A Methodology for Evaluating Wellbeing Implications of Activity-Travel Engagement and Time Use Patterns

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ABSTRACT

The notion that people's activity-travel patterns influence wellbeing and overall quality of life is well recognized. Nonetheless, activity-travel demand model outputs do not provide explicit measures of wellbeing that can be used to assess the impacts of alternative policies, investments, and technologies. This study presents a model of wellbeing that overcomes this challenge. The model is developed using the 2010, 2012, and 2013 wellbeing modules of the American Time Use Survey (ATUS). A joint model of latent activity wellbeing score (AWS) is estimated using data available in the ATUS wellbeing modules, yielding a set of equations that compute wellbeing scores as a function of socio-economic characteristics and attributes of the activities or travel episodes. The episode-level wellbeing scores provided by the model system (for all in-home/out-of-home activities and travel episodes) can be aggregated to derive a daily activity-travel wellbeing metric for each individual (personal wellbeing score or PWS). The paper presents model estimation results together with applications of the wellbeing model system to demonstrate its efficacy. The wellbeing model system is found to replicate patterns of wellbeing observed in the 2021 ATUS wellbeing module reasonably well. In addition, the model provides measures of wellbeing over time for different socio-economic groups that are both intuitive and consistent with evidence in the literature. The model can serve as a tool to assess the quality of life implications of changes in activity-travel patterns that may occur as a result of alternative transporta\ investments and policies.

Keywords: subjective wellbeing; quality of life; time use; activity engagement; joint modeling

1. INTRODUCTION

Transportation plays a critical role in shaping the quality of life in communities around the world by making it possible for people to engage in activities, participate in societal functions, and interact with various entities that make up a region's ecosystem. Additionally, transportation enables mobility, thus providing people and businesses access to goods, services, and opportunities. By enabling these functions, transportation and logistics systems directly impact the economic vitality of a region, along with the state of the environment, energy consumption, public health, and safety and security.

Because of the tight connection between transportation and quality of life, considerable attention has been paid to understanding the linkage between mobility and subjective wellbeing (Gao et al., 2017; Friman et al., 2018). Measures of subjective wellbeing capture the emotions that people feel as they go about their daily lives, undertake activities, and travel. While quality of life may be viewed as a notion that captures the broader and longer-term outlook that people have on their lives, the notion of subjective wellbeing may be viewed as capturing the emotions experienced in a specific context or situation (Mokhtarian and Pendyala, 2018). Although important distinctions can and should be drawn between broader quality of life measures and measures of subjective wellbeing, it can be conjectured that a healthy accumulation of positive feelings of wellbeing will contribute (over time) to a higher quality of life. To the extent that transportation can engender such positive feelings of wellbeing (through access to opportunities and destinations, enabling participation in activities and society at large, and provision of pleasant mobility experiences and options), it would be of value if measures of wellbeing that people derive from their daily activity-travel and time use patterns could be computed. Armed with knowledge about the wellbeing implications of the activity-travel ecosystem, transportation professionals will be able to plan built environments, design mobility systems, and implement policies that enhance wellbeing – and consequently, quality of life.

However, transportation demand forecasting models do not output measures of wellbeing, and household travel surveys never collect information about feelings of wellbeing associated with various activity-travel episodes reported in a travel diary. In the absence of any knowledge or data about subjective feelings of wellbeing that are derived from activities and trips, inferences about wellbeing are often drawn based on the level of travel engagement. There is a rich body of literature that is devoted to the notions of time poverty (Williams et al., 2016; Batur, 2023) and social exclusion (Delbosc and Currie, 2018). This body of literature has generally posited that individuals who do not travel (report zero trips) may be experiencing social exclusion, i.e., they are not participating in society activities and functions. In the absence of interactions with the outside world, they may suffer from loneliness, depression, and other mental health issues. In the time poverty literature, individuals who do not have discretionary time available for a duration that exceeds a certain threshold are considered to be "time poor" (Batur, 2023). The time poverty criterion is often pegged to the median (or some fraction of the median) leisure activity time depicted by the population under consideration. Those who experience time poverty are considered to have a lower wellbeing and overall quality of life.

While a time-based definition of wellbeing (and quality of life) certainly has merit, there remains some uncertainty as to the extent to which time use based metrics truly represent the feelings of wellbeing experienced by individuals. Some may find staying at home to be pleasurable (especially if the in-home activities are of a discretionary and social nature), while others may find work very rewarding and satisfying (even though they spend little to no time on discretionary leisure activities). In other words, there is a need to develop a measure of wellbeing that can be computed based on standard outputs of an activity-based transportation demand forecasting model while recognizing the heterogeneity in feelings of wellbeing that different people derive from their activity engagement. Activity-based travel models, which simulate activity-travel patterns at the level of the individual agent, are able to provide rich information about individual activity-travel patterns under a wide range of conditions, essentially providing an output that mimics data collected in a travel diary survey. For each and every individual in a representative synthetic population of agents, the activity-based model furnishes activity-travel records at fine-grained spatial and temporal resolution. It would be of considerable value if the activity-travel and time use measures associated with an individual's pattern can be translated into a measure of wellbeing, thus enabling planners to assess the wellbeing implications of alternative investments and policies.

This paper presents an integrated model of activity-travel behavior and subjective wellbeing that can essentially serve as a wellbeing scoring tool for activity-travel patterns. The model, when interfaced with an activity-based travel demand model that outputs activity-travel records at the level of the individual agent, can be used to compute wellbeing scores at individual and aggregate market levels. In this study, wellbeing information from the 2010, 2012, and 2013 editions of the American Time Use Survey (ATUS) data collected in the United States is used to develop a joint model capable of estimating wellbeing scores as a function of activity engagement and time use allocation patterns in addition to socioeconomic attributes.

It should be recognized, however, that activity-based travel models do not provide information about in-home activity engagement and time use patterns. The application of the model developed in this paper to the output generated by an activity-based travel model system would require an intermediate step where the output of the activity-based model is enhanced and supplemented with detailed information about in-home activity engagement. The development of such an intermediate step, which may be accomplished through data fusion approaches, remains a work in progress to be addressed by future research efforts. In this paper, the efficacy of the integrated model of wellbeing is therefore demonstrated by applying the model to the 2021 edition of the American Time Use Survey (ATUS) where wellbeing information was collected once again.

The remainder of this paper is organized as follows. A brief literature review is presented in the next section. The third section presents the modeling methodology and conceptual framework. The fourth section offers a description of the data. The fifth section presents model estimation results, while the sixth section presents illustrative model application results. Concluding thoughts are offered in the seventh and final section.

2. A BRIEF REVIEW OF LITERATURE

In recent decades, wellbeing has garnered considerable attention as a critical dimension of quality of life assessment across societies (Lee and Sener, 2016). Scholars often distinguish between objective wellbeing – encompassing quantifiable metrics such as income and health – and subjective wellbeing, which captures self-reported measures of life satisfaction, happiness, and emotional experiences (Diener et al., 2018). Increasingly, subjective wellbeing has been recognized as an essential metric for understanding both individual and societal wellbeing. The drive to incorporate subjective wellbeing in public policy is fueled by its capacity to reveal disparities and inform interventions across various domains, including health, education, and transportation (Graham et al., 2018). Martela and Ryan (2023) argue that wellbeing metrics have the potential to reshape policymaking by offering a comprehensive perspective on societal quality of life. This shift in focus is evident in the growing advocacy for integrating subjective wellbeing metrics into governmental policy frameworks (Frijters et al., 2020). Wellbeing (or similarly termed happiness or quality of life) has been explicitly adopted as a policy objective by numerous international and national bodies, such as the World Health Organization (WHO), the Organization for Economic Cooperation and Development (OECD), the Australian Federal Treasury, and the UK Government (Delbosc, 2012; Office for National Statistics, 2024). As a result, many agencies have systematically integrated a core set of wellbeing indicators – most notably, life satisfaction – into their regular survey programs.

Most research on subjective wellbeing has traditionally relied on evaluative measures, such as overall life satisfaction and the Cantril Ladder (Stone et al., 2018; Yin et al., 2023). While these measures capture how individuals reflect on their lives over extended periods, they are also inherently shaped by personal values and aspirations. Consequently, evaluative measures are prone to biases, as responses may mirror personal beliefs and expectations rather than the actual lived experiences. To overcome these limitations, researchers have increasingly focused on experiential wellbeing, which measures the immediate emotional states individuals experience throughout their daily lives, including both positive emotions and negative ones, such as pain and stress (Stone et al., 2018; Fors Connolly and Gärling, 2024). For example, the Gallup-Healthways Wellbeing Index and recent surveys conducted by the British Office for National Statistics have used overall “yesterday” ratings to collect experiential wellbeing data (Harter and Gurley, 2008; Office for National Statistics, 2024). While this approach provides a straightforward way to collect experiential wellbeing data, it offers only a broad overview of the day, lacking the granular details of how experiences fluctuate throughout daily activities.

