# Linking Elderly Transport Mobility and Subjective Well-Being: A Multivariate Latent Modeling Approach

**Srinath Ravulaparthy***
Graduate Student, Department of Geography and GeoTrans Lab
University of California, Santa Barbara
Santa Barbara, CA 93106
Phone: 805-893-3663
E-mail: srinath@geog.ucsb.edu

**Seo Youn Yoon**
Post-doctoral Researcher, Department of Geography and GeoTrans Lab
University of California, Santa Barbara
Santa Barbara, CA 93106
Phone: 805-893-3663
E-mail: yoon@geog.ucsb.edu

**Konstadinos G. Goulias**
Professor, Department of Geography and GeoTrans Lab
University of California, Santa Barbara
Santa Barbara, CA 93106
Phone: 805-893-3663
E-mail: goulias@geog.ucsb.edu

***Corresponding Author**

Word Count Abstract: 243
Word Count Manuscript: 6,547 + 5 Tables (1250) + 2 Figures (500) = 8,297

Paper submitted for 92nd Annual Transportation Research Board Meeting, Washington, D.C., January 13 – 17, 2013.

Prepared on July 25, 2012

**ABSTRACT**
It is widely accepted that mobility is critical for social integration in a complex urban society and is essential to the maintenance of life satisfaction and well-being. Subjective well-being has recently become a topic of interest within the transportation research community. In this paper we aim at understanding the fundamental linkages between subjective well-being or happiness and transport mobility/travel behavior of the elderly population. The research here is based on data from Disability and Use of Time (DUST) 2009, which specifically targets senior couples with an average age of 68 years. Using scores to a set of satisfaction questions about life, health, memory, finances, marriage, we estimate latent class clusters. This leads to four distinct clusters of respondents depending on the degree of happiness in each of the satisfaction questions.

Using the membership to each cluster as a dependent variable, we estimate ordered probit and multinomial logistic regression models to study the relationship between clusters and individual characteristics including socio-demographics, activity patterns, time use and use of active modes (walking/bicycling). The results show that respondents who are engaging in activities out of home, socializing and enjoy better mobility, also report higher levels of subjective well-being leading to a better quality of life. The model findings also show that illness and pain are related to lower well-being and that quality of life in older age is correlated to mobility.

***Keywords:*** subjective well-being, elderly travel behavior, time use, activity patterns and latent class cluster analysis

## INTRODUCTION

Subjective well-being has three separable components as identified by (*1*): life satisfaction (global judgments of one's life), satisfaction with important domains (e.g. work and marital satisfaction) and experiencing positive and negative effects of emotions and moods. This paper specifically focuses in understanding the relationship between global subjective well-being and elderly transport mobility. Subjective well-being as defined by (*2*) is the degree to which individuals positively evaluate the overall quality of their lives. As noted by (*3*) subjective well-being consists of three components: positive affect and negative affect related to immediate experiences, and a cognitive component consisting of judgment of satisfaction with life as a whole. Researchers have tried to understand the nature, determinants and consequences of subjective well-being with the emergence of new fields such as hedonic psychology, positive psychology and happiness economics (*4,5,6*). Subjective well-being recently became a topic of interest within the transportation research community. In travel behavior research, travel is generally viewed as instrumental for participation in activities in different places. There are instances, however, as (*7*) have recognized that travelers may also value travel in itself as contributing to the positive utility of driving. In this context, a number of studies have measured travel stress, travel decision-making processes and activity participation with happiness and satisfaction (*2,8,9*).

The proportion of older people in the population is increasing in developed countries due to demographic trends, increased longevity and declining fertility (*10,11*). The aging population has a variety of implications for the society and the quality of life of the elderly is an important issue. Recent evidence also suggests that elderly (65+ years) population of today is healthier, more affluent and more mobile than earlier generations of elderly people, thus producing greater demand for social and leisure activities (*12,13*). Based on the findings from (*14,15*) quality of life in old age is related to mobility.

Furthermore, mobility is critical for social integration in a complex urban society and is essential to the maintenance of life satisfaction and subjective well-being; because it allows one to readily meet other life needs (*16,17*). In this context, we can assume that mobility is significantly correlated with elderly quality of life. The majority of the seniors in the US as noted by (*18*) confront an array of medical and other constraints on their mobility even as they continue to seek active community. This restriction on an individual's ability to participate in social and leisure activities may lead to growing isolation and depression. This leads to social exclusion that is especially relevant for the elderly (*19,20*). For these reasons, there have been many studies that attempt to understand the travel needs of the elderly in the field of travel demand modeling. For example, (*21*) developed a simplified activity-based travel model for the elderly using the framework of lifestyle groups, which are based on the socio-demographic characteristics of the individuals. This study investigated the dimensions of travel behavior such as total daily activities; activities engaged by lifestyle groups, total daily trips, tours and mode splits. Furthermore, (*22*) investigates elderly travel behavior particularly focusing on individual's trip chaining, complexity, trip purpose and sequence and mode choice in a chain. This study also explores satisfying elderly travel demand by focusing on special transport services, in particular electric scooters. Also, (*23*) studies the met and unmet urban transportation needs of seniors through mail-out-mail-in survey conducted in Hennepin County, Minnesota. The study reports that seniors are generally independent and rely mainly on auto usage for their daily travel needs. Similarly, (*11*) quantify the impacts of transport mobility and investigate their impacts on quality of life for non-working elderly Canadians using contextually derived time-budgets with the measure of daily exposure to psychological, exercise and community benefits of transport mobility.

To partially fill the gap in literature, in this paper we explicitly aim at understanding the fundamental linkages between subjective well-being/happiness and travel behavior/transport mobility of the elderly population. The research is based on data from Disability and Use of Time (DUST) 2009, which is a supplement to the Panel Study of Income Dynamics. DUST 2009 data specifically target senior couples with an average age of 68 years. In our analysis we estimate latent class clusters using the reported subjective well-being or happiness measures. The measures include life, health, memory, financial and marital satisfaction. These variables are measured on a scale of 0 through 6, with 0 representing not satisfied at all and 6 representing very satisfied. Using these variables we identify through latent class cluster analysis four distinct clusters, each capturing the degree and nature of happiness or subjective well-being of the elderly population. Using the membership of each person in this finite set of latent class clusters, we estimate ordered probit and multinomial logistic regression models to study the relationship between clusters and individual characteristics. Individual characteristics are from the sample socio-demographic characteristics, overall activity patterns along with reported active living measures such as use of active modes (walking/biking) and engaging in physical exercise.

The remainder of the paper is organized as follows. The next section describes the data that were used for this study. This section also details the survey methodology that was implemented in collecting the final DUST 2009 data. The following section discusses in detail the modeling framework adopted and the model specification along with estimation results. The final section of the paper concludes with the summary of findings and next steps.

