

Well-being and activity-based models

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Abstract We present empirical and theoretical analyses to investigate the relationship between happiness (or subjective well-being) and activity participation and develop a framework for using well-being data to enhance activity-based travel demand models. The overriding hypothesis is that activities are planned and undertaken to satisfy needs so as to maintain or enhance subjective well-being. The empirical analysis consists of the development of a structural equations exploratory model of activity participation and happiness using data from a cross-sectional survey of a sample of commuters. The model reveals significant correlations between happiness and behavior for different types of activities: higher propensity of activity participation is associated with greater activity happiness and greater satisfaction with travel to the activity. The theoretical analysis consists of the development of a modeling framework and measures for the incorporation of well-being within activity-based travel demand models. The motivation is that activity pattern models have been specified in ad-hoc ways in practice as a function of mobility, lifestyle, and accessibility variables. We postulate that well-being is the ultimate goal of activity patterns which are driven by needs and propose two extensions of activity pattern models. The first extension consists of the use of well-being measures as indicators of the utility of activity patterns (in addition to the usual choice indicators) within a random utility modeling framework. The second extension models conceptually the behavioral process of activity generation based on needs satisfaction. We present an example of an operational activity pattern model and propose well-being measures for enhancing it.

Keywords Activity-based models · Activity-schedule approach · Happiness · Subjective well-being · Random utility models

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Introduction

The study of happiness or subjective well-being in relation to activity participation is of relevance for predicting time allocation to activities and resulting travel demand, assessing people's well-being, and monitoring trends in happiness. The link between activity participation and overall well-being has been established in various studies (Cantor and Sanderson 1999; Ettema et al. 2010; Spinney et al. 2009; Waters et al. 1989). The purpose of this paper is to develop a modeling framework for representing this link between well-being and activities in activity-based models of travel demand (Axhausen and Gärling 1992; Ben-Akiva et al. 1996; Kitamura et al. 1996).

Activity-based models, which are based on the premise that the demand for travel is derived from the demand for activities, explicitly model the generation of activities or activity patterns. The activity-based approach currently constitutes the state of the art in metropolitan travel demand forecasting. Yet operational models typically represent activity pattern generation as a function of lifestyle, mobility, and accessibility variables without systematically accounting for well-being. We postulate, however, that activities are planned and undertaken to satisfy various human needs so as to maintain and enhance subjective well-being (Ben-Akiva 2007, 2009). The objective of this paper is to develop a modeling framework to enhance the specification of activity pattern models and to propose new measures of activity pattern well-being that can be used to support the extended modeling framework.

This paper is organized as follows. “[Measurement of activity happiness](#)” and “[An exploratory model of activity happiness and frequency](#)” sections provide empirical evidence for the relationship between happiness and activities based on direct measurements and exploratory models. “[Well being and activity pattern models](#)” section develops a modeling framework that extends standard activity pattern models (and static random utility models in general) to account for well-being and proposes and tests new well-being measures. “[Discussion](#)” section concludes the paper.

Measurement of activity happiness

A number of instruments for the measurement of activity happiness have been developed and tested, such as the experience sampling method (Hektner et al. 2006; Larson and Csikszentmihalyi 1983) which captures emotions for a sample of activity episodes in real-time, the day reconstruction method (Kahneman et al. 2004), which measures emotions for all activity episodes conducted on a previous day, and instruments that measure enjoyment of activities in general (not tied to specific recent episodes; see Juster 1985). For a more elaborate discussion of measurement instruments and findings from the subjective well-being literature, see Ettema et al. (2010) and Krueger et al. (2008).

Using these instruments, a number of recent empirical studies have shown that happiness varies significantly by activity type and socio-economic group (Csikszentmihalyi and Hunter 2003; Jakobsson Bergstad et al. 2011; Kahneman et al. 2004; Kahneman and Krueger 2006; Krueger et al. 2008; Turcotte 2008). For example, using the Princeton affect and time survey which is based on the concept of the day reconstruction method, Krueger (2007) found that people in his sample were happiest when they conducted engaging leisure and spiritual activities, and were least happy when they conducted unpleasant personal maintenance activities. Using a 2005 time-use survey, he found that people spent about 17% of their day on average doing the former activity and 4% of their day doing the latter activity. Using a survey that we conducted in 2007 with a sample of commuters (Abou-Zeid and Ben-Akiva 2011) which measured happiness experienced when

conducting different activities and satisfaction with travel to those activities, we found that people in our sample were happiest when they conducted social and recreational activities and least happy when they conducted personal business activities. They were also most satisfied with their travel to eat-out activities and least satisfied with their travel to organizational, volunteer, or religious activities.

Thus, having direct measurements of happiness by activity type is useful for analyzing time allocation or frequency of activity participation in relation to happiness derived from different activities, as described next.

An exploratory model of activity happiness and frequency

Using the 2007 survey referenced above (Abou-Zeid and Ben-Akiva 2011), we developed exploratory models to test for the presence of correlations between activity/travel well-being and the propensity to participate in activities. It is postulated that the greater the happiness derived from an activity and the greater the satisfaction with travel to the activity, the higher is the propensity to participate in the activity. In addition to measuring activity happiness for different types of activities (on a 5-point scale ranging from “Very unhappy” to “Very happy”) and satisfaction with travel to these activities (on a 5-point scale ranging from “Very dissatisfied” to “Very satisfied”), the survey measured the weekly frequency of conducting the activities, distance and travel mode used to travel to the activities, and various socio-economic and demographic characteristics.

Figure 1 shows this exploratory model structure. In this figure and other figures in the paper, variables shown in ovals are latent (or unobserved) while those shown in rectangles are observed; solid arrows represent structural relationships while dashed arrows represent measurement relationships. Socio-economic variables influence both activity propensity and activity happiness. The direct link between socio-economic variables and activity propensity is included for two reasons. First, since the model is exploratory, it is important to control for socio-economic variables in different parts of the model so as to be conservative in identifying whether a relationship exists between activity happiness and

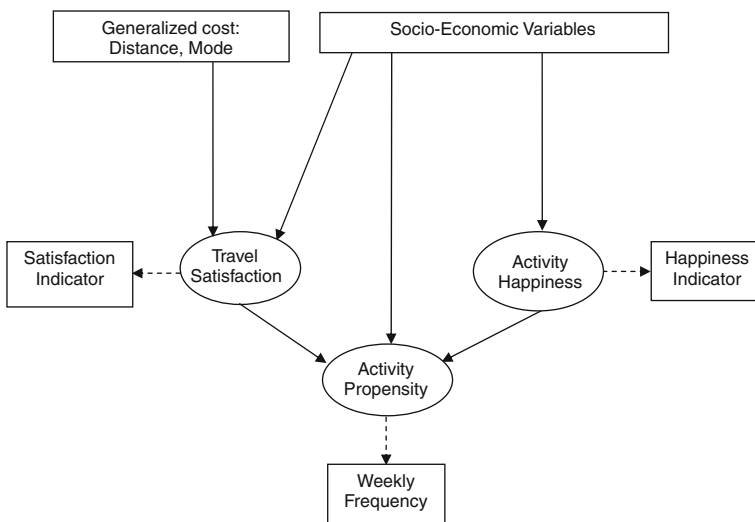


Fig. 1 Activity propensity model

activity propensity. Second, the direct effect of socio-economic variables on activity propensity has a behavioral interpretation. It reflects the needs for conducting activities that may differ by socio-economic group and that may also be independent of the level of happiness associated with the activities. The socio-economic variables that affect activity propensity can then be interpreted as proxies for needs, which were not measured in the survey. Finally, travel satisfaction is a function of the generalized cost of travel (mode and distance) which could be interacted with socio-economic variables.

Activity propensity, activity happiness, and travel satisfaction are latent variables and are measured by activity frequency and the activity and travel happiness indicators, respectively, collected in the survey. Another important measure that can be used to capture activity propensity is the duration of participation in an activity. This measure was, however, not collected in the survey.

Models were estimated for the following activity types: shopping, social/recreational, eat-out, organizational/volunteer/religious, and personal business. The model estimation results are available in Abou-Zeid (2009). For all types of activities, it was found that the propensity to participate in an activity is positively and significantly correlated with the happiness derived from the activity and the satisfaction with travel to the activity. This result provides evidence for the existence of relationships between well-being and behavior in the context of travel and activities; according to the causation structure specified in Fig. 1, the greater the well-being derived from a given behavior, the more frequently people engage in that behavior.

It should be noted that the model presented above is an exploratory model that investigates whether a relationship exists between well-being and activity participation. If the model were to be used for prediction, other issues would need to be considered, including the direction of causality between well-being and behavior (activity propensity) and potential correlations between the propensities to conduct different types of activities.

Well-being and activity pattern models

With the evidence cited above on the correlations between well-being and behavior for different types of activities, we now turn to modeling well-being at the level of an activity pattern (i.e. group of activities) and show how it can be incorporated within activity-based models of travel demand. The rationale is that while well-being is a driver of activities through the satisfaction of needs, existing activity-based models do not account for this relationship.

“[The activity-schedule approach](#)” section provides an overview of a class of activity-based models widely used in practice and known as the activity-schedule approach. “[Extended modeling framework](#)” section discusses the relationship between happiness and utility and develops a modeling framework for the extension of static random utility models that accounts for well-being. Two extensions are then presented to incorporate well-being in the activity-schedule approach. “[An example](#)” section shows an example of an operational activity pattern model along with new measures that can capture well-being from activity participation.

The activity-schedule approach

Theory and model formulation

One approach that has been widely used in practice for developing activity-based model systems is the activity-schedule approach (Ben-Akiva et al. 1996; Bowman 1995, 1998;

Bowman and Ben-Akiva 2001). It decomposes the activity–travel decision into two sets of models: an activity pattern model and tour models. The activity pattern model sets a schedule for the day; it determines the number, purposes, priorities, and structure of activities and travel. The tour models determine the destinations, timing, and access modes for activities on the primary and secondary tours. The tour models are conditional on the activity pattern. The choice of activity pattern is in turn sensitive to travel conditions through expected utility arising from the tour models. Discrete choice models based on random utility theory are used for the different components of the model system.

Bowman (1998) specified the systematic utility V_i of a pattern i as consisting of three components: a component \tilde{V}_i for the overall pattern i to capture activity synergy and related time and energy limitations, a component V_a related to every activity a in the pattern, and a component V_t related to the expected maximum utility of each tour t in pattern i . The systematic utility for pattern i is therefore given as follows:

$$V_i = \tilde{V}_i + \sum_{a \in A_i} V_a + \sum_{t \in T_i} V_t \quad (1)$$

where A_i denotes the set of activities in pattern i , and T_i denotes the set of tours in pattern i .