A more comprehensive approach is to integrate experiential data with activity-time use patterns, wherein respondents break their day into episodes based on activities and provide emotional ratings for each – thus offering a more granular view of experiential wellbeing. Stone et al. (2018) illustrate that this method, which combines time use data with affective (emotional) assessments, yields deeper insights into how specific activities, such as commuting or leisure, impact wellbeing. These findings are consistent with the Day Reconstruction Method (DRM) proposed by Kahneman et al. (2004), which aims to capture episodic emotions to provide a more nuanced understanding of the dynamic and context-specific nature of wellbeing.

In the transportation sector, wellbeing research has also gained substantial attention for its potential to inform policies aimed at enhancing quality of life (Ettema et al., 2010; De Vos et al., 2013). Numerous studies have examined the relationship between travel satisfaction and overall wellbeing (e.g., Olsson et al., 2020), as well as the influence of different transportation modes – such as cars, public transit, and active modes like walking – on travel satisfaction (Mouratidis et al., 2020; Magassy et al., 2022). Commuting, in particular, has been associated with lower experiential wellbeing, especially for longer or more stressful trips (Stone and Schneider, 2016). On the other hand, with a focus on understanding how the absence of commuting from one’s activity-travel patterns impacts their wellbeing, Maheshwari et al. (2024) suggest that teleworking can enhance wellbeing by mitigating the stress associated with commuting for certain worker groups. Moreover, socioeconomic and demographic characteristics also play a pivotal role in shaping the relationship between travel and subjective wellbeing. Indeed, person-level attributes such as gender, income, age, and household structure are not merely background factors but fundamental determinants of wellbeing (Mokhtarian and Pendyala, 2018), influencing both the quality of travel experiences and the broader activity-travel engagement. A growing body of literature highlights how various factors such as gender, age, income, and race/ethnicity significantly influence travel experiences and activity engagement of individuals (Archer et al., 2013; Bergstad et al., 2011; Ferenchak and Katirai, 2015; Delbosc and Currie, 2018; Nikolaev, 2018; Fong and Shaw, 2024).

Despite these advancements, much of the wellbeing research in transportation remains focused on specific activity-travel episodes (or their absence), leaving a substantial gap in understanding the broader implications of activity-travel patterns on wellbeing. Mokhtarian (2019) provides a pivotal perspective on how travel impacts subjective wellbeing. Drawing on conceptual models from prior research, her study identifies five distinct pathways through which travel influences wellbeing: travel as an activity in itself; the wellbeing derived from secondary activities undertaken during travel; engagement in out-of-home activities enabled by travel; travel as the activity (e.g., leisure drives); and the potential to travel, known as *motility*. Mokhtarian argues that while the direct contribution of travel as an activity to wellbeing may be relatively modest, its instrumental role in providing access to other activities at destinations is profoundly significant. This underscores the need to view travel not just as a utilitarian means of mobility but as an integral component of daily life with far-reaching implications for wellbeing.

This dual focus on immediate travel experiences and their broader contributions to life satisfaction reveals significant gaps in the literature. Few studies, such as Shi et al. (2024), have examined the cumulative impacts of activity-travel and time use patterns on wellbeing throughout the day. Much of the existing research remains concentrated on specific modes or trip characteristics, without fully addressing the broader, dynamic interactions between activity engagement and time use and wellbeing across various contexts. To bridge these gaps, this study adopts a holistic approach that integrates subjective and experiential wellbeing across in-home, out-of-home, and travel activities. By developing a daily wellbeing scoring method at the individual level, the study seeks to provide deeper insights into the complex ways in which transportation shapes quality of life across diverse population groups. This framework not only enhances methodological rigor but also builds the capacity to eventually evaluate the impacts of transportation policies on wellbeing, equity, and societal progress.

3. CONCEPTUAL FRAMEWORK AND MODEL STRUCTURE

This section presents the conceptual framework adopted in this study. The underlying fundamental premise is that wellbeing is determined by how people feel spending time traveling and engaging in different types of activities inside and outside the home. This necessitates capturing data on people's emotional experiences during their daily participation in activities and travel. The 2010, 2012, 2013, and 2021 editions of the ATUS provide precisely this type of data. These ATUS editions included a wellbeing module, where survey respondents were asked to rate three randomly identified activities from their time use diary on six measures of emotion: happiness, meaningfulness, sadness, painfulness, stress, and tiredness. This study uses the 2010, 2012, and 2013 wellbeing module data to develop a daily wellbeing estimation method, while leaving the 2021 wellbeing module data as a holdout sample for testing and validation purposes.

Figure 1 presents a simplified version of the conceptual framework for developing and computing a daily person-level wellbeing score (PWS) based on activity-travel and time use patterns of individuals on a given day. The steps involved in this process are as follows:

- Compile the activities for which respondents reported their feelings in the ATUS 2010, 2012, and 2013 wellbeing modules, and randomly retain only one activity per respondent. This is because the error structure in the model formulation is specified such that it does not account for the error component across activities common to the same individual.
- Classify activities into three subgroups: in-home, travel, and out-of-home.

- Develop a joint model system that relates the six emotions to one latent variable, which can be viewed as the Activity Wellbeing Score (AWS), while accounting for sociodemographic attributes and activity characteristics of individual episodes.
- Estimate this joint model system separately for each category of in-home, travel, and out-of-home activities.
- Apply the three models to any ATUS dataset to compute AWS for each activity in the dataset.
- Normalize activity wellbeing scores (AWS) between 0 and 1 to ensure consistency of scale.
- Aggregate the AWS over all activities of a respondent to compute their daily PWS. Note that the summation operation here implies that the scores associated with various activities are additive, deriving a daily wellbeing score as the accumulation of emotions experienced during individual activity-travel episodes throughout the day. While summation may not precisely represent the exact way in which people aggregate their emotional experiences over the course of a day, this approach was adopted for simplicity.

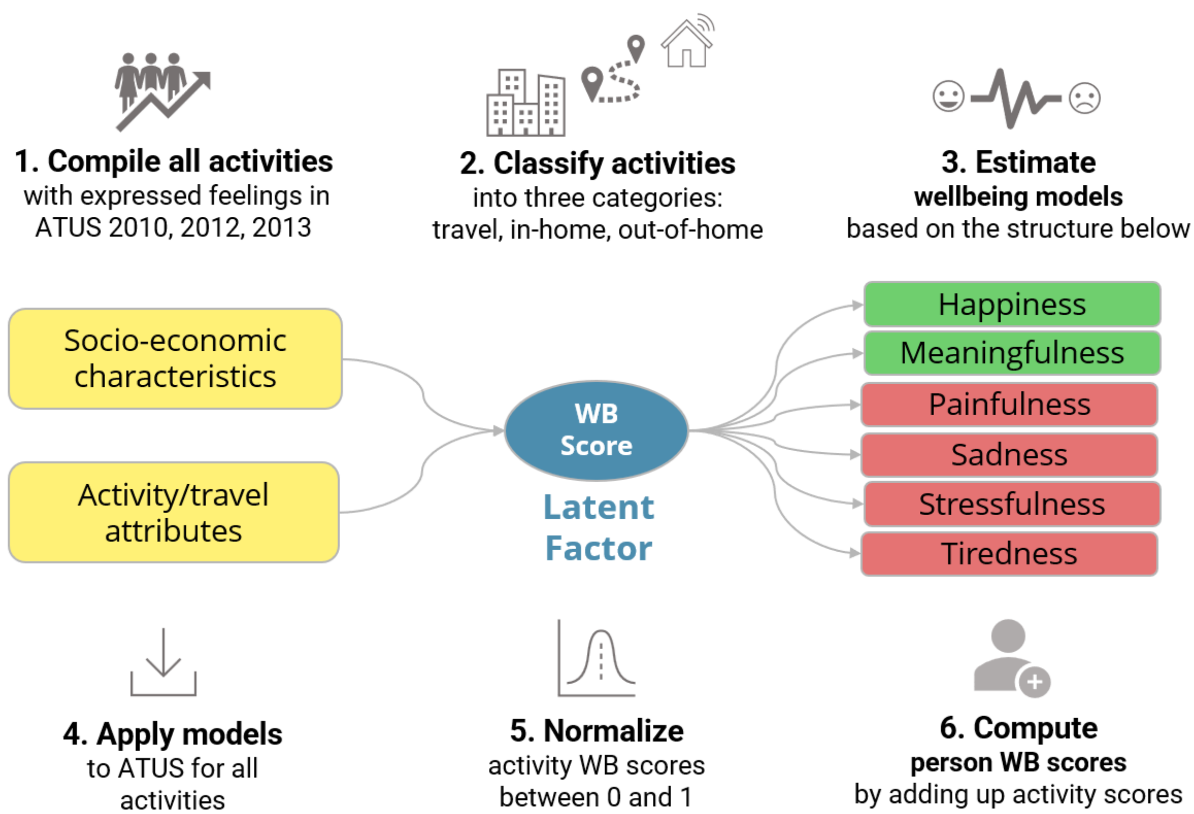

Figure 1 Summary of the Approach to Compute Daily Person Wellbeing Score (PWS)

In the end, the developed model system provides a single day-level PWS computed as the accumulation of activity wellbeing scores associated with in-home, travel, and out-of-home activity episodes over 24 hours for each individual. This model system can be applied to any synthetic population of an activity-based travel demand model to output daily wellbeing scores for each agent in the population, thus enabling equity assessments through comparisons of wellbeing scores across different market segments.

2.1. Model Estimation Methodology

A Structural Equations Model (SEM) with one latent variable is developed in this study. The SEM is estimated separately for in-home, travel, and out-of-home activities and is comprised of two components: a measurement model and a structural model. The measurement model maps the latent variable underlying AWS to the observed emotion scores, while the structural model estimates the latent variable as a function of socio-demographic characteristics and activity attributes. The corresponding mathematical formulations are presented briefly in this section.

If z represents the latent AWS (activity wellbeing score) variable, then the measurement model can be specified as:

$$y_i = \lambda_i z + \epsilon_i \quad \text{for } i = 1,2,\ldots,6$$

where y_i are the observed indicators (the six emotion scores); λ_i are the factor loadings; and ϵ_i are the random error terms. Next, the structural model that specifies the relationship between the latent variable (z) and the observed covariates is defined as:

$$z = \sum_{j=1}^{k} \beta_j x_j + \zeta$$

where x_j are the covariates (i.e., observed socio-demographic characteristics and activity attributes); β_j are the corresponding regression coefficients; and ζ is the random error term for the regression equation.

Any non-linear relationships between the latent variable and its indicators, as well as between the latent variable and the covariates, are captured through the use of dummy variables. The error terms (ϵ_i and ζ) are assumed to be independently and identically distributed (*i.i.d.*) and normally distributed with a mean of zero and constant variance as:

$$\epsilon_i \sim \mathcal{N}\left(0, \sigma_{\epsilon_i}^2\right) \quad \text{for } i=1,2,\ldots,6$$
$$\zeta \sim \mathcal{N}\left(0, \sigma_{\zeta}^2\right)$$

Following this, the likelihood function for the sample can be formulated based on the joint distribution of the observations in the dataset. Assuming multivariate normality for the error terms, the likelihood function for a sample of size N can be expressed as:

$$L(\theta; Y) = \prod_{i=1}^{N} \left(\frac{1}{(2\pi)^{p/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (y_i - \mu)^T \Sigma^{-1} (y_i - \mu) \right) \right)$$

where, θ represents the vector of model parameters (factor loadings, regression coefficients, and variances); Y is the matrix of observed variables; y_i is the vector of observed variables for the i-th individual; μ is the vector of means of the observed variables; Σ is the covariance matrix of the observed variables; and p is the number of observed variables. Maximizing this likelihood function with respect to the model parameters θ yields parameter estimates. For this study, this is accomplished using the *lavaan* package in *R* (Rosseel, 2012).

4. DATA DESCRIPTION

This section presents an overview of the data used for model development. As noted previously, the primary source of data is the American Time Use Survey (ATUS), which is administered on an annual basis by the Bureau of Labor Statistics (BLS) in the United States to a representative sample of individuals aged 15 years or over. The survey involves collecting detailed activity engagement and time use information with a very detailed activity purpose classification scheme, thus providing a high degree of fidelity in terms of activity attributes. In addition to all of the attributes of the activity episodes, the data set includes information about travel episodes as well as socio-economic and demographic characteristics of the individual and the household to which the individual belongs. In 2010, 2012, 2013, and 2021, the ATUS included a wellbeing module in which individuals were asked to rate their feelings on a scale of 0 through 6 for six different emotions – happiness, meaningfulness, sadness, tiredness, painfulness, and stress. A higher score implied a higher intensity or degree of a particular emotion. Respondents were asked to do this for three randomly identified activity or travel episodes in their time use diary. In these four years, a total of 41,467 respondents provided this information for a total of 123,257 activity and travel episodes. Since the 2021 sample is used as a holdout sample for validation purposes and not included in the model estimation, the 2021 records were excluded.

Table 1 shows the distribution of ratings in the pooled sample from 2010, 2012, and 2013 for all six emotions, considering three broad activity types – in-home, out-of-home, and travel episodes. These activity types are further disaggregated using the time poverty taxonomy, which categorizes activities into necessary, committed, and discretionary activities (Batur, 2023). Personal care activities, such as sleeping, are considered necessary; household activities, adult and childcare, and work are treated as committed; and all other activities are classified as discretionary. Travel activities are similarly classified depending on their destination purposes. For ease of interpreting emotion scores, necessary and committed activities (and trip purposes) are treated as mandatory and discretionary activities (and trip purposes) are treated as non-mandatory.

A higher rating on the positive (negative) emotions implies that the individual derived more positive (negative) feelings from the activity episodes. In general, people rate their activity episodes positively and derive positive feelings of emotion. This is quite consistent with expectations as people are likely to shun activities that they do not enjoy or find undesirable to the extent possible. In the table, each row adds up to 100 percent, thus enabling the identification of the fraction of episodes of any given type rated at each level of an emotional measure.

An examination of the positive emotions shows that nearly one-third of activities are rated at the highest level of happiness and nearly 40 percent are rated at the highest level of meaningfulness. Only small fractions of activities of any type fall into the lowest ratings of happiness and meaningfulness; the percentages at either end of the spectrum are higher for meaningfulness than happiness. It appears that individuals are able to draw a clearer distinction for meaningfulness than for happiness. Between five and 10 percent of episodes are characterized as not being meaningful. It is interesting to note that travel depicts a higher percent of episodes that are deemed not meaningful, relative to in-home and out-of-home activities. This is reasonable in that travel is often a means to access and pursue an activity; the activity at the destination is what provides value and meaningfulness, with the travel episode merely serving as the conduit to access the activity. For both happiness and meaningfulness, it is found that non-mandatory in-home activities are viewed a little less positively than non-mandatory out-of-home activities, while mandatory in-home activities are rated slightly higher than mandatory out-of-home activities.

TABLE 1 Distribution of Emotion Ratings by Activity Type in the ATUS Wellbeing Modules

Emotion	Activity	Type	Emotion Level (%)							N
			0	1	2	3	4	5	6	
Happiness	In-home	Mandatory	5.1	2.3	6.2	16.9	18.1	21.8	29.7	22,255
		Non-mandatory	4.6	2.1	5.0	14.8	17.3	22.8	33.5	29,686
	Out-home	Mandatory	4.4	2.5	6.3	18.2	20.9	23.5	24.4	7,692
		Non-mandatory	3.6	1.7	4.2	11.9	16.9	24.5	37.3	16,967
	Travel	Mandatory	4.5	2.2	6.1	17.9	19.5	22.3	27.6	7,032
		Non-mandatory	3.7	1.7	4.6	13.8	18.3	24.5	33.4	15,857
	All	Mandatory	4.8	2.3	6.2	17.3	19.0	22.3	28.2	36,979
		Non-mandatory	4.1	1.9	4.7	13.8	17.4	23.7	34.5	62,510
Meaningfulness	In-home	Mandatory	7.2	3.2	5.9	12.4	12.2	16.5	42.7	22,255
		Non-mandatory	9.2	3.8	7.3	13.9	13.0	15.3	37.5	29,686
	Out-home	Mandatory	5.5	2.2	4.6	12.6	14.4	19.9	41.0	7,692
		Non-mandatory	5.8	2.7	5.1	11.7	13.1	17.2	44.4	16,967
	Travel	Mandatory	12.1	5.1	6.9	13.8	11.3	13.6	37.2	7,032
		Non-mandatory	10.8	4.0	7.0	13.1	13.0	14.8	37.3	15,857
	All	Mandatory	7.8	3.3	5.8	12.7	12.5	16.7	41.3	36,979
		Non-mandatory	8.7	3.5	6.6	13.1	13.0	15.7	39.3	62,510
Painfulness	In-home	Mandatory	65.4	6.6	7.1	7.3	6.3	4.0	3.3	22,255
		Non-mandatory	66.9	6.1	6.6	7.1	6.0	3.9	3.5	29,686
	Out-home	Mandatory	70.0	6.7	7.4	6.2	4.7	2.8	2.2	7,692
		Non-mandatory	71.9	6.5	6.7	6.1	4.3	2.5	2.0	16,967
	Travel	Mandatory	73.3	6.7	6.0	5.7	4.1	2.3	1.9	7,032
		Non-mandatory	73.0	6.3	6.3	5.6	4.1	2.8	1.9	15,857
	All	Mandatory	67.9	6.6	7.0	6.8	5.5	3.4	2.8	36,979
		Non-mandatory	69.8	6.3	6.6	6.4	5.0	3.2	2.7	62,510
Sadness	In-home	Mandatory	77.5	6.1	5.3	4.7	2.8	1.9	1.8	22,255
		Non-mandatory	76.4	6.0	5.4	5.0	3.1	2.0	2.1	29,686
	Out-home	Mandatory	74.4	7.9	6.7	4.9	2.9	1.7	1.6	7,692
		Non-mandatory	80.5	6.0	4.6	3.8	2.1	1.3	1.6	16,967
	Travel	Mandatory	76.7	6.7	6.0	4.8	2.5	1.5	1.7	7,032
		Non-mandatory	79.4	6.3	4.7	4.0	2.5	1.6	1.5	15,857
	All	Mandatory	76.7	6.6	5.7	4.8	2.8	1.8	1.7	36,979
		Non-mandatory	78.3	6.1	5.0	4.4	2.7	1.7	1.8	62,510
Stressfulness	In-home	Mandatory	51.9	11.1	12.1	10.3	7.1	4.2	3.4	22,255
		Non-mandatory	60.8	9.6	9.8	8.1	5.3	3.3	3.1	29,686
	Out-home	Mandatory	36.7	10.8	14.6	14.8	11.3	6.7	5.1	7,692
		Non-mandatory	58.5	10.7	10.6	8.6	5.5	3.4	2.8	16,967
	Travel	Mandatory	45.2	11.9	14.1	12.1	8.4	4.8	3.6	7,032
		Non-mandatory	56.9	11.2	11.4	8.6	5.8	3.5	2.8	15,857
	All	Mandatory	47.5	11.2	13.0	11.6	8.2	4.8	3.8	36,979
		Non-mandatory	59.2	10.3	10.4	8.4	5.5	3.4	2.9	62,510
Tiredness	In-home	Mandatory	29.3	8.8	13.4	16.9	14.5	9.8	7.3	22,255
		Non-mandatory	33.7	8.3	12.8	15.7	13.8	9.1	6.7	29,686
	Out-home	Mandatory	27.5	10.5	15.2	17.8	13.5	9.0	6.5	7,692
		Non-mandatory	37.1	10.1	13.8	15.5	11.6	7.3	4.6	16,967
	Travel	Mandatory	28.3	10.5	14.1	16.7	14.0	9.2	7.2	7,032
		Non-mandatory	36.5	10.0	13.3	15.4	11.9	7.8	5.1	15,857
	All	Mandatory	28.8	9.5	13.9	17.0	14.2	9.5	7.1	36,979
		Non-mandatory	35.3	9.2	13.2	15.6	12.7	8.3	5.7	62,510