## DATA AND SURVEY METHODOLOGY

Disability and Use of Time (DUST) 2009 is a supplement to the Panel Study of Income Dynamics (PSID) a longitudinal study of representative sample of U.S. individuals and the families in which they live. The DUST survey was supported by the National Institute on Aging, which has two goals: (a) to assess the feasibility of including time diaries for adults on a large scale in the PSID and (b) to produce a rich and nationally focused data archive to support innovative research on disability, time use and well-being for older married couples.

DUST sampled couples in the PSID in which both spouses were at least of age 50 years and at least one spouse was of age 60 years or older. In the summer and fall of 2009, couples were interviewed twice with a CATI instrument, with husbands and wives interviewed separately about the same randomly selected weekday and weekend day (*24*). In order to enhance the opportunities for studying disability, couples with one or both spouses having a health limitation were oversampled, and the strata was further divided by husband's age (<70 years, +70 years) so that the sample consisted of 100 couples in which both spouses have a limitation, 100 in which neither do and the remaining split evenly between couples with only the wife or only the husband having a limitation.

Overall, 831 couples were identified as eligible for DUST. Among these, 558 were sampled, and 14 of these were found ineligible as one of the spouses had died or the couple was no longer married. Of the 544 finally eligible couples who were sampled, screeners were completed with 75% or 407. Of the 407 couples, at least one diary was completed with 395 couples (97%). The overall response rate was therefore 73%. The final number of completed diaries in the DUST survey was 1510.

As described by *(24)* the DUST instrument was designed as a 30-40 minute diary, which was paired during the first of two interviews with a 15-20 minute supplemental questionnaire. The DUST 2009 survey collected data on global well-being, impairments and limitations, use of assistive devices, medications, behavioral change, cognitive functionality, marital quality, activity diaries and detailed well-being episodic questions. At the end of the survey, respondents received a financial incentive of $50 for participating in the study ($100 for the couple). Table 1 illustrates the descriptive statistics from the DUST 2009 data. The variables used to develop the clusters are labeled as subjective well-being and the rest are used to identify the composition of each cluster in terms of socio-demographics and activity-travel behavior.

**TABLE 1 Sample Descriptive Statistics**

| Variable | | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Socio-demographics | Age of individual | 50.00 | 95.00 | 68.03 | 8.58 |
| | Total family income in USD | 7,300.00 | 829,000.00 | 79,703.38 | 70,742.50 |
| | Number of vehicles | 0.00 | 7.00 | 2.09 | 1.06 |
| | Number of children in family | 0.00 | 3.00 | 0.07 | 0.33 |
| Subjective Well-being | Life satisfaction | 0.00 | 6.00 | 4.98 | 1.11 |
| | Health satisfaction | 0.00 | 6.00 | 4.28 | 1.39 |
| | Memory satisfaction | 0.00 | 6.00 | 4.74 | 1.17 |
| | Financial satisfaction | 0.00 | 6.00 | 4.49 | 1.52 |
| | Marital satisfaction | 0.00 | 6.00 | 5.55 | 0.90 |
| Activity duration in minutes | Self-care | 39.92 | 396.00 | 110.69 | 44.32 |
| | Productive | 2.00 | 260.00 | 63.48 | 41.09 |
| | Shopping | 1.50 | 135.00 | 24.08 | 16.79 |
| | Physical activity | 1.00 | 460.00 | 39.97 | 35.91 |
| | Socialize with family or friends | 1.00 | 480.00 | 40.59 | 33.85 |
| | Non-active leisure | 5.00 | 592.50 | 90.11 | 50.06 |
| | Leisure activity | 10.00 | 855.00 | 70.67 | 88.79 |
| | Physical care | 1.00 | 180.00 | 32.10 | 30.47 |

**LATENT CLASS CLUSTER ANALYSIS**

Latent class cluster analysis is a category of latent class analysis (also known as finite mixture modeling) involving identification of relationships between variables using both observed indicators, as is used in traditional regression models, as well as unobserved or latent variables *(25)*. The idea behind latent class cluster analysis is to analyze the patterns in variance across many dependent variables and identify groups of people with relatively homogenous scores of the criteria questions used (often describing behavior but expandable to other questions as well). This is done by assuming that a categorical latent variable exists which can be analyzed from the data at hand and this latent variable is used to explain the data variance. In this way we can identify patterns in the data and distinguish between groups of individuals that have varying levels of subjective well-being or happiness, which are measured through global satisfaction questions on overall life, health, job, marriage and financial status. For example the questions are framed as "taking all things together, how satisfied are you with your life these days? Please use a scale from 0 to 6, where 0 means not at all satisfied and 6 means very satisfied".

We estimate latent class clusters using the reported subjective well-being or happiness measures from the DUST 2009 data. The measures include life, health, and memory, financial and marital satisfaction. These variables are measured on a scale of 0 through 6, with 0 representing not satisfied at all and 6 representing very satisfied. The basic form for a latent class cluster model is as follows.

$$f(y_i|\theta) = \sum_{k=1}^{K} \pi_k \prod_{j=1}^{J} f_k(y_{ij}|\theta_{jk}) \qquad (1)$$

$y_i$ – object's scores on a set of observed variables (in this case are the measures for subjective well-being or happiness)
K – number of clusters (derived iteratively in this section and settled for K=4)
J – number of variables/indicators (five indicators in this analysis) in the latent class cluster model
$\pi_k$ – prior probability of belonging to latent cluster k (estimated by the models)
θ – model parameters (estimated by the model)
$f(y_i|\theta)$ - distribution of $y_i$ given the model parameters θ

The parameters of the latent class cluster model are estimated through maximum likelihood (ML) or posterior mode (PM) estimation techniques. The probability density likelihood function provides the likelihood function in ML and PM estimation. The expectation maximization algorithm is employed in ML or PM estimation due to its simplicity and stability and relative robustness against the initial values.

By specifying a series of models with different categories of their latent variable, we estimate different models and select the model that balances parsimony and goodness of fit in the best possible way. Through an iterative process of testing multiple numbers of latent class clusters, a four cluster latent class model was found to be ideal for this study. The four clusters model has the lowest Bayesian Information Criterion (BIC) of *10261.99* and least classification error of *0.188* as suggested by *(26)* for model selection. With four latent classes, the model exhibits a significant improvement over other models with a log-likelihood (LL) of *-4971.95* when compared with single cluster model with log-likelihood of *-5214.45*. The result of the four latent class cluster model is classified as in Table 2 that shows the mean scores of subjective well-being. As seen from Table 2, persons belonging to Cluster#4 (31.8% of sample) report high levels of satisfaction for all measures. In contrast, respondents belonging to Cluster#1 (14.7% of sample) reports the lowest level of satisfaction than all the other three clusters. However, respondents in Cluster#2 (7.2% of sample) report very distinct pattern of "happiness" than the other three clusters showing highest level of satisfaction for overall life and marriage and low satisfaction for health and financial status. Therefore, as shown from results in Table 2 we rank the clusters as: Cluster#4 represents individuals who are very happy; Cluster#3 represents individuals who are uniformly happy; Cluster#2 are individuals who are moderately happy and Cluster#1 are individuals who are unhappy.

