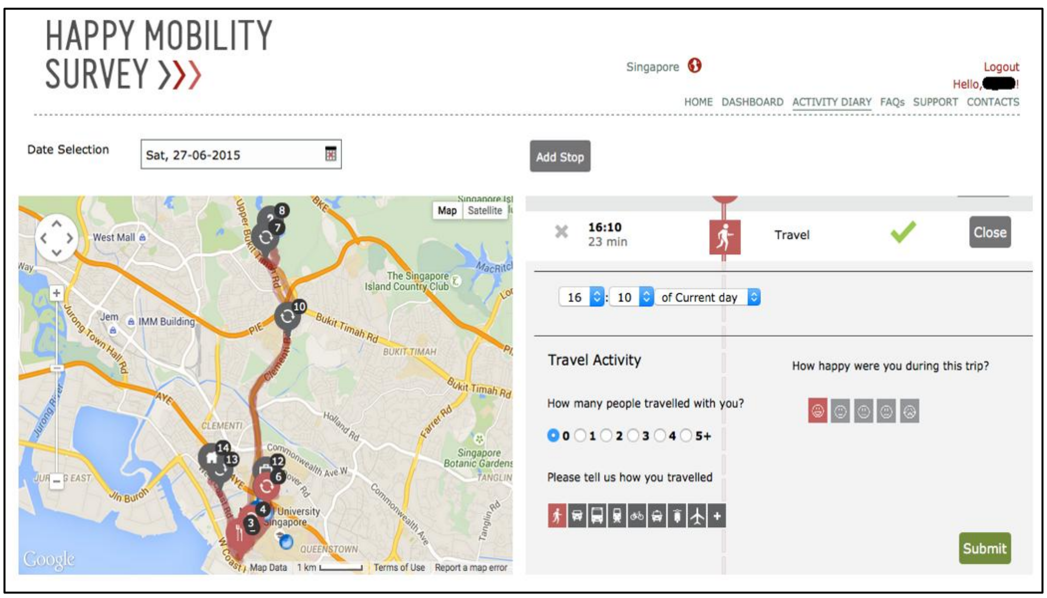


FIGURE 5 FMS Activity Diary Interface to Collect Retrospective Happiness Level Responses

As mentioned, two surveys were conducted using the FMS platform. The first pilot survey helped us improve and make changes to the second survey. The total sample size consisted of 737 real-time happiness measures, for different activities. For 147 of those activities, retrospective happiness measures were provided by the FMS users when verifying 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, United Kingdom, and United States.

Table 1 presents the responses to the real-time happiness measures by activity type. For analysis and modelling 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. It is interesting to note that Work and Education activities tend to be associated with lower happiness levels than the rest of the activities, including Travelling (which is the only activity that might not provide direct benefit). These results follow the trend of other studies, such as Kahneman *et al*. [14] who found that working and commuting were among the least enjoyed activities. 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 when compared to other activities as Travelling (for example, drivers should not be able to answer the question while travelling, but rather when performing their next activity). The latter issue applies only to the first pilot study but not the second. Moreover, the longer duration of the work and home activities compared to other activities increases their probabilities of being randomly sampled for the happiness question.

TABLE 1 Real-Time Happiness Measures

First Pilot Survey								
Activity	**Very Unhappy**	**Unhappy**	**Slightly Unhappy**	**Neutral**	**Slightly Happy**	**Happy**	**Very Happy**	**Total**
Work	5	8	-	22	-	21	5	**61**
Education	-	5	-	5	-	2	2	**14**
Home	-	4	-	20	-	21	8	**53**
Travelling	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**
Travelling	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**

The comparison between Real-Time and Retrospective happiness measures for the first pilot survey is shown in Table 2, while the same comparison for the second survey is shown in Table 3. This comparison is made using the sample of activities for which both retrospective and real-time happiness measures were reported by the respondents. The values in the diagonal represent 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 represent higher happiness levels in retrospect than in real-time (29% of the instances in the first pilot survey, 43% in the second survey), while the lower left cells in pink represent higher happiness in real-time than in retrospect (24% of the instances on the pilot survey, 32% on the second survey). As expected, the 7-level happiness responses have a higher dispersion, but the results have the same general trends in both surveys.

