Trapped by Transport: Exploring the Everyday Impact of Mobility Challenges and Transportation Insecurities in the United States

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ABSTRACT

The inability to travel safely and reliably when, where, and how needed (referred to as *transportation insecurity*) limits access to jobs and opportunities, restricts participation in daily activities, and diminishes wellbeing. Using data from the nationwide Transportation Heartbeat of America Survey, this study examines the prevalence and impacts of transportation insecurity in the United States and provides a comprehensive analysis across five dimensions: needing to skip trips, being unable to leave home, having relationships with others adversely affected, arriving late at destinations, and needing to reschedule appointments. Using a joint modeling framework, transportation insecurity is modeled alongside its five dimensions, to account for interdependencies among these outcomes while controlling for a range of socio-demographic, contextual, and latent attitudinal factors. Results show that transportation insecurity is real and experienced by a majority of individuals; however, its manifestations vary widely across population groups, as individuals experience different constraints and adapt to transportation challenges in different ways. The study finds that certain groups are more likely to experience transportation insecurity, including younger adults, individuals with lower educational attainment, low-income households, larger households (particularly those with children), vehicle-deficient households, those residing in less mixed-use environments, and individuals with higher perceived transportation limitations. The findings underscore the need for directed policies that expand multimodal accessibility, improve the reliability and affordability of transit services, and enhance the safety, comfort, and usability of walking, biking, and transit facilities to reduce transportation insecurity and improve quality of life.

Keywords: Transportation Insecurity, Social Participation, Travel Problems, Transportation Barriers, Transportation Perceptions

1. INTRODUCTION

The ability to access and utilize safe, reliable, and efficient transportation systems is a critical component of social participation, economic opportunity, health outcomes, and overall quality of life and wellbeing. From a social participation perspective, transportation barriers can impact the ability of individuals to engage in out-of-home activities, thus limiting community engagement, increasing social isolation, and reducing the quantity and quality of interpersonal connections and interactions (Hartell, 2008; Bascom and Christensen, 2017; Bruno et al, 2024). From an economic perspective, transportation insecurity can lead to an inability to access jobs and educational opportunities, reducing labor productivity and upward economic mobility (Hu, 2017; Jin and Paulsen, 2018). Health and wellbeing outcomes can also be adversely affected due to transportation constraints, as accessing healthcare services and providers may be difficult for those experiencing transportation barriers (Syed et al, 2013; Wolfe et al, 2020; Etminani-Ghasrodashti et al, 2021). At the same time, the lack of access to transportation can lead to deterioration in mental health stemming from social isolation and economic instability that contribute to increased stress and depression (Conceicao et al, 2023; McDonald-Lopez et al, 2023).

A growing body of research in recent years has focused on examining the determinants of access to good transportation, barriers to mobility, and transportation insecurity (Batur et al, 2019; Murphy et al, 2021; Jamei et al, 2022; Singer and Martens, 2023). For example, in terms of physical accessibility, studies have examined specific supply-side measures such as proximity to public transportation, vehicle ownership, and spatial/temporal accessibility to different modes of transportation to assess mobility limitations (Malekzadeh and Chung, 2020; Park and Goldberg, 2021). There is, however, another stream of research that extends potential transportation barriers beyond mere physical access, emphasizing also the role of individual perceptions of transportation alternatives, individual-specific travel needs and desires, and attitudes and preferences in shaping transportation insecurity (Lattman et al, 2016; De Vos et al, 2023; Pot et al, 2024; Murphy et al., 2025).

Despite the growing body of research dedicated to understanding, quantifying, and explaining transportation insecurity and barriers to mobility (and their implications/impacts), the focus of many studies remains on the supply-side indicators of transportation availability and accessibility (Verlinghieri and Schwanen, 2020; Merlin et al, 2021) or the overall individual- or community-level outcomes of accessibility to specific services and modes of transportation, overall mobility levels, and health factors (Pyrialakou et al, 2016; Maleki and Smith-Colin, 2025). Less attention has been accorded to the disaggregate-level social outcomes, differences in strategies used to navigate transportation limitations, and actual experiential impacts arising from transportation insecurity at a day-to-day activity participation level (Verlinghieri and Schwanen, 2020).

Thus, there is an important gap in understanding how transportation insecurity translates into specific experiential activity-travel and social outcomes that fundamentally define and shape people's participation in out-of-home activities. This gap is addressed in this paper through two main objectives. First, the study identifies variations in perceived transportation insecurity among different socio-economic and demographic groups of individuals. Second, the study provides a deep dive into the specific impacts of transportation insecurity on activity engagement, social connections and interactions, and activity scheduling. In order to achieve these objectives, the study considers a broad range of socio-economic and demographic characteristics, examines specific activity participation compromises that may have been induced by transportation insecurity, and explicitly accounts for the role of attitudes, perceptions, and lifestyle preferences in shaping transportation insecurity and its consequences on activity engagement.

The current study utilizes data collected as part of the Transportation Heartbeat of America (THA) Survey conducted in late 2024 and early 2025 by the National University Transportation Center for the Future of Understanding Travel Behavior and Demand (TBD Center). The comprehensive data set includes detailed information about mobility challenges and limitations/barriers, and how these transportation constraints impacted specific aspects of activity participation, scheduling, and social engagement. The study considers a series of endogenous variables that are defined based on the outcomes resulting from transportation insecurity (as reported by respondents in the survey). A multivariate joint model system that accounts for the complex relationships characterizing transportation insecurity outcomes and their consequences on daily activity-travel engagement is adopted. A variety of latent attitudinal constructs are embedded in the model system to reflect their influence on transportation insecurity and its effects.

The remainder of this paper is organized as follows. The following section presents a detailed description of the survey and the dataset used in this study, along with a detailed description of the endogenous variables and the latent attitudinal constructs. The third section presents the modeling framework. The fourth section provides a detailed discussion of the model estimation results, along with a presentation of average treatment effects to illustrate the influence of different variables and factors on transportation insecurity and its outcomes. The fifth and final section offers concluding remarks.

2. DATA DESCRIPTION

This section summarizes the survey and dataset used in this study. The survey and sample characteristics are described first. A more detailed descriptive analysis of endogenous variables and attitudinal indicators is provided subsequently.

2.1. Survey Overview and Sample Characteristics

Data for this study are derived from the Transportation Heartbeat of America (THA) Survey conducted in the United States between October 2024 and January 2025. The nationwide survey is intended to obtain detailed information about traveler behaviors and values, mobility trends and choices, activity-travel patterns, attitudes and perceptions, and lifestyle preferences and personality traits from a large nationwide sample of residents. The survey was administered to an online panel of participants assembled by a commercial firm. Quotas were specified on an extensive set of socio-economic and demographic attributes to ensure that the respondent sample captured the variation in attributes that would be prevalent in the general population. In particular, the quota-based sampling approach ensured that reasonable sample sizes were obtained in each of multiple demographic subgroups defined by race, age, gender, educational attainment, household income, area type of residence (urban/rural), and census division of residence. Eligible participants included adults aged 18 years or over residing in the United States; multiple attention checks and quality control questions were inserted in the survey to ensure robust response quality.

The survey dataset includes detailed coverage of attitudes regarding transportation and mobility, current transportation behaviors and choices, values and preferences regarding transportation development and economic investments in transportation infrastructure, knowledge and opinions about potential future transportation technologies, and specific preferences and behaviors regarding online activity participation. Additional built environment attributes (population density, employment density, car network density, and transit accessibility) were appended to the survey records (based on residential zip code) using information from the Environmental Protection Agency Smart Location Database (Chapman, 2021). While the original survey data set included a total of 8,212 responses, the final analysis dataset that was cleaned of missing data and obviously erroneous records included 8,008 observations.

The socio-economic and demographic characteristics of this dataset are shown in the upper portion of Table 1. There is a slightly larger proportion of women in the sample, relative to men. All age groups are well represented in the survey sample with 21.4 percent aged 65 years or over, 20.0 percent aged 35-44 years, and 12.5 percent aged 18-24 years. Full-time workers comprise 45.6 percent of the sample, and part-time workers comprise an additional 10.9 percent. About one-third of respondents have an educational attainment of high school or less, while 14.8 percent have a graduate degree. 65.3 percent of the sample identifies as White, while 15.4 percent identifies as Black. Only 20.1 percent of respondents identify as Hispanic, while the remaining 79.9 percent indicate their ethnicity as non-Hispanic. In terms of household income, 11.1 percent reside in households making $150,000 or more per year, while 17.1 percent reside in households making less than $25,000. 19.4 percent of respondents reside in single-person households, and 47.8 percent reside in households with three or more occupants. Just about two-thirds reside in single-family stand-alone homes, and 59.2 percent indicate that they own their home. While 50.9 percent of individuals reside in households with two or more cars, 8.5 percent reside in households with no cars. Finally, 19.6 percent of respondents identify their residential location as rural. In general, the sample depicts a variation in attributes that renders the dataset suitable for a multivariate econometric model estimation exercise such as that undertaken in this study.

Table 1 Sample Socio-Demographic Characteristics and Transportation Insecurity Experiences

Individual Demographics		*Household Characteristics*	
Variable	**%**	**Variable**	**%**
Gender		**Annual household income**	
Female	53.3	Less than $25,000	17.1
Male	46.7	$25,000 to $49,999	22.0
Age category		$50,000 to $99,999	30.5
18 to 24 years	12.5	$100,000 to $149,999	19.3
25 to 34 years	13.8	$150,000 to $199,999	7.1
35 to 44 years	20.0	$200,000 or more	4.0
45 to 54 years	16.5	**Household size**	
55 to 64 years	15.8	One	19.4
65 years or older	21.4	Two	32.8
Employment status		Three or more	47.8
Full-time worker	45.6	**Housing unit type**	
Part-time worker	10.9	Stand-alone home	66.7
Non-worker	43.5	Attached home/apartment	27.0
Educational attainment		Other	6.3
High school or less	33.0	**Homeownership status**	
Some college or technical school	29.5	Own	59.2
Bachelor's degree(s)	22.7	Rent	35.5
Graduate degree(s)	14.8	Other	5.3
Race		**Vehicle ownership**	
Asian or Pacific Islander	7.6	Zero	8.5
Black	15.4	One	40.6
White	65.3	Two	34.1
Other	11.7	Three or more	16.8
Ethnicity		**Location**	
Hispanic	20.1	Urban	80.4
Non-Hispanic	79.9	Rural	19.6

Main Outcome Variables

Overall Prevalence of Transportation Insecurity Experiences	
Experienced at least one insecurity (N=4,392)	54.8
Did not experience any insecurity (N=3,616)	45.2

Frequency of Specific Transportation Insecurity Experiences *(among respondents who reported at least one experience; N=4,392)*	**Never or rarely**	**Sometimes**	**Often**
You skipped going somewhere because of a problem with transportation	29.7	54.0	16.3
You were not able to leave the house when you wanted to because of a problem with transportation	38.4	44.4	17.2
Problems with transportation affected your relationships with others	51.7	32.6	15.7
You were late getting somewhere because of a problem with transportation	27.0	54.7	18.3
You had to reschedule an appointment because of a problem with transportation	35.9	45.5	18.6

2.2. Endogenous Outcomes

In order to capture transportation insecurity, the survey employed several items adapted from the Transportation Security Index, a validated scale used to measure this phenomenon (Murphy et al, 2021). Participants were asked whether they experienced each of the following events "Never or Rarely," "Sometimes," or "Often" in the past 30 days:

- You skipped going somewhere because of a problem with transportation.
- You were not able to leave the house when you wanted to because of a problem with transportation.
- Problems with transportation affected your relationships with others.
- You were late getting somewhere because of a problem with transportation.
- You had to reschedule an appointment because of a problem with transportation.

Based on these questions, the study created six distinct outcome variables. The first is a binary outcome variable that indicates whether an individual experienced any transportation insecurity (that is, they answered "sometimes" or "often" to any of the specific transportation insecurity questions listed above). Descriptive statistics towards the bottom half of Table 1 show that transportation insecurity is quite prevalent, with 54.8 percent of respondents reporting that they had undergone one or more of the five experiences of transportation insecurity at least "sometimes" in the prior 30 days.

Then, for those who experienced transportation security (at all), five ordered response variables indicating the degree to which they experienced each of the five outcomes were constructed. Breaking these outcomes down in this way makes it possible to not only determine who is experiencing transportation insecurity overall, but also understand the actual experiences and ways in which this insecurity is manifested differently for different people. The descriptive statistics show that, among those who experience transportation insecurity, it is relatively less common that problems with transportation impact relationships (51.7 percent indicate that this happens "never or rarely"). In contrast, being late or needing to reschedule appointments due to problems with transportation are the experiences most commonly cited as happening "often." These distributions, shown at the bottom of Table 1, suggest that transportation insecurity is a prevalent phenomenon that needs to be understood and modeled to develop remedies.

2.3. Stochastic Latent Constructs

The survey dataset also included a host of attitudinal statements that provided rich information about values, preferences, perceptions, and opinions on a wide range of mobility and lifestyle aspects. This information provides the ability to explicitly account for the influence of such variables in shaping transportation insecurity experiences and outcomes. In this study, four latent factors were constructed and included in the modeling framework (described in the next section). Extensive tests and trials were conducted on the attitudinal statements to define a set of meaningful latent factors that were behaviorally intuitive, interpretable, statistically significant and sound, and meaningfully correlated with the outcome variables of interest (representing transportation insecurity). Exploratory factor analysis (EFA) was followed by confirmatory factor analysis (CFA) to finalize a set of four latent constructs for inclusion in this study.

Each of the four latent constructs represents a composite of three attitudinal statements or indicators as depicted in Figure 1. The first latent construct is Perceived Travel Limitations. This latent factor captures attitudes and perceptions related to the availability (or lack thereof) of alternative modes of transportation (relative to the mode they use most often), the difficulty in using public transportation, and the degree to which the respondent likes the idea of public transit as a means of transportation to fit their particular travel needs. The second latent construct represents Safety Consciousness. This latent construct is comprised of indicators that reflect the degree to which respondents prioritize safety, support using technology to enhance safety and curtail risky driving behaviors, and feel safer driving themselves rather than relying on others. The third latent construct is called Congestion Sensitivity. This latent construct reflects the degree to which respondents feel that traffic congestion is a major problem, make efforts to adjust their schedule to avoid congestion, and are willing to pay more money to have a faster trip. Finally, the fourth latent construct is called Positive Travel Engagement. This construct captures the degree to which respondents enjoy the act of traveling itself, try to make good use of the time spent traveling, and are satisfied with their current transportation options.

This set of four latent constructs was developed based on insights derived from the theory of planned behavior (Ajzen, 1991), the capabilities approach (Nussbaum and Sen, 1993; Vecchio and Martens, 2021), and the social-ecological model (Stokols and Nocavo, 1981; Sallis and Owen, 2002). In the context of the theory of planned behavior, the inclusion of Perceived Travel Limitations and Positive Travel Engagement align with the concept of perceived behavioral control, capturing the effect of an individual's beliefs about their ability to exercise certain choices. Similarly, the capabilities approach reflects the distinction between theoretical access and actual capabilities, such as that captured by the Perceived Travel Limitations latent construct. In addition, Safety Consciousness and Congestion Sensitivity reflect interactions between individual-level circumstances and community-level conditions that shape transportation behaviors, as suggested by the social-ecological model. For example, the Congestion Sensitivity factor reflects the combination of environmental factors (whether traffic congestion is a problem) that create barriers to mobility and individual-level resources and capacity to shape the impacts of these effects.

The attitudinal indicators in Figure 1 reveal that a good fraction of individuals (a) perceive a lack of good multimodal options (the first indicator in the figure), (b) place a high premium on reducing crashes and a willingness to adopt camera-based traffic enforcement/penalty programs (see the second panel associated with the safety consciousness latent construct), and (c) schedule/reschedule participations to avoid traffic congestion (the second indicator of the congestion sensitivity latent construct). At the same time, a high fraction of individuals also indicate that they enjoy the act of traveling and are reasonably content with their current transportation options, as manifested in the indicators for the final positive travel engagement latent construct.

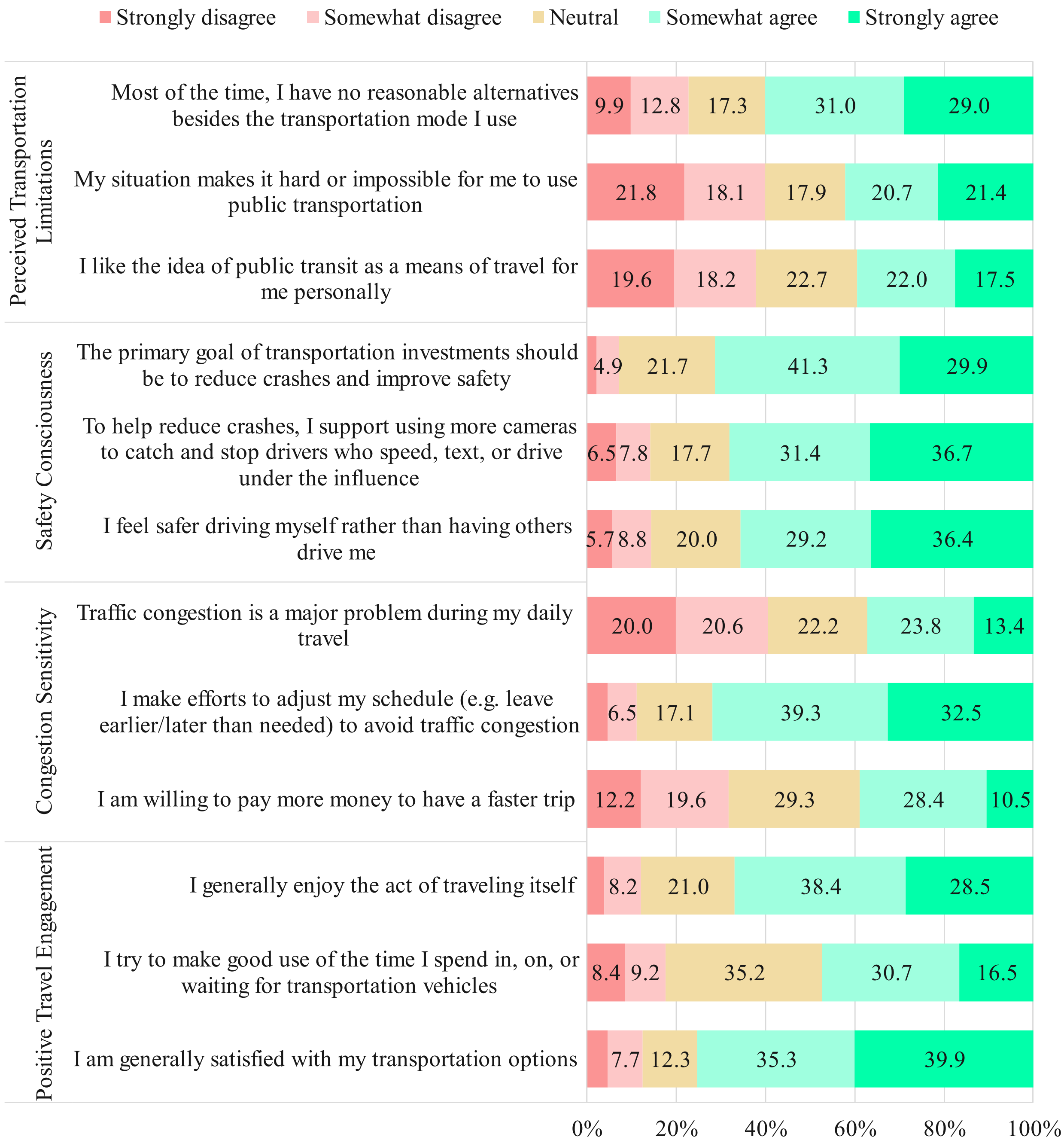

Figure 1 Agreement with Attitudinal Indicators Defining Latent Constructs

3. MODELING FRAMEWORK

This section presents a brief overview of the modeling framework adopted in this study. Figure 2 constitutes a simplified representation of the model structure. The main outcome variables appear on the right-hand side of the figure. As discussed previously, there are six endogenous variables. These include the overall (binary) experience of transportation insecurity together with five ordinal endogenous variables that represent the frequency of experience of specific aspects/outcomes of transportation insecurity. These ordinal variables are denoted as: skipped trip, unable to leave home, impacted relationships, arrived late, and rescheduled appointments. Exogenous variables shown on the left-hand side of the figure are comprised of socio-economic and demographic attributes and travel and other characteristics that may be treated as exogenous in nature for purposes of this study. These variables influence the key outcome variables in two ways. First, they impact the main transportation insecurity outcome variables directly as depicted by the arrows at the top and bottom of the figure. Second, they influence the outcomes through their effects on each of the four stochastic latent constructs, with the latent constructs providing insights into the effects of attitudes, perceptions, and preferences on transportation insecurity experiences. In addition, as part of the model formulation, the latent constructs are treated as stochastic in nature, creating a parsimonious error correlation structure among the main outcome variables. For instance, if the perceived travel limitations latent construct positively influences both the binary main outcome representing the overall experience of transportation insecurity and the ordered outcome representing "skipped trips," then the immediate result is a positive correlation generated between these two outcomes. Concurrently, the latent constructs themselves are considered endogenous to the main outcomes through the accommodation of common unobserved correlation factors that may affect the latent constructs and the main outcomes, leading some individuals to exhibit specific lifestyle preferences while also being more likely to experience transportation insecurity in certain ways. For example, an individual with disabilities may exhibit a higher level of perceived travel limitations because of challenges in accessing and using certain modes of transportation (thus limiting them to a smaller set of options). At the same time, these individuals may experience difficulty in using the modes and travel options that they do consider available to them (say, due to unreliable ramps and disability accommodations), causing them to be more likely to skip going places (because of these unobserved transportation infrastructure constraints). If such unobserved factors exist and were ignored, it would lead to an over-estimation of the effect of the perceived travel limitations latent construct on the outcome corresponding to skipped trips. Such unobserved factor correlations are depicted in the figure by the two-way arrow connecting the box containing the latent constructs and the box containing the main outcome variables.

The entire model system is formulated and estimated as a simultaneous equations model system that incorporates error correlations as depicted by the two-way curved arrows in Figure 2. The model is estimated using the Generalized Heterogeneous Data Model (GHDM) methodology developed by Bhat (2015). The mathematical formulation of the model is presented in the following section.

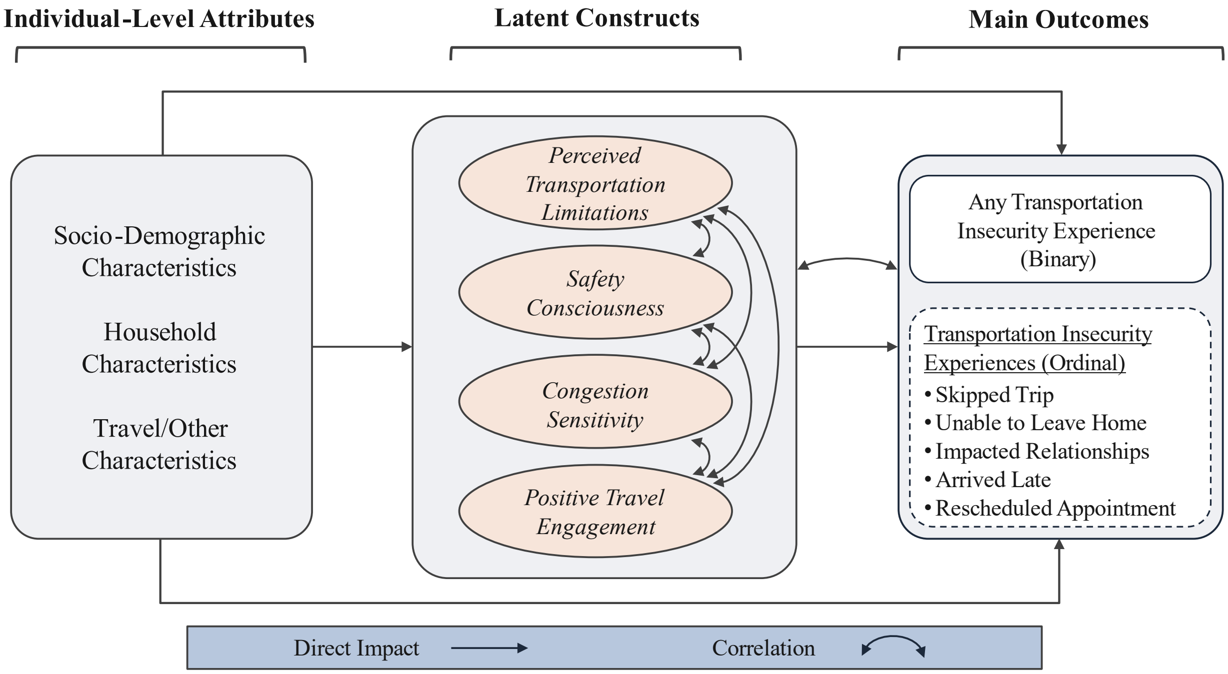

Figure 2 Model Framework

3.1. Model Estimation Methodology

As mentioned above, Bhat's (2015) GHDM framework is employed for this study. For the formulation of the model in the current context, the study considers the binary variable corresponding to the overall experience of any transportation insecurity as a special case of an ordered response variable and formulates the model as consisting of solely ordered response outcomes. This is done simply for ease of presentation and does not otherwise impact the structure of the model or empirical findings. For the model formulation, let l be the index corresponding to the stochastic latent constructs $(l = 1, 2, \ldots, L)$. In the current context $L = 4$, corresponding to the four latent constructs shown in the center of Figure 2. Then, each underlying continuous latent construct z_l^* may be written as a function of covariates, as:

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

where $\boldsymbol{w}$ is a $(D \times 1)$ vector of observed exogenous variables (excluding a constant) impacting the latent construct and $\boldsymbol{\alpha}_l$ is a corresponding $(D \times 1)$ vector of coefficients. Further, η_l is a random error term, which is assumed to be standard normally distributed and captures the effects of unobserved factors that influence the latent construct, after controlling for the observed exogenous variables. Next, stack these variables across the latent constructs to obtain the $(L \times D)$ 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 $\boldsymbol{\eta} = (\eta_1, \eta_2, \ldots, \eta_L)'$. Thus, in matrix form, it may be written:

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

To accommodate the interactions among the stochastic latent constructs (see the two-headed arrows connecting the latent construct in the center of Figure 2), a multivariate normal correlation structure is specified for $\boldsymbol{\eta}$. $\boldsymbol{\eta} \sim MVN_L[\mathbf{0}_L, \boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L\times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is an $(L\times L)$ correlation matrix.

Next, consider N ordinal outcomes corresponding to the indicator variables for the latent constructs (see Figure 1), the binary outcome for the experience of transportation insecurity (which is recast as an ordinal outcome, as discussed above), and the five ordinal outcomes relating to the specific experiences of transportation insecurity. Let n be the index for the ordinal outcomes $(n = 1, 2, ..., N)$. In the current context, $N = 18$, corresponding to the 12 indicators of the four latent constructs and the six main outcome dimensions. However, note that, because individuals who never experience transportation insecurity do not have responses to the five ordinal outcomes related to the specific experiences of transportation insecurity, these individuals will have only $N = 13$ ordinal outcomes, corresponding to the 12 indicators and a single main outcome for the binary experience of transportation insecurity. In the remainder of this section, and purely for presentation ease, only individuals with a complete set of $N = 18$ ordinal outcomes are considered, as only a slight modification is needed to marginalize the likelihood function for those individuals with $N = 13$ ordinal outcomes.

To proceed, let J_n be the number of ordinal categories for the n^{th} ordinal outcome $\left(J_n \geq 2\right)$ and let j_n be the corresponding index $(j_n = 1, 2, ..., J_n)$. Then, assume that the individual under consideration chooses the a_n^{th} ordinal category and denote the underlying latent variable for each ordinal outcome as $\tilde{y}_n^*$ such that the horizontal partitioning of $\tilde{y}_n^*$ leads to the observed outcome. In the usual ordered response formulation, for the individual, it may be written:

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

with $\tilde{\psi}_{n,a_n-1} < \tilde{y}_n^* < \tilde{\psi}_{n,a_n}$, and where $\boldsymbol{x}$ is an $(A\times 1)$ vector of observed exogenous variables (including a constant), $\tilde{\boldsymbol{\gamma}}_n$ is a corresponding vector of coefficients to be estimated, and $\tilde{\boldsymbol{d}}_n$ is an $(L\times 1)$ vector of latent variable loadings on the n^{th} ordinal outcome. The $\tilde{\psi}$ terms represent thresholds partitioning the underlying latent variable and $\tilde{\varepsilon}_n$ is the standard normal random error for the n^{th} ordinal outcome. However, note that the $\boldsymbol{x}$ vector will only appear in Equation (3) for the ordinal outcomes, not the ordinal indicator variables. Further, the thresholds for each ordinal outcome must be ordered $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} ... < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$, with $\tilde{\psi}_{n,0} = -\infty$, $\tilde{\psi}_{n,1} = 0$, and $\tilde{\psi}_{n,J_n} = +\infty$. Let $\tilde{\boldsymbol{\psi}}_n = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3}, ..., \tilde{\psi}_{n,J_n-1})'$ and $\tilde{\boldsymbol{\psi}} = (\tilde{\boldsymbol{\psi}}_1', \tilde{\boldsymbol{\psi}}_2', ..., \tilde{\boldsymbol{\psi}}_N)'$. Stack the N underlying continuous variables $\tilde{y}_n^*$ into an $(N\times 1)$ vector $\tilde{\boldsymbol{y}}^*$, and the N error terms $\tilde{\varepsilon}_n$ into an $(N\times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$. Define the $(N\times A)$ matrix $\tilde{\boldsymbol{\gamma}} = (\tilde{\boldsymbol{\gamma}}_1, \tilde{\boldsymbol{\gamma}}_2, ..., \tilde{\boldsymbol{\gamma}}_N)'$ and the $(N\times L)$ matrix $\tilde{\boldsymbol{d}} = \left(\tilde{\boldsymbol{d}}_1, \tilde{\boldsymbol{d}}_2, ..., \tilde{\boldsymbol{d}}_N\right)$, and let $\boldsymbol{IDEN}_N$ be an identity matrix of dimension N that represents the correlation matrix of $\tilde{\boldsymbol{\varepsilon}}$ (note that, as described above, correlations among the ordinal outcomes are not considered directly but engendered through the effects of the stochastic latent constructs). Finally, for each decision maker, stack the N lower thresholds $\tilde{\psi}_{n,a_n-1}$ into an $(N\times 1)$ vector $\tilde{\boldsymbol{\psi}}_{low}$ and the N upper thresholds $\tilde{\psi}_{n,a_n}$ into a vector $\tilde{\boldsymbol{\psi}}_{up}$. Then the ordinal outcomes for the individual may be written in matrix form as:

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}} \boldsymbol{x} + \tilde{\boldsymbol{d}} \boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{low} < \tilde{\boldsymbol{y}}^* < \tilde{\boldsymbol{\psi}}_{up}. \tag{4}$$

As described in the previous section, correlations between the four latent constructs and the main outcomes ($\boldsymbol{\eta}$ is correlated with $\tilde{\boldsymbol{\varepsilon}}$) are also considered, accommodating the possibility that unobserved factors jointly influence the latent constructs and main outcomes. Let the $(L \times N)$ matrix $\boldsymbol{\Omega}_{\mathrm{LN}}$ contain the correlation elements between each of the latent constructs and the ordinal outcomes (see the two-headed arrow between the latent constructs and the main outcomes in Figure 2).

Finally, replace the right side of Equation (2) for $\boldsymbol{z}^*$ in Equation (4) to obtain the following:

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}} = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}(\boldsymbol{\alpha}\boldsymbol{w} + \boldsymbol{\eta}) + \tilde{\boldsymbol{\varepsilon}} = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{\alpha}\boldsymbol{w} + \tilde{\boldsymbol{d}}\boldsymbol{\eta} + \tilde{\boldsymbol{\varepsilon}}\,. \tag{5}$$

Define $\boldsymbol{B} = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{\alpha}\boldsymbol{w}$ and $\boldsymbol{\Omega} = \tilde{\boldsymbol{d}}\boldsymbol{\Gamma}\tilde{\boldsymbol{d}}' + \boldsymbol{IDEN}_N + \tilde{\boldsymbol{d}}\boldsymbol{\Omega}_{\mathrm{LN}} + \boldsymbol{\Omega}'_{\mathrm{LN}}\tilde{\boldsymbol{d}}'$. Then, $\tilde{\boldsymbol{y}}^* \sim \boldsymbol{MVN}_N(\boldsymbol{B},\boldsymbol{\Omega})$ is the N-dimensional multivariate joint distribution of the main outcomes and indicators.

Finally, define $\boldsymbol{\delta} = [\mathrm{Vech}(\boldsymbol{\alpha}), \mathrm{Vechup}(\boldsymbol{\Gamma}), \mathrm{Vech}(\tilde{\boldsymbol{\gamma}}), \mathrm{Vech}(\tilde{\boldsymbol{d}}), \tilde{\boldsymbol{\psi}}, \mathrm{Vech}(\boldsymbol{\Omega}_{\mathrm{LN}})]$ as the set of parameters to be estimated, where the operator $\mathrm{Vech}(\cdot)$ vectorizes all the non-zero elements of the matrix/vector on which it operates and $\mathrm{Vechup}(\cdot)$ indicates strictly upper diagonal elements. Then the likelihood function may be written as:

$$L(\boldsymbol{\delta}) = \Pr\left[\tilde{\boldsymbol{\psi}}_{low} \le \tilde{\boldsymbol{y}}^* \le \tilde{\boldsymbol{\psi}}_{up}\right] = \int_{D_r} f_N(\boldsymbol{r} \mid \boldsymbol{B},\boldsymbol{\Omega})\,dr\,, \tag{6}$$

where the integration domain $D_r = \{\boldsymbol{r} : \tilde{\boldsymbol{\psi}}_{low} \le \boldsymbol{r} \le \tilde{\boldsymbol{\psi}}_{up}\}$ is the multivariate region of the elements of the $\tilde{\boldsymbol{y}}^*$ vector determined by the observed ordinal outcomes. The likelihood function for the entire sample of decision-makers is obtained as the product of the individual-level likelihood functions. Additionally, the above likelihood function involves the evaluation of an integral of up to 18 dimensions for each decision-maker. Therefore, Bhat's (2018) matrix-based approximation method is used for evaluating the multivariate normal cumulative distribution function to evaluate this integral.

4. MODEL ESTIMATION RESULTS

This section presents the model estimation results. The results for the effects of exogenous variables on the latent constructs are discussed first in Section 4.1, followed by the discussion of the main estimation results in Section 4.2. Then, Section 4.3 includes a discussion of the model fit, while Section 4.4 presents average treatment effects of each exogenous variable on each of the main outcomes.

4.1. Latent Constructs

Estimation results for the latent construct portion of the model are presented in Table 2 for each of the four stochastic latent constructs. The upper portion of the table presents the effects of exogenous variables on the continuous latent constructs (the structural equation modeling component of the GHDM).

As shown in Table 2, women exhibit a higher level of safety consciousness than men, consistent with findings in the literature (see Jing et al., 2023). Women (compared with men) also exhibit lower levels of congestion sensitivity and lower levels of positive travel engagement. Women travel fewer miles than men on a weekly basis (Gauvin et al., 2020) and are therefore less likely to experience and be sensitive to congestion. As women tend to shoulder a greater share of household and childcare responsibilities (Zamarro and Prados, 2021), it is also not surprising that they are more time-constrained and view travel more negatively (see the negative coefficient for positive travel engagement). Relative to the youngest age group (18-34 years), all other older age groups are less sensitive to congestion, presumably because they have greater travel flexibility, both in terms of auto availability and scheduling. The coefficients are increasingly negative, suggesting that congestion sensitivity decreases with age, with those aged 65 years and older expressing the least sensitivity. On the other hand, those 65 years and over are more safety conscious (see also, Jing et al., 2023) and express less positive travel engagement then those under the age of 65, presumably due to mobility and driving limitations that set in for that age cohort (Lin and Cui, 2021).

Minority groups (including non-White and Hispanic individuals) tend to be more familiar with and use alternative modes of transportation more so than White non-Hispanic individuals (Giuliano and Hanson, 2017). As such, it is not surprising that they perceive lower levels of transportation limitations. On the other hand, these minority individuals are also more sensitive to congestion, reflecting the disproportionate impact of congestion on these communities/groups and the limited flexibility that they may enjoy in work schedules when compared to other groups (Shearston et al., 2024). Non-White and Hispanic individuals are also more safety conscious, reflecting potential infrastructure disparities and disproportionate exposure to transportation safety challenges in their neighborhoods (Haddad et al, 2023).

Education and employment are key variables that influence the latent attitudinal constructs. In general, the highest levels of educational attainment are associated with heightened congestion sensitivity and perceived transportation limitations. These individuals (compared to those with less education) are likely to be time-constrained, and hence more sensitive to congestion and poor transportation system performance. They are also more aware of safety challenges and hence more safety conscious. Finally, these individuals with more education also exhibit higher positive travel engagement reflecting the higher vehicle ownership levels that they typically enjoy and their inclination towards multitasking to put travel time to good use (Varghese and Jana, 2018). Employed individuals exhibit a similar pattern (to highly educated individuals) but have a lower level of perceived transportation limitations compared with unemployed individuals, presumably because these individuals are able to travel without (much) difficulty to access jobs. Retired individuals are more safety conscious (consistent with the older age character of this group) and enjoy higher levels of positive travel engagement, presumably because they are not as time constrained as other groups.

As expected, those in higher-income households have greater levels of congestion sensitivity (compared with those in lower-income households), reflecting the higher value of time for these groups (Binsuwadan et al., 2023). However, higher income levels are associated with greater positive travel engagement, reflecting their relatively higher levels of vehicle availability and ability to afford on-demand mobility options. For similar reasons, those in the highest income bracket ($200,000 or more) experience lower levels of perceived transportation limitations compared to those in lower income households. The presence of children, which imposes schedule constraints and raises safety concerns among adults (He, 2013; Amiour et al., 2022), is associated with higher safety consciousness and congestion sensitivity. On the other hand, the presence of children is associated with more positive travel engagement, reflecting the greater satisfaction derived from travel with household member accompaniment (Zhu and Fan, 2018). Single adults are less worried about safety (lower level of safety consciousness) and perceive lower levels of travel limitations (as they are able to use a variety of modes of transportation in the absence of household constraints). Single parents, who are generally under greater time pressure, exhibit higher levels of congestion sensitivity. Further, living in apartments or renting a home (compared with owning or living in a single-family home) is associated with lower levels of perceived transportation limitations because these communities tend to be higher density and better served by alternative modes of transportation. Those living in apartments (compared with single-family homes) are also less sensitive to congestion while renters (compared with homeowners) tend to be more safety conscious, which is also likely due to the higher-density multimodal nature of these communities.

Finally, the lower portion of Table 2 presents the correlations among the error terms embedded in the stochastic latent constructs as well as the factor loadings on the attitudinal indicators for each of the four latent constructs. All error correlations are statistically significant, justifying the multivariate structure of the econometric model specification. Further, the factor loadings are all statistically significant and intuitive in sign and magnitude, suggesting that the attitudinal indicators are indeed appropriate for describing the latent constructs.

TABLE 2 Determinants of Latent Variables and Loadings on Indicators

Explanatory Variables (base category[*])		Structural Equations Model Component							
		Perceived Transportation Limitations		Safety Consciousness		Congestion Sensitivity		Positive Travel Engagement	
		Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Individual Characteristics									
Gender (not female)	Female	—		0.103	2.28	-0.203	-4.53	-0.204	-5.03
Age (18 to 34 years)	35 to 44 years	—		—		-0.277	-5.19	—	
	45 to 54 years	—		—		-0.414	-7.04	—	
	55 to 64 years	—		—		-0.556	-9.19	—	
	65 years or older	—		0.170	1.71	-0.803	-12.33	-0.334	-3.39
Race (White)	Non-White	-0.438	-10.60	0.120	2.61	0.143	3.15	0.301	6.50
Ethnicity (not Hispanic)	Hispanic	-0.193	-4.00	0.064	1.74	0.127	2.33	—	
Education (high school or less)	Some college or bachelor's degree(s)	—		—		0.088	2.12	—	
	Graduate degree(s)	0.275	2.52	0.089	2.15	0.375	3.24	0.096	1.67
Employment status (neither employed nor retired)	Employed	-0.476	-12.41	0.157	2.98	0.196	3.81	0.477	8.94
	Retired	—		0.103	2.05	—		0.505	8.03
Household Characteristics									
Household income (less than $25,000)	$25,000 - $49,999	—		—		0.160	2.83	—	
	$50,000 - $99,999	—		—		0.355	6.41	0.126	2.43
	$100,000 - $199,999	—		—		0.535	8.02	0.182	2.33
	$200,000 or more	-0.235	-2.48	—		0.780	7.20	0.317	3.17
Presence of children (none)	One or more	—		0.149	3.09	0.123	2.52	0.126	2.43
Household composition (multi-adult family)	Single adult	-0.128	-3.43	-0.078	-1.90	—		—	
	Single parent	—		—		0.132	1.91	—	
Home type (single family home)	Apartment	-0.289	-5.20	0.125	2.45	—		—	
Tenure type (own or other)	Rent	-0.261	-5.86	—		-0.095	-2.27	—	
Correlations Between Latent Constructs									
Perceived Transportation Limitations		1.000	—	0.555	7.71	-0.207	-3.45	-0.207	-3.05
Safety Consciousness				1.000	—	-0.294	-4.74	0.260	4.25
Congestion Sensitivity						1.000	—	0.273	5.05
Positive Travel Engagement								1.000	—

TABLE 2 (Continued)

Loadings of Latent Variables on Indicators	Measurement Equations Model Component							
	Perceived Transportation Limitations		Safety Consciousness		Congestion Sensitivity		Positive Travel Engagement	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Most of the time, I have no reasonable alternatives besides the transportation mode I use	0.872	31.48	—				—	
My situation makes it hard or impossible for me to use public transportation	1.177	31.82	—				—	
I like the idea of public transit as a means of travel for me personally	-0.622	-25.08	—				—	
The primary goal of transportation investments should be to reduce crashes and improve safety	—		0.826	19.12	—		—	
To help reduce crashes, I support using more cameras to catch and stop drivers who speed, text, or drive under the influence	—		0.723	18.72	—		—	
I feel safer driving myself rather than having others drive me	—		0.969	19.64	—		—	
Traffic congestion is a major problem during my daily travel	—		—		0.831	22.51	—	
I make efforts to adjust my schedule (e.g. leave earlier/later than needed) to avoid traffic congestion	—		—		0.654	21.74	—	
I am willing to pay more money to have a faster trip	—		—		0.794	23.84	—	
I generally enjoy the act of traveling itself	—		—		—		0.937	30.76
I try to make good use of the time I spend in, on, or waiting for transportation vehicles	—		—		—		0.749	25.94
I am generally satisfied with my transportation options	—		—		—		0.825	23.60

Notes: Coeff. = coefficient; "—" = not statistically significant at the 90% confidence level or not applicable for the latent construct. (*) Base category is not identical across the model equations and corresponds to "listed base category" and all omitted categories.

4.2. Main Estimation Results

4.2.1. Effects of Latent Constructs

Table 3 presents detailed estimation results for the effects of the exogenous variables and latent constructs on the main outcomes (corresponding to the measurement equation modeling component of the GHDM). The coefficients refer to the effects of exogenous variables on the underlying latent propensities of each of the transportation insecurity outcomes. For the ordered-response outcomes, even the signs of coefficients do not immediately translate to unambiguous directions of effects on the ordinal outcomes themselves, except for the two extreme categories of "Never or Rarely" and "Often". But, for presentation simplicity, a positive effect will be referred to as increasing the tendency of experiencing each transportation insecurity outcome (with the understanding that this strictly implies a higher probability of selection of the "Often" ordinal category, and a lower probability of selection of the "Never or Rarely" ordinal category).

The first section of the table depicts the influence of latent constructs and associated interaction terms on transportation insecurity overall and on the five specific experiences that define transportation insecurity in this study. As expected, individuals with higher levels of perceived transportation limitations are more likely to experience transportation insecurity overall and have a heightened propensity for each of the five insecurity experiences. For those aged 65 years and over, the effect is amplified for skipping trips but mitigated with respect to problems with transportation impacting their relationships. In other words, older individuals are more likely (compared with younger adults) to be influenced to skip trips by any perceived transportation limitations but are able to adapt their relatively less constrained lifestyles to mitigate impacts on their relationships. Individuals with higher levels of safety consciousness experience less transportation insecurity overall, but they are more likely to skip trips and reschedule appointments. This reflects the tendency of these individuals to change travel plans to ensure that they arrive safely on time when they do travel; if they perceive a safety risk (for instance, perceive a need to drive fast to make an appointment), they will choose to skip the trip and reschedule the appointment so that they arrive safely on time. The impacts of perceived safety risks that increase the propensity to reschedule when experiencing transportation difficulties are amplified for women (compared with men), suggesting that women are more likely to act on their safety concerns by planning ahead to make actual travel adjustments by rescheduling appointments. However, women and individuals in households with children are less likely to skip trips even when they perceive safety issues, reflecting the pseudo-mandatory nature of their travel (chauffeuring kids, for example).

Individuals with a heightened congestion sensitivity are more likely to experience transportation insecurity overall and have a greater tendency for arriving late (although this late arrival may also cause heightened sensitivity to congestion in the reverse direction). On the other hand, those with higher congestion sensitivity are less likely to skip trips or be unable to leave home, suggesting that these individuals are able to travel, but do so under stress and have compromised arrival times. The effect of congestion sensitivity on overall transportation insecurity is mitigated for those in rural locations, presumably because lower levels of congestion in such locales mean that congestion may perceived as an issue even at lower levels (as those who experience congestion more routinely are desensitized to its effects) though this perceived congestion impact is less likely to substantially impact travel outcomes (Conceicao et al, 2023). Finally, positive travel engagement is associated with a lower likelihood of experiencing transportation insecurity overall (consistent with the notion that these individuals consider their travel options quite adequate and enjoy traveling). However, higher positive travel engagement leads to a greater propensity to experience all types of insecurity except for skipping trips. It appears that these individuals enjoy traveling to the extent that they do not skip trips; but in trying to fulfill all of their activity-travel desires, they may make compromises and experience other types of insecurity such that arrival times are delayed, appointments need to be rescheduled, and relationships are impacted. The effects of positive travel engagement on the probability of experiencing transportation insecurity overall is further reduced for high-income individuals, an unsurprising result as this group may have greater access to mobility tools (such as household vehicles and ridehailing services) and greater schedule flexibility.

4.2.2. Effects of Individual Characteristics

Several individual-level characteristics affect transportation insecurity, even after accounting for the indirect effects that occur through the latent constructs and their interactions. Women (compared with men) are less likely to experience transportation insecurity overall. However, they have a heightened propensity for experiencing all types of insecurity compared with men, except for having relationships impacted by problems with transportation, suggesting that women are less able to mitigate the effects of transportation insecurity on their daily routines (Pani et al, 2023). The age effect on transportation insecurity outcomes is intuitive. Relative to the youngest age group (18-24 years), all other age groups exhibit a lower likelihood of experiencing transportation insecurity overall, with a decreasing trend as age increases. The same trend is observed across all insecurity outcomes, with older individuals exhibiting an improved ability to mitigate the effects of transportation problems across all five domains of insecurity compared with younger individuals. Hispanic individuals (compared with non-Hispanic individuals) are more likely to skip trips, be unable to leave home, and/or arrive late because of difficulties with transportation. As Hispanic individuals exhibit lower levels of vehicle ownership and higher levels of utilization of transit and other slower modes (Maharjan et al., 2024), this finding is consistent with expectations.

Education and employment status also affect transportation insecurity in predictable ways. Those in the highest college-educated group exhibit a lower likelihood of experiencing transportation insecurity overall, consistent with the findings of Murphy et al. (2022). Additionally, as education level rises, the propensity of being unable to leave home decreases, and those in higher education groups are also less likely to have to reschedule appointments. Both employed and retired individuals (compared to unemployed individuals) are less likely to experience transportation insecurity overall and are particularly less prone to skipping trips or being unable to leave home. Employed individuals need to find a way to leave home in order to access their job location; hence, these findings are behaviorally intuitive for employed people. Similarly, retired individuals may have the scheduling flexibility and social relationships needed to mitigate any inability to leave home due to transportation challenges (Wang, 2025).

4.2.3. Effects of Household Characteristics

Increasing household income is associated with a decreasing likelihood of experiencing transportation insecurity overall and of needing to reschedule appointments in particular. Higher-income households generally have higher levels of vehicle ownership (Sabouri et al., 2021), are able to afford using ridehailing services (Zhang and Zhang, 2018), and have potentially flexible work schedules and arrangements (Ray and Pana-Cryan, 2021) that mitigate any need for rescheduling appointments. However, individuals in high-income households do have a greater propensity for skipping trips and having relationships impacted, presumably due to poor work-life balance (Filippi et al., 2023). The presence of children is associated with a heightened probability of experiencing transportation insecurity, as well as the particular impact of needing to reschedule appointments, presumably due to time and schedule constraints associated with meeting childcare obligations (He, 2013). Single adults, on the other hand, have no such household obligations, thus exhibiting a decreased chance of experiencing transportation insecurity overall and a lower tendency to skip trips or be unable to leave home due to transportation challenges. Those who rent their dwellings are more likely to experience transportation insecurity overall and more likely to skip trips, be unable to leave home, and arrive late. Renters may have lower levels of vehicle ownership and be more reliant on fixed-route fixed-schedule public transit, thus contributing to these transportation insecurity outcomes. Finally, as expected, those who reside in vehicle-sufficient households (where the number of vehicles is greater than or equal to the number of drivers) compared to vehicle-deficient households (those with fewer vehicles than drivers) exhibit a lower likelihood of experiencing transportation insecurity overall and a lower propensity of experiencing any of the five specific insecurity outcomes.

4.2.4 Effects of Built Environment Characteristics

In terms of built environment characteristics, rural residents are less likely to experience transportation difficulties that cause them to skip trips or be unable to leave home (compared to their urban counterparts), most likely due to higher vehicle ownership and use rates in rural areas (Wang et al., 2025). Land use diversity is associated with a lower probability of experiencing transportation insecurity, presumably because of the greater access to a wider array of activity destinations that such environments foster (Suraweera et al., 2025). In particular, the propensity of skipping trips or arriving late is reduced in these environments simply because of the convenient proximity of activity locations. A higher car network density is associated with a higher propensity for skipping trips due to challenges with transportation. This may occur, for example, when individuals with limited access to an automobile find themselves in a car-intensive environment and end up needing to skip trips because they are unable to reach activity destinations (Bozovic et al., 2021). Individuals in areas of high transit accessibility experience higher levels of transportation insecurity overall (simply because of the reliance on fixed-route fixed-schedule public transit service) and have a greater tendency to arrive late due to challenges with transportation (likely caused by unreliable transit service). However, they are less prone to being unable to leave home or have relationships impacted, suggesting that transit accessible environments do facilitate additional travel opportunities that allow individuals to leave home and access social relationships (mitigating the most severe forms of transportation insecurity) even if they are less reliable.

4.2.5. Thresholds and Correlations between Latent Constructs and Main Outcomes

The thresholds presented in Table 3 (below the effects of the exogenous variables) are estimated to match the observed choice proportions in the sample. As such, they do not have substantially meaningful interpretations. Below the thresholds, three correlation terms are shown between the latent constructs and the main outcomes that are statistically significant. Each of these three correlation terms takes the same sign as the main effect of the latent construct on the respective outcomes (shown at the top of the table). This indicates that if these correlations were ignored, the effects of these latent constructs on the main outcomes would be overestimated. For instance, the positive correlation between perceived travel limitations and skipped trips suggests that there are unobserved factors that cause some individuals to be more likely to skip trips in general and to perceive themselves to have fewer mode options. This could be, for instance, a low level of perceived behavioral control that could lead to a perceived inability to use specific modes, such as public transit, as well as a greater propensity to skip trips when facing travel constraints.

4.2. Model Fit

The model goodness-of-fit measures are presented in the bottom portion of Table 3. The proposed GHDM (with calculated fit metrics shown in the central panel in the lower portion of Table 3) is compared to a restricted GHDM that does not allow for correlations between the latent constructs and the main outcomes (shown on the left in Table 3; that is, the restricted GHDM considers the matrix $\mathbf{\Omega}_{\mathrm{LN}}$ to be a zero matrix) and to an independent heterogeneous data model (IHDM) that does not consider any correlations between the main outcomes in the model (shown on the right in Table 3). To remove the dependencies between the main outcomes, the IHDM does not consider the latent constructs, which engender correlations among the outcomes, but considers all exogenous variables that indirectly (through the latent constructs) or directly affect the endogenous insecurity-related outcomes. Several goodness-of-fit metrics are presented in the table to show that the proposed GHDM outperforms both restricted models. Based on an examination of the log-likelihood values, Bayesian Information Criterion (BIC), and adjusted likelihood ratio index, the proposed GHDM with correlations is superior to the GHDM model that ignores the correlations between the latent constructs and main outcomes. The two GHDM models may also be compared using a formal log-likelihood ratio test. The test statistic of 264.33 is greater than the chi-square value at any reasonable level of significance, again confirming the suitability of the proposed GHDM model. However, because the IHDM does not include stochastic latent constructs, it is not nested within the GHDM framework. So, the IHDM is compared with the GHDM based on the predictive performance for the main outcomes (ignoring the latent construct components for the GHDM). At this predictive level, the proposed GHDM outperforms both the IHDM and restricted GHDM based on the predictive BIC and predictive adjusted likelihood ratio index. Additionally, while the GHDM and IHDM models are not nested, so cannot be compared using a formal likelihood ratio test, they may be compared using an informal non-nested likelihood ratio test. For this test, the probability that the difference between the predictive adjusted likelihood ratio index for the GHDM model ($\bar{\rho}^2_{GHDM}$) and the index for the IHDM model ($\bar{\rho}^2_{IHDM}$) could have occurred by chance is no larger than $\Phi\{-[-2(\bar{\rho}^2_{GHDM} - \bar{\rho}^2_{IHDM})\mathcal{L}(c) + (M_{GHDM} - M_{IHDM})]^{0.5}\}$, where $\mathcal{L}(c)$ is the log-likelihood at constant, and M is the number of non-constant parameters. Given the small value of this probability, the proposed GHDM model is preferred because it has a larger value of the adjusted likelihood ratio index. Once again, it can be observed that the proposed GHDM is superior in fit when compared with the two other model specifications, based on the suite of predictive performance metrics presented.

TABLE 3 Estimation Results of the Main Outcome Model Components

Explanatory Variables (base category*)		Any Transportation Insecurity Experience		Skipped Trip		Unable to Leave Home		Impacted Relationships		Arrived Late		Rescheduled Appointment	
		Binary: Yes or No (base)		*Ordinal Variables (3-Level): Never/Rarely, Sometimes, and Often*									
		Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Latent Constructs													
Perceived Transportation Limitations		0.190	2.17	0.413	4.42	0.532	5.78	0.382	3.71	0.323	2.91	0.447	3.40
Perceived Transportation Limitations × Age 65+ years		—		0.128	1.70	—		-0.179	-2.81	—		—	
Safety Consciousness		-0.216	-1.99	0.262	3.10	—		—		-0.145	-1.67	0.192	1.94
Safety Consciousness × Female		—		-0.123	-2.16	—		—		—		0.145	2.56
Safety Consciousness × Presence of children		—		-0.140	-2.90	—		—		—		—	
Congestion Sensitivity		0.339	3.38	-0.231	-1.78	-0.266	-2.12	—		0.246	1.67	—	
Congestion Sensitivity × Rural location		-0.141	-1.69	—		—		—		—		—	
Positive Travel Engagement		-0.218	-1.94	-0.556	-5.69	0.347	3.55	0.515	3.46	0.656	5.32	0.682	4.78
Positive Travel Engagement × Income $100,000 or more		-0.153	-1.87	—		—		—		—		—	
Individual Characteristics													
Gender (male)	Female	-0.231	-5.16	0.143	2.93	0.194	3.31	—		0.097	2.55	0.101	1.98
Age (18 to 24 years)	25 to 34 years	-0.450	-5.34	—		—		—		—		—	
	35 to 44 years	-0.480	-5.83	-0.139	-1.72	-0.155	-2.24	—		-0.101	-2.14	—	
	45 to 54 years	-0.824	-9.88	-0.263	-2.54	-0.355	-4.31	-0.255	-3.34	-0.226	-2.44	—	
	55 to 64 years	-1.137	-13.06	-0.397	-3.05	-0.449	-4.39	-0.304	-3.47	-0.411	-4.13	-0.141	-1.75
	65 years or older	-1.348	-13.31	-0.775	-4.28	-0.635	-4.68	-0.374	-4.02	-0.535	-4.84	-0.457	-4.38
Ethnicity (not Hispanic)	Hispanic	—		0.189	2.47	0.159	2.49	—		0.093	1.74	—	
Education (less than high school)	High school	—		—		-0.230	-1.83	—		—		-0.132	-1.65
	Some college/technical school	—		—		-0.297	-2.32	—		—		-0.170	-1.73
	Bachelor's degree(s) or higher	-0.126	-2.64	—		-0.571	-4.37	—		—		-0.453	-2.93
Employment status (neither employed nor retired)	Employed	-0.179	-3.09	-0.185	-2.37	-0.109	-2.03	—		—		—	
	Retired	-0.196	-2.99	—		-0.138	-1.72	—		—		—	
Household Characteristics													
Household income (less than $25,000)	$25,000 - $49,999	-0.350	-5.19	—		—		—		—		-0.206	-2.34
	$50,000 - $99,999	-0.591	-8.58	—		—		—		—		-0.287	-3.28
	$100,000 - $199,999	-0.673	-8.38	0.137	3.19	—		0.084	1.68	—		-0.319	-3.29
	$200,000 or more	-0.867	-6.61	0.137	3.19	—		0.084	1.68	—		-0.323	-2.84
Presence of children (none)	One or more	0.093	2.80	—		—		—		—		0.217	3.50
Household composition (multi-adult family)	Single adult	-0.227	-3.78	-0.148	-1.69	-0.129	-1.65	—		—		—	

TABLE 3 (Continued)

Explanatory Variables (base category)		Any Transportation Insecurity Experience		Skipped Trip		Unable to Leave Home		Impacted Relationships		Arrived Late		Rescheduled Appointment	
		Binary: Yes or No (base)		*Ordinal Variables (3-Level): Never/Rarely, Sometimes, and Often*									
		Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Home type (single-family)	Apartment	—		—		-0.121	-1.82	—		—		—	
Tenure type (own or other)	Rent	0.161	3.16	0.359	4.64	0.293	4.57	—		0.183	3.02	—	
Vehicle ownership (deficient)	Sufficient	-0.224	-8.96	-0.163	-4.88	-0.130	-4.63	-0.174	-6.36	-0.157	-5.14	-0.212	-6.69
***Built Environment Characteristics* (^)**													
Location (urban)	Rural	—		-0.189	-1.87	-0.165	-1.95	—		—		—	
Land-use diversity (continuous)		-0.500	-3.18	-0.439	-1.71	—		—		-0.304	-1.76	—	
Car network density (continuous)		—		0.118	7.32	—		—		—		—	
Transit accessibility (continuous)		0.411	3.44	—		-0.150	-1.73	-0.332	-3.01	0.296	2.69	—	
Thresholds													
1|2		-2.706	-22.46	-1.450	-8.96	-1.188	-8.20	-0.214	-3.69	-0.861	-7.03	-0.943	-5.93
2|3		—		0.743	4.39	0.452	3.03	0.941	15.43	1.089	8.90	0.732	4.57
Correlations													
Positive Travel Engagement		—		-0.30	-2.80	—		—		—		—	
Perceived Travel Limitations		—		0.27	2.32	0.11	1.67	—		—		—	

Data Fit Measures	GHDM (without correlations)	GHDM (proposed)	IHDM
Log-likelihood at convergence	-167135.87	-167003.70	-25907.33
Log-likelihood at constants	-170445.15	-170445.15	-27902.01
Number of non-constant parameters	168	171	146
Bayesian information criterion	168156.03	168037.34	26828.62
Adjusted likelihood ratio index	0.018	0.019	--
Likelihood ratio test	264.33		--
Predictive log-likelihood at convergence	-25801.23	-25782.48	-25907.33
Predictive log-likelihood at constants	-27902.01	-27902.01	-27902.01
Predictive Bayesian information criterion	26821.39	26816.13	26828.62
Predictive adjusted likelihood ratio index	0.069	0.070	0.066
Informal predictive likelihood ratio test	37.48		--
Informal predictive non-nested likelihood ratio	--	-14.99	
Average probability of correct prediction	0.225	0.235	0.220

Note: Coef. = coefficient; "—" = not statistically significant at the 90% confidence level. (*) Base category is not identical across the model equations and corresponds to "listed base category" and all omitted categories. (^) Land-use diversity reflects the balance between trip production and attraction; car network density is link-miles per square mile; transit accessibility is the share of jobs within ½ mile of a fixed-guideway transit stop.

4.3. Average Treatment Effects

The estimated coefficients presented in Table 3 represent the effects of exogenous variables on the underlying propensities for each of the outcomes after accounting for indirect effects through the latent constructs. As such, they do not provide the sign and true magnitude of the effects of each of the exogenous variables on the probability of experiencing each of the possible outcomes at each ordinal level. In order to quantify and understand the total effects of exogenous variables on transportation insecurity outcomes, average treatment effects (ATEs) are computed and presented in Table 4. The ATEs represent the change in the proportion of individuals who exhibit a specific outcome when the exogenous variable is changed from a baseline level to a treatment level. In other words, ATEs reflect the impacts of a treatment on an endogenous variable of interest.

In Table 4, ATEs are shown for all six endogenous variables of interest in this study. For computational convenience and ease of interpretation, the share of individuals *not* experiencing each dimension of transportation insecurity (that is, never experiencing any transportation insecurity overall or responding "Never or Rarely" to each specific experience) is computed for the baseline and treatment levels (based on the direct effects of the exogenous variables as well as indirect effects of these variables through the latent constructs). The difference in the share of individuals not experiencing transportation insecurity outcomes then represents the ATE presented in the table. It should be noted that this table uses the share of individuals *not* experiencing each dimension of insecurity, so that a positive effect (ATE) refers to an improvement in overall transportation outcomes/experiences, which is the opposite of the interpretation of a positive coefficient in Table 3. Also, for compactness, the ATEs are presented only for the two extreme categories for any exogenous variables that can take multiple states. For instance, for age, Table 3 only presents the change from the lowest age category to the highest.

The interpretation of the values shown in Table 4 is as follows. In the first row, the effect of shifting from a baseline level of male to a treatment level of female is documented. The total effect of this shift is 0.075 for not experiencing any transportation insecurity overall. This means that a change in sample composition from 1000 men to 1000 women would see 75 more instances of individuals not experiencing any transportation insecurity. In terms of the incidence of specific transportation insecurity experiences, there would be 68 fewer individuals "never or rarely" skipping trips, 55 fewer individuals "never or rarely" being unable to leave home, 35 more individuals "never or rarely" having relationships impacted, 29 more individuals "never or rarely" arriving late, and 19 more individuals "never or rarely" having to reschedule appointments in the sample of 1000 women compared with 1000 men (these outcomes are not, however, mutually exclusive and hence the numbers are not additive). The remainder of Table 4 may be interpreted in a similar fