WELL-BEING AND ACTIVITY-BASED MODELS

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ABSTRACT

Instruments such as the Experience Sampling Method and the Day Reconstruction Method have been applied to measure happiness by activity type and shown that happiness varies significantly by activity type and socio-economic group. The relationship between happiness and activities has also been supported by models of time allocation to activities.

We pursue this line of research to investigate the relationship between happiness and activity participation. The overriding hypothesis is that activities are planned and undertaken to maintain or enhance subjective well-being. We present both an empirical and a theoretical analysis to support this hypothesis and develop a framework for its application to enhance activity-based travel demand models.

The empirical analysis consists of the development of structural equations models of activity participation and well-being using data from a web-based cross-sectional survey of a sample of commuters. The models reveal significant correlations between well-being 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, thus supporting our study hypothesis.

The theoretical analysis consists of the development of a modeling framework and measures for the incorporation of well-being within activity-based models of travel demand. 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 a driver of activity patterns and propose 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. We present examples of measures that can be used to capture well-being at the level of an activity pattern and its activity and travel components.

Keywords: activity-based models, happiness, subjective well-being

1. 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 and for monitoring trends in happiness. The purpose of this paper is to study empirically the relationship between happiness and activity participation, and to develop a framework for modeling this relationship within the context of activity-based models of travel demand.

The idea that happiness or utility varies by activity type has been discussed in studies of time allocation. As Jara-Díaz et al. (2008) put it, "time assignment theories can make a contribution to a better understanding of individual well-being within the ever evolving work and social environments, as they have since long established theoretical relations among the different values of time… After all, understanding time allocation is just as understanding life itself." They empirically estimated values of work and leisure time using observed data for Swiss, German, and Chilean samples. A number of recent empirical studies, reviewed in the next section, have directly measured happiness for different activity types and shown that happiness varies significantly by activity type and socio-economic group.

This paper studies happiness and activities with the objective of enhancing travel demand models. The demand for travel is derived from the demand for activities. That is, people travel in order to conduct activities, and this in turn provides a sense of well-being (Cantor and Sanderson, 1999). Activity-based models of travel demand have been developed to explicitly model activity generation in an effort to enhance travel demand estimation. Yet these models determine activity 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 maintain and enhance subjective well-being. The paper aims therefore at first testing this hypothesis empirically and second developing a framework for incorporating well-being within activity-based models of travel demand.

The paper is organized as follows. Section 2 presents empirical evidence on the relationship between happiness and activities based on a review of past studies as well as a survey that we conducted. Section 3 extends the analysis from a single activity to study well-being at the level of a group of activities or an activity pattern. It reviews the state of the practice in activity-based models of travel demand and develops a modeling framework and measures for incorporating well-being within the activity pattern components of these models. Section 4 concludes the paper.

2. EMPIRICAL EVIDENCE

This section reviews empirical evidence on the relationship between happiness and activity participation. It consists of a literature review of past studies and a description of an activity and travel well-being survey that we conducted to measure this relationship.

2.1 Literature Review

Instruments such as the Experience Sampling Method, which captures emotions for a sample of activities in real-time (see, for example, Hektner et al., 2006), and the Day Reconstruction Method (Kahneman et al., 2004), which measures emotions for all activities conducted on a previous day, have been applied to measure happiness by activity type. Evidence from this line of research shows that happiness varies significantly by activity type and socio-economic group. Findings from selected studies are described below.

Kahneman et al. (2004) and Kahneman and Krueger (2006) used the Day Reconstruction Method with a convenience sample of employed women from Texas. They found that net affect, defined as the average positive affect minus the average negative affect experienced in a given activity episode, was largest for intimate relations and then for socializing after work. Net affect was smallest for the morning commute and then for working.

Krueger (2007) conducted the Princeton Affect and Time Survey which involves reconstruction of the activities conducted on the day preceding the survey. For every activity, respondents indicated the activity duration and assessed their subjective experiences. Using this survey, 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. Thus, having direct measurements of happiness by activity type is useful for analyzing trends in time allocation in relation to happiness derived from different activities.