It can be seen that people tend to be consistent in the happiness levels they provide. In the first pilot survey only in 7 cases (11%) the difference between real-time and retrospective happiness is higher than one level. In the second survey there are 24 (29%) such cases, and in only 6 of those cases (7%) the difference between real-time and retrospective happiness is higher than two levels. It is observed that 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 extreme levels (i.e. very unhappy and very happy) seem to remain over time. The Hedonic Treadmill effect relates to the human tendency of quickly returning to relatively stable levels of happiness (i.e. centred around neutral in this case) despite experiencing major positive or negative events. Another explanation for the differences in both happiness measures could be that in real-time people evaluate a particular instance of the activity, while on retrospect they may evaluate the overall activity or certain specific moments (Peak-End Rule).

TABLE 2 Real-Time versus Retrospective Happiness (First Pilot Survey)

		Retrospective Happiness					
		Very Unhappy	**Unhappy**	**Neutral**	**Happy**	**Very Happy**	**Percentage of Total**
Real-Time Happiness	**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 %	

TABLE 3 Real-Time versus Retrospective Happiness (Second Survey)

		Retrospective Happiness							
		Very Unhappy	**Unhappy**	**Slightly Unhappy**	**Neutral**	**Slightly Happy**	**Happy**	**Very Happy**	**Percentage of Total**
Real-Time Happiness	**Very Unhappy**	-	1	-	-	-	-	-	1%
	Unhappy	-	-	1	3	-	-	-	5%
	Slightly Unhappy	-	1	-	7	1	2	-	14%
	Neutral	1	1	4	7	6	3	1	28%
	Slightly Happy	1	-	2	4	6	4	3	25%
	Happy	-	-	-	4	4	5	3	20%
	Very Happy	-	-	-	1	1	2	2	7%
	Percentage of Total	2%	4%	9%	32%	22%	20%	11%	

5.- UNDERSTANDING HAPPINESS

To understand the relationship between happiness measures (both in real-time and retrospectively) and activities, an Ordinal Logit Model was estimated. Based on this approach, the latent happiness experienced by individual n during activity a, h_{an}, is a function of socio-economic characteristics S_n and activity attributes A_{an}, according to Equation (1), were η_{an} is a random error. The relationship between the latent happiness and the explanatory variables is assumed to be linear.

$$h_{an} = h_{an}\left(S_n, A_{an}\right) + \eta_{an} \qquad (1)$$

The observed measure of happiness, d_{an} (which could be either real-time or retrospective) is indicated by a set of thresholds, 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.

$$d_{an} = \begin{cases} \text{Very Unhappy} & , \text{ if } \quad -\infty < h_{an} \leq \tau_1 \\ \text{Unhappy} & , \text{ if } \quad \tau_1 < h_{an} \leq \tau_2 \\ \text{Slightly Unhappy} & , \text{ if } \quad \tau_2 < h_{an} \leq \tau_3 \\ \text{Neutral} & , \text{ if } \quad \tau_3 < h_{an} \leq \tau_4 \\ \text{Slightly Happy} & , \text{ if } \quad \tau_4 < h_{an} \leq \tau_5 \\ \text{Happy} & , \text{ if } \quad \tau_5 < h_{an} \leq \tau_6 \\ \text{Very Happy} & , \text{ if } \quad \tau_6 < h_{an} < \infty \end{cases} \qquad (2)$$

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: (i) activity-specific binary variables, (ii) gender of the respondent, (iii) activity duration, which has a quadratic specification to capture non-linear effects, and (iv) an individual-based random term to capture a potential panel effect. The panel effect is included for two purposes: (i) to capture potential heterogeneity among the individuals (as happiness is highly subjective) and (ii) to capture correlation among responses from the same individual.

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

Interestingly, 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 socio-demographic 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 can relate to the Duration Neglect phenomena [33], where in retrospect people do not consider the duration (or overall pleasantness) of an event, but only certain key moments like its peak and its end. In real time, longer work and education activity durations have a negative effect on happiness levels; this effect is non-linear. On the other hand, 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 different ways: (i) there is no strong heterogeneity among the individuals (which is unexpected, as happiness tends to be highly subjective), and (ii) there is no strong correlation among answers from the same individuals.