Figure 1 shows in a tabular format the cluster membership for husbands and wives. Only 42.3% of these couples have the same membership in clusters. Husbands (heads) appear to be slightly more satisfied. Moreover there are many observations for which husbands and wives appear to have diametrically opposite membership in clusters. This may be due to different impediments to activity participation and travel as well as different social and demographic status.

As noted by *(16)*, mobility is critical for social integration in a complex urban society and is essential to the maintenance of life satisfaction and well-being because it allows an individual to more readily meet all other life needs. In this context, Figure 2 illustrates the cross tabulation of the four latent class cluster model with reported activities of individuals from the DUST 2009 data. The activities that are reported in Figure 2 can be used as proxies to mobility and social integration of the elderly. For example, only 18% of individuals in Cluster#4 (very happy) report to have avoided walking to pursuing activities, while 74% in Cluster#3 and 61% in Cluster#2 report to have undertaken walking to pursue activities. This comparison shows a very close association among ability or willingness to use active modes of transport with overall health and life satisfaction. However, about 46% of individuals in Cluster#1 (unhappy) report to have avoided walking to pursue activities. This could be attributed to elderly people that have to walk due to other constraints but have difficulty walking.

Similar comparisons among clusters can be made for other reported activity patterns. For example, 31% of individuals in Cluster#4 report to have undertaken socializing activity for 3 or 4 days with family or friends in the past 7 days. This is significantly higher when compared to the other clusters. Furthermore, 25% of individuals in Cluster#1 and Cluster#2 report to have not undertaken any socializing activity, which is very high when compared with Clusters 4 and 3. A similar pattern across the clusters is also observed for conducting leisure activities for 3 or 4 days in the past 7 days. Also, 44% of individuals in Cluster#1 report to have not undertaken any leisure activities in the past 7 days. These results validate the relationship between subjective well-being and social interaction for the elderly. In fact, the samples in Cluster#2 and Cluster#1 report significantly lower level of satisfaction with their health and financial status, which are important factors in social interactions and pursuing leisure activities.

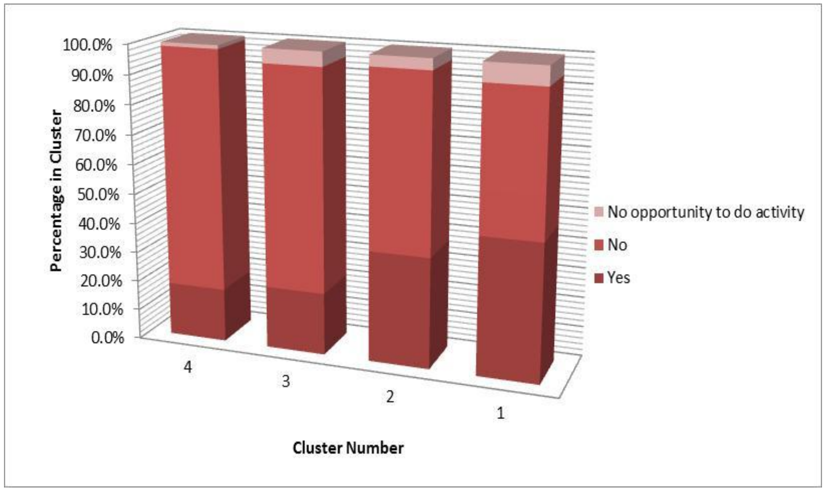
In the next section, we estimate regression models to further study and better understand the relationship between these latent class clusters and individual characteristics.

**TABLE 2 Profile of four latent class cluster model measures**

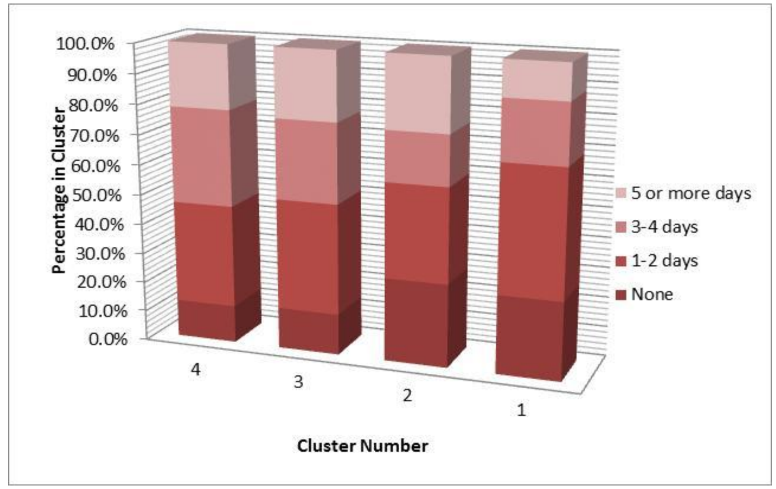
| Cluster size | Cluster#1 | Cluster#2 | Cluster#3 | Cluster#4 |
|---|---|---|---|---|
| | 0.147 | 0.072 | 0.464 | 0.318 |
| **Mean scores of measures of subjective well-being** | | | | |
| Life satisfaction | 2.99 | 5.64 | 4.81 | 5.97 |
| Health satisfaction | 2.75 | 2.42 | 4.47 | 5.04 |
| Memory satisfaction | 3.92 | 3.92 | 4.86 | 5.1 |
| Financial satisfaction | 2.84 | 3.62 | 4.49 | 5.38 |
| Marital satisfaction | 4.55 | 6.00 | 5.5 | 5.95 |

| | | | LATENT CLASS CLUSTER WIFE | | | | Total |
|---|---|---|---|---|---|---|---|
| | | | Cluster#4 (Very Happy) | Cluster#3 (Uniformly Happy) | Cluster#2 (Moderately Happy)` | Cluster#1 (Unhappy) | |
| LATENT CLASS CLUSTER HEAD | Cluster#4 (Very Happy) | Count | 51 | 42 | 4 | 13 | 110 |
| | | % of Total | 14.90% | 12.20% | 1.20% | 3.80% | 32.10% |
| | Cluster#3 (Uniformly Happy) | Count | 47 | 79 | 15 | 24 | 165 |
| | | % of Total | 13.70% | 23.00% | 4.40% | 7.00% | 48.10% |
| | Cluster#2 (Moderately Happy) | Count | 9 | 16 | 0 | 1 | 26 |
| | | % of Total | 2.60% | 4.70% | 0.00% | 0.30% | 7.60% |
| | Cluster#1 (Unhappy) | Count | 3 | 20 | 4 | 15 | 42 |
| | | % of Total | 0.90% | 5.80% | 1.20% | 4.40% | 12.20% |
| Total | | Count | 110 | 157 | 23 | 53 | 343 |
| | | % of Total | 32.10% | 45.80% | 6.70% | 15.50% | 100.00% |