The component \tilde{V}_i reflects activity placement options (e.g. which secondary activities occur on which tours, position with respect to the primary activity, and presence of multiple secondary stop placements on primary tours) and inter-tour effects (combination of tour purposes used in the pattern). It depends on lifestyle and mobility variables in addition to attributes of the pattern. The utility component V_a is also a function of lifestyle and mobility variables and is defined for both primary and secondary activities. Finally, the component V_t depends on variables—including the generalized cost of travel—that affect the time of day, mode, and destination attributes of the tours.

Application in practice

Examples of operational model systems in the U.S. using the activity-schedule approach include the models developed for Atlanta, Columbus, Denver, Jacksonville, Lake Tahoe, New York, Ohio, Oregon, Sacramento, San Francisco County, and San Francisco Bay Area. Other model systems currently under development in the U.S. using the activity-schedule approach include models for Houston, Phoenix, San Diego, and Seattle (see, for example, Bradley et al. 2008 and Rossi et al. 2009).

The specification of activity-based models in operational model systems strikes a different balance between behavioral realism and complexity (Shiftan and Ben-Akiva 2008). For example, some models introduce joint decision making through household interactions which is more behaviorally realistic but makes the model more complex. The number of activity purposes and person types and the level of temporal disaggregation also vary among these models.

Perhaps the most striking differences are related to the specification of the activity pattern model. Different model types, including logit and nested logit, have been used. Choice sets of different sizes have been used. For example, the San Francisco County model has 49 alternatives for the pattern choice, while the Portland model has 570 alternatives. The utility functions, formulated as in Eq. 1, usually combine in ad-hoc ways variables related to mobility, lifestyle, socio-economics, and accessibility.

The main point to be made here is that activity pattern models as they are currently used in practice do not account in a systematic way for the main drivers of activities. As we have argued above, activity patterns are chosen to satisfy needs so as to maintain or enhance

well-being. Therefore, including well-being and needs and measures of them in these models will allow for better behavioral representation of the drivers of activities and for more efficient models (as will be discussed later). The next section develops a modeling framework that extends the standard activity pattern model of the activity-schedule approach so as to account for well-being.

Extended modeling framework

In this section, we discuss how well-being can be incorporated in the specification of activity pattern models in the activity-schedule approach. The incorporation of well-being measures in activity-based models which are based on random utility theory implies a certain relationship between utility and well-being. So we start this section by discussing this relationship and showing a general framework that extends random utility models. Then we elaborate on two specific extensions of activity pattern models. Finally, we describe one of these extensions in the context of an operational activity-based model and propose new measures of activity pattern well-being.

Happiness and utility

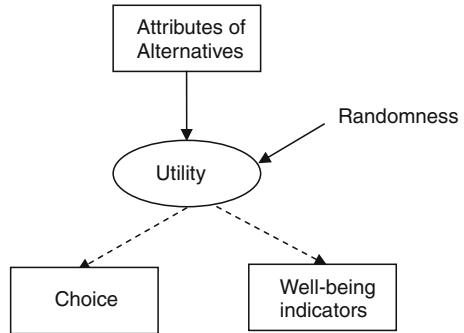
Conceptual overview The relationship between happiness and utility has been conceptualized differently in different eras of consumer theory (for a review, see Abou-Zeid 2009; Ettema et al. 2010; McFadden 2005). While in the classical era Jeremy Bentham (1789) defined utility as the experiences of pleasure and pain, neoclassical economists associated utility with the weight of outcomes in making decisions, where preferences can only be inferred from choices. In the modern behavioral revaluation of consumer theory, Daniel Kahneman and his colleagues (Kahneman et al. 1997; Kahneman 2000) referred to Bentham's definition of utility as experienced utility and to the modern usage of utility by neoclassical economists as decision utility. They also distinguished among three forms of experienced utility: remembered utility which is a retrospective global assessment of an experience; moment utility which characterizes the affective states of the real-time experience; and predicted utility which represents the anticipated feeling of pleasure or pain. Interrelationships between these different notions of utility have also been observed through various experiments (see Kahneman et al. 1993; Redelmeier et al. 2003; Schreiber and Kahneman 2000; Wirtz et al. 2003).

Extended random utility model Based on the above, we have proposed that subjective well-being and utility are the same concept, but a distinction needs to be made among the different notions of utility. We developed a dynamic modeling framework that extends the standard random utility model by using well-being measures as indicators of utility in addition to the usual choice indicators, and also models the interrelationships between the different notions of utility (Abou-Zeid and Ben-Akiva 2010).

Since household travel surveys are typically conducted cross-sectionally, we develop below an extended static random utility modeling framework and discuss the measurement issues that arise in a static context. This framework is shown in Fig. 2.

The extended modeling framework consists of a discrete choice model, where the utility of an alternative is a latent variable that is determined by attributes of the alternative and random unobserved factors and is reflected in the choice through utility maximization. We

Fig. 2 Extended random utility model with well-being measures in a static context



extend the standard model by adding the well-being measures as indicators of utility. The measurement model for alternative i then consists of the following two equations:

$$y_i = \begin{cases} 1 & \text{if } U_i \geq U_j \quad \forall j \neq i, \quad \forall i \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$h_i = h(U_i) + v_i, \text{ for } i \text{ such that } y_i = 1. \quad (3)$$

Equation 2 is utility maximization, where y_i is a choice indicator which is equal to 1 if alternative i is chosen and 0 otherwise, and U_i is the (decision) utility of alternative i . Equation 2 applies for all alternatives i . Equation 3 is the happiness measurement equation, where h_i is the happiness measure associated with alternative i , $h(\cdot)$ is a function that relates the utility to the happiness measure, and v_i is a measurement error. Equation 3 applies only for the chosen alternative since, in a static context, happiness measures are typically available for the chosen alternative only (i.e. people are asked how happy they are with their chosen alternative).