TABLE 4 Happiness Model Results

	Real-Time Happiness		Retrospective Happiness	
Explanatory Variable	**Parameter**	***t*-Value**	**Parameter**	***t*-Value**
Home Activity *	0	Fixed	0	Fixed
Work Activity *	-0.193	-2.54	-0.193	-2.54
Education Activity on Weekday *	-0.101	-2.35	-0.101	-2.35
Education Activity on Weekend *	-0.378	-2.11	-0.378	-2.11
Other Activity *	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
$(\text{Education/Work Activity Duration})^2$	-0.00691	-2.87	-0.00212	-1.23
(Other Activity Duration)	0.0276	2.07	0.00340	1.26
$(\text{Other Activity Duration})^2$	0.00575	2.28	0.00145	1.20
Panel Effect (Mean) *	0.152	1.11	0.152	1.11
Panel Effect (Standard Deviation) *	0.0201	0.98	0.0201	0.98
First Pilot Survey Thresholds	**Parameter**	***t*-Value**	**Parameter**	***t*-Value**
Very Unhappy – Unhappy Threshold τ_1	-3.12	-3.78	-3.22	-2.15
Unhappy – Neutral Threshold $\tau_{2/3}$	-1.70	-2.21	-1.76	-2.81
Neutral – Happy Threshold $\tau_{4/5}$	0	Fixed	0	Fixed
Happy – Very Happy Threshold τ_6	1.80	2.55	1.04	2.31
Second Survey Thresholds	**Parameter**	***t*-Value**	**Parameter**	***t*-Value**
Very Unhappy – Unhappy Threshold τ_1	-2.47	-3.21	-2.24	-2.75
Unhappy – Slightly Unhappy Threshold τ_2	-1.15	-2.04	-1.49	-2.78
Slightly Unhappy – Neutral Threshold τ_3	-0.49	-1.98	-0.45	-2.34
Neutral – Slightly Happy Threshold τ_4	0	Fixed	0	Fixed
Slightly Happy – Happy Threshold τ_5	0.67	1.65	0.54	1.78
Happy – Very Happy Threshold τ_6	1.10	2.51	1.58	2.24
Sample Size	884			
Adjusted ρ^2	0.221			

* The parameters for these variables were assumed to be the same for real-time and retrospective happiness.

6.- CONCLUSIONS AND EXTENSIONS

This study presented a comparison and analysis of real-time and retrospective happiness measures. Both measures were obtained by adapting the FMS platform, through a non-intrusive smartphone-based survey. When comparing real-time and retrospective happiness measures, two cognitive biases are observed: the Peak-End Rule and the Hedonic Treadmill Effect. The extreme (i.e. peak) real-time measures of “Very Unhappy” and “Very Happy” seem to last over time, while the less extreme measures tend to more neutral levels in retrospect.

When modelling and understanding the happiness measures provided by the respondents, a third cognitive bias appears: the Duration Neglect, as 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 the respondents' gender. An extension of this study would be to include these happiness measures in traditional transportation and mobility models (such as mode choice, route choice, activity scheduling), in order to enhance their explanatory and forecasting capabilities.

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

In the first pilot survey, it was also observed that many responses were concentrated between levels Neutral and Happy. Because of this, in the second survey we adopted a finer resolution for the happiness measure (with a 7-point scale instead of a 5-point scale). A continuous happiness measure is also an alternative to evaluate (this can be done in FMS through a sliding bar, instead of providing pre-defined happiness levels to the respondents).

An issue to work on is the verification rate of respondents, where they provide the retrospective happiness measures. As seen in Section 4, for most of the 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 where the participant will be asked about happiness retrospectively.

The next stage of this study could focus on analyzing and modelling the differences between the real-time and retrospective happiness measures, in terms of individual characteristics. This would help understand the circumstances that affect how activities are remembered by the respondents. The time between the real-time measure and the retrospective measure (which is provided by the respondents when verifying their activity diaries) can also be analysed further, and be used in the modelling stage as an explanatory variable, as recent activities are remembered in more detail. These analyses will be included in a next stage of the study, as they require higher verifications rates.

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