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Influence of Mode Use on Level of Satisfaction with Daily Travel Routine: A Focus on Automobile Driving in the United States

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Abstract
How does the extent of automobile use affect the level of satisfaction that people derive from their daily travel routine, after controlling for many other attributes including socio-economic and demographic characteristics, attitudinal factors, and lifestyle proclivities and preferences? This is the research question addressed by this paper. In this study, data collected from four automobile-dominated metropolitan regions in the United States (Phoenix, Austin, Atlanta, and Tampa) are used to assess the impact of the amount of driving that individuals undertake on the level of satisfaction that they derive from their daily travel routine. This research effort recognizes the presence of endogeneity when modeling multiple behavioral phenomena of interest and the role that latent attitudinal constructs reflecting lifestyle preferences play in shaping the association between behavioral mobility choices and degree of satisfaction. The model is estimated using the generalized heterogeneous data model (GHDM) methodology. Results show that latent attitudinal factors representing an environmentally friendly lifestyle, a proclivity toward car ownership and driving, and a desire to live close to transit and in diverse land use patterns affect the relative frequency of auto-driving mode use for non-commute trips and level of satisfaction with daily travel routine. Additionally, the amount of driving positively affects satisfaction with daily travel routine, implying that bringing about mode shifts toward more sustainable alternatives remains a formidable challenge—particularly in automobile-centric contexts.

Keywords
planning and analysis, traveler behavior and values, attitudes/attitudinal data, behavior analysis, pattern (behavior, choices, etc.)

Transportation planning agencies around the world are investing in sustainable modes of transportation such as transit and bicycle/walk infrastructure, besides implementing a variety of voluntary behavior change programs, in an effort to render the transportation ecosystem more sustainable and livable. Voluntary behavior change programs include—but are not limited to—the provision of free or subsidized transit passes, implementation of ridesharing programs and the construction of high-occupancy vehicle lanes (to promote carpooling), provision of incentives and use of gamified platforms to encourage use of alternative modes of transportation, and investments in bicycle lanes and pedestrian paths.

Despite all of the efforts being made to stem the tide of automobile use, why does it continue to grow and be the dominant mode of transportation in jurisdictions across the U.S.A.? To what extent does automobile mode use affect the level of satisfaction that people derive from their daily travel routine? Is automobile use largely caused by the unavailability of competitive sustainable transportation alternatives, and people use the automobile simply because they have to—even though

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automobile use contributes nothing to (and possibly takes away from) the level of satisfaction they derive from their daily travel routine? And how does the extent of automobile use affect the level of satisfaction that people derive from their daily travel routine, after controlling for many other attributes including socio-economic and demographic characteristics, attitudinal factors, and lifestyle proclivities and preferences? These are the research questions that this study attempts to answer, in the quest to understand better why it is proving to be a formidable challenge to stem the growing use of the private automobile in cities worldwide.

There is considerable prior research connecting mode use and level of satisfaction derived from daily travel. The literature has shown that this relationship tends to be somewhat context specific and sensitive to the way in which survey questions are asked. In some contexts, it is clear that riding public transit is seen as more burdensome and less preferred when compared with using the automobile, largely because of poor public transit service, concerns about safety and security, exposure to the elements, access/egress and waiting times (out-of-vehicle travel time) that tend to be perceived as onerous, and poor reliability (*1*, *2*). On the other hand, walking and bicycling are often viewed quite positively and associated with a higher level of travel satisfaction, particularly in social-recreational contexts (*1, 3–5*). In most studies of mode use and travel satisfaction, however, it has been found that automobile use is associated with positive levels of reported travel satisfaction (*6*, *7*). A few researchers have explored why traveling by automobile may be appealing and have attempted to identify policies and investments that would motivate travelers to eschew the automobile in favor of alternative modes of transportation (e.g., Eriksson et al. [*8, 9*]). However, these studies do not capture the direct relationship between mode use and travel satisfaction, and it is uncertain whether travelers would indeed behave as they state they would even if policies and investments that incentivize alternative mode use were implemented.

There is also a widespread perception that driving is undesirable and contributes to a degradation in quality of life (e.g., Kristal and Whillans [*10*]). It is this perception that leads to the implementation of travel demand management strategies and policies and investments that are meant to foster alternative mode use. However, it is clear that these strategies are meeting with little success. To understand fully why this is so, the extent to which automobile use affects level of satisfaction with daily travel routine needs to be explored further, particularly because the connection between these dimensions—after controlling for a host of socio-economic and demographic variables and attitudinal and lifestyle preference variables—is not yet fully understood (*11*). In particular, much of the literature on this topic to date has focused on the commute journey and the choice of commute mode (and the implications of the commute for overall life satisfaction or well-being). There is very little research devoted to understanding how mode choice and usage for non-work travel affects level of satisfaction with the daily travel routine specifically. Thus this paper makes an important contribution to the literature by focusing on how non-commute related mode use affects travel satisfaction, in the hope that insights on this relationship may shed light on why decades of travel demand management strategies and investments in alternative modes of transportation have done little to draw travelers away from the automobile.

In this study, data collected from four automobile-dominated metropolitan regions in the United States (Phoenix, Austin, Atlanta, and Tampa) are used to assess the impact of the amount of driving that individuals undertake on the level of satisfaction that they derive from their daily travel routine. Unlike previous studies, a holistic and comprehensive modeling framework is adopted in this research effort, recognizing the presence of endogeneity when modeling multiple behavioral phenomena of interest and the role that latent attitudinal constructs reflecting lifestyle proclivities and preferences may play in shaping the association between the frequency of automobile driving and satisfaction with daily travel routine. In the modeling framework adopted in this study, the relative frequency of driving (alone or with passengers on a weekly basis) and the self-reported level of satisfaction with daily travel routine are treated as endogenous variables with an error covariance that accounts for correlated unobserved attributes that jointly influence both of these endogenous variables. In addition, the model structure incorporates a host of latent attitudinal constructs (besides the usual socio-economic and demographic variables), therefore the influence of driving on daily travel routine satisfaction is modeled while controlling for all of the many other confounding relationships that may be at play. The model system is estimated in one step using the Generalized Heterogeneous Data Model (GHDM) methodology developed by Bhat (*12*).

The remainder of this paper is organized as follows. The next section presents a detailed description of the data and the endogenous variables of interest. The third section presents the modeling framework and methodology. The fourth section presents detailed model estimation results. The fifth section offers a discussion of the study implications and concluding thoughts.

Data Description

This section of the paper presents a brief overview of the dataset used in this study. The section furnishes a description of the survey and descriptive statistics of the survey sample. A presentation of socio-economic and demographic characteristics is provided first, and a more in-depth examination of the endogenous variables and latent attitudinal constructs is presented second.

Overview of Survey and Sample Characteristics

The data set used in this study is derived from the 2019 TOMNET – D-STOP Transformative Technologies in Transportation (T4) survey conducted in four major metropolitan regions of the United States. The four regions are Phoenix, Austin, Atlanta, and Tampa. These four regions are all located in warmer climates and are very automobile-centric in their transportation ecosystems. Transit services are generally limited and poor, and modal shares for transit and other modes of transportation are very low. A comprehensive survey instrument was deployed in fall 2019. The survey was administered by sending hundreds of thousands of email invitations and a few tens of thousands of mail invitations to addresses purchased from a commercial vendor. A total of 3,465 responses were received. Complete information about the survey design, content, and administration and sampling methodology is available elsewhere (*13*). The data set was filtered and cleaned of obviously erroneous data and records with missing data. The final analysis sample consisted of 3,365 records.