Measurement issue We discuss next a measurement issue related to the use of happiness indicators in a static context. Utility is used in discrete choice models in a predictive sense. That is, people make choices based on decision utility (before they actually experience the outcomes). Thus, the choice indicator reflects decision utility and the choice is made before the actual experience of the outcome. On the other hand, the happiness measures are obtained through surveys after people experience the outcomes of the choice, which means that the happiness measures reflect remembered utility (and indirectly the experienced utility which precedes remembered utility). Thus, in a static context, the choice and happiness indicators measure two concepts of utility. This is problematic to the extent that the decision and remembered utilities are different. If one uses then the happiness measures as indicators of decision utility as in the framework of the discrete choice model shown in Fig. 2, the happiness measures would be “imperfect” measures of decision utility.

This issue can nevertheless be accounted for by obtaining measures of how different the experience was from expectations or to what extent the implemented actions/activity choices differed from plans. The idea is that when people make a choice, they need to predict or form some expectations of the utilities of different courses of action and then make plans to implement the actions. So if the outcome of the experience turns out to be close to what was expected/planned before making the decision, then the happiness measure which reflects this experience would also be reflecting the prior expectations/plans related to the experience, i.e. the decision utility, and in this case it is justified to use the happiness measures as indicators of decision utility as in the framework of Fig. 2.

Letting E denote a measure of how different the experience was from expectations/plans, the happiness Eq. 3 can now be modified by making the happiness indicator a function of the expectations/plans indicator as follows:

$$h_i = h(U_i, E_i) + v_i. \tag{4}$$

The expectations/plans indicator would be available only for the chosen alternative. The effect of this indicator on model formulation is as follows. If E is binary (e.g. $E_i = 1$ if the experience of alternative i was as expected/planned and 0 otherwise), the happiness measure would be used as an indicator of decision utility of the chosen alternative (and Eq. 4 would be included in the model) only if the experience was as expected or planned. This essentially means that if E_i is equal to 0, the happiness measure is not predictive of the decision utility and the variance of v_i is infinity. On the other hand, if E_i is equal to 1, the happiness measure is predictive of the decision utility and the variance of v_i is minimum.

In the more general case, E can be measured on an ordinal scale, e.g. from 1 to 5, where 1 would represent the largest negative deviation of experience from expectations/plans, i.e. “much worse than expected”, 3 would represent no deviation, i.e. “as expected”, and 5 would represent the largest positive deviation, i.e. “much better than expected”. In this case, the happiness measure would be used as an indicator of decision utility regardless of the difference between experience and expectations/plans, but the relationship between the happiness measure and utility will depend on the extent of this difference. That is, compared to the case where the experience was as expected/planned, the happiness measure would be less predictive of utility if the experience negatively deviated from expectations/plans and more predictive of utility if the experience positively deviated from expectations/plans. This can be modeled as follows. First, the function $h()$ that relates the utility to the happiness measure can be specified as a function of the difference of experience from expectations/plans. If the measurement equation takes the form $h_i = \lambda U_i + v_i$, then the parameter λ can be expressed as:

$$\lambda = \lambda(E_i). \tag{5}$$

Second, the degree to which the activity pattern differs from prior expectations/plans affects the variance of v_i , with the minimum variance attained when the activity pattern happens as expected/planned, and with the variance increasing as the experience deviates from expectations/plans. This can be modeled by making the variance of v_i a function of the difference between experience and expectations/plans as in Eq. 6:

$$\sigma_{v_i}^2 = \sigma^2(E_i) \tag{6}$$

where $\sigma_{v_i}^2$ denotes the variance of v_i .

In both Eqs. 5 and 6, the specific functional forms used ($\lambda()$ and $\sigma^2()$) would be chosen to capture the different effects of negative and positive deviations of experience from expectations/plans on the relationship between utility and the happiness measure.

Extensions of activity pattern model

We propose two extensions of the standard specification of the activity pattern model as used in the activity-schedule approach. The first extension is econometric and involves adding happiness measurement equations to enhance the measurement of utility. The second extension is behavioral and involves modeling explicitly the drivers of activities in the specification of the activity pattern utility equation.

Extension 1: adding well-being measurement equations The first extension is a direct application of the extended framework presented in “[Happiness and utility](#)” section. In this case, an alternative represents an activity pattern. We consider the availability of one or more well-being measures at the level of the activity pattern. If the well-being measure is broad enough to consider all aspects of the pattern, then it can be used as an indicator of the pattern utility. Since an individual faces a very large number of activity patterns to choose from, it is impractical to collect well-being measures for every activity pattern in the choice set. Therefore, we consider the case where well-being measures are available only for the chosen activity pattern, and corresponding indicators of how different the chosen pattern was from prior expectations/plans are also available.

The structural part of the activity pattern model is a specification of activity pattern utility. The utility is specified in the usual way as a function of attributes of the pattern, characteristics of the individual, and an error term (e.g. with the systematic utility specified as in Eq. 1). The measurement model for pattern i then consists of the choice and happiness equations as in Eqs. 2 and 4.

Extension 2: modeling the drivers of activities The second extension which is presented at a conceptual level here involves reformulating the standard specification of the systematic utility of the activity pattern model ($V_i = \tilde{V}_i + \sum_{a \in A_i} V_a + \sum_{t \in T_i} V_t$). This extension basically attempts to formulate the main hypothesis of the paper: that activities are pursued to satisfy needs so as to maintain or enhance well-being.

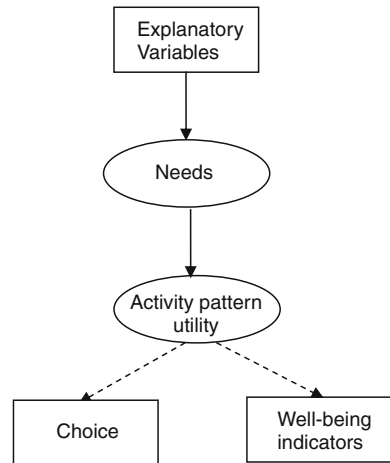
In the context of travel demand, the idea that activities are driven by needs has been discussed elsewhere (e.g. Adler and Ben-Akiva 1979 and the references contained therein; Westelius 1972). Individuals and households have needs for food, shelter, recreation, etc., which build up over time and get replenished when an activity that satisfies the need is conducted. In choosing activities to satisfy their needs, individuals would also account for the generalized cost of traveling to the corresponding activities given time and budget constraints.

A generic modeling framework for incorporating both needs and well-being into the activity pattern model is shown in Fig. 3. Needs to conduct activities are latent variables that depend on characteristics of the individual and on the time elapsed since the last time the corresponding activities were conducted. One can associate a “psychological inventory” with every need which represents the amount in “stock” one has of a certain need at a given point in time. This psychological inventory gets depleted over time and replenished when an activity is conducted. An individual would then choose an activity pattern that maximizes the average level of psychological inventory (or utility or well-being) over time from different needs subject to time and budget constraints. As before, well-being measures can be used as indicators of the pattern utility.

The full specification of the model involves defining the needs and their correspondence with activities and specifying the rate at which psychological inventory gets depleted over time, the threshold point at which a need is triggered, the level of increase in inventory when a pattern is conducted, satiation and fatigue effects, and the effect of transportation level of service. Such a model formulated in a dynamic context would then need to be applied in a static context, where observations of chosen activity patterns are often available from one or two-day household surveys.

There are several recent works on needs-based activity modeling in the literature, including exploratory studies (e.g. Nijland et al. 2010), rule-based models (e.g. Märki et al. 2011), and analytical formulations (e.g. Arentze and Timmermans 2009, and Arentze et al. 2011) who propose an estimation method of a dynamic needs-based activity generation model

Fig. 3 Needs-based activity pattern model framework (error terms are not shown for simplicity)



using one-day travel survey data). In Pattabhiraman et al. (2012), we have recently developed a steady-state needs-based utility-maximizing model (in the sense of maximizing the average level of psychological inventory over time subject to time and budget constraints) of activity location, duration, and frequency for the case of a single activity and proposed an empirical estimation procedure. For the needs-based approach to become operational in activity-based travel demand modeling systems, the ideas outlined above need to be extended to models that predict the generation, location, duration, frequency, and all travel attributes of an entire activity pattern. These formulations are an exciting avenue for future research which we are currently pursuing but are beyond the scope of this paper.

An example

To put the conceptual arguments presented earlier in context, this section shows an example of an activity pattern model from the Denver Regional Council of Governments (DRCOG) activity-based model and then presents examples of well-being measures that can be used to enhance the specification of this model.

The DRCOG activity pattern model

DRCOG's activity-based model follows the activity-schedule approach. The activity pattern model jointly predicts the number (0 or 1+) of home-based tours by purpose and the number (0 or 1+) of additional secondary stops by purpose that an individual undertakes in a given day. The purposes modeled are work, school, escort, personal business, shopping, meal, and social/recreational. The model type is logit and the choice set consists of 2^{14} alternatives reduced through some simplifications to 2,080 activity patterns.

The systematic utility of a pattern consists of individual and household characteristics, land use and accessibility (logsum) variables, and constants related to combinations of different tour and stop purposes on the pattern. For example, the systematic utility of a pattern consisting of 1+ work tours and 1+ escort stops includes the variables shown in Table 1. Each of these variables, with the exception of the tour and stop constants, is multiplied in the utility equation by two parameters, one that is work specific and one that is escort specific. The variables in the "Individual" column are dummy variables for person type (worker, student, etc.), gender interacted with presence of children in the household, age, and whether the individual works at home. The variables in the "Household" column are number of cars per

adult in the household, household income, and dummy variables related to the individual's status in the household. The accessibility variable is a logsum variable computed over all travel modes available between the home and work locations of the individual for the work purpose, and over all travel modes and destinations for the escort purpose. The tour and stop constants include constants for the two purposes on the pattern and their combination.

The utility specification of other activity patterns uses similar types of variables. The specification does not reflect a behavioral theory about how individuals make activity choices. The variables are selected based on the overall goodness of fit of the model, the statistical significance of the variables, and the reasonableness of the signs of the corresponding coefficients. The detailed model specification and estimation results can be found in Cambridge Systematics (2010).