Using the 2005 time-use General Social Survey which asked respondents to report their level of liking of different activities, Turcotte (2008) found that Canadian respondents in this sample liked most having supper at home or at a restaurant and liked least cleaning the house and doing grocery shopping.

2.2 Activity and Travel Well-Being Survey

Further empirical evidence to the relationship between happiness and activities comes from a survey that we conducted to measure activity and travel well-being using a sample of commuters. This section describes the survey and sample, shows a descriptive analysis of activity and travel well-being, and develops a structural equations model of activity participation and well-being.

2.2.1 Survey

The survey measured satisfaction with the commute to work and with travel to other types of activities, happiness with different types of activities, travel attributes (distance and mode used to travel to various activities, etc.), weekly frequency of conducting activities, and various socio-economic and demographic characteristics.

Measures of activity happiness were rated on a “Very unhappy” to “Very happy” 5-point scale (“How happy do you feel when you conduct the following activities?”). The question covered the following types of activities: work, shopping, personal business (e.g. banking, errands, etc.), eating out, social / recreational (e.g. visiting friends, going to the movies, sports and hobbies, etc.), organizational / volunteer / religious, and at-home activities. For each of these activity types, respondents also rated their satisfaction with their travel to the activity (“How satisfied are you with your travel to these activities?” 5-point scale ranging from “Very dissatisfied” to “Very satisfied).

2.2.2 Sample

A sample of commuters was recruited via emails sent by the authors to friends, colleagues, and anonymous web users. The sample included respondents from different countries with the largest proportion coming from the United States. The survey was web-based but also included a few personal interviews. The survey covered the following modes of commuting to work: solo car driver, car driver with others in the car, car passenger, bus, subway/train, walk, and bike. The data used in this paper were collected between June and October 2007. The data were checked for inconsistencies of responses, and observations that were deemed unreliable were removed. After cleaning and accounting for missing values, the sample used in model estimation consists of 558-676 observations for the different activity participation models.

The majority of the sample was male (66%), young (58% less than 40 years old), and highly educated (56% with a graduate degree and 32% with an undergraduate degree). The average household size was 2.5 and 26% of respondents had kids in the household. Most commuters (89%) had partially or completely flexible work schedules. Of those who reported their job type, the majority (74%) worked in management / professional / technical jobs followed by education / research (17%) and self-employed (3%) jobs. The average annual pre-tax personal income was distributed almost evenly among various categories, possibly due to the fact that different countries are included, with an average value of $69,000.

2.2.3 Activity and Travel Happiness

Table 1 shows the percentage of survey respondents by the self-reported happiness levels that they experience when they conduct different activities. The results indicate that people in this sample are happiest when they conduct social and recreational activities and least happy when they conduct personal business activities.

Table 1 – Happiness by activity type.

Activity	% Unhappy	% Neither happy nor unhappy	% Happy
Social and recreational	0.6	4.4	95.0
Eating out	1.6	10.6	87.9

At home activities	3.9	17.3	78.8
Organizational, volunteer, or religious	3.2	26.9	69.9
Work	8.2	36.2	55.6
Shopping	15.7	45.1	39.2
Personal business	13.1	61.3	25.6

Table 2 shows the percentage of survey respondents by their self-reported level of satisfaction with travel to different non-work activities. Overall, most respondents are satisfied with their travel to different types of activities. They are most satisfied with their travel to eat-out activities and least satisfied with their travel to organizational, volunteer, or religious activities. Reports of travel satisfaction may be confounded with happiness or satisfaction with the activity (see also Ory and Mokhtarian, 2005).

Table 2 – Non-work travel satisfaction.