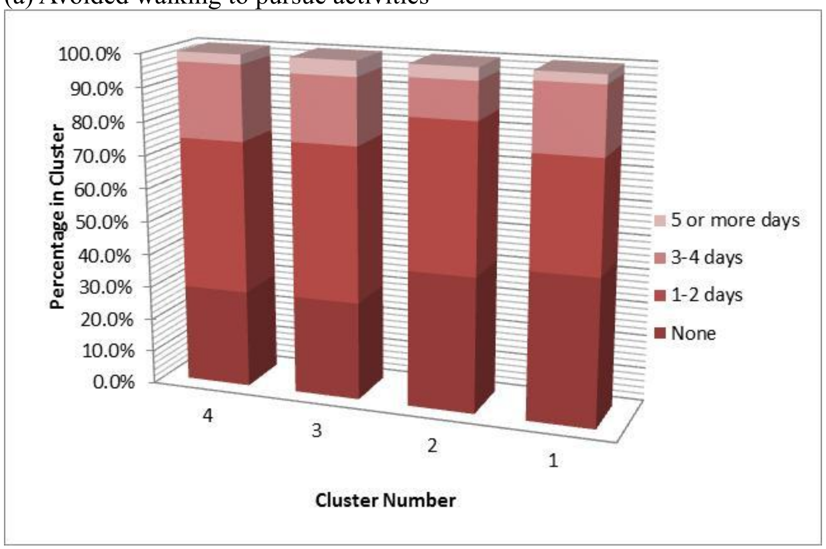
**FIGURE 1 Discrepancy and Agreement of Cluster Membership in Couples**



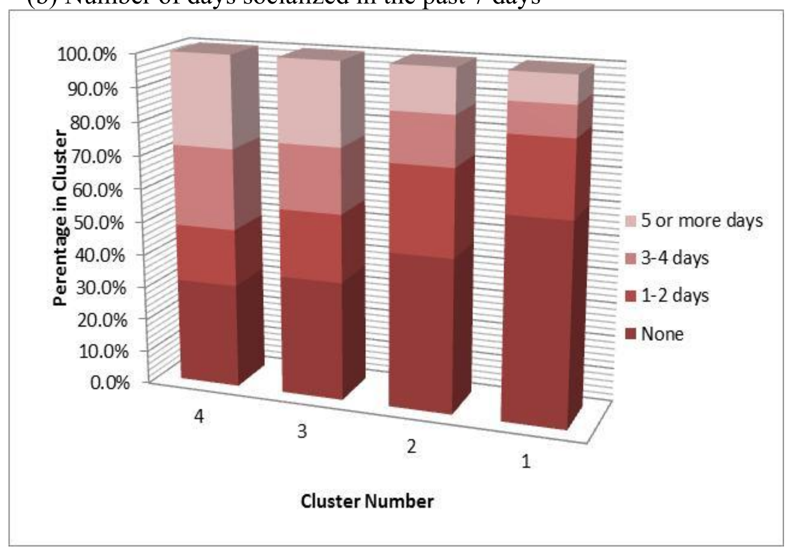

(a) Avoided walking to pursue activities




(b) Number of days socialized in the past 7 days




(c) Number of days leisure activities conducted in the past 7 days




(d) Number of days physical activities conducted in the past 7 days

**FIGURE 2 Cross tabulation of happiness clusters and reported activity**

## MODEL SPECIFICATION

As noted by *(27)* estimating models of subjective well-being or happiness requires some consideration of the measurement attributes, the scales and eventually on how best to represent and analyze the rank order. In view of this statement, the dependent variable in our study is an indicator of membership in each of the four mutually exclusive latent class clusters that were estimated using the reported subjective well-being or happiness measures from the DUST 2009 data. The estimated clusters represent the degree of happiness or subjective well-being observed from the sample. Cluster#4 represents individuals who are very happy (an overall mean score of 5.48) and Cluster#1 represents individuals that are (relatively) unhappy (an overall mean score of 3.41). However, it should be noted that there is some level of variation within each cluster with the reported scores on the measures of subjective well-being. For example, individuals in Cluster#2 (moderately happy) report very high levels of life and marital satisfaction, while reporting lower levels of satisfaction for health, memory and financial status.

In this analysis, the dependent variable (four latent class clusters) is categorical in nature. On the one hand, this variable can be assumed to have a natural ordering or rank such as the degree of happiness or satisfaction for global subjective well-being measures. One the other hand, each category of this dependent variable may be considered to be fundamentally distinct and therefore a multinomial dependent variable with multiple outcomes would be most appropriate. Therefore, we employ both the ordered probit and multinomial logistic (MNL) regression techniques to study the cluster membership correlation with individual socio-demographic, regional, activity participation, and travel and health conditions on subjective well-being or happiness.

The structural model specification for ordered probit and multinomial logistic model is as represented in (2)

$$Y_i^* = \alpha' x_i + \beta' z_i + \varepsilon_i \qquad (2)$$

Where, $Y_i^*$ - the latent continuous measure of happiness or subjective well-being as experienced by an individual $i$

$x_i$ - a vector of explanatory variables describing individual's $i$ socio-demographic and health characteristics

$z_i$ - a vector of explanatory variables describing individual's $i$ activity participation and travel characteristics

$\varepsilon_i$ - a random error term (assumed to be standard normal distribution for ordered probit and logistic distribution for MNL model)

$\alpha, \beta$ - a vector of parameters to be estimated

In the case of ordered probit model, the estimated four latent class clusters which represent the degree of subjective well-being or happiness are assumed to be the observed level of happiness, which are coded as follows in the variable $Y_i$:

$$Y_i = \begin{cases} 1 \; if -\infty \le Y_i^* \le \mu_1 \; (not\ at\ all\ satisfied) \\ 2 \qquad\qquad if\ \mu_1 < Y_i^* \le \mu_2 \\ 3 \qquad\qquad if\ \mu_2 < Y_i^* \le \mu_3 \\ 4 \quad if\ \mu_3 < Y_i^* \le \infty \; (very\ satisfied) \end{cases}$$

$\mu_i$'s represent the threshold parameters that are to be estimated.

In the case of multinomial logistic regression model, the dependent variable $Y_i$ is categorical and unordered with $k$ categories (the four latent class clusters) for $k$ = 1, 2, 3, 4. The first category with $k=1$ (cluster representing the lowest level of satisfaction) is the reference category in our analysis. The model specification for the MNL model takes the form as in (3) below.

$$logit[P(Y_i = k)] = \alpha' x_{ik} + \beta' z_{ik} \tag{3}$$

Where, $P(Y_i = k)$ - probability that an individual $i$ has a propensity to belong to cluster (or category) $k$

$x_{ik}$ - a vector of explanatory variables describing individual's $i$ socio-demographic and health characteristics for cluster $k$

$z_{ik}$ - a vector of explanatory variables describing individual's $i$ activity participation and travel characteristics for cluster $k$

$\alpha, \beta$ - a vector of parameters to be estimated

The probabilities associated with ordered probit and MNL models given as $P(Y_i = k)$ that are computed under the assumption of random error term distribution for the models respectively. The model parameters ($\alpha$, $\beta$ and $\mu_i$'s) in (2) and (3) are estimated using the maximum likelihood method. For more information on the model specification and estimation refer to *(28)*.