Model extension using new well-being measures

In 2010, DRCOG conducted a new and extensive household travel survey. We added to this survey new measures to capture well-being from the chosen activity pattern. These measures will be used in the future to update the model specification shown in Table 1 based on the first extension proposed in “[Extensions of activity pattern model](#)” section. This will be done by retaining a similar activity pattern utility specification to the one currently used in DRCOG's model (e.g. Table 1) while adding to the model well-being measurement equations. This section describes these measures and shows some related descriptive statistics from the survey data.

Activity pattern well-being measures At the activity pattern level, a well-being measure that can be used as an indicator of the utility of the pattern should be general enough to

Table 1 Utility specification of the 1+ work tours/1+ escort stops activity pattern

Individual	Household	Accessibility	Tour and stop constants
Part-time worker	Cars per adult in household	Logsum	Work tour
Retired			Escort stop
	Income 0–15 K		
Other non-worker	Income over 75 K		Work tour and escort stop
University student	Missing income		1 tour purpose and 1 stop purpose
Student age 16+			
Student age 5–15	Only adult in household		
Child age 0–4			
Age 18–25	Only worker in household		
Female with no children			
Female with children age 0–4			
Female with children age 5–15			
Male with children age 0–4			
Male with children age 5–15			
Work at home			

capture all aspects of the pattern, including activities and travel. The following measure (h_i in “[Happiness and utility](#)” section) was used in DRCOG’s survey:

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?

Respondents would answer using a 7-point ordinal scale ranging from “Very dissatisfied” to “Very satisfied”.

Another question specific to the measurement of mood could be used (but not collected in DRCOG’s survey), such as the following measure adapted from the day reconstruction method (Kahneman et al. 2004):

Thinking overall about how you felt and what your mood was like yesterday, would you say you were most of the time in a bad mood, a little low or irritable, in a mildly pleasant mood, or in a very good mood?

Deviations from expectations/plans measures The degree to which the activity pattern happened as expected or planned (E_i in “[Happiness and utility](#)” section) was measured by two questions in DRCOG’s survey. The first question is related to deviations of the chosen pattern from prior expectations:

In general, would you say that yesterday was a typical day for you? Did all your activities and travel happen as you had expected?

Respondents would answer using a Yes/No response scale, and if they answered no, they were asked for the reason the day was not typical (respondents were also probed to see whether all workers worked and all students went to school that day).

The second question is related to deviations of the chosen pattern from plans:

Was most of your travel and activities for this day planned in advance or did you change your plans as the day progressed?

Respondents would indicate whether they changed their plans, and if so, what happened that caused the change in plans.

Descriptive statistics Data on 16,210 individual activity patterns were recorded in DRCOG’s survey conducted in 2010, 5,880 of which were recorded through proxy interviews and thus did not include answers to the satisfaction and expectations/planning questions. Of the remaining 10,330 activity patterns, answers to the pattern satisfaction question were obtained from 9,105 respondents (the rest said “do not know” or refused to answer), all of whom indicated whether the pattern deviated from expectations but only 6,596 of whom indicated whether the pattern happened as planned (the rest said “do not know”). Figure 4 shows the distribution of respondents by their satisfaction levels with the chosen activity pattern. The distribution is shown separately for those whose patterns happened as expected (i.e. where the day was typical) and for those whose patterns differed from expectations. Figure 5 shows the satisfaction distribution for those whose patterns happened as planned and those who had to make deviations from the plan. In both Figs. 4, 5, it can be seen that the distribution of satisfaction shifts to the right for the case where the day pattern was as expected (i.e. typical day) or happened as planned relative to the case where it was not as expected/planned. This makes sense since in general if activities and travel take place as expected and people are able to execute their planned activity

Fig. 4 Distribution of respondents by satisfaction level and by whether the activity pattern happened as expected or not (N = 9,105 respondents)

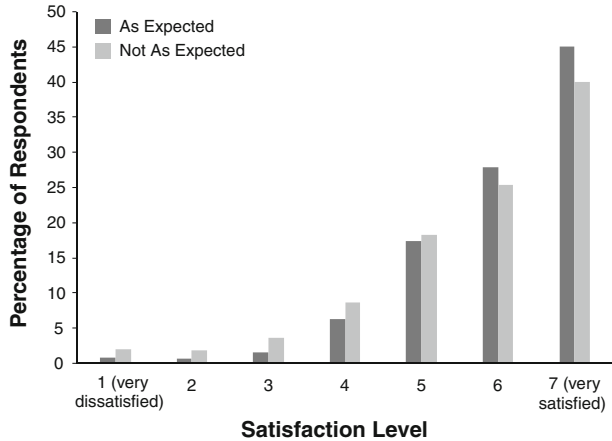
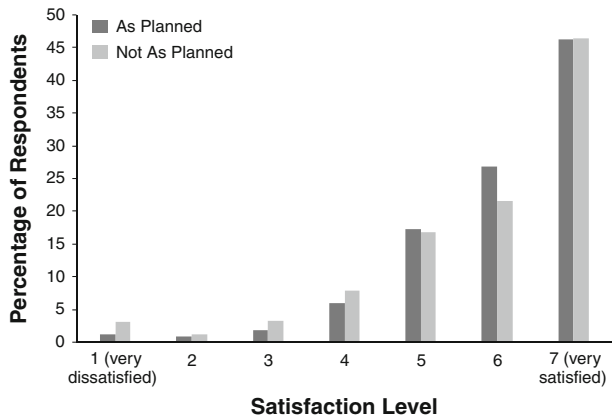


Fig. 5 Distribution of respondents by satisfaction level and by whether the activity pattern happened as planned or not (N = 6,596 respondents)



schedules, then they are more satisfied than if they have to make changes to their plans. That is, in this case the pre-choice expectation and the post-choice experience or realization should converge, and the happiness measure should be a good indicator of decision utility. The average satisfaction level is also higher for those whose activity patterns happened as expected/planned (6.02 for respondents with typical day patterns vs. 5.75 for respondents with non-typical day patterns; 6.04 for respondents with patterns happening as planned vs. 5.85 for respondents with deviations from the plans). The effect should not be overstated, however, since changes in expectations/plans could sometimes be positively perceived (e.g. an unplanned nice dinner with a friend) and would in those cases be associated with a higher satisfaction level than the “as expected/as planned” case.

A closer look at the reasons for having non-typical days (different from expectations) or for change in plans, for those who indicated that their days were not typical or their plans changed as the day progressed, gives some further insights about the correlation between the direction of the deviation from expectations/plans and the resulting pattern satisfaction. The various reasons given were grouped into 14 categories for the expectations indicator and 10 categories for the planning indicator. These categories were either stated by the

Table 2 Satisfaction with chosen activity pattern by reason for non-typical days (different from expectations) (N = 1,305 respondents)

Reason for non-typical day	Number of respondents	Average satisfaction	Standard deviation of satisfaction
No school	28	6.14	1.15
Holiday/vacation	42	6.10	1.23
Less travel than usual	158	5.97	1.42
Day off from work	87	5.97	1.28
Medical appointment	55	5.96	1.12
More travel than usual	431	5.95	1.18
Out of area	19	5.79	1.18
Bad weather	160	5.75	1.37
Did not travel	41	5.73	1.67
Other	112	5.70	1.32
Different mode/vehicle used for travel	26	5.27	1.61
Personal problems	28	5.14	1.65
Traffic issues	7	4.86	2.19
Sick	111	4.62	2.16

respondents (e.g. “sick”, “errands”, etc.) or grouped to have a sufficient number of observations per group where a meaningful grouping was possible (e.g. “personal problems”, “activities were added”, etc.).

Table 2 shows the average pattern satisfaction level for each of the 14 reasons for non-typical days, as well as the number of respondents and standard deviation of satisfaction by reason for non-typical day. Three reasons, namely “no school”, “holiday/vacation”, and “day off from work”, which can generally be classified as positive deviations from typical days, have among the highest average satisfaction levels associated with them. Four reasons that can be classified as negative deviations from typical days are “bad weather”, “personal problems” (e.g. car problems), “traffic issues”, and “sick”, and are generally classified with lower satisfaction levels. The remaining reasons given cannot be clearly classified as positive or negative.

Similarly, Table 3 shows the average pattern satisfaction level for each of the 10 reasons for change in plans, as well as the number of respondents and standard deviation of satisfaction by reason for change in plan. Three reasons for change in plan, namely “bad weather”, “travel problems” (e.g. traffic delays, change in mode, etc.), and “sick”, which can be clearly classified as negative deviations from plans, have the lowest average satisfaction levels associated with them. The remaining reasons given cannot be clearly classified as positive or negative and on average have higher satisfaction levels associated with them.

These findings indicate that negative deviations from expectations/typical days and plans lower the satisfaction with the chosen pattern and it is therefore important to measure and model this effect, while positive deviations (although not clearly discerned in the data for the case of plans) are associated with greater satisfaction levels. These issues will be further explored through an update of DRCOG’s activity pattern model.

Table 3 Satisfaction with chosen activity pattern by reason for change in plans (N = 598 respondents)

Reason for change in plans	Number of respondents	Average satisfaction	Standard deviation of satisfaction
Decided to shop	12	6.42	0.79
Errands	36	6.25	1.32
Unexpected trips were added	220	6.15	1.13
Activities were cancelled	37	6.11	1.41
Medical appointment	16	6.06	1.24
Other	43	5.95	1.02
Activities were added	37	5.95	1.31
Bad weather	92	5.79	1.45
Travel problems	32	5.47	1.39
Sick	73	4.58	2.14

Discussion

Activity-based modeling has become a widely used approach for modeling travel demand. The purpose of this paper was to present a framework for incorporating well-being within activity pattern models (which model activity and tour generation), starting from the hypothesis that activities are planned to satisfy needs so as to maintain and enhance subjective well-being. This section summarizes the paper, discusses the practical and theoretical implications, and concludes with directions for future research.

Summary

The paper presented an empirical analysis and a theoretical analysis of the relationship between well-being and activities. The empirical analysis consisted of an exploratory model of the effects of activity and travel well-being on the propensity to participate in activities. Using a convenience universal sample of highly-educated commuters, we found significant correlations between activity/travel well-being and activity participation for a number of different activity types: the greater the happiness while performing an activity and the greater the satisfaction with travel to the activity, the more frequently an activity is conducted.

The theoretical analysis consisted of developing a model framework for the extension of activity pattern models based on the activity-schedule approach (Ben-Akiva et al. 1996) which structures the day into an overarching activity pattern and then determines the timing, destination, and modes of tours and trips comprising the pattern. It was argued that activity pattern models have been specified in ad-hoc ways in practice as a function of socio-economic and level of service variables. We presented two extensions to these models. The first extension is econometric and attempts to better estimate the utility of an activity pattern by adding a measurement equation where satisfaction with a pattern is used as an indicator of its utility. This extension can be applied to other choice contexts that are modeled using the static random utility model. A way to account for possible divergence between decision utility (on which the choice is based) and remembered utility (which is captured by the satisfaction or well-being indicators) was proposed. An example of well-being measures was also presented within the context of an operational activity-based

model. The second extension, presented conceptually in this paper, is behavioral and attempts to formulate the activity pattern utility so as to account for the behavioral process of activity generation, based on the idea that activities are conducted to satisfy needs.

Practical and theoretical implications

Our empirical analysis of activity and travel well-being showed that well-being matters for activity choices. Accounting for well-being will result in better prediction of activity choices and consequently travel behavior. This issue is very timely as activity-based models continue to be increasingly adopted by metropolitan planning organizations in the U.S. and elsewhere. Even after more than a decade of activity-based model development in operational model systems in the U.S. as a replacement of four-step models, there are still a number of conceptual issues in the development of these models, including model specification (e.g. including household interactions), model validation, policy sensitivity, etc. Accounting for well-being will be one further direction in the efforts to enhance activity-based models.

One direct practical implication of the well-being approach is that household travel surveys used in transportation planning to support the development of activity-based models should start collecting systematically measures of activity and travel well-being. We have proposed in this paper few such measures and are in the process of testing them using an operational activity-based model in Denver, Colorado. The incremental cost of incorporating these measures in household travel surveys (which are already quite long and are conducted not so frequently) is minimal. In addition to their use in modeling, one practical benefit of these measures is in assessing people's activity and travel well-being and in better understanding how well-being relates to time use (e.g. for policy design and evaluation). This is an important and timely benefit, given a large body of recent literature calling for more extensive and systematic measurement of well-being to supplement national economic performance indicators (see e.g. Diener and Seligman 2004, and the recent French government report by Stiglitz et al. 2009).

As to the modeling implications, first and as already argued before, the resulting activity pattern models which incorporate well-being are expected to be more behaviorally realistic. Second, the use of well-being measures as indicators of activity pattern utility is expected to enhance the efficiency of activity pattern models, and consequently the prediction of travel patterns, since additional information about the utility is provided by the well-being measures beyond what is indicated by the choice. While the gain in efficiency has not been demonstrated yet in the context of activity participation, some evidence to that effect has been obtained in a small-scale experiment of well-being and commute mode choice (Abou-Zeid 2009). In that study, measures of satisfaction with commuting by car and by public transportation were included as indicators of utility in a commute mode choice model (in addition to the usual choice indicators). Compared to a choice-only model, the extended model with well-being measures resulted in smaller standard errors of the parameter estimators and substantially smaller variance of the systematic utilities. Note that the well-being measurement equations are added only in the estimation stage of the model but not in application (similarly to how attitudinal indicators are used in model estimation in the hybrid choice modeling framework (Walker and Ben-Akiva 2002) but not in application). If predictions of activity pattern well-being are desired, one can calculate the expected maximum utility (Ben-Akiva and Lerman 1985), since the happiness measure is an indicator of utility.

Future research directions

The arguments and theoretical developments in this paper have been mostly conceptual in nature. Empirical tests are needed to evaluate the benefits of the proposed (as well as alternative) measures and modeling frameworks.

In terms of measurement, the proposed well-being measures focused on retrospective overall activity pattern well-being. Alternative measures of well-being and methods to collect them could be tested. These include satisfaction and emotions related to individual activities and travel episodes in the pattern collected retrospectively (e.g. using the day reconstruction method) or in real-time (e.g. using the experience sampling method). In this paper, we have proposed a way to account for well-being measures collected retrospectively by using additional measures of the deviation of experience from expectations/plans. Real-time data collection could provide another way for more accurately measuring the decision utility of activity choices since the well-being measures would be collected close to the moment of decision-making. In Abou-Zeid (2009) and Abou-Zeid et al. (2012), we discussed the dynamic measurement of commute satisfaction and showed that retrospective measures could be significantly different from those collected at the time of decision-making. In addition to using subjective well-being measures, one can also obtain well-being measures based on the capabilities approach of Amartya Sen (1985), which conceives well-being as arising from people's freedom and capabilities to do certain functionings. In the context of activities and travel, these measures would capture well-being derived from the broader activity and travel opportunities that are available to people even if they didn't use them (e.g. ability to get around and reach places easily, satisfaction with the overall transportation system and the places and activities within reach, etc.). Finally, it would also be desirable to obtain measures of needs that can be used in the needs-based extension of activity-based models. Issues related to needs definitions, shared needs in a household, and scale would have to be accounted for by these measures.

In terms of modeling, the extended modeling frameworks proposed in this paper need to be tested empirically. As a first step, we are currently working on testing the first extension by adding well-being measurement equations to the activity pattern model of DRCOG's activity-based model. The extended model will be compared to the existing model without well-being measures on a number of criteria including goodness of fit, prediction capabilities, and efficiency. As to the second extension, the needs-based framework should be translated into an empirical model which should then help identify data collection needs for bringing such a model into practice.

Acknowledgments This research was supported by a grant from the University Transportation Center of New England while the first author was at the Massachusetts Institute of Technology. The authors are grateful to Erik Sabina and Suzanne Childress from the Denver Regional Council of Governments for sharing their activity-based model reports and for extending their survey to accommodate our research needs, Varun Pattabhiraman for his assistance in processing the survey data, and three anonymous reviewers for their valuable suggestions.

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