Travel to Activity	% Dissatisfied	% Neither satisfied nor dissatisfied	% Satisfied
Eating out	4.8	23.1	72.2
Social and recreational	6.5	21.9	71.6
Personal business	10.0	26.2	63.9
Shopping	12.9	25.0	62.0
Organizational, volunteer, or religious	6.0	36.1	58.0

2.2.4 Activity Participation Model

In order to demonstrate the relationship between happiness and activity participation, structural equations models that represent the propensity of activity participation as a function of activity and travel happiness were developed as shown in Figure 1. Models were estimated for the following activity types: shopping, social / recreational, eat-out, organizational / volunteer / religious, and personal business.

Activity propensity is affected by activity happiness, satisfaction with travel to the activity, and socio-economic variables. Activity propensity, activity happiness, and travel satisfaction are latent (or unobserved) variables and are measured by activity frequency and the activity and travel happiness indicators, respectively, collected in the survey. Activity happiness is modeled as a function of socio-economic variables. Travel satisfaction is a function of the generalized cost of travel (mode and distance) and socio-economic variables.

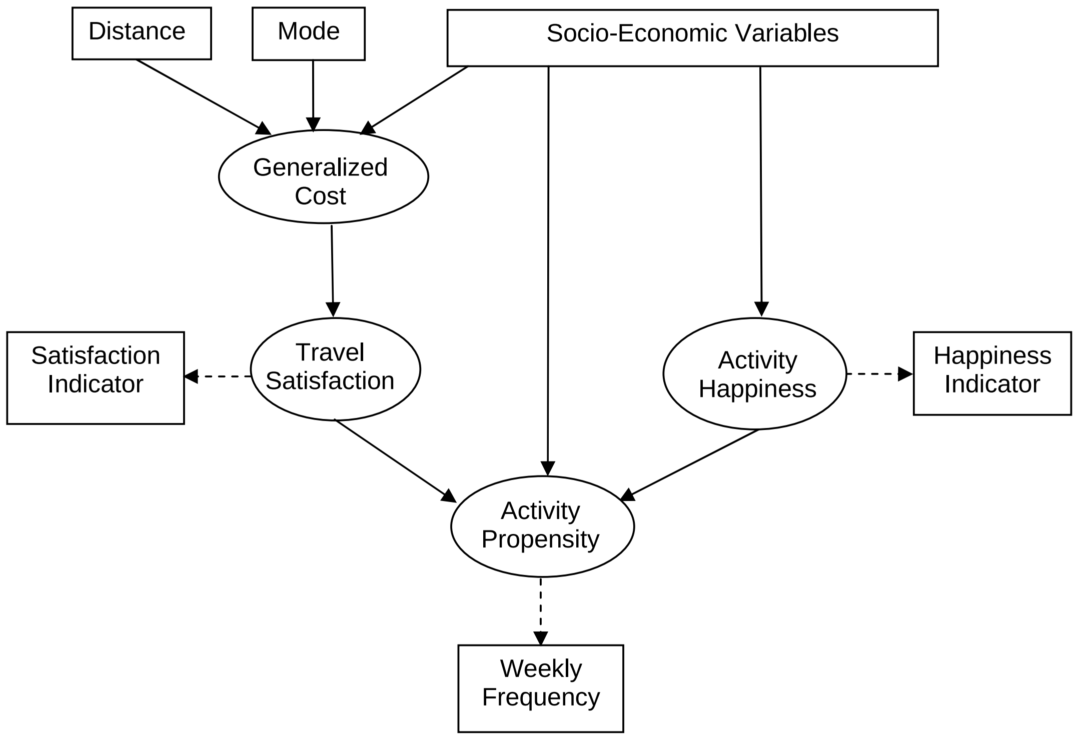

Figure 1 - Activity propensity model.