Note: Each row adds up to 100%, with cells color-coded from red (lower) to green (higher).

An examination of the distribution of ratings on negative emotions reveals a somewhat similar pattern. Larger ratings imply greater displeasure with the activities in question. Less than two percent of all activities are rated in the highest level of sadness, and less than three percent are rated in the highest level of painfulness. In general, it appears that individuals do not feel that their activities engender sadness or create pain. Large percentages of activities are rated with a zero on the painfulness and sadness scales. The sentiment shifts a little bit for the stressfulness and tiredness emotions. About three to five percent of activities are viewed as engendering the highest level of stress. When it comes to tiredness, about five to seven percent of activities are rated at the highest level. Only about one-third of activities are rated zero on the tiredness scale, suggesting that people do experience tiredness more so than other negative emotions. In general, out-of-home activities are rated lower on the sadness, painfulness, and tiredness scales than in-home activities. This implies that people generally enjoy out-of-home activities more than in-home activities, supporting the notion that engaging in travel and out-of-home activities has a positive impact on wellbeing (and consequently quality of life). In the case of stress, however, it is found that out-of-home activities are generally viewed as being more stressful than in-home activities. Travel activities depict a slightly lower level of painfulness when compared with in-home and out-of-home activities, presumably because there is nothing painful about travel episodes (for the most part). However, travel episodes are associated with a slightly higher level of tiredness than out-of-home activities. As travel may involve physical and mental exertion (walking, bicycling, waiting for transit, driving), it is not surprising that people rate travel episodes more negatively on this emotion.

5. MODEL ESTIMATION RESULTS

Table 2 presents model estimation results separately for each of in-home, out-of-home, and travel categories. The latent variable that represents AWS in all three models is a function of individual-level characteristics as well as activity-level attributes. It is also mapped to six indicators (i.e., the corresponding emotion ratings). The results show that, across the three activity types, the two positive emotions loaded positively, and the four negative emotions loaded negatively onto the AWS. It is found that happiness engenders more positive wellbeing than meaningfulness while sadness and stressfulness are more dominant indicators of negative wellbeing.

The results offer behaviorally intuitive interpretations. Determinants of wellbeing encompass *both* socio-demographic characteristics of the activity participants, as well as the attributes of the activities themselves. The activity attributes that influence activity wellbeing scores include activity or travel purpose, timing and duration of activities, presence of accompaniments, travel modes, and some interaction terms. This signifies that, while wellbeing is strongly correlated with, and dependent upon, socio-economic and demographic characteristics, it is important to account for the attributes of the activity and travel episodes to more accurately estimate the wellbeing experienced by individuals on a day-to-day basis in the context of their activity-travel episodes.

TABLE 2 Joint Model Estimation Results for Latent Activity Wellbeing Scores (AWS)

Variable (base)		**In-home**		**Out-of-home**		**Travel**	
		Coef	t-stat	Coef	t-stat	Coef	t-stat
Person and household attributes							
Gender (*)	Female	-0.15	-8.25	--	--	-0.11	-4.06
Gender and age (*)	Female × 30-49 years	--	--	-0.05	-2.30	--	--
Age (*)	15-19 years	0.47	9.71	0.11	1.69	0.34	5.00
	20-29 years	0.22	7.12	--	--	--	--
	65 years or older	0.41	15.96	0.28	6.35	0.39	8.94
Race (not black)	Black	0.15	5.99	--	--	0.09	2.24
Education (≥ high school)	Less than high school	-0.16	-5.67	-0.18	-3.86	-0.12	-2.60
Employment (non-worker)	Worker	0.21	10.21	0.10	2.80	0.22	6.14
Household income (up to $50,000)	$50,000 to $100,000	0.15	6.73	0.12	3.98	0.08	2.37
	$100,000 or more	0.14	5.20	0.12	3.36	0.13	3.37
Household size (*)	One	-0.07	-2.98	--	--	--	--
	Three or more	--	--	0.09	3.27	--	--
Household presence of children (no)	Yes	0.08	3.37	--	--	--	--
Time poverty (no)	Yes	--	--	-0.20	-5.85	-0.11	-2.87
Daily trip count (≥1 trip)	Zero	-0.16	-6.99	--	--	--	--
Daily activity count (medium)	Low (<12)	-0.11	-3.94	--	--	--	--
	High (≥24)	-0.05	-2.12	--	--	--	--
Activity attributes							
Activity/travel purpose (*)	Work	-0.32	-5.54	-0.41	-8.63	-0.21	-4.93
	Education	-0.70	-7.17	-0.33	-2.69	--	--
	Eating and drinking	0.11	4.60	--	--	0.25	5.37
	Eating and drinking × accompanied	--	--	0.33	7.66	--	--
	Social or leisure	0.08	3.60	0.23	5.77	0.08	1.92
	Recreational	--	--	0.25	4.14	0.22	3.14
	Religious	--	--	0.34	4.58	0.28	3.78
	Volunteering	--	--	0.24	2.47	--	--
	Household services	--	--	-0.43	-1.80	--	--
Day (weekend)	Weekday	-0.10	-5.53	-0.12	-4.45	-0.18	-6.24
Time of day (*)	Evening	--	--	--	--	-0.15	-3.99
	Night	-0.30	-4.25	-0.22	-2.47	-0.26	-2.00
Accompaniment (alone)	Accompanied	0.08	4.23	0.07	2.26	--	--
Travel mode (not car)	Car	--	--	--	--	0.14	3.32
Duration in 100 min		--	--	0.09	3.15	-0.23	-3.06
Duration in 100 min (squared)		-0.01	-3.97	-0.02	-4.32	-0.04	-1.93
Factor Loadings							
Happiness		0.66	50.85	0.75	42.74	0.64	33.17
Meaningfulness		0.25	15.90	0.35	16.91	0.20	7.75
Painfulness		-0.90	-66.29	-0.67	-38.63	-0.66	-36.21
Sadness		-0.94	-88.33	-0.71	-50.57	-0.80	-50.93
Stressfulness		-1.23	-94.38	-1.24	-63.26	-1.28	-61.45
Tiredness		-0.93	-59.38	-0.93	-43.47	-0.93	-39.57
Data Fit Measures	Sample size	18,014		8,589		7,754	
	Log-likelihood of the baseline model	-204,683.9		-94,460.7		-86,818.3	
	Log-likelihood of the proposed model	-200,398.5		-92,557.0		-85,297.4	
	AIC	409,435.7		188,989.5		173,700.5	
	BIC	409,700.9		189,229.5		173,923.1	

Note: *Base category is not identical across the model equations and corresponds to all omitted categories.

Coefficient estimates indicate that females are more likely to have a lower AWS for in-home and travel activities compared to males, while their AWS for out-of-home activities is lower only for those aged 30 to 49 years. On the other hand, the oldest and youngest age groups consistently exhibit a higher degree of AWS for all three types of activities: in-home, travel, and out-of-home. While this can be attributed to the lower prevalence of work episodes among these age groups, it can also be attributed to the fact that middle age groups are likely to experience more time constraints and stresses, limiting their enjoyment of activities in the wake of work-, household maintenance, and adult/childcare-related responsibilities. The positive coefficient observed for the young age group (20-29 years old) in the context of in-home episodes suggests that this group experiences higher wellbeing in activities pursued at home, likely attributable to their relatively lower levels of responsibility regarding child and adult care activities compared to their older mid-age counterparts. It is found that Black individuals experience higher wellbeing during in-home and travel episodes, which may be attributable to cultural and social dynamics (Cobb et al., 2020; Edwards, 2024). Family and community-oriented individuals may find more joy in activities at home or within their community, and in travel activities that provide opportunities for social interactions and community engagement (Hook et al., 2023). Across in-home, out-of-home, and travel activities, those with less than a high school degree consistently experience lower wellbeing, while workers experience higher wellbeing. Lower education is often associated with less stable and lower-quality jobs, which can negatively impact overall quality of life and how activities are perceived and enjoyed (Nikolaev, 2018). On the other hand, employment provides greater financial stability and creates a structured routine, leading to enhanced life satisfaction and the ability to enjoy activities (Killingsworth, 2023).

Regarding household composition, individuals living alone report lower AWS for in-home activities, while those living in households with two or more members experience higher AWS for out-of-home activities. Income has a consistent impact on all three activity contexts. Compared to members of low-income households, those with medium and high incomes experience greater AWS, with the effect being slightly more pronounced for high-income individuals. These income effects are consistent with expectations and findings in the literature (Killingsworth, 2023). Lastly, it is worth mentioning that the presence of children in the household increases AWS for in-home activities, but it does not significantly impact AWS for other activities.

In addition to the impacts of socio-demographic and economic attributes, the structure of people's daily lives significantly affects the wellbeing derived from activity and travel episodes. Time-poor individuals (those with relatively less discretionary time for leisure activities) experience lower AWS for out-of-home and travel activities, but not for in-home activities. Time pressure likely amplifies negative emotions for these activities, as they often require more time due to travel when compared to engaging in similar activities at home. However, spending the entire day at home (being a zero-trip maker) is associated with diminished AWS. This aligns with the notion that out-of-home activities foster more positive emotions and a higher sense of community engagement, and the lack of these activities can lead to diminished wellbeing, stemming from social exclusion and other mental health issues (Delbosc and Currie, 2018). It is found that individuals who engage in very few (<12) or a large number (≥24) of activities overall experience lower AWS for their in-home activities. This is likely due to a lack of variety and stimulation in the former case and a potential feeling of being overwhelmed and stressed in the latter.

When examining the coefficients associated with activity purpose, it is evident that most activities are generally regarded more favorably than work, education, and out-of-home household services. However, some activities are regarded more positively than others. Eating and drinking, as well as social and leisure purposes, have a positive impact on AWS, except that out-of-home eating and drinking has a positive impact only in the presence of accompaniments. Recreational and religious activities are also viewed more positively in the context of out-of-home and travel activities (Ermagun, 2023), whereas volunteering activities are viewed more positively only when pursued out-of-home. These purposes do not impact wellbeing associated with in-home activity episodes.

Other activity attributes also significantly influence AWS. Activities carried out on weekdays and during nighttime generally have a negative impact on AWS across all contexts. Evening travel activities are also viewed negatively, likely due to higher congestion levels and the fatigue people feel in the evening. Activities undertaken with companions, whether at home or out-of-home, are viewed positively, likely because social interactions enhance the enjoyment of these activities. However, this positive effect does not extend to travel activities. It is found that individuals experience higher wellbeing when traveling by personal vehicle. This supports previous findings that traveling by car is associated with greater travel satisfaction (Magassy et al., 2022). The duration of an activity also significantly affects AWS, but the relationship between duration and wellbeing is nuanced. Two types of duration measures are considered: activity duration (in 100 minutes) and the square of this duration. For in-home activities, longer durations have a progressively negative impact on AWS, as the negative effect increases with the square of the duration. For out-of-home activities, AWS increases with duration up to a certain point, after which the positive effect diminishes and eventually turns negative as the squared duration impact becomes dominant. For travel activities, longer durations consistently negatively impact AWS, with the negative effect becoming more pronounced as duration increases, reflecting the compounding negative effects of both the linear and squared duration terms.

Data fit measures are presented at the bottom of Table 2. These measures indicate that the proposed joint model system offers better data fit than baseline independent models. However, there may still be potential for further improvement of model specifications in the future by incorporating additional activity attributes, leading to a more comprehensive representation of the factors that influence AWS.

6. WELLBEING MODEL VALIDATION AND APPLICATION EXERCISES

The robustness and temporal transferability of the proposed activity-wellbeing model is examined using ATUS wellbeing modules across four years (2010, 2012, 2013, and 2021). It is important to note that the ATUS 2021 wellbeing module data was not used in the model estimation process; it was held out for testing and validation exercises only. The 2021 ATUS data presents a unique opportunity to test the validity of the model system at a unique moment in time. Collected nearly ten years after the 2010, 2012, and 2013 wellbeing data and during the COVID-19 pandemic – a period marked by extreme uncertainty, stress, and profound changes in activity-travel and time-use patterns – this data allows for the examination of how emotional intensities and wellbeing were affected under such extraordinary conditions. This data, together with the data from prior years, is used in two ways to accomplish this validation.

The assumption underlying any application of the model system estimated based on the 2010, 2012, and 2013 ATUS wellbeing modules for predictive purposes is that the emotional intensities associated with different activities remain relatively stable over time. That is, the intensity of emotions such as stress, happiness, meaningfulness, and painfulness experienced for specific activity types would remain stable for individuals with similar characteristics over time.

This stability is crucial for applying the model system to activity time use patterns in different years. The ATUS wellbeing data, spanning 11 years from 2010 to 2021, provides a valuable basis for testing temporal stability.

Figures 2 and 3 show average emotional ratings in each ATUS Wellbeing Module year for a select set of in-home and out-of-home activities, with travel activities included as part of the out-of-home category. The figures reveal a rather remarkable level of stability in emotional intensities. The levels of emotions associated with virtually all activity types remain notably stable for both in-home and out-of-home activities over the years. This stability is particularly noteworthy given that the data from 2021 was collected during the pandemic. Despite the extraordinary conditions of that year, emotional intensities do not exhibit differences when compared to the prior years. This finding lends credence to the notion that the developed model system is temporally transferable and can be used to compute activity- and person-level wellbeing scores (AWS and PWS) for different points in time, regardless of the circumstances, as long as activity-travel records for individual agents are available.

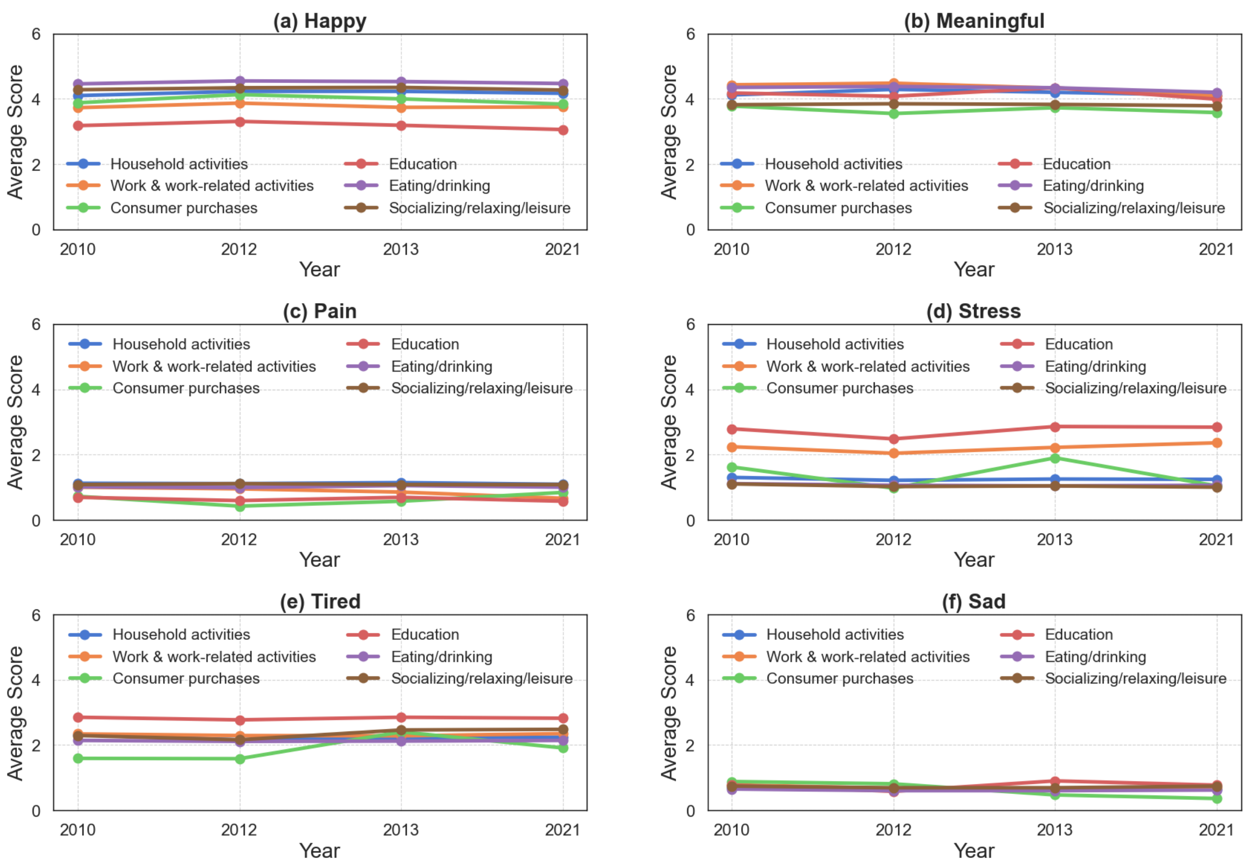

Figure 2. Average Emotion Ratings of Select In-home Activities in ATUS WB Modules (N_{act}=64,830)

After establishing the stability of emotional intensities, the proposed model system is further validated using two questions from the 2011, 2012, and 2021 ATUS Wellbeing Modules:

(1) *Thinking about yesterday as a whole, how would you say your feelings, both good and bad, compared to a typical [FILL=DAY]? Were they better than a typical [FILL=DAY], the same as a typical [FILL=DAY], or worse than a typical [FILL=DAY]?*
(2) *Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. If the top step is 10 and the bottom step is 0, on which step of the ladder do you feel you personally stand at the present time?*

These two questions provide a basis to test the extent to which the developed model system can predict the wellbeing profiles of respondents in both the 2012 and 2013 samples (used in the model estimation) and the 2021 sample (held out for validation). The first question pertains to how people view their wellbeing on the survey day compared to a typical day, offering a comparative context to check if the predicted PWS can reflect the wellbeing of individuals on worse, same, and better days. The second question, on the other hand, is often used to measure individual self-evaluation of overall life satisfaction. These two questions thus serve as sources of observed wellbeing measures that can be compared against model-predicted values of PWS to assess the model's ability to capture differences in wellbeing across different subgroups of the population in these three years.

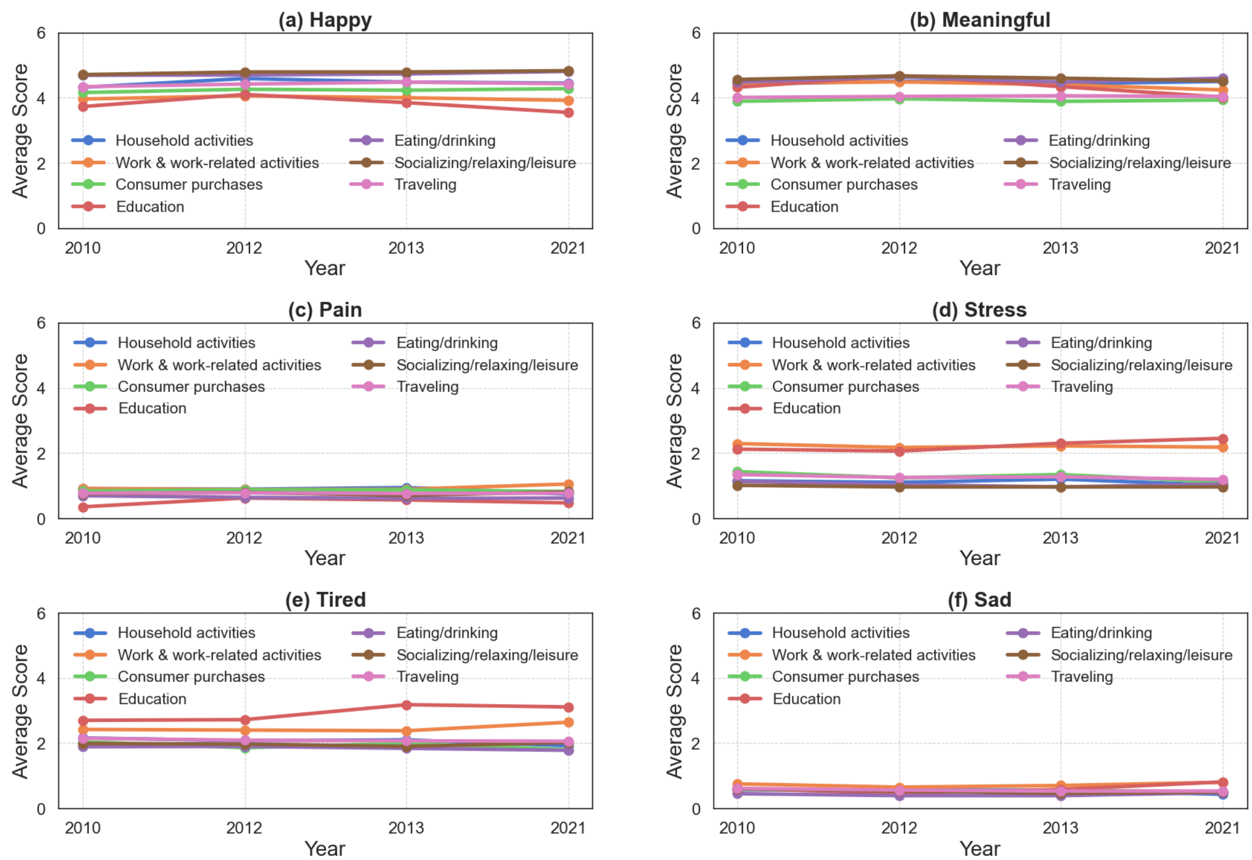

Figure 3. Average Emotion Ratings of Select Out-of-home Activities in ATUS WB Modules (N_{act}=56,057)

Table 3 shows the results of these comparisons. What is immediately discernible from the table is that the predicted wellbeing aligns quite closely with the observed wellbeing, except for a few anomalies. For the comparison of "yesterday" to a typical day question, the average PWS progressively increases from the worse to better groups. Those who indicated experiencing a worse day than a typical day have lower PWS, while those who experienced a better day have higher PWS. This trend is consistent across virtually all population groups considered in the table. For the ladder question (consolidated into three groups: bottom, middle, and top for ease of interpretation), the same pattern is observed. Those who are not satisfied with their current life conditions (at the bottom) are predicted to have lower PWS, and those reporting to be on higher rungs of the life satisfaction ladder are predicted to have higher PWS. These trends hold not only in 2012 and 2013 but also for the holdout data sample of 2021. These findings further speak to the validity of the proposed model system in capturing differences in wellbeing across different contexts and population groups.

TABLE 3 Average Person Wellbeing Scores (PWS) in 2012, 2013, and 2021

Segment	Year	Count	Avg PWS	Comparison of Yesterday to Typical Day			Current Position on Life Satisfaction Ladder		
				Worse	Same	Better	Bottom (0-4)	Middle (5-7)	Top (8-10)
All	2012	11,358	9.57	9.11	9.33	10.30	7.47	9.52	10.01
	2013	10,378	9.73	8.54	9.47	10.77	7.72	9.47	10.31
	2021	6,902	9.44	8.50	9.22	10.34	7.69	9.02	10.02
Female	2012	6,306	9.07	8.54	8.83	9.80	6.69	9.09	9.43
	2013	5,763	9.24	8.29	8.98	10.28	7.32	8.96	9.78
	2021	3,742	9.01	8.06	8.83	9.79	7.41	8.64	9.49
Age 20 to 29	2012	1,267	10.01	9.10	9.81	10.74	9.22	10.18	9.98
	2013	1,122	9.93	8.62	9.61	11.00	9.28	9.77	10.25
	2021	680	9.48	8.99	9.01	10.55	9.41	9.14	10.03
Age 65 or older	2012	2,272	11.81	11.90	11.48	12.99	10.32	11.75	12.03
	2013	2,142	11.89	11.23	11.63	12.99	10.22	11.53	12.33
	2021	2,034	11.92	11.30	11.86	12.36	9.46	11.43	12.43
Black	2012	1,701	9.15	9.42	8.91	9.63	7.93	9.17	9.38
	2013	1,538	9.07	7.96	8.84	10.05	6.79	9.19	9.36
	2021	850	9.35	9.11	9.24	9.68	8.02	9.25	9.66
White	2012	9,014	9.67	9.11	9.44	10.43	7.31	9.60	10.15
	2013	8,226	9.88	8.71	9.62	10.92	7.89	9.56	10.50
	2021	5,553	9.49	8.51	9.23	10.47	7.59	9.00	10.12
Worker	2012	6,700	10.43	9.92	10.17	11.18	8.99	10.31	10.77
	2013	6,104	10.58	9.42	10.25	11.70	9.51	10.35	10.95
	2021	3,932	9.85	9.02	9.42	11.08	9.08	9.52	10.23
Low income (≤ $35,000)	2012	4,223	7.33	6.62	7.22	7.86	5.90	7.47	7.63
	2013	3,804	7.39	6.07	7.20	8.41	6.05	7.28	7.92
	2021	1,700	6.67	5.15	6.65	7.36	5.25	6.49	7.22
High income (≥$100,000)	2012	2,098	12.16	11.74	11.86	12.95	11.67	12.23	12.15
	2013	2,009	12.21	10.37	12.18	12.99	11.47	11.95	12.43
	2021	2,123	11.06	10.49	10.75	11.94	10.11	10.75	11.34
Household size 1	2012	3,056	7.95	7.25	7.70	8.93	6.26	7.92	8.45
	2013	2,754	8.16	6.66	7.95	9.32	6.42	7.90	8.93
	2021	1,878	8.10	7.10	7.84	9.33	6.69	7.87	8.68
Household size 3 or more	2012	5,303	10.39	10.40	10.10	10.97	8.40	10.55	10.56
	2013	4,712	10.72	9.67	10.51	11.53	9.22	10.54	11.09
	2021	2,648	10.02	9.14	9.69	10.98	8.72	10.06	10.16
Non-metropolitan	2012	1,874	9.30	8.55	9.07	10.19	6.89	9.18	9.85
	2013	1,695	9.11	7.46	8.76	10.49	6.76	8.97	9.65
	2021	922	8.75	8.10	8.76	8.97	6.82	8.11	9.54
Zero-trip maker	2012	1,888	4.49	4.17	4.35	5.23	2.87	4.55	4.88
	2013	1,670	4.55	3.77	4.55	5.12	3.24	4.39	5.06
	2021	1,798	5.38	4.89	5.35	5.80	4.36	5.24	5.71
Time poor	2012	2,553	7.20	7.12	7.16	7.41	5.80	7.33	7.36
	2013	2,428	7.32	6.68	7.25	8.04	6.50	7.31	7.45
	2021	1,688	7.23	7.19	7.09	7.76	6.42	7.19	7.38

Note: In the "Comparison of Yesterday to Typical Day" and "Current Position on Life Satisfaction Ladder" sections, each row is color-coded separately, with the average PWS value increasing from red to green.

Finally, the proposed model is tested by applying it to all ATUS datasets from 2003 through 2023 to estimate and track wellbeing changes over time. This analysis aims to determine the extent to which trends depicted by the model are meaningful and interpretable in light of evidence in the literature. Figures 4, 5, and 6 show average predicted PWS across the years, distinguished by weekdays and weekends for the overall population and select socio-economic and demographic subgroups. The key observation from these figures is that wellbeing has generally declined over the last two decades. This decline in wellbeing in the United States has also been reported in the World Happiness Reports by Gallup (Helliwell, 2024). The figures capture the special dip in wellbeing during two major disruptions within the last two decades, namely, the 2008 global financial crisis and the COVID-19 pandemic. The former period was marked by high unemployment rates and economic instability, while the latter significantly altered activity engagement patterns as people were confined to their homes, practiced social distancing, shunned social interactions, and limited their exposure to outside activities (Batur et al., 2023). The decrease in wellbeing predicted during these periods is consistent with what has been reported in prior literature (Deaton, 2012; VanderWeele et al., 2021; Batur et al., 2023; Blanchflower and Bryson, 2024).

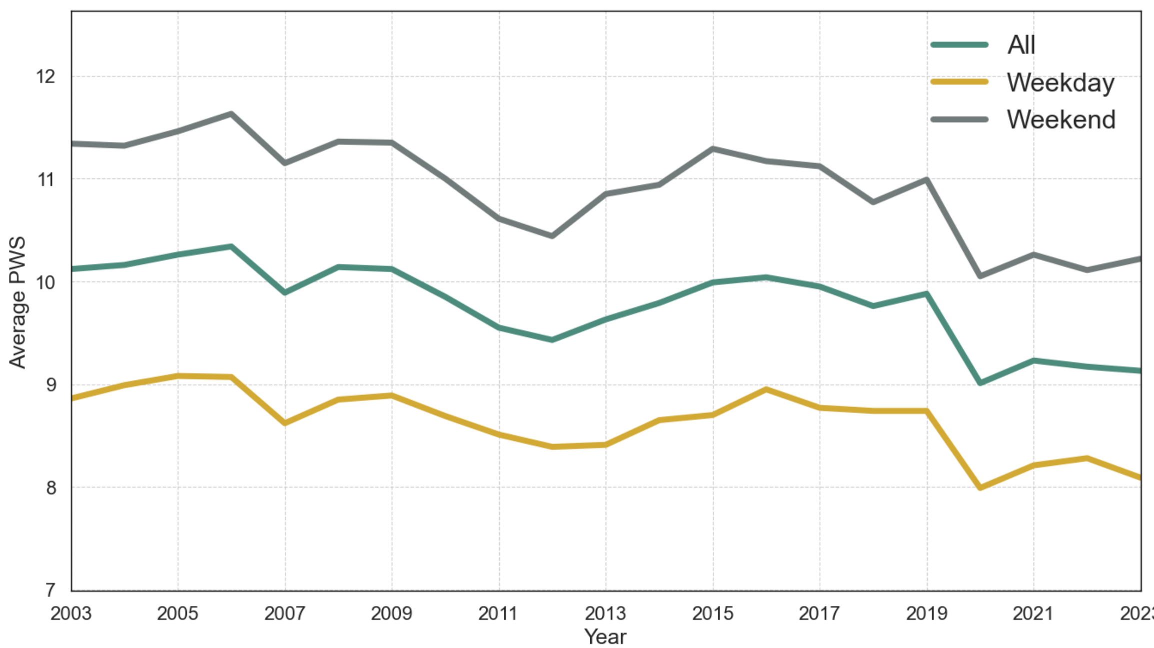

Figure 4. Average Person Wellbeing Scores (PWS) Between 2003 and 2023

The figures also reveal other intuitive trends. On weekends, people experience higher wellbeing. Women experience lower wellbeing compared to men. The commonly reported U-shaped relationship between age and wellbeing is also observed (Frijters and Beatton, 2012), indicating that younger and older age groups have higher wellbeing compared to middle-aged groups, presumably due to higher rates of work, household, and childcare-related responsibilities for middle-aged adults. The relationship between income and wellbeing shows that wellbeing increases substantially from low to mid-income levels, but the rate of increase is smaller from mid to high-income levels, a finding consistent with previous studies (Killingsworth, 2023). Other findings specific to different socio-economic groups include workers generally experiencing higher wellbeing than non-workers, although the gap between these groups has diminished over the years (BambooHR, 2023). Among racial groups, Asians and Whites have similar levels of wellbeing, while Blacks experience lower wellbeing (Lee et al., 2022). Individuals living alone have significantly lower wellbeing than those living in larger households, although the drop in wellbeing among those living in larger households is more pronounced, presumably due to financial pressures and challenges brought on by the pandemic.

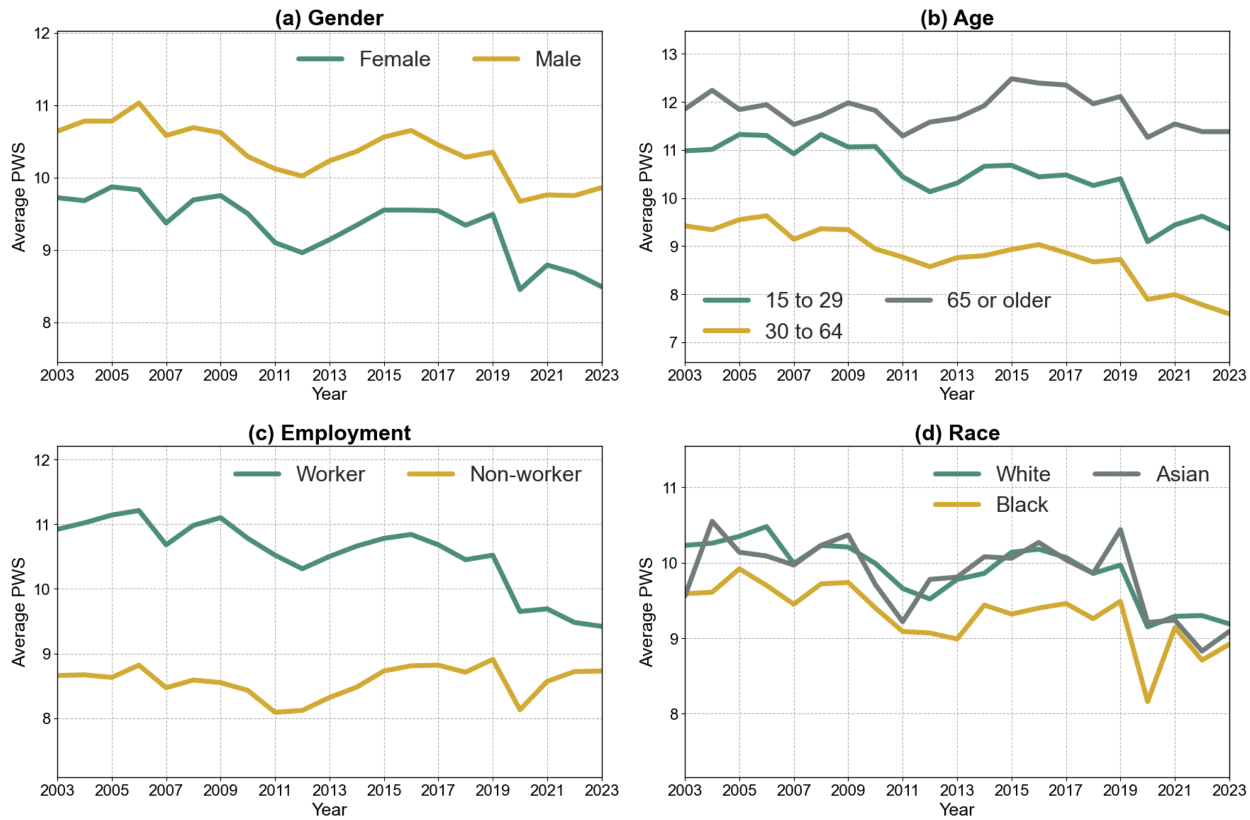

Figure 5. Average Person-Wellbeing Scores (PWS) Between 2003 and 2023
(a) Age, (b) Employment, (c) Education, (d) Race

Lastly, Figure 6 shows how trip making (mobility poverty) and time poverty impact wellbeing over the years. Zero-trip makers and time-poor individuals consistently experience lower wellbeing compared to trip-makers and non-time-poor individuals. This connection is important because, while both notions have been associated with poorer wellbeing in the literature (Krueger et al., 2009; Delbosc et al., 2020), there has been little to no empirical evidence to assess the extent to which mobility poverty (zero-trip making) and time poverty can be considered indicators of poor wellbeing. This study provides crucial empirical evidence of this linkage.

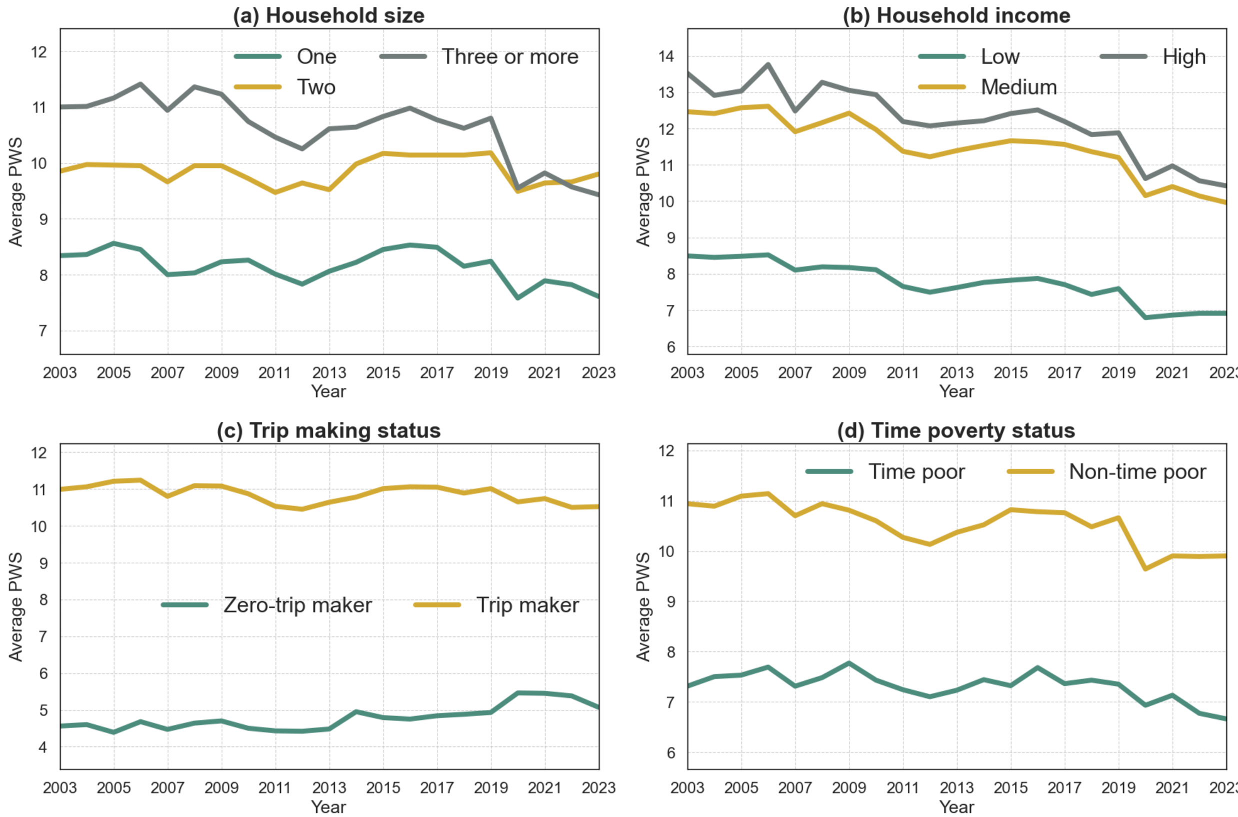

Figure 6. Average Person-Wellbeing Scores (PWS) Between 2003 and 2023: (a) Household size, (b) Household income, (c) Trip-making status, (d) Time poverty status

7. DISCUSSION AND CONCLUSIONS

Transportation and wellbeing are inextricably connected with one another due to the activities and experiences that mobility enables. Transportation planners and policy makers strive to implement policies and direct investments in ways that would enable mobility, enhance access to destinations and opportunities, and increase quality of life *for all*. Despite the widespread recognition of the connection between wellbeing and activity-travel patterns, little progress has been made in translating measures of activity-travel behavior into measures of wellbeing. As a result, the time use patterns themselves are often viewed as indicators of wellbeing and quality of life. Those who do not travel are viewed as experiencing isolation and social exclusion; those who do not engage in discretionary activities are viewed as experiencing time poverty. While these notions are useful, the lack of a model that explicitly delivers measures of wellbeing as a function of socio-economic attributes, built environment attributes, and activity-travel pattern attributes renders it challenging to truly assess the quality of life (wellbeing) impacts of alternative investments, technologies, and policies.

To fill this void, this paper presents a comprehensive model system of activity-travel wellbeing. The model development process involved using the wellbeing module of the American Time Use Survey (ATUS) to develop models of wellbeing scores as a function of socio-economic and activity-travel variables. With the benefit of detailed information available in the ATUS data series about the in-home and out-of-home activities and travel undertaken by individuals, wellbeing scores can be computed for each individual using the model system developed in this study. The paper summarizes model estimation results and validates the model's reliability, reasonableness, and transferability using the ATUS 2021 wellbeing module as a holdout sample.

The results are intuitive and consistent with the notion that out-of-home discretionary activity engagement contributes positively to wellbeing (De Vos, 2024). While some discretionary activity engagement inside the home also contributes positively to wellbeing, zero-trip making (not leaving home the entire day) is negatively associated with wellbeing, offsetting the positive wellbeing gains from in-home discretionary activities. Additionally, time poverty (i.e., having little time available for discretionary activities) strongly correlates with diminished wellbeing. Despite the positive wellbeing gains from out-of-home discretionary activities and travel, those experiencing time poverty report lower wellbeing for these activities when compared to in-home activities, presumably due to time stress. It is also found that high amounts of travel are associated with lower levels of wellbeing. The findings suggest that it is important to take a holistic accounting of all activity engagement, both inside and outside the home, to assess wellbeing, degree of social exclusion, and quality of life.

The efficacy of the model system was illustrated by applying the model to the entire ATUS data series from 2003 to 2023. This application enabled tracking changes in wellbeing over the years and revealed intuitive wellbeing disparities across different population groups that have also been reported in the literature. The key finding is that wellbeing has been declining over the last two decades. The results also showed that many disadvantaged population groups (including communities of color, women, and those experiencing mobility and time poverty) experience lower levels of wellbeing, corroborating findings in the literature. An exception is that older individuals do not appear to experience lower wellbeing; in fact, they seem to experience the highest wellbeing, presumably due to their discretionary activity engagement (inside the home) and relief from work obligations and stresses of life. Conversely, although Blacks were found to report higher wellbeing for their in-home activity episodes and travel episodes, the lower levels of out-of-home activity engagement – together with other financial and household constraints – resulted in their overall daily wellbeing being consistently lower than average over the last two decades (although the gap is narrowing). While workers score low on the wellbeing metric due to substantial work-related constraints, unemployed individuals also score low despite having more discretionary time. These individuals spend more time sleeping (which yields diminishing returns above a certain threshold) and fulfilling in-home obligations and maintenance activities, which do not significantly contribute to wellbeing. For this group, the substantial time spent at home may indeed diminish quality of life, indicating that the connection between wellbeing and out-of-home activity engagement (and travel) is nuanced and varies across demographic segments.

Overall, the model system developed in this study can be used in conjunction with activity-based travel models to assess the wellbeing implications of transportation investments and actions for different population subgroups. This is particularly useful for environmental justice and equity analyses. However, a key challenge is that travel model outputs do not provide information about in-home activity engagement and time use patterns, which are crucial for estimating measures of wellbeing. Future research should focus on deploying data fusion methods that enable the prediction of in-home time use patterns for each individual in a synthetic population (Khalil and Fatmi, 2023). In-home activity time use patterns derived from the ATUS can be used as the basis to predict and/or impute information about in-home activities for synthetic agents in activity-based travel models. Additionally, future research could involve enriching the models of wellbeing scores with additional attributes (such as built environment variables) and applying the model system to a full-fledged activity-based travel model output of millions of agents to test the model's efficacy in real-world settings.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: I. Batur, S. Khoeini, R.M. Pendyala; data collection: I. Batur, S. Sharda; analysis and interpretation of results: I. Batur, R.M. Pendyala, X. Ye; draft manuscript preparation: I. Batur, S. Khoeini, T. Magassy, R.M. Pendyala. All authors reviewed the results and approved the final version of the manuscript.

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