Table 1 depicts the socio-economic and demographic characteristics of the sample of 3,365 respondents. The survey collected very detailed information about respondents' characteristics and their attitudes, perceptions, and preferences related to new and emerging transportation technologies and mobility services including ridehailing services, micromobility, and autonomous vehicles. In addition, the survey included a battery of attitudinal statements that aimed to capture the general values, preferences, and perceptions of individuals in the sample. The sample offers a rich variation in socio-economic and demographic characteristics, thus rendering the dataset appropriate for a modeling effort of the type undertaken in this study.

The respondent sample is slightly skewed in favor of females who comprise just over 58% of the sample. About 26% of the sample is in the young age group of 18–30 years. There is a healthy representation of every age group in the sample. Just over 93% of respondents have a driver's license. About 52% are part- or full-time workers, and 26.6% are neither workers nor students. The sample exhibits a high level of educational attainment, with 36.7% having a Bachelor's degree and 24.5% having a graduate degree. Just under 10% have a high school diploma or less. More than three-quarters of the sample is White, just under 10% is Asian, and nearly 8% is Black, reflecting a reasonable level of racial diversity in the respondent sample.

The sample depicts the full range of annual household income with 11.1% earning less than $25,000 per year and 18.7% earning $150,000 or more per year. It is found that 40.1% of the respondents reside in households with three or more people, suggesting that household sizes are rather high in this respondent sample relative to the general population. Only 4% reside in households with no vehicles; this distribution is not surprising, given the very automobile-oriented nature of the four metropolitan regions. The sample is rather evenly distributed across Atlanta, Austin, and Phoenix, with a smaller share in Tampa. The survey also asked respondents to indicate if they have disabilities that prevent them from using different modes of transportation. The percentage of respondents indicating that they have a disability is very small (only 2% indicate that they cannot drive a vehicle); consequently, within the context of this study, disability status is unlikely to be a statistically significant explanatory variable (because of the very small sample size of individuals with disabilities). However, it should be recognized that those with disabilities experience diminished quality of life, well-being, and satisfaction with daily activity-travel patterns (*14*).

Endogenous Variables and Attitudinal Indicators

Table 1 also shows the distribution of the endogenous variables of interest in this study. Two endogenous variables are of interest here: first, the proportion of automobile driving (alone or with a passenger) that an individual undertakes in a week for non-commute trips, and second, the level of satisfaction that an individual self-reports for their typical daily travel routine. Among the battery of attitudinal statements is a statement requesting individuals to indicate their level of agreement with the statement "My daily travel routine is generally satisfactory." Responses were recorded on a five-point Likert scale ranging from strongly disagree to strongly agree. The proportion of automobile driving is computed based on a question requesting individuals to indicate the weekly frequency of use for different modes of transportation. The responses to this question were converted to a numeric scale and then used to compute a relative proportion of automobile driving (alone or with a passenger). This fraction varied from zero to one; a value of zero meant that the individual did not engage in automobile driving at all, while a value of one implied that the individual used only the automobile driving mode and did not report using any other mode of transportation at all. The question was asked separately for commute and non-commute purposes, thus enabling the calculation of this proportion for non-commute travel.

Table 1. Socio-Economic and Demographic Sample Characteristics

Individual characteristics (N = 3,365)		Household characteristics (N = 3,365)	
Variable	%	Variable	%
Gender		Household annual income	
Female	58.3	Less than $25,000	11.1
Male	41.7	$25,000 to $49,999	15.7
Age category		$50,000 to $74,999	18.6
18–30 years	26.3	$75,000 to $99,999	15.5
31–40 years	11.5	$100,000 to $149,999	20.4
41–50 years	14.8	$150,000 to $249,999	12.6
51–60 years	16.6	$250,000 or more	6.1
61–70 years	16.1	Household size	
71 + years	14.7	One	21.3
Driver's license possession		Two	38.6
Yes	93.4	Three or more	40.1
No	6.6	Housing unit type	
Employment status		Stand-alone home	70.1
Student (part-time or full-time)	10.2	Condo/apartment	20.6
Worker (part-time or full-time)	52.1	Other	9.3
Both worker and student	11.1	Home ownership	
Neither worker nor student	26.6	Own	68.1
Education attainment		Rent	26.2
High school or less	9.4	Other	5.7
Some college or technical school	29.4	Vehicle ownership	
Bachelor's degree(s)	36.7	Zero	4.0
Graduate degree(s)	24.5	One	23.7
Race		Two	40.0
Asian or Pacific Islander	9.6	Three or more	32.3
Black or African American	7.9	Location	
Multi race	3.9	Atlanta, GA	29.7
Native American	0.6	Austin, TX	32.5
Other	1.8	Phoenix, AZ	30.5
White or Caucasian	76.3	Tampa, FL	7.4
Endogenous variables			
Satisfaction with daily travel routine	%	Proportion of driving for non-commute trips	%
Very dissatisfied	4.5	Less than 20%	12.2
Dissatisfied	12.3	⩾20% and <40%	5.9
Neutral	15.2	⩾40% and <60%	12.9
Satisfied	48.9	⩾60% and <80%	19.7
Very satisfied	19.0	⩾80%	49.4

The question on frequency of mode use for non-commute trips was asked for 12 modes: (i) drive private vehicle, alone; (ii) drive private vehicle, with passengers; (iii) ride in private vehicle, with others; (iv) carsharing services (e.g., Zipcar); (v) bus; (vi) light rail; (vii) Uber/Lyft/ridehailing service; (viii) taxi; (ix) bicycle (including bikesharing); (x) e-scooter; (xi) walk; (xii) other mode. For each mode, respondents could choose among the following frequency categories: not available; available but never use it; less than 1 day a month; 1–3 days a month; 1–2 days a week; and 3 or more days a week. As these response options did not directly lend themselves to calculating the relative amount of driving, they were converted into numeric frequency values representing the number of days that various travel modes were used on a weekly basis. For instance, someone that reported using bicycle 1–2 times a week was considered to have an average frequency of 1.5 days per week. Similarly, a respondent who drives alone less than one day a month was assumed to use the mode every other month (which translates to 0.125 days per week). This assumption was considered appropriate, given the automobile-centric nature of the survey areas. The response categories were converted to numeric weekly frequency scores as follows:

0, if *"not available"* was selected;
0, if *"available but never use it"* was selected;
0.125, if *"less than one day a month"* was selected;

0.5, if *"1–3 days a month"* was selected;
1.5, if *"1–2 days a week"* was selected; and
5, if *"3 or more days a week"* was selected.

The relative proportion of driving could then be computed as a share of the total weekly mode usage pattern. For example, suppose a respondent reported using four travel modes for his/her non-commute trips: driving alone three or more days a week, driving with passengers 1–3 times a month, e-scooter less than one day a month, and walk 1–3 times a month (clearly, drive alone is the dominant mode). The proportion of non-commute driving for this respondent would be:

$$\frac{5 + 0.5}{5 + 0.5 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0.125 + 0.5 + 0} = \frac{5.5}{6.125} = 0.898 = 89.8\%$$

The aim of the study is to understand the relationship between automobile driving frequency and feeling of satisfaction with the daily travel routine while explicitly accounting for socio-economic variables as well as other attitudinal variables. To support such a modeling effort, three attitudinal constructs are defined and used in this study. Each latent (unobserved) attitudinal construct is mapped to two attitudinal statements or indicators from the survey. The distributions on the six attitudinal statements are depicted in Figure 1.

Most individuals deem their daily travel routine satisfactory. Table 1 shows that 19% strongly agree that their daily travel routine is generally satisfactory; another 49% somewhat agree with this statement. The distribution for the relative proportion of automobile driving for non-commute trips is also shown in Table 1. It is seen that nearly one-half of the sample have a relative driving proportion between 0.8 and 1, and at the other end of the spectrum, only 12.2% of individuals have a relative driving proportion less than 0.2.

Figure 2 constitutes a chart depicting average proportion of driving for non-commute trips (in the form of a dot) for respondents in each Likert-scale category of the daily travel satisfaction statement. For example, the dot corresponding to the strongly agree category is at 72.3%. This means that the 641 individuals in this category drive, on average, 72.3% of the time on a weekly basis. As the bivariate relationship appears somewhat unclear, possibly because there are many confounding factors, an econometric modeling framework capable of shedding light on the direct relationship between relative proportion of driving and level of satisfaction with daily travel routine (while controlling for all other factors) is estimated in this study. This framework is described in the next section.

Modeling Framework

This section presents the model structure and the model formulation and estimation methodology. The model structure is capable of accommodating multiple endogenous variables and multiple stochastic latent constructs that are endogenous themselves. First, an overview of the model structure is furnished, and second, a brief description of the model formulation and estimation methodology is presented.

Model Structure

A simplified version of the model structure is shown in Figure 3. A host of socio-economic and demographic characteristics, household characteristics, and routine travel and mobility characteristics (that may be treated as exogenous for purposes of this study) serve as exogenous variables. The two endogenous variables include the proportion of driving for non-commute trips and the level of agreement that the daily travel routine is generally satisfactory. The proportion of driving for non-commute trips is a continuous variable while the level of agreement is an ordered discrete variable that ranges from strongly disagree to strongly agree. Whether the proportion of driving for non-commute trips significantly affects satisfaction with the daily travel routine is the hypothesis that is being tested in this modeling exercise.

A note is due here on the direction of causality that is implied and explicitly assumed in the model structure shown in Figure 3. In this study, it is conjectured that level of satisfaction with the daily travel routine is derived from the various activity and mobility choices that an individual exercises on a daily or weekly basis. For the purposes of this study and in the context of the endogenous variables used here, assuming such a causal structure appears reasonable and robust. The measure of satisfaction used in this study is specific to the daily travel routine, and does not address an individual's overall well-being, happiness, or satisfaction with life. It is possible that happy people drive (travel) more (suggesting a reverse causality to that assumed in this paper). Exploring alternative directions of causality between behaviors and attitudes/perceptions (*15*, *16*), and determining the extent to which individuals with higher overall well-being drive more (or less), remain fruitful areas for future research.

The host of latent attitudinal constructs act as intermediaries between the exogenous variables and the behavioral outcomes of interest. Exogenous socio-economic and demographic variables may affect the behavioral outcome variables directly or indirectly through the mediating influence of latent attitudinal constructs. The three latent attitudinal constructs are themselves endogenous

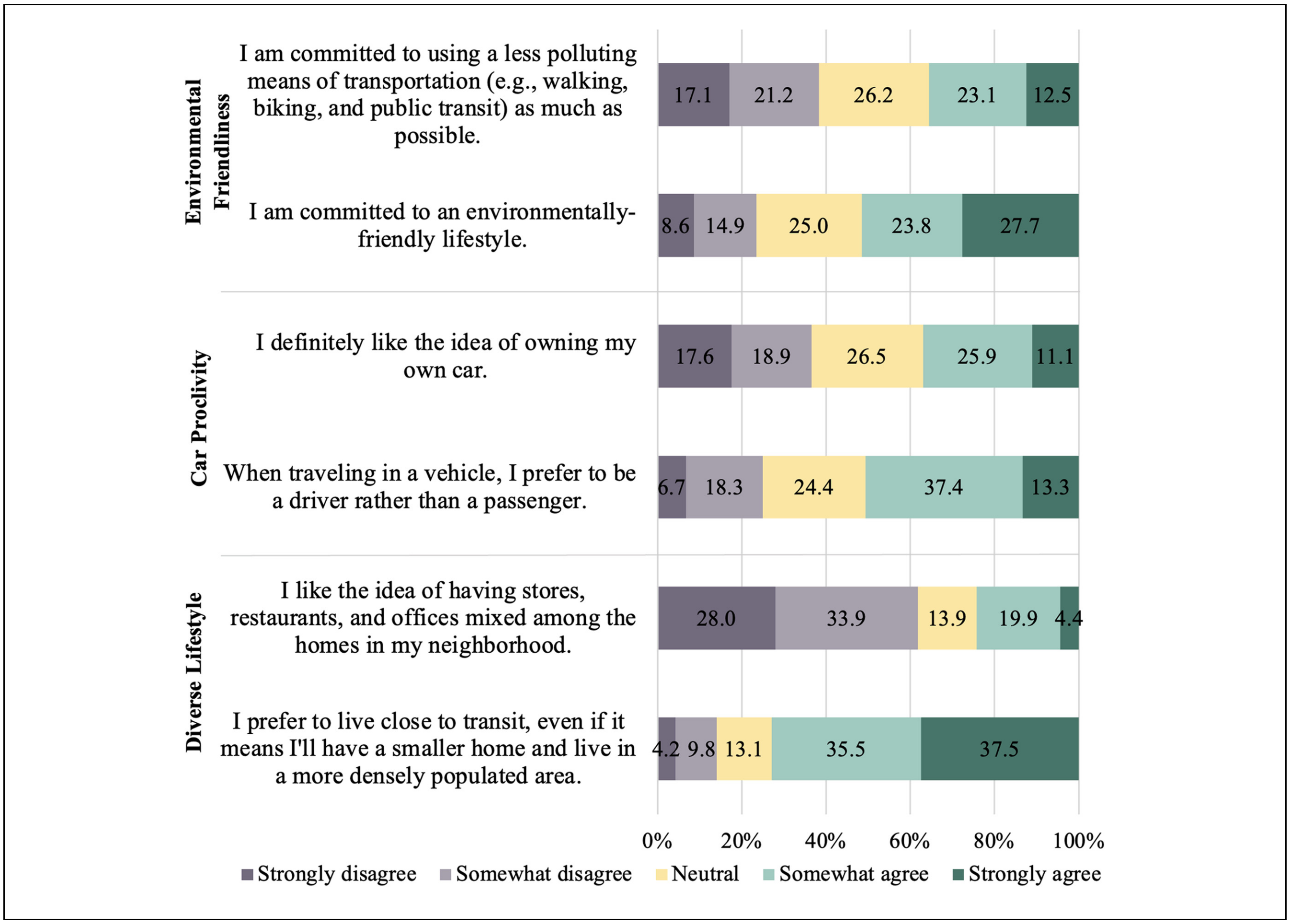

Figure 1. Distribution of attitudinal indicators of latent factors ($N = 3,365$).

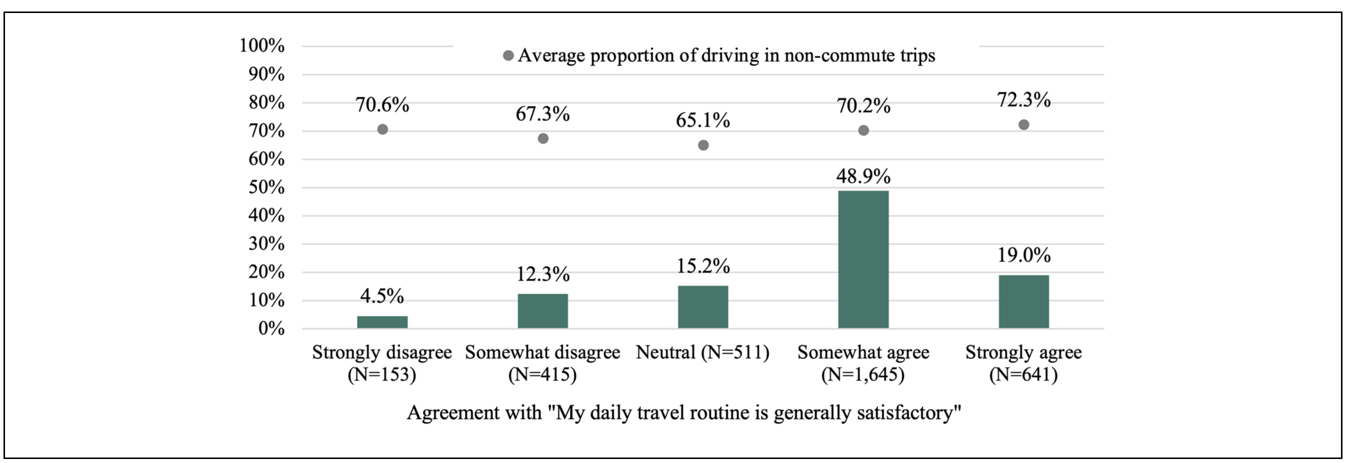

Figure 2. Relationship between main endogenous outcome variables (N = 3,365).

and are therefore influenced by exogenous variables. At the same time, they influence the two behavioral outcome variables. The latent attitudinal constructs are stochastic and incorporate an error term. Thus, it is possible to compute error correlations between the latent constructs; by virtue of the stochastic nature of the

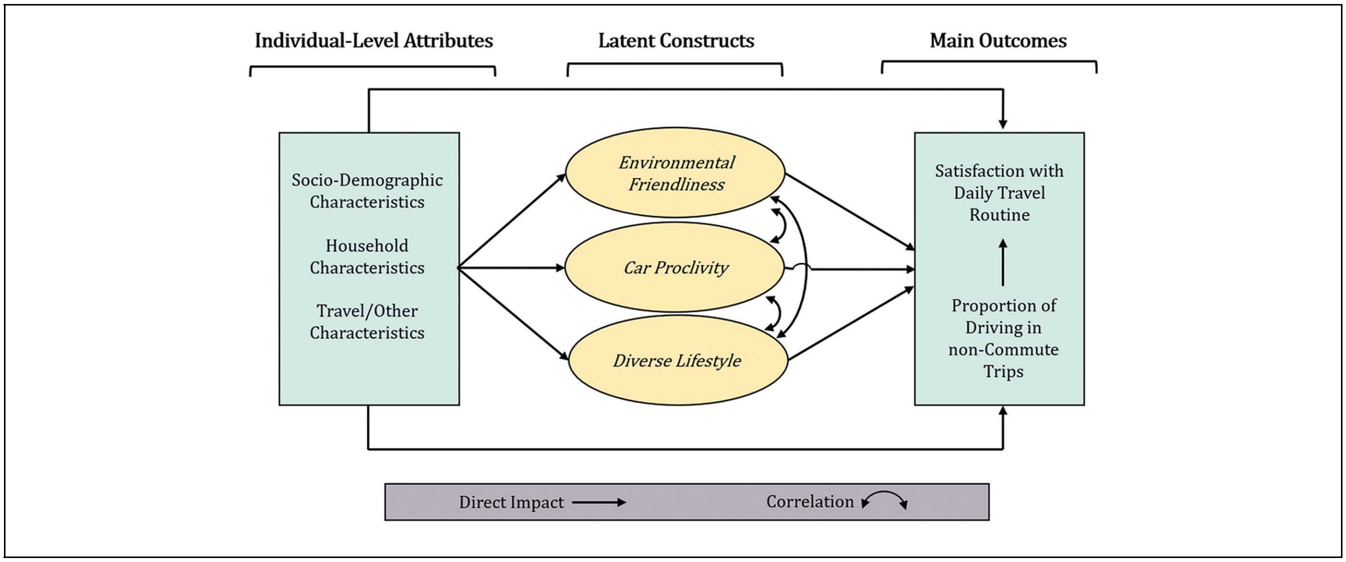

Figure 3. Model structure and framework.

constructs, an implied error correlation between the two behavioral outcome variables is realized and can be computed as well. Thus, the model structure accounts for endogeneity, the stochastic nature of latent constructs, and error correlations between latent constructs and between the two endogenous variables of interest. The entire model structure is estimated in a single step using the GHDM framework. The model formulation and estimation methodology are presented next.

Model Estimation Methodology

Consider the case of an individual $q \in \{1, 2, ..., Q\}$. For ease of presentation, the index q for decision-makers will be suppressed. It is assumed that all error terms are independent and identically distributed across decision-makers. Let l be an index for latent variables (l = 1,2,…,L). Consider the latent variable z_l^* and write it as a linear function of covariates:

$$z_l^* = \boldsymbol{\alpha}'_l \boldsymbol{w} + \eta_l, \tag{1}$$

where $\boldsymbol{w}$ is a $(\tilde{D} \times 1)$ vector of observed covariates (excluding a constant), $\boldsymbol{\alpha_l}$ is a corresponding $(\tilde{D} \times 1)$ vector of coefficients, and η_l is a random error term assumed to be standard normally distributed for identification purpose. Next, define the $(L \times \tilde{D})$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, ..., \boldsymbol{\alpha}_L)'$, and the $(L \times 1)$ vectors $\boldsymbol{z}^* = (z_1^*, z_2^*, ..., z_L^*)'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3, \ldots, \eta_L)'$. A multivariate normal (MVN) correlation structure for $\boldsymbol{\eta}$ is adopted to accommodate interactions among the unobserved latent variables: $\boldsymbol{\eta} \sim MVN_L[\boldsymbol{0_L}, \boldsymbol{\Gamma}]$, where $\boldsymbol{0_L}$ is an $(L \times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is $(L \times L)$ correlation matrix. In matrix form, Equation 1 is:

$$\boldsymbol{z}^* = \boldsymbol{\alpha w} + \boldsymbol{\eta}. \tag{2}$$

Let there be H continuous outcomes $(y_1, y_2, ..., y_H)$ with an associated index h $(h = 1, 2, ..., H)$. Let $y_h = \boldsymbol{\gamma}'_{\boldsymbol{h}} \boldsymbol{x} + \boldsymbol{d}'_h \boldsymbol{z}^* + \varepsilon_h$ in the usual linear regression fashion, where $\boldsymbol{x}$ is an $(A \times 1)$ vector of exogenous variables (including a constant), $\boldsymbol{\gamma_h}$ is a coefficient vector, $\boldsymbol{d_h}$ is an $(L \times 1)$ vector of latent variable loadings on the hth continuous outcome, and ε_h is a normally distributed measurement error term. Stack the H continuous outcomes into an $(H \times 1)$ vector $\boldsymbol{y}$, and the H error terms into another $(H \times 1)$ vector $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_H)'$. Also, let $\boldsymbol{\Sigma}$ be the covariance matrix of $\boldsymbol{\varepsilon}$, which is restricted to be diagonal. This helps in identification. Define the $(H \times A)$ matrix $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, ...\gamma_H)'$ and the $(H \times L)$ matrix of latent variable loadings $\boldsymbol{d} = (\boldsymbol{d_1}, \boldsymbol{d_2}, ..., \boldsymbol{d_H})'$. Then, the following measurement equation for the continuous outcomes may be written in matrix form:

$$\boldsymbol{y} = \boldsymbol{\gamma x} + \boldsymbol{d z}^* + \boldsymbol{\varepsilon}. \tag{3}$$

Now, consider N ordinal outcomes (indicator variables and main outcomes) for the individual, and let n be the index for the ordinal outcomes $(n = 1, 2, ..., N)$. Also, let J_n be the number of categories for the nth ordinal outcome $(J_n \geqslant 2)$ and let the corresponding index be j_n $(j_n = 1, 2, ..., J_n)$. Let $\tilde{y}_n^*$ be the latent underlying variable whose horizontal partitioning leads to the observed outcome for the nth ordinal variable. Assume that the individual under consideration chooses the a_n^{th} ordinal category. Then, in the usual ordered response formulation, for any individual:

$$\tilde{y}_n^* = \tilde{\boldsymbol{\gamma}}'_{\boldsymbol{n}} \boldsymbol{x} + \tilde{\boldsymbol{d}}'_n \boldsymbol{z}^* + \tilde{\varepsilon}_n, \text{ and } \tilde{\psi}_{n, a_n - 1} < \tilde{y}_n^* < \tilde{\psi}_{n, a_n}, \tag{4}$$

where $\boldsymbol{x}$ is a vector of exogenous variables (including a constant) and observed values of other endogenous continuous variables or other endogenous ordinal variables (although only in a recursive fashion). $\tilde{\boldsymbol{\gamma}}_n$ is a corresponding vector of coefficients to be estimated, $\tilde{\boldsymbol{d}}_n$ is an $(L \times 1)$ vector of latent variable loadings on the nth underlying continuous propensity, the $\tilde{\psi}$ terms represent thresholds, and $\tilde{\varepsilon}_n$ is the standard normal random error for the nth ordinal outcome. For each ordinal outcome, $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} \cdots < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$; $\tilde{\psi}_{n,0} = -\infty$, $\tilde{\psi}_{n,1} = 0$, and $\tilde{\psi}_{n,J_n} = +\infty$. For later use, let $\tilde{\boldsymbol{\psi}}_n = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3} \ldots, \tilde{\psi}_{n,J_n-1})'$ and $\tilde{\boldsymbol{\psi}} = (\tilde{\boldsymbol{\psi}}_1', \tilde{\boldsymbol{\psi}}_2', \ldots, \tilde{\boldsymbol{\psi}}_N)'$. Stack the N underlying continuous variables $\tilde{y}_n^*$ into an $(N \times 1)$ vector $\tilde{y}^*$, and the N error terms $\tilde{\varepsilon}_n$ into another $(N \times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$. Define $\tilde{\boldsymbol{\gamma}} = (\tilde{\boldsymbol{\gamma}}_1, \tilde{\boldsymbol{\gamma}}_2, \ldots, \tilde{\boldsymbol{\gamma}}_H)'$ [$(N \times A)$ matrix] and $\tilde{\boldsymbol{d}} = \left(\tilde{\boldsymbol{d}}_1, \tilde{\boldsymbol{d}}_2, \ldots, \tilde{\boldsymbol{d}}_N\right)$ [$(N \times L)$ matrix], and let $\mathbf{IDEN_N}$ be the identity matrix of dimension N representing the correlation matrix of $\tilde{\boldsymbol{\varepsilon}}$, so, $\tilde{\boldsymbol{\varepsilon}} \sim MVN_N(\mathbf{0}_N, \mathbf{IDEN_N})$; again, this is for identification purposes, given the presence of the unobserved $\boldsymbol{z}^*$ vector to generate covariance. Finally, stack the lower thresholds for the decision-maker $\tilde{\psi}_{n,a_n-1}(n = 1, 2, \ldots, N)$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{\psi}}_{low}$ and the upper thresholds $\tilde{\psi}_{n,a_n}(n = 1, 2, \ldots, N)$ into another vector $\tilde{\boldsymbol{\psi}}_{up}$. Then, in matrix form, the measurement equation for the ordinal outcomes (indicators) for the decision-maker may be written as:

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{low} < \tilde{\boldsymbol{y}}^* < \tilde{\boldsymbol{\psi}}_{up}. \tag{5}$$

Let $E = (H + N)$. Define $\overleftrightarrow{\boldsymbol{y}} = \left(\boldsymbol{y}', [\tilde{\boldsymbol{y}}^*]'\right)'$ $[E \times 1$ vector], $\overleftrightarrow{\boldsymbol{\gamma}} = (\boldsymbol{\gamma}', \tilde{\boldsymbol{\gamma}}')'$ $[E \times A$ matrix], $\overleftrightarrow{\boldsymbol{d}} = (\boldsymbol{d}', \tilde{\boldsymbol{d}}')'$ $[E \times L$ matrix], and $\overleftrightarrow{\boldsymbol{\varepsilon}} = (\boldsymbol{\varepsilon}', \tilde{\boldsymbol{\varepsilon}}')'$ $(E \times 1$ vector). Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta} = [\text{Vech}(\boldsymbol{\alpha}), \text{Vech}(\boldsymbol{\Sigma}), \text{Vech}(\overleftrightarrow{\boldsymbol{\gamma}}), \text{Vech}(\overleftrightarrow{\boldsymbol{d}}), \tilde{\boldsymbol{\psi}}]$, where the operator "$Vech(.)$" vectorizes all the non-zero elements of the matrix/vector on which it operates.

With the matrix definitions above, the continuous components of the model system may be written compactly as:

$$\boldsymbol{z}^* = \boldsymbol{\alpha}\boldsymbol{w} + \boldsymbol{\eta}, \tag{6}$$

$$\overleftrightarrow{\boldsymbol{y}} = \overleftrightarrow{\boldsymbol{\gamma}}\boldsymbol{x} + \overleftrightarrow{\boldsymbol{d}}\boldsymbol{z}^* + \overleftrightarrow{\boldsymbol{\varepsilon}} \text{ with } \mathrm{Var}(\overleftrightarrow{\boldsymbol{\varepsilon}}) = \overleftrightarrow{\boldsymbol{\Sigma}} = \begin{bmatrix} \boldsymbol{\Sigma} & \mathbf{0} \\ \mathbf{0} & \mathbf{IDEN_N} \end{bmatrix} \quad (E \times E \text{ matrix}). \tag{7}$$

To develop the reduced form equations, replace the right side of Equation 6 for $\boldsymbol{z}^*$ in Equation 7 to obtain the following system:

$$\overleftrightarrow{\boldsymbol{y}} = \overleftrightarrow{\boldsymbol{\gamma}}\boldsymbol{x} + \overleftrightarrow{\boldsymbol{d}}\boldsymbol{z}^* + \overleftrightarrow{\boldsymbol{\varepsilon}} = \overleftrightarrow{\boldsymbol{\gamma}}\boldsymbol{x} + \overleftrightarrow{\boldsymbol{d}}(\boldsymbol{\alpha}\boldsymbol{w} + \boldsymbol{\eta}) + \overleftrightarrow{\boldsymbol{\varepsilon}} = \overleftrightarrow{\boldsymbol{\gamma}}\boldsymbol{x} + \overleftrightarrow{\boldsymbol{d}}\boldsymbol{\alpha}\boldsymbol{w} + \overleftrightarrow{\boldsymbol{d}}\boldsymbol{\eta} + \overleftrightarrow{\boldsymbol{\varepsilon}} \tag{8}$$

Now, consider

$$\boldsymbol{B} = \overleftrightarrow{\boldsymbol{\gamma}}\boldsymbol{x} + \overleftrightarrow{\boldsymbol{d}}\boldsymbol{\alpha}\boldsymbol{w} \text{ and } \boldsymbol{\Omega} = \overleftrightarrow{\boldsymbol{d}}\boldsymbol{\Gamma}\overleftrightarrow{\boldsymbol{d}}' + \overleftrightarrow{\boldsymbol{\Sigma}}. \tag{9}$$

Then $\overleftrightarrow{\boldsymbol{y}} \sim MVN_E(\boldsymbol{B}, \boldsymbol{\Omega})$.

For the purpose of estimation, partition the vector $\boldsymbol{B}$ into components that correspond to the mean of the vectors $\boldsymbol{y}$ (for the continuous variables) and $[\tilde{\boldsymbol{y}}^*]'$ $[N \times 1$ vector], (for the ordinal outcomes), and the matrix $\boldsymbol{\Omega}$ into the corresponding variances and covariances:

$$\boldsymbol{B} = \begin{bmatrix} \boldsymbol{B}_y \\ \boldsymbol{B}_{\tilde{y}^*} \end{bmatrix} (E) \times 1 \text{ vector and}$$

$$\boldsymbol{\Omega} = \begin{bmatrix} \boldsymbol{\Omega}_y & \boldsymbol{\Omega}_{y\tilde{y}^*} \\ \boldsymbol{\Omega}'_{y\tilde{y}^*} & \boldsymbol{\Omega}_{\tilde{y}^*} \end{bmatrix} (E) \times (E) \text{matrix}. \tag{10}$$

The conditional distribution of $[\tilde{\boldsymbol{y}}^*]'$, given $\boldsymbol{y}$, is MVN with mean $\overleftrightarrow{\boldsymbol{B}}_{\tilde{y}^*} = \boldsymbol{B}_{\tilde{y}^*} + \boldsymbol{\Omega}'_{y\tilde{y}^*}\boldsymbol{\Omega}_y^{-1}(\boldsymbol{y} - \boldsymbol{B}_y)$ and variance $\overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{y}^*} = \boldsymbol{\Omega}_{\tilde{y}^*} - \boldsymbol{\Omega}'_{y\tilde{y}^*}\boldsymbol{\Omega}_y^{-1}\boldsymbol{\Omega}_{y\tilde{y}^*}$.

Then the likelihood function may be written as:

$$\begin{aligned} L(\boldsymbol{\delta}) &= f_H(\boldsymbol{y}|\boldsymbol{B}_y, \boldsymbol{\Omega}_y) \times \Pr\left[\tilde{\boldsymbol{\psi}}_{low} \leqslant \tilde{\boldsymbol{y}}^* \leqslant \tilde{\boldsymbol{\psi}}_{up}\right], \\ &= f_H(\boldsymbol{y}|\boldsymbol{B}_y, \boldsymbol{\Omega}_y) \times \int_{D_r} f_N(\boldsymbol{r}|\overleftrightarrow{\boldsymbol{B}}_{\tilde{y}^*}, \overleftrightarrow{\boldsymbol{\Omega}}_{\tilde{y}^*})d\boldsymbol{r}, \end{aligned} \tag{11}$$

where the integration domain $D_r = \{\boldsymbol{r} : \tilde{\boldsymbol{\psi}}_{low} \leqslant \boldsymbol{r} \leqslant \tilde{\boldsymbol{\psi}}_{up}\}$ is simply the multivariate region of the elements of the $\tilde{\boldsymbol{y}}^*$ vector determined by the observed ordinal indicator and main outcomes. $f_H(\boldsymbol{y}|\boldsymbol{B}_y, \boldsymbol{\Omega}_y)$ is the MVN density function of dimension H with a mean of $\boldsymbol{B}_y$ and a covariance of $\boldsymbol{\Omega}_y$, and evaluated at $\boldsymbol{y}$. The likelihood function for a sample of Q decision-makers is obtained as the product of the individual-level likelihood functions. The reader is referred to Bhat (*12*) for further nuance on the identification of coefficients in the GHDM framework.

Since a closed form expression does not exist for this integral and evaluation using simulation techniques can be time consuming, the one-variate univariate screening technique proposed by Bhat (*17*) is used for approximating this integral. The estimation of parameters was carried out using the *maxlik* library in the GAUSS matrix programming language.

Model Estimation Results

The key contribution of this paper, relative to the body of literature that has striven to document the relationship between mode use and level of satisfaction with (or well-being derived from) the daily travel routine, is that the

Table 2. Determinants of Latent Variables and Loadings on Indicators ($N = 3,365$)

	Latent construct model					
	Environmental friendliness		Car proclivity		Diverse lifestyle	
Explanatory variables (base category)	Coef	*t*-Stat	Coef	*t*-Stat	Coef	*t*-Stat
Age (*)						
18–30 years	−0.13	−5.93	na	na	na	na
65 years or older	na	na	0.21	11.10	na	na
Race (*)						
White	na	na	0.27	16.55	na	na
Black	na	na	na	na	0.34	11.34
Native American	0.41	4.79	na	na	na	na
Ethnicity (not Hispanic)						
Hispanic	na	na	na	na	0.24	9.32
Employment (*)						
Student	0.34	14.82	na	na	na	na
Worker	na	na	na	na	0.23	13.21
Education (*)						
Some college or technical school	−0.20	−12.74	na	na	na	na
Some college or technical school or higher education	na	na	0.21	8.61	na	na
Household income (*)						
Less than $25,000	na	na	−0.40	−16.97	na	na
$50,000 to $150,000	na	na	na	na	−0.20	−11.84
Correlations between latent constructs						
Environmental friendliness	1.00	na	−0.33	−4.04	0.78	6.78
Car proclivity	na	na	1.00	na	−0.49	−2.66
Diverse lifestyle	na	na	na	na	1.00	na
Attitudinal indicators	Loadings of latent variables on indicators (measurement equation model component)					
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.	1.34	32.55	na	na	na	na
I am committed to an environmentally friendly lifestyle.	0.64	29.97	na	na	na	na
I definitely like the idea of owning my own car.	na	na	0.97	26.72	na	na
When traveling in a vehicle, I prefer to be a driver rather than a passenger.	na	na	1.03	27.05	na	na
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	na	na	na	na	0.56	27.73
I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area.	na	na	na	na	0.92	29.82

Note: Coef = coefficient; na = not applicable.
*Base category is all other complementary categories for that variable.

relationship is being studied here while controlling for attitudinal factors that may mediate and influence the nature and strength of the relationship. This section presents estimation results for the integrated model system which was estimated using the GHDM methodology. The estimation results are presented in two parts: first, for the latent construct components and second, for the endogenous outcomes of interest.

Latent Construct Model Components

Table 2 presents results for the latent construct model components. In this study, three attitudinal constructs were developed based on a set of six indicators (two indicators per factor). All three latent constructs are significantly correlated with one another; as expected, environmental friendliness is negatively correlated with car proclivity and positively correlated with a diverse lifestyle preference. The factor representing diverse lifestyle preference is negatively correlated with the car proclivity factor.

The table shows that socio-economic and demographic variables significantly influence all three latent constructs. It is found that the younger age group, 18–30 years old, are less likely to be environmentally friendly than older generations. This is a somewhat surprising finding as there is evidence to suggest that younger individuals are more environmentally conscious; however, there is also evidence to suggest that environmental consciousness is less about age and more about awareness, knowledge, and information (*18*). On the other hand, those aged 65 years and older are clearly more car-oriented, reflecting decades of dependency on the automobile for meeting mobility needs (*19*). Race is also significant. Whites are more car-oriented, Blacks embrace a more diverse lifestyle, and Native Americans are more environmentally friendly. These findings are consistent with those reported in the literature (e.g., Polzin et al. [*20, 21*], Rentziou et al. [*22*]) and the finding about Native Americans reflects their sensitivity to preserving their lands and ecosystems (*23*). Hispanics are also found to embrace a more diverse lifestyle, consistent with previous research (*24*).

Employment, education level, and income are all socio-economic variables that affect latent attitudinal constructs. Students are more environmentally friendly (because they have greater exposure to information and greater awareness) and workers embrace a more diverse lifestyle, presumably for greater access to jobs and opportunities. Those with at least some college education are less environmentally friendly and more car-oriented, reflecting their greater dependence on and use of the automobile to access jobs, destinations, and opportunities. These findings are consistent with those reported in the literature (e.g., Durr et al. [*25*], Blazanin et al. [*26*]). Finally, low-income individuals are less car-oriented, while those in the middle-income bracket are less prone to embracing a diverse lifestyle. Those in the middle-income bracket are more likely to embrace affordable suburban living where lifestyle is less diverse (*27–29*). Low-income individuals are less car-oriented by virtue of their greater alternative mode use (*2*, *30*).

Bivariate Model of Behavioral Outcomes

The bivariate model in this study takes the form of a discrete-continuous model with endogenous latent factors that account for complex interrelationships driving behavioral dimensions of interest. Results are shown in Table 3. The key finding is that, after controlling for the influence of latent attitudinal factors and all socio-economic and demographic variables in the data set, the proportion of driving for non-commute trips (on a weekly basis) significantly and positively affects level of satisfaction with daily travel routine. The coefficient is positive and significant and suggests that, all other things being equal, the higher proportion of private automobile use (as a driver) is associated with a higher level of satisfaction with the daily travel routine. Note that this effect may be considered a "true" causal effect, after accommodating the spurious unobserved correlation between the two variables engendered by the stochastic latent construct effects.

This finding is consistent with results reported in the literature; in metro regions that are sprawled and auto-oriented, the finding that driving is associated with a higher level of satisfaction with the daily travel routine is not surprising and reinforces the notion that bringing about noticeable shifts in mode choice (away from automobile use) remains a formidable challenge in such contexts (*27*, *31*). It should be recognized, however, that the determination of true causality in any behavioral context is a complex exercise; and given that there are many other observed and unobserved latent factors that may affect an individual's level of satisfaction with daily travel routine, interpreting the relationship between the endogenous choice variables of this study as a true causal effect should be done with caution. It should also be recognized that this relationship holds true in the context of this sample, which is drawn from four sprawling metropolitan regions of the United States that are very auto-oriented and lack rich transit services.

When it comes to the influence of latent constructs, the findings are quite intuitive. Those who are environmentally friendly exhibit a lower level of driving (relative to use of other modes) and a lower level of satisfaction with the daily travel routine—suggesting that they are still driving more than they would like. Those who are auto-oriented exhibit a greater level of proportion of driving. Individuals who embrace a diverse lifestyle express a greater level of satisfaction with their daily travel routine. This is because these individuals have consciously self-selected themselves to reside in neighborhoods that are diverse and dense, and well served by transit (e.g., De Vos and Witlox [*27*], Bhat et al. [*32*], Schwanen and Mokhtarian [*33*], Cao and Ettema [*34*]). By virtue of self-selecting themselves into such neighborhoods, they are able to live and move according to their preferences and therefore they have a high level of satisfaction (*35*). The same does not necessarily apply to those who are environmentally friendly; many environmentally friendly individuals reside in low density auto-oriented environments, thus resulting in a level of driving dependency that is out of sync with their preferences and approach to sustainability.

Among socio-economic and demographic characteristics, it is clear that the youngest age group (18–30 years) has a lower proportion of driving and a tendency to report a lower level of satisfaction with their daily travel routine. The degree to which the dissatisfaction directly stems from the lower level of driving is uncertain and merits further investigation in future research. Nevertheless, the correlation is undeniable. Those with a lower educational attainment and students exhibit lower

Table 3. Estimation Results of the Joint Model of Driving Proportion and Satisfaction With Daily Travel Routine ($N = 3{,}365$)

Explanatory variables (base category)	Main outcome variables: Satisfaction with daily travel routine (five-point Likert scale: strongly disagree to strongly agree) Coef	t-Stat	Proportion of driving for non-commute trips (continuous, ranging from 0 to 1) Coef	t-Stat
Endogenous variable				
Proportion of driving in non-commute trips	0.31	4.38	na	na
Latent constructs				
Environmental friendliness	−0.12	−4.02	−0.04	−7.57
Car proclivity	na	na	0.09	16.17
Diverse lifestyle	0.10	3.41	na	na
Age (31 years or older)				
18–30 years	−0.21	−9.67	−0.10	−17.57
Education (more than high school)				
High school or less	na	na	−0.09	−15.38
Student status (not a student)				
Student	na	na	−0.09	−16.72
Household income ($25,000 or more)				
Less than $25,000	−0.20	−7.22	−0.08	−13.79
Household size (less than 3)				
3 or more	−0.08	−5.60	na	na
Tenure status (not a homeowner)				
Homeowner	na	na	0.05	10.40
Commute distance (*)				
Less than 5 mi	na	na	−0.04	−8.50
10 mi or more	−0.61	−37.03	na	na
Population density (⩾3,000 people/square mile)				
Low density (<3,000 people/square mile)	−0.07	−4.77	0.05	12.76
Constant	na	na	0.68	122.75
Thresholds				
1|2	−1.89	−37.79	na	na
2|3	−1.12	−22.48	na	na
3|4	−0.59	−11.87	na	na
4|5	0.82	15.83	na	na
Correlation				
Proportion of driving for non-commute trips	0.08	na	na	na
Normalizing scale	na	na	0.26	123.36

Data fit measures	GHDM	Independent model
Log-likelihood at convergence	−4935.22	−4956.3
Log-likelihood at constants	−5455.78	−5455.78
Number of parameters	82	32
Likelihood ratio test	0.045	0.039

Note: Coef = coefficient; na = not applicable; GHDM = generalized heterogeneous data model.
*Base category is all other complementary categories for that variable.

proportions of driving. Similarly, lower-income individuals drive less and exhibit a propensity toward lower levels of daily travel satisfaction, reflecting a correlation between driving proportion and daily travel satisfaction. Home ownership is associated with a higher level of driving, consistent with the notion that home ownership tends to be higher in suburban areas where automobile dependence is higher (*32*, *36*, *37*). Residing in larger households (which generally have more complex activity-travel patterns) is associated with lower levels of satisfaction with the daily travel routine.

As expected, those with short commutes have a lower proportion of driving even for non-commute trips (as non-commute trips are often chained to longer commutes and tend to be auto-oriented). Individuals with longer commutes are likely to express a lower level of satisfaction with their daily travel routine; this finding is consistent with prior research showing long commutes are generally deemed less desirable (*4*, *6*). Individuals residing in low density areas drive more and have a higher probability of being less satisfied with their daily travel routine. This finding may appear counterintuitive but is in fact consistent with expectations. Some (but not all) individuals reside in low density areas for the sake of affordability, large yards and homes, and quality of schools. They end up driving more than they would like and consequently become unhappy with their daily travel routine. Such lifestyle relationships and outcomes have been reported previously in the literature and this study corroborates earlier findings (*1*, *31*).

The key result that the proportion of driving for non-commute travel contributes positively to a degree of satisfaction with the daily travel routine should be interpreted with caution and accuracy. This finding does *not* imply that more driving leads to greater satisfaction or happiness. The dependent variable used represents the proportion of non-commute travel undertaken by driving; this is not a measure of the quantity or amount of driving (although these terms have been used in this paper for ease of presentation and readability). The result implies that individuals who undertake a greater *proportion* of their non-commute travel by the auto-driving mode report a higher degree of satisfaction with their daily travel routine relative to those who undertake a smaller *proportion* of their non-commute travel by the auto-driving mode. In other words, relying on or using alternative modes of transportation for a larger *proportion* of trip-making results in a diminished sense of satisfaction with the daily travel routine. Thus, the focus is on the *relative* use of the auto-driving mode versus other modes of transportation, and not on the actual amount of driving (which may be measured in units of trips, travel time, or vehicle miles of travel). One would fully expect the degree of satisfaction with the daily travel routine to diminish for individuals who undertake excessive amounts of driving, with the threshold that defines excessive driving varying across individuals based on lifestyle preferences, attitudes, and perceptions.

Study Implications and Conclusion

The ability to access destinations and pursue activities that are distributed in time and space has been shown to affect a person's well-being and quality of life. However, there is limited evidence on how daily mode use affects an individual's level of satisfaction with his or her daily travel routine. This study attempts to fill this critical gap in the literature by analyzing the relationship between the degree (frequency) of automobile driving that an individual typically undertakes in a week and the degree to which an individual considers the daily travel routine satisfactory. Does an individual who drives more feel less satisfaction or more? Do individuals in automobile-oriented cities (with poor transit service, sprawled land use patterns) experience low levels of satisfaction with their daily travel routine (because of the high levels of driving required)? Or is a high level of driving associated with a high level of satisfaction with the daily travel routine because of the generally superior performance, convenience, and comfort of the personal automobile mode relative to other modes of transportation? Insights on these questions may help inform policy directions and future transportation investments. If people in automobile-oriented cities are unhappy with their daily travel routine (and drive a lot) and there is a clear negative effect of amount of driving on daily travel routine satisfaction, then it is clear that municipalities should and could invest in alternative modes of transportation—such investments are likely to yield benefits and result in mode shifts away from the automobile. On the other hand, if people in automobile-oriented cities are generally happy and satisfied with their daily travel routine, and the amount of driving has a positive effect on level of daily travel satisfaction, then it would appear that bringing about a mode shift would be extremely challenging in the absence of policies that strongly disincentivize driving.

In this paper, the relationship between the relative amount of weekly driving for non-commute trips and the level of satisfaction associated with the daily travel routine is explored. A joint model that considers the relationship between these two endogenous variables is estimated. The joint model explicitly incorporates the effects of latent attitudinal factors that capture people's preferences, values, and perceptions. These latent attitudinal factors are themselves endogenous and influenced by exogenous variables. The entire model system is estimated jointly in a GHDM framework to assess the true effect of amount of driving on level of daily travel satisfaction, after controlling for all other variables. The joint model is found to offer a statistically superior goodness-of-fit than a corresponding independent model that ignores jointness and endogeneity in the model structure.

The joint model, by virtue of its ability to control for many confounding variables, is able to reveal that the relative amount of weekly driving for non-commute trips positively and significantly affects the level of satisfaction that an individual associates with his or her daily travel routine. The data reveal that 68% of survey respondents find their daily travel routine to be satisfactory and only 17% deem their daily travel routine unsatisfactory. Model estimation results show that latent attitudinal factors representing an environmentally friendly lifestyle, a proclivity toward car ownership and driving, and a desire to live close to transit and in diverse land use neighborhoods affect both endogenous variables, namely, relative frequency of auto-driving for non-commute trips and degree of agreement that the daily travel routine is satisfactory. Even after controlling for these latent attitudinal factors, the effect of driving on daily travel routine satisfaction is positive and significant.

The findings suggest that auto-driving mode use is not necessarily an undesirable activity that leads to diminished satisfaction. In fact, it appears to contribute positively to satisfaction. In areas that have poor transit service and sprawled land use patterns, it is very difficult for other modes of transportation to compete effectively with the automobile. However, based on the findings in this study, mere investments in alternative modes of transportation and improving their level of service (as explored in Eriksson et al. [*8, 9*] and De Vos et al. [*38*]) are not necessarily going to draw people away from the automobile if the use of the auto-driving mode is itself associated with higher levels of satisfaction. This points to the continuing struggle of policymakers in creating effective alternatives to automobile driving and removing system constraints for switching to alternative modes of transportation (*39*). It appears that the way to bring about noticeable shifts in mode use would entail the application of strong disincentives to automobile mode use, which are often challenging to implement.

One of the interesting findings is that those who prefer living close to transit and in the midst of shops and restaurants are more likely to report higher levels of satisfaction with the daily travel routine. These individuals likely self-select into such neighborhoods and pursue a lifestyle that is consistent with their preferences. At the same time, it is found that those who have an environmentally friendly attitude are relatively dissatisfied with their daily travel routine even though they drive less than those who do not have an environmentally friendly attitude, presumably because of poor transit service. It is this group of dissatisfied environmentally friendly individuals that may be motivated to drive less and shift more to alternative modes if investments were made to upgrade service. Alternatively, they need to be provided the amenities they seek (affordable housing, good schools, open spaces) in areas well served by transit and other modes of transportation. By offering alternative residential lifestyle options, it may be possible to draw these dissatisfied environmentally friendly individuals to a more non-automobile-centric mode use pattern. Future research efforts should aim to characterize this market segment so that targeted interventions can be done. Also, future modeling efforts should account for the role of daily time use, the amount of driving in mileage and time, and activity participation (at trip destinations) in determining level of satisfaction with daily travel routine.

There are several limitations that point to fruitful directions for future research. The survey data set used in this study did not specifically include any insights on *why* respondents derived greater satisfaction from a travel routine characterized by a higher proportion of driving. There is some evidence to date concerning this (e.g., Eriksson et al. [*8, 9*], Kristol and Whillans [*10*]), but additional in-depth survey efforts are needed to truly understand why automobile driving is so alluring.

Measuring overall daily travel routine satisfaction is rather complex and there is no single well-established way of doing so. A key limitation of this study is that a single attitudinal statement is used as the basis to measure level of daily travel satisfaction. While this is rather similar to prior research efforts (e.g., Susilo and Cats [*40*], Mao et al. [*41*]), several studies have employed multidimensional scales and more sophisticated measures to quantify travel satisfaction (e.g., De Vos et al. [*1*], Cao and Ettema [*34*], Friman et al. [*42*]). It would be of value to the profession to establish a consistent and uniform multidimensional measure of satisfaction with the daily travel routine. In addition, it is worth recognizing that there are likely to be many other observed and latent factors (not considered in this paper) that affect travel satisfaction. Variables and latent constructs such as physical activity levels, personality traits, overall well-being or happiness, and disability status could significantly influence satisfaction with daily travel routine (and amount of driving). Likewise, a host of activity-travel attributes including travel time expenditures, trip purpose, activity duration, accompaniment (joint activity-travel participation), and travel experience (e.g., traffic congestion) are likely to influence level of satisfaction with the daily travel routine. The addition of more endogenous variables and latent factors presents computational challenges in model estimation. Methodological advances that integrate machine learning methods and econometric choice modeling techniques may offer a mechanism to incorporate a host of additional factors and endogenous activity-mobility choice variables in a computationally tractable modeling framework.

Furthermore, caution should be exercised before generalizing results to other locations. The sample used in this study is comprised of survey respondents from four U.S. automobile-oriented metropolitan areas (Phoenix, Austin, Atlanta, and Tampa); while the study results may hold true in other similar fair weather auto-oriented metropolitan areas, there is a need for additional studies of this nature in geographic regions of different types (e.g., transit-oriented cities, rural areas) before drawing conclusions on the generalizability of results presented in this paper.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: T. B. Magassy, I. Batur, S. Khoeini,

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