## MODEL RESULTS

The model estimation results for both ordered probit and MNL models are presented in Table 3, 4, and 5. For the ordered probit model, since the dependent variable or the index of subjective well-being increases with satisfaction, positive coefficients suggest a likelihood of increased levels of satisfaction. The negative coefficients from the model results for ordered probit model suggest the likelihood of decreased levels of satisfaction. However, for MNL model we assume the dependent variable to be unordered with $k$ categories. Therefore, a positive coefficient suggests a higher propensity towards the category $k$, while negative coefficient suggests a decreased level of propensity towards the category $k$. In this analysis, the $k$ categories are the four latent class clusters.

### Socio-demographic characteristics

The population of elderly people is increasing in developed countries, both absolutely and relative to population as a whole *(10)*. As a result, in this study we would like to understand the association of individual socio-demographic characteristics of the elderly with global well-being or happiness as related to transport mobility. For example, an increment in an individual age would be associated with an increase in level of satisfaction or happiness. This trend is observed both in the ordered probit and MNL model results. We also tested for dummy variables for different age groups, and found that individuals above the age of 75 years old are more satisfied or happy than individuals younger to them. Furthermore, individuals living in elderly housing have decreased levels of satisfaction or happiness. This trend is also observed from the MNL model results, as individuals in Cluster#3 and Cluster#4 have lower propensities of subjective well-being. A similar pattern of lower levels of satisfaction or happiness is observed for households of white ethnic background.

However, individuals who report to be living in elderly housing in retirement communities show a higher level of satisfaction with life. As seen from Table 4, individuals who are living in retirement communities have a higher propensity to belong to Cluster#3 and Cluster#4, when compared with other clusters. This could be attributed to the fact that living in a community would provide better access to socializing activities, civic participation, which in turn have significant benefits on transport mobility of the elderly.

Estimated coefficients from the sample for both ordered probit and MNL models for high-income individuals and individuals living in Northeast and Western part of the US do not seem to have a major significant impact on subjective well-being.

**Walking conditions**

The walking conditions of an individual were measured by the variables that reported difficulty in walking and avoided walking to pursue activities. As seen from the model results for both ordered probit and MNL models, the coefficient estimates are negative. However, from the MNL model results, individuals in Cluster#2 (moderately happy) are more likely to have difficulty in walking than any other cluster. This result can be attributed to the fact that individuals in Cluster#2 (moderately happy) report the lowest level of health satisfaction among the four clusters. However, interestingly, the same individuals in Cluster#2 are also the least likely to avoid walking (the coefficient estimate is -*1.01* from the MNL model) and report very high global life satisfaction (mean=5.64). This distinct relationship between behavior and subjective well-being of Cluster#2 could be attributed to the built environment around them, the level of help/support they receive or their attitude toward walking difficulty or having walking trips, although we cannot find concrete evidence about this from the dataset we used. However, this result suggests that the relationship among physical difficulty, built environment, help from others and attitudinal aspects related to mobility and their contribution to subjective well-being of elderly is one of the research topics that should be investigated further. The parameter estimates also support the argument by *(14,15)* that quality of life in older age is related to mobility. Furthermore, illness and pain are also associated with lower well-being of the elderly people *(29).*

**Activity engagement**

In travel behavior analysis, it is acknowledged that travel is valued because it is instrumental for engagement in daily activities. Previous research provides evidence of the impact of activity participation on subjective well-being *(11,30,31)*. In this context, activity engagement is measured by variables in which individuals report the total number of days an activity was conducted in the past seven days. For the model estimation results, we include indicator variables for no or zero number of days activities engaged out of home in past seven days and one to two days of activities engaged in the past seven days.

Model estimation results for the variables zero days volunteered in the past seven days and zero days socialized with friends and family in the past seven days consistently show negative coefficients for both ordered probit and MNL models. It should be noted that coefficient estimates for these variables are not statistically significant for Cluster#2 (moderately happy) as seen from the MNL model. From the MNL model individuals who reported to have not socialized with family and friends has a negative coefficient of -*0.663* and -*0.807* associated with Cluster#3 and Cluster#4 respectively. The parameter estimates indicate that individuals who do not engage in activities in social interaction outside of home have a higher likelihood of being unhappy. This result reaffirms the argument by *(11)* that people who engage in volunteer and socializing activities outside of the home are more satisfied with their lives. Similarly, individuals who reported to have not undertaken any physical activity (sport, working out, walking or any exercise) in the past seven days also have negative coefficients for both ordered probit and MNL models. This agrees with findings from *(32)* that examine episode-by-episode "happiness" for activities that are active leisure.

Furthermore, individuals not engaging in physical activities as from Cluster#2 (moderately happy) have a negative coefficient of -*1.37* from the MNL model results. This indicates that respondents in Cluster#2 (moderately happy) are more likely to engage in physical activities when given an opportunity than those respondents in Cluster#1 (unhappy). This result is evident for individuals from Cluster#2, who report higher levels of life satisfaction, but lower levels of health satisfaction.

Quality of life benefits of transport mobility could be captured using the frequency of engagement of activities in social interaction outside of home *(14,33)*. Therefore, individuals who report to have engaged in leisure activities (movies, out for dinner or other leisure) for one or two days in the past seven days, consistently report positive coefficients for both the models. Thus, this result supports the suggestion from *(33)* that frequency of engagement in leisure activities is an important determinant of quality of life.

Individuals reported to have socialized or conducted physical activities for one or two days in the past seven days have negative coefficient estimates from the model results. As these are dummy variables, we can conclude that individuals who conduct socializing and physical activities less frequently within the past seven days have a higher likelihood of lower satisfaction levels. The same interpretation also holds for the individuals who reported to have not conducted any socializing or physical activity in the past seven days. Thus, individuals who engage more frequently in socializing and physical activities are more likely to have higher satisfaction levels. This demonstrates a positive relationship between physical activity and social interaction with subjective well-being as noted by (*11)*.

**Mode for activity engagement**

As defined by *(10)* mobility refers to the physical or mental ability to safely and independently move around, whether inside or outside the home. Furthermore, to study the exercise benefits of transport mobility, *(14)* suggests including walk and bicycling modes into studies of this type. From the model estimation results, it is evident that individuals who use active modes (walking or biking) for activity engagement are more likely to be dissatisfied than individuals who use an automobile to engage in activities. This result enforces the popular belief of importance to having access to an automobile *(34)*. However, the coefficients of walking and biking are not strongly significant and this may be pointing out to other confounding factors such as availability of bike paths and walking networks but also some interaction with difficulty walking and related physical impediments. Furthermore, the dissatisfaction gained from using walk or bicycling for elderly could be attributed to deteriorating physical mobility, reduced mobility and other socioeconomic variables *(15,35,36)*. Therefore, there appears to be a relationship between travel options and activity engagement, implying that changes in characteristics of travel options will affect the ease with which activities are carried out, which may potentially have implications for subjective well-being. This is very important for land use policies and the removal of barriers to physically active travel will have benefits for the environment, health of the individuals, and subjective well-being.

**Activity duration**

Stemming from the idea by *(11)* of developing time budgets for activity episode in understanding quality of life and transport mobility, we use derived mean activity durations (in minutes) by activity types to further study the relationship between time use and subjective well-being. Mean activity duration is the computed average of activity duration (in minutes) by activity type as reported from the two-day time use diary for the DUST 2009 sample. As seen from Tables 3, 4 and 5, individuals spending more time in socializing, leisure and physical care (providing assistance to others) have positive coefficients associated with subjective well-being. However, it should be noted that coefficients for activity duration in social and leisure activities are not strongly significant from the MNL model results for all the clusters except Cluster#4 (very happy). These results indicate that for both the models (ordered probit and MNL), individuals who desire to spend more time in activities outside of home or with someone certainly contributes to one's sense of well-being. Furthermore, individuals participating in activities by providing assistance to others (physical care) have a higher and positive association with Cluster#2 (moderately happy). This could be again attributed to the fact that individuals in Cluster#2 are more likely to be happy than other clusters despite lower health, memory and financial satisfaction. In Cluster#2 (moderately happy) persons have a higher association with a person that spends more time in self-care. In contrast, individuals spending more time on physical activities have negative coefficients associated with subjective well-being in the ordered probit model and are less likely to belong to Cluster#2 and Cluster#4 in the MNL model. This result is indicative of the disutility (or dissatisfaction) that an individual gains when spending more time in physical activities. This again can be attributed to an individual's physical fit in pursuing physical activities but it also depends on the type of activities as shown in *(32)*.

Also, high-income individuals who spend more time in leisure activities have a higher propensity of reduced levels of satisfaction. This result is indicative of more desirable trade-offs between activity participation and time use for higher income individuals.

**Goodness of fit measures**

As seen from the model results for ordered probit model the estimated threshold parameters $\mu_i$'s are statistically significant at *95%* confidence level. Moreover, the threshold parameters as estimated from the model are in the right order, which supports and justifies the assumption of ordering of the classification of subjective well-being as derived from the four latent class clusters. In addition, the MNL model, which assumes the four latent class clusters to be unordered also, produces parameter estimates that are consistent with the ordered probit model. However, the MNL model is able to account for heterogeneity within each category of the four latent class clusters. For example, individuals who report having difficulty walking also have a negative coefficient associated with Cluster#3 (uniformly happy) and Cluster#4 (very happy) but a positive coefficient of *1.287* with Cluster#2 (moderately happy), which indicates that the factors have certain characteristics that are not necessarily ordered and those characteristics cannot be explained using the ordered probit model. Furthermore, the MNL model has a higher log-likelihood function of *-753.984* and pseudo R-squared of *0.138* when compared with ordered probit model. It should be noted that the goodness of fit measures for both the models cannot be compared directly.

**TABLE 3 Ordered Probit Model Estimation Results**

| Variable | | Coefficient | t-statistic |
|---|---|---|---|
| Constant | | 0.743 | 1.645* |
| Socio-demographics | Age of an individual | 0.019 | 3.649** |
| | Number of children in household | -0.153 | -1.205 |
| | Own a house | 0.109 | 0.637 |
| | Living in an elderly housing | -0.761 | -2.359** |
| | Living in a retirement community | 1.006 | 2.629** |
| | High income individual | 0.043 | 0.32 |
| | Individual living in North East | 0.327 | 1.558 |
| | Individual living in West | -0.171 | -1.541 |
| | Household is white | -0.342 | -2.708** |
| | Individual living in a retirement community in North East | -1.012 | -1.954** |
| Walking conditions | Difficulty in walking | -0.508 | -4.502** |
| | Avoided walking to pursue activities | -0.203 | -1.724* |

| | | | |
|---|---|---|---|
| Activities conducted for 0 days in the past 7 days | Volunteered | -0.184 | -1.764* |
| | Socialized with friends or family | -0.307 | -2.313** |
| | Physical activities conducted | -0.404 | -3.868** |
| Activities conducted for 1-2 days in the past 7 days | Socialized with friends and family | -0.227 | -1.957** |
| | Physical activities conducted | -0.433 | -3.687** |
| | Leisure activities conducted | 0.115 | 1.327 |
| | High income individuals socialized with friends or family | 0.207 | 1.131 |
| Mode used to conduct activities | Walk/Bike | -0.036 | -1.625** |
| | Auto | 0.0027 | 0.274 |
| Activity duration | Self-care | -0.0007 | -0.751 |
| | Physical activity | -0.0036 | -1.948* |
| | Socialize with family or friends | 0.0028 | 1.984** |
| | Leisure activity | 0.0074 | 2.991** |
| | Physical care | 0.0026 | 1.135 |
| | High income individual conducting leisure activity | -0.01 | -2.88** |
| | High income individuals conducting physical activity | 0.0045 | 1.437 |
| | Individual socializing living in North East | -0.009 | -2.211** |
| Thresholds | $\mu_1$ | 0.000 | 0.000 |
| | $\mu_2$ | 0.328 | 8.688** |
| | $\mu_3$ | 1.764 | 27.041** |
| **Goodness of fit measures** | | | |
| Number of observations | | | 737 |
| Number of parameters | | | 32 |
| Log likelihood | | | -798.414 |
| Restricted log likelihood | | | -875.210 |
| Akaike Information Criterion (AIC) | | | 2.253 |
| Pseudo R-squared | | | 0.087 |
| Chi-squared | | | 153.591 |
| Prob [Chi-squared > value] | | | 0.000 |

** *P<0.05; *P<0.1*

**TABLE 4 Multinomial Logistic Regression Model Estimation Results**

| **Variable** | | Cluster#2 | | Cluster#3 | | Cluster#4 | |
|---|---|---|---|---|---|---|---|
| | | **coefficient** | **t-statistic** | **coefficient** | **t-statistic** | **coefficient** | **t-statistic** |
| Constant | | -0.3004 | -0.162 | -0.0612 | -0.048 | -0.0898 | -0.064 |
| Socio-demographics | Age of an individual | 0.0126 | 0.54 | 0.0408 | 2.55** | 0.0601 | 3.491** |
| | Number of children in household | -0.1612 | -0.344 | -0.0157 | -0.05 | -0.504 | -1.238 |
| | Own a house | -0.437 | -0.757 | 0.219 | 0.472 | 0.12 | 0.24 |
| | Living in an elderly housing | -0.772 | -0.866 | -2.479 | -2.642** | -1.944 | -2.167** |
| | Living in a retirement community | 0.289 | 0.196 | 2.715 | 2.367** | 2.42 | 2.148** |
| | High income individual | 0.361 | 0.581 | 0.261 | 0.606 | 0.269 | 0.584 |
| | Individual living in North East | -0.106 | -0.112 | 0.268 | 0.425 | 0.864 | 1.307 |
| | Individual living in West | 0.083 | 0.17 | 0.24 | 0.698 | -0.406 | -1.064 |
| | Household is white | -0.568 | -1.13 | -0.377 | -1.00 | -1.059 | -2.674** |
| | Individual living in a retirement community in North East | 1.545 | 0.817 | -1.001 | -0.786 | -29.44 | 0 |
| Walking conditions | Difficulty in walking | 1.287 | 2.835** | -0.849 | -2.741** | -1.105 | -3.208** |
| | Avoided walking to pursue activities | -1.01 | -2.321** | -0.548 | -1.744* | -0.796 | -2.255** |
| Activities conducted for 0 days in the past 7 days | Volunteered | -0.647 | 1.251 | -0.581 | -1.526 | -0.807 | -2.035** |
| | Socialized with friends or family | 0.139 | 0.279 | -0.633 | -1.705* | -0.881 | -1.996** |
| | Physical activities conducted | -1.37 | -2.846** | -1.243 | -3.698** | -1.595 | -4.459** |
| Activities conducted for 1-2 days in the past 7 days | Socialized with friends and family | -0.523 | -1.064 | -0.643 | -1.971** | -0.743 | -2.095** |
| | Physical activities conducted | -0.695 | -1.295 | -1.227 | -3.241** | -1.581 | -3.939** |
| | Leisure activities conducted | 0.815 | 2.132** | 0.537 | 2.03** | 0.571 | 2.008** |
| | High income individuals socialized with friends or family | -0.239 | -0.259 | 0.689 | 1.18 | 0.621 | 0.996 |

*** P<0.05; *P<0.1*

**TABLE 5 Multinomial Logistic Regression Model Estimation Results**

| **Variable** | | Cluster#2 | | Cluster#3 | | Cluster#4 | |
|---|---|---|---|---|---|---|---|
| | | **coefficient** | **t-statistic** | **coefficient** | **t-statistic** | **coefficient** | **t-statistic** |
| Mode used to conduct activities | Walk/Bike | -0.132 | -0.998 | -0.091 | -1.581 | -0.141 | -1.943* |
| | Auto | 0.015 | 0.323 | 0.0524 | 1.633* | 0.0198 | 0.577 |
| Activity duration | Self-care | 0.0034 | 0.961 | 0.00091 | 0.325 | -0.0014 | -0.438 |
| | Physical activity | -0.0286 | -2.29** | -0.005 | -1.306 | -0.013 | -2.419** |
| | Socialize with family or friends | 0.0015 | 0.215 | 0.0055 | 1.142 | 0.0085 | 1.703* |
| | Leisure activity | 0.009 | 0.841 | 0.0007 | 0.097 | 0.017 | 2.35** |
| | Physical care | 0.0383 | 3.026** | 0.0079 | 1.197 | 0.0143 | 1.877* |
| | High income individual conducting leisure activity | -0.022 | -1.276 | -0.0124 | -1.221 | -0.028 | -2.764** |
| | High income individuals conducting physical activity | 0.015 | 1.005 | 0.0034 | 0.38 | 0.0135 | 1.314 |
| | Individual socializing living in North East | -0.005 | -0.296 | -0.1 | -0.809 | -0.025 | -1.897* |
| **Goodness of fit measures** | | | | | | | |
| Number of observations | | | | | | | 737 |
| Number of parameters | | | | | | | 32 |
| Log likelihood | | | | | | | -753.984 |
| Restricted log likelihood | | | | | | | -875.21 |
| Akaike Information Criterion (AIC) | | | | | | | 2.29 |
| Pseudo R-squared | | | | | | | 0.138 |
| Chi-squared | | | | | | | 242.45 |
| Prob [Chi-squared > value] | | | | | | | 0.000 |

*** P<0.05; *P<0.1*

**SUMMARY AND CONCLUSIONS**

In this paper we aim at understanding the fundamental linkages between subjective well-being or happiness and transport mobility/travel behavior of the elderly population. This understanding is of paramount importance especially in the context of the ageing population in developed countries, who need and want better travel services today. Furthermore, this linkage is also important in addressing policy issues concerning increased number of elderly drivers and increasing mobility and accessibility strategies for those elderly people who are no longer able to drive. As a first step, the sample is classified into four latent class clusters. The classification is based on the reported subjective well-being or happiness measures from the DUST 2009. The measures include life, health, memory, and financial and marital status. From the model results, Cluster#1 represents the individuals who are unhappy and Cluster#4 represents individuals that are very happy. Clusters#2, and #3 are somewhere between these two extremes of a "happiness" propensity. Using cluster membership as a dependent variable we further estimate a set of regression models to examine the relationship between subjective well-being and individual characteristics with variables that include socio-demographics, activity patterns, and time use.

The regression model estimation results show that illness and pain are related to lower well-being of the elderly people and that quality of life in older age is related to mobility (*14,15,29*). Furthermore, the results also reaffirm the argument by (*11*) that people engaged in volunteer and socializing activities outside home are more satisfied with their lives. The model estimation results in this study also account for an individual's restriction and disability to participate in social and leisure activities, which leads to a growing isolation and exclusion. This concept of social exclusion is especially relevant for the elderly. As governmental bodies need to recognize these added constraints of the elderly and create transportation policies that address access to social interaction, affordable and reliable transportation options for critical needs.

The methods described in this study are able to account for the degree of variation in subjective well-being as a function of socio-demographic characteristics, activity patterns and time use. This study also attempts to partially fill the gap in literature by explicitly linking the concepts of subjective well-being and elderly travel behavior, which for many years was ignored. In this way subjective well-being or happiness of the elderly population can be incorporated in travel behavior analysis for policies promoting active living, sustainable mobility, social equity, health and safety. The findings here point out to the need in collecting data about physical or other barriers to older persons movement and access to opportunities that in turn should be used in developing models describing the microenvironment within which this population segment lives. It also points out to the need of collecting data on subjective well-being.

Our study is limited in many ways. First, due to the type of data used here we do not have detailed descriptors of the environment in which these couples live. Second, the analysis was done on a person-by-person basis and this did not enable within the couple interactions to be studied (except for Figure 1 that offers a hint of potential discrepancies and *(32)* that examines each activity episode). Third, additional data may be available about ability to drive in different conditions and access to autos. Fourth, using cluster analysis we may have masked other relationships among the satisfaction questions due to grouping.

**ACKNOWLEDGEMENTS**
Funding for this research was provided by The University of California Transportation Center, and the University of California Office of the President for the Multi-campus Research Program Initiative on Sustainable Transportation and the UC Lab Fees program on Next Generation Agent-based Simulation. This paper does not constitute a policy or regulation of any Local, State, or Federal agency.

**REFERENCES**

1. Diener, E. (2000). Subjective Well-Being: The Science of Happiness and a Proposal for a National Index. American Psychologist, vol.55, no.1, pp.34-43.
2. Ettema, D., Garling, T., Olsson, L.E. and Friman, M. (2010). Out of home activities, daily travel and subjective well-being. Transportation Research Part A: Policy and Practice, vol.44, pp.723-732.
3. Diener, E., Emmons, R.A., Larsen, R.J. and Griffen, S. (1985). The satisfaction with life scale. Journal of Personal assessment, vol.49, pp.71-75.
4. Kahneman, D. and Krueger, A.B. (2006) Development in Measurement of Subjective Well-Being. Journal of Economic Perspectives, vol.20, no.1, pp.3-24.
5. Kahneman, D., Kruger, A., Schkade, D., Schwartz, N. and Stone, A. (2004). A survey method for characterizing daily life experience: the day reconstruction method (DRM). Science, vol.306, pp.1776-1780.
6. Frey, B.S. and Stutzer, A. (2005). Testing Theories of Happiness. In Bruni and Porta (eds.), Economics and Happiness: Framing the Analysis. Oxford University Press, Oxford.
7. Mokhtarian, P.L. and Salomon, I. (2001). How Derived is the Demand for Travel? Some Conceptual and Measurement Considerations. Transportation Research Part A: Policy and Practice, vol.35, no.8, pp. 695-719.
8. Abou-Zeid, M. and Ben-Akiva, M. (2010). A Model of Travel Happiness and Mode Switch. In Choice Modelling: The State-of-the-art and the State-of-Practice: Proceedings from Inaugural International Choice Modelling Conference, S.Hess and A. Daly (ed.), Emerald Group Publishing Limited, pp. 289-307.
9. Polydoropoulou, A., Limao, S., Tsirimpa, A., Garcia, C., and Litinas, N. (2010). Modelling Travel Well-Being and Mode Choice Behaviour. Presented at 12th WCTR, July 11-15, 2010, Lisbon, Portugal.
10. Alsnih, R. and Hensher, D.A. (2003). The mobility and accessibility expectations of seniors in an aging population. Transportation Research Part A: Policy and Practice, vol.37, no.10, pp.903-916.
11. Spinney, J.E.L., Scott, D.M. and Newbold, K.B. (2009). Transport mobility benefits and quality of life: A time-use perspective of elderly Canadians. Transport Policy, vol.16, pp.1-11.
12. Chen, J. and Millar, W.J. (2000). Are recent cohorts healthier than their predecessors? Health Reports, vol.11, no.4, pp.9-24.
13. Zhou, M. and Lyles, R.W. (1997). Mobility patterns of next generation of older persons. Transportation Research Record, vol.1553, pp.99-104.
14. Metz, D.H. (2000). Mobility of older people and their quality of life. Transport Policy, vol.7, no.2, pp. 149-152.
15. Tacken, M. (1998). Mobility of the elderly in time and space in the Netherlands: An

analysis of the Dutch National Travel Survey. Transportation, vol.25, no.4, pp.379-393.
16. Irwin, N. (1970). Public transit and the quality of urban living. Ekistics, vol.29, pp. 47-57.
17. Lawton, M.P. and Nahemow, L. (1973). Ecology and the aging process. In: Eisdorfer, C., Lawton, M.P. (Eds.), The Psychology of Adult Development and Aging. American Psychological Association, Washington, DC.
18. Rosenbloom, S. (2003). The mobility needs of older Americans: Implications for transportation reauthorization. Transportation Reform Series, published by The Brookings Institution.
19. Church, A., Frost, M. and Sullivan, K. (2000). Transport and social exclusion in London. Transport Policy, vol.7, pp.195-205.
20. Schonfelder, S. and Axhausen, K.W. (2003). Activity spaces: measures of social exclusion? Transport Policy, vol.10, pp.273-286.
21. Hildebrand, E.D. (2003). Dimensions of elderly travel behaviour: a simplified activity-based model using lifestyle clusters. Transportation, vol.30. no.3, pp.285-306.
22. Su, F.M. (2007). Understanding and Satisfying Older People's Travel Demand. Doctoral Dissertation, Imperial College University of London.
23. Wasfi, R., Levinson, D. and El-Geneidy, A. (2011). Measuring the Transportation Needs of seniors. Journal of Transportation Literature (in press).
24. Freedman, V.A. and Cornman, J.C. (2012). The Panel Study of Income Dynamics' Supplement on Disability and Use of Time (DUST) User Guide. Institute for Social Research, University of Michigan.
25. Vermunt, J.K. and Magindson, J. (2005). Technical guide for latent gold 4.0: basic and advanced. Statistical Innovations Inc., Belmont, MA.
26. Schwartz, G. (1978). Estimating dimension of a model. Annals of Statistics, vol.6, no.2, pp.461-464.
27. Rasciute, S. and Downward, P. (2010). Health or Happiness? What is the Impact of Physical Activity on the Individual? KYKLOS, vol.63, no.2, pp.256-270.
28. Greene, W. (2000). Econometric Analysis, Prentice Hall, 4th edition, New Jersey.
29. Kendig, H. Browning, C.J. and Young, A.E. (2000). Impacts of illness and disability on the well-being of older people. Disability and Rehabilitation, vol.22, no.1, pp.15-22.
30. Pychyl, T.A. and Little, B.R. (1998). Dimensional specificity in the prediction of subjective well-being: personal projects in pursuit of the Phd. Social Indicators Research, vol.45, pp. 423-473.
31. Oishi, S., Diener, E.F., Lucas, R.E and Suh, E.M. (1999). Cross-cultural variations in predictors of life satisfaction: perspectives from needs and values. Personality and Social Psychology Bulletin, vol.25. pp. 980-990.
32. Goulias, K.G., Ravulaparthy, S.K., Polydoropoulou, A. and Yoon, S.Y. (2012). An Exploratory Analysis on the Time-of-Day Dynamics of Episodic Hedonic Values of Activities and Travel. Paper presented at 13th International Conference on Travel Behaviour Research, Toronto, 15-20, July 2012.
33. Vemuri, A.W. and Costanza, R. (2006). The role of human, social, built and natural capital in explaining life satisfaction at the country level: toward a National Well-Being Index (NWI). Ecological Economics, vol.58, pp.119-133.
34. Carp, F.M., (1988). Significance of mobility for the well-being of the elderly. In: Transportation Research Board (Ed.), Transportation in an Aging Society: Improving

Mobility and Safety for Older Persons, vol. 2. National Research Council, Washington, DC, pp. 1–19.
35. Evans, E.L. (1999). Influences on mobility among non-driving older Americans. Transportation Research Circular, vol. E-C026.
36. Kim, S. (2002). Analysis of Elderly Mobility by Structure Equation Modelling. Transportation Research Record, vol.1854.