The structural equations of the shopping model are given below, with the models for other activity types specified similarly.

$$\begin{aligned}\text{Activity propensity} = \; & \beta_1 * \text{travel satisfaction} + \beta_2 * \text{activity happiness} \\ & + \beta_3 * \text{Age(0-30)} + \beta_4 * \text{Age(30-60)} + \beta_5 * \text{Age(60+)} \\ & + \beta_6 * \text{1-person household dummy} + \zeta_1\end{aligned} \tag{1}$$

$$\begin{aligned}\text{Travel satisfaction} = \; & \beta_7 * \text{distance/income} \\ & + \beta_8 * \text{distance*missing income dummy} \\ & + \beta_9 * \text{missing distance dummy} \\ & + \beta_{10} * \text{missing income dummy} \\ & + \beta_{11} * \text{car dummy} + \beta_{12} * \text{public transportation dummy} + \zeta_2\end{aligned} \tag{2}$$

$$\begin{aligned}\text{Activity happiness} = \; & \beta_{13} * \text{Age(0-30)} + \beta_{14} * \text{Age(30-60)} + \beta_{15} * \text{Age(60+)} \\ & + \beta_{16} * \text{male dummy} + \beta_{17} * \text{income} \\ & + \beta_{18} * \text{missing income dummy} + \zeta_3\end{aligned} \tag{3}$$

The measurement model consists of three measurement equations, one for each latent variable (activity happiness, travel satisfaction, and propensity to engage in an activity). Since each of these latent variables has only one observed indicator, each of these latent variables is set equal to a continuous latent response variable for identification purposes. This normalization implies a factor loading of 1 and an error variance of zero in each measurement equation. Since the indicators of travel satisfaction, activity happiness, and activity propensity are ordered categorical, a threshold model is specified as in Equation (4).

$$I = \begin{cases} 1 & \text{if } \tau_0 < I^* \le \tau_1 \\ 2 & \text{if } \tau_1 < I^* \le \tau_2 \\ \vdots & \\ M & \text{if } \tau_{M-1} < I^* \le \tau_M \end{cases} \tag{4}$$

where I is an indicator, I^* is a latent response variable, M is the number of categories, and τ denotes a threshold parameter with $\tau_0 = -\infty$ and $\tau_M = +\infty$.

The models were estimated using the Mplus software (Muthén and Muthén, 1998-2006). The estimation results for the shopping activity propensity model are shown in Tables 3 and 4. The factor loadings in the measurement equations are not shown as they are all normalized for identification purposes.

The propensity to participate in shopping activities is positively and significantly correlated with the happiness derived from shopping and the satisfaction with travel to shopping activities. This result provides evidence for the existence of relationships between well-being and behavior in the context of travel and activities; the greater the well-being derived from a given behavior, the more frequently people engage in that behavior.

The propensity to participate in shopping activities is also affected by socio-economic variables. Not all these variables are significant; however, they are retained in the models if the parameter estimates agree with apriori hypotheses. Age is specified as a piecewise linear variable with breakpoints at the ages of 30 and 60. The estimated coefficients of age imply that the propensity to shop increases till the age of 30, continues increasing till the age of 60 but at a slower rate, and then decreases afterwards. Individuals who live alone have a higher propensity to shop than those who live with others, possibly because of the sharing of shopping responsibilities in multi-person households.

Travel satisfaction is modeled as a function of level of service, which is determined by distance divided by income and mode of travel. The distance coefficient is negative and significant as expected. The car and public transportation dummy variables have negative coefficients, signifying that all else equal, traveling by non-motorized modes leads to greater travel satisfaction. Dummy variables for income with missing values and distance with missing values are also included.

Shopping activity happiness is modeled as a function of socio-economic variables. Age is specified as a piecewise linear variable with breakpoints at the ages of 30 and 60. The estimated coefficients of age imply that shopping activity happiness is a decreasing function of age, with the greatest rate of decrease past the age of 60. Compared to females, males tend to dislike shopping. Higher income is associated with higher activity happiness as might be expected, but the effect is not significant.

The thresholds can be interpreted as scales for the corresponding latent response variables. Their values are different for different latent response variables (frequency versus happiness/satisfaction), but are relatively close for the travel satisfaction and activity happiness measures which indicates that people use the travel satisfaction and activity happiness scales similarly. Most of the thresholds are significant.

The estimation results for other activity types (not shown here for space limitations; see Abou-Zeid (2009)) also indicated that the propensity to participate in activities is positively correlated with the happiness derived from the activities and the satisfaction with travel to the activities.

Table 3 - Structural model estimation results for shopping activity propensity.

Parameter	Estimate	t-stat
Propensity to shop		
Travel satisfaction	0.219	5.50
Activity happiness	0.220	5.18
Age (0-30)	0.0563	2.69
Age (30-60)	0.0243	3.86
Age(60+)	-0.0296	-1.14
1-person household dummy	0.167	1.48
Travel satisfaction		
Distance/income	-0.822	-2.20
Distance * missing income dummy	-0.0297	-0.74
Missing distance dummy	-0.584	-1.27
Missing income dummy	-0.0312	-0.098
Car dummy	-0.483	-4.22
Public transportation dummy	-0.255	-1.60
Activity happiness		
Age (0-30)	-0.00696	-0.37
Age (30-60)	-0.00568	-0.92
Age(60+)	-0.0389	-1.18
Male dummy	-0.668	-7.27
Income	0.000440	0.29
Missing income dummy	-0.401	-1.34

Table 4 - Estimated thresholds for shopping activity propensity.

Parameter	Estimate	t-stat
Thresholds		
Activity frequency		
τ_{11}	0.460	0.83
τ_{12}	2.37	4.21
τ_{13}	3.28	5.70
Travel satisfaction		
τ_{21}	-3.11	-5.45
τ_{22}	-2.05	-3.86
τ_{23}	-1.22	-2.30
τ_{24}	0.521	0.98
Activity happiness		
τ_{31}	-2.48	-4.90
τ_{32}	-1.61	-3.17
τ_{33}	-0.222	-0.44
τ_{34}	1.06	2.10

3. WELL-BEING AND ACTIVITY PATTERNS

With the evidence cited above on the correlations between well-being and behavior for different types of activities, we now turn into 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, existing activity-based models do not account for this relationship.

In this section, we first give an overview of activity-based models including the theory underlying them, major classes of these models, and the formulation of the activity-schedule approach as applied in operational models. Then we develop a modeling framework that accounts for well-being at the level of an activity pattern and its individual activity and travel components and provide examples of well-being measures that can be used in these models.

3.1 Activity-Based Models

3.1.1 Activity-Based Travel Theory

Activity-based approaches to travel demand modeling are based on the idea that the demand for travel is derived from the demand for activities. These approaches explicitly model activities, trip chaining, and the interdependence among tours. They account for temporal and spatial constraints that limit activity schedule choice. The models usually have a fine temporal resolution and are consequently better able (compared to four-step travel demand models) to represent complex responses to transportation policies such as congestion pricing.

Three classes of activity-based approaches characterized by the above features can be distinguished. The first class is based on Markov models that represent the scheduling decision as a sequence of transitions (signifying trips) between states (signifying activities). The second class is rule-based models that use rules to eliminate alternatives and apply utility maximization for modeling the choice among a small number of alternatives. The third class is based on multi-dimensional choice models that employ deterministic choice set generation rules and focus on the representation of utility-based multi-dimensional probabilistic choice. For a review of the features and limitations of each of the three classes of activity-based models, the reader is referred to Bowman (1998). In this paper, we will focus on the review and development of the third class as it is grounded in consumer theory and based on utility maximization.

Two main approaches that fall within the class of multi-dimensional choice models are the activity-travel simulator (Kitamura et al., 1996) and the activity-schedule approach (Ben-Akiva et al., 1996). The activity-travel simulator approach is based on sequential scheduling of activities and travel. It decomposes the activity-travel decision into the following dimensions: activity type choice, destination choice, mode choice conditional on destination, and activity duration choice. It generates activities using a detailed representation of spatial and temporal constraints within time-space prisms (Hagerstrand, 1970). The activity-schedule approach is based on simultaneous scheduling of activities and travel. It decomposes the activity-travel decision into two sets of models: an activity pattern model and tour models and also accounts for spatial and temporal constraints but at a less detailed level than the activity-travel simulator. For a discussion of the two approaches, see, for example, Ben-Akiva (2009). In the remainder of the paper, we focus on the review and extension of the activity-schedule approach.

3.1.2 Activity-Schedule Approach

Figure 2 shows the structure of the activity-schedule approach. The activity pattern model (upper level) sets a schedule for the day; it determines the number, purposes, priorities, and structure of travel and activities. It replaces the trip generation step of four-step models. The tour models (middle and lower levels) 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 and activity 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.

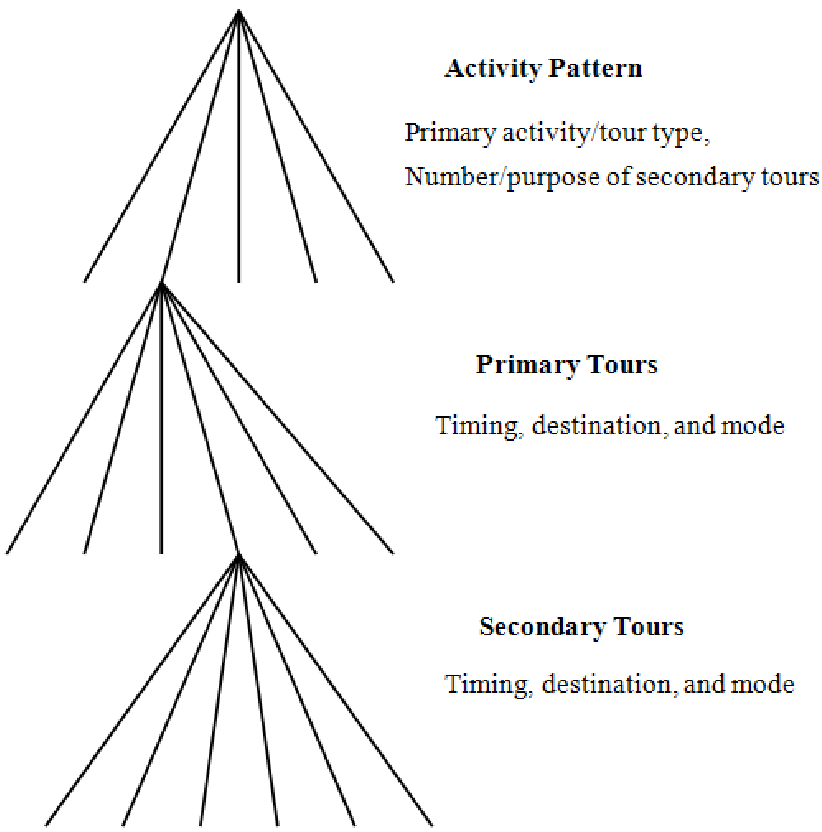

Figure 2 – Activity-schedule approach (Ben-Akiva et al., 1996; Bowman and Ben-Akiva, 2001).

The first applications of the activity-schedule approach were the work done by John Bowman in his master's and doctoral theses (Bowman, 1995; Bowman, 1998; Bowman and Ben-Akiva, 2001). He empirically demonstrated the approach to Boston, Massachusetts, and to Portland, Oregon. Since then, a number of metropolitan planning organizations in the U.S. and elsewhere have adopted the activity-schedule approach to travel demand modeling. Examples of operational model systems using this approach in the U.S. include the models developed for Columbus, Lake Tahoe, New York, Portland, Sacramento, and San Francisco County. Other model systems currently under development include models for Atlanta, Denver, Jerusalem, Ohio, Oregon, San Francisco Bay Area, Seattle, and Tel-Aviv (see, for example, Bradley et al., 2008 and Rossi et al., 2009).

We show next the formulation of activity pattern models in the activity-schedule approach. Bowman (1998) specified the systematic utility of a pattern *p* as consisting of three components: a component $\tilde{V}_p$ for the overall pattern *p* 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 *p*. The systematic utility is therefore given as follows:

$$V_p = \tilde{V}_p + \sum_{a \in A_p} V_a + \sum_{t \in T_p} V_t \tag{5}$$

where A_p denotes the set of activities in pattern *p*, and T_p denotes the set of tours in pattern *p*.

The component $\tilde{V}_p$ 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.

In practice, 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 Equation (5), 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 maintain or enhance well-being. Therefore, including well-being in these models will allow for better behavioral representation of the drivers of activities. One can go even further by explicitly accounting for how various patterns satisfy people's needs differently and relating need satisfaction to well-being. This will not be pursued here, but the reader is referred to Arentze and Timmermans (2009) and Ettema et al. (2009) for discussions about need satisfaction and activities.

3.2 Well-Being at the Activity Pattern Level

In this section, we discuss how well-being can be incorporated in the specification of activity pattern models in the activity-schedule approach. We also discuss measurement needs.

3.2.1 Modeling Framework

We consider two cases. First, we consider the case where well-being measures are available at the activity pattern level. We show how the standard model formulation is extended by adding measurement equations for the utility of the pattern. Second, we consider the case where in addition to the availability of well-being measures at the activity pattern level, explanatory variables and indicators related to the utility of different components (activities and travel) of the pattern are available. We show how the pattern utility specification is re-formulated.

Well-Being Measures Available at the Activity Pattern Level

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. The advantage of having this measure is that it provides more information about the utility beyond what is provided by the choice and makes the estimation more efficient. For a discussion of the relationships between happiness and utility in any choice context, the reader is referred to Abou-Zeid (2009) where static and dynamic model frameworks are developed and incorporate happiness measures as indicators of 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 patterns.

Moreover, 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). In a static context though, well-being measures reflect 'remembered utility' (after people experience the outcomes) and are therefore imperfect indicators of decision utility. To account for this issue, we consider the availability of a measure of how different the chosen pattern was from prior expectations, and use the well-being measure as an additional indicator of the decision utility of a pattern only if the pattern happened as expected.

Let U_p denote the total utility of pattern p. y_p is a choice indicator (dummy variable equal to 1 if the chosen pattern is p and equal to 0 otherwise), h_p is a well-being measure associated with pattern p, and E_p is a measure of how different pattern p was from prior expectations (e.g. $E_p = 1$ if p happened as expected and is 0 otherwise). h_p and E_p are collected for the chosen pattern only.

The structural part of the activity pattern model is a specification of activity pattern utility. U_p 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 Equation 5).

The measurement model consists of the choice and happiness equations specified for every pattern p as follows:

$$y_p = \begin{cases} 1 & \text{if } U_p \geq U_{p'} \quad \forall p' \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$h_p = h_p\left(U_p, y_p, E_p\right) \tag{7}$$

<u>Well-Being Measures Available for Individual Components of the Activity Pattern</u>

In addition to the availability of the measures discussed above, we consider the availability of well-being measures for the different components of the activity pattern, such as all activities and travel. Equation (5) specifying the systematic utility of an activity pattern can now be re-formulated so that the total utility of a pattern is a function of the utility from all activities and tours on the pattern. Activity utility is a function of the attributes of the activity and characteristics of the individual. Tour utility is a function of the attributes of destinations, modes, and times-of-travel that are available for the tour. The measures of well-being for the overall pattern, for every activity, and for every tour are indicators of the pattern utility, activity utility, and tour utility, respectively.

Let U_p denote the total utility of pattern p. Let U_{ap} and U_{tp} denote the utility of activity a and tour t, respectively, in pattern p. X_{ap} is the set of attributes of activity a in pattern p, and X_{tp} is the set of attributes of tour t in pattern p. Denote by A_p the number of activities composing pattern p and T_p the number of tours in pattern *p*. E_p is a measure of how different pattern p was from prior expectations (e.g. $E_p = 1$ if p happened as expected and is 0 otherwise). E_{ap} and E_{tp} are defined similarly for activities and tours, respectively.

For an activity pattern p, the structural model is given by Equations (8) – (10) which specify the utilities of the overall pattern, the activities in the pattern, and the tours in the pattern.

$$U_p = U_p\left(U_{ap}, U_{tp}, X_p; a = 1,\ldots,A_p; t = 1,\ldots,T_p\right) \tag{8}$$
$$U_{ap} = U_{ap}\left(X_{ap}\right),\ a = 1,\ldots,A_p \tag{9}$$
$$U_{tp} = U_{tp}\left(X_{tp}\right),\ t = 1,\ldots,T_p \tag{10}$$

Although we do not specify the exact functional forms, we note that these functions should be flexible enough to allow for complementarities and substitutions across activity types and to represent effects such as satiation and variety-seeking.

The measurement model is given by Equations (11) – (14). Equation (11) is the choice equation, and Equations (12) – (14) are the happiness equations for the overall pattern, the activities in the pattern, and the tours in the pattern.

$$y_p = \begin{cases} 1 & \text{if } U_p \geq U_{p'} \quad \forall p' \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

$$h_p = h_p\left(U_p, y_p, E_p\right) \tag{12}$$

$$h_{ap} = h_{ap}\left(U_{ap}, y_p, E_p, E_{ap}\right) \tag{13}$$

$$h_{tp} = h_{tp}\left(U_{tp}, y_p, E_p, E_{tp}\right) \tag{14}$$

3.2.3 Measurement

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 capture all aspects of the pattern, including activities and travel. An example of such a measure (h_p in the previous section) is a broad satisfaction question as follows:

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?

Respondents would answer using an ordinal scale ranging from “Very dissatisfied” to “Very satisfied”.

Another question that is specific to the measurement of mood, adapted from the Day Reconstruction Method (Kahneman et al., 2004), is the following.

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?

The degree to which the activity pattern happened as expected (E_p in the previous section) can be measured by a question such as:

In most ways, did yesterday’s activities (including travel) happen as you had expected?

Respondents could answer on a Yes/No scale or using an ordinal scale expressing their level of agreement with the statement.

The utility of various activities and tours can be measured by satisfaction questions such as:

Taking all things together, how satisfied were you with this activity / tour?

Respondents would answer using an ordinal scale ranging from “Very dissatisfied” to “Very satisfied”.

Affective measures of activity and tour happiness can also be obtained by asking respondents to rate the extent to which they experienced certain emotions during the corresponding activity and travel episodes.

4. CONCLUSION

Activity-based modeling has become a widely used approach for modeling travel demand. These models are based on the assumption that the demand for travel is derived from the demand for activities. The purpose of this paper was to present a framework for incorporating well-being within activity pattern models, starting from the hypothesis that activities are planned to maintain and enhance subjective well-being.

We started by presenting empirical evidence on the relationship between happiness and activities. We reviewed a number of recent studies that have used the Experience Sampling Method or the Day Reconstruction Method to measure emotions for different activities types, and have shown that happiness varies by activity type and socio-economic group. We provided further evidence based on an activity and travel well-being survey that we conducted with a sample of commuters; we developed structural equations models which revealed significant correlations between activity / travel well-being and activity participation for a number of different activity types.

Then we provided an overview of the theory of activity-based models and major classes of these models. We focused on one particular method called 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 composing the pattern. We showed how activity pattern models have been specified in ad-hoc ways in practice. We then presented a framework showing how the specification of activity pattern models can be improved by using well-being measures as additional indicators of the utility of the pattern and/or its component activities and travel. We also provided examples of these measures.

As activity-based models continue to be increasingly adopted by metropolitan planning organizations in the U.S. and elsewhere, the incorporation of well-being measures into surveys supporting the development of these models will lead to more systematic and behaviorally realistic specifications of these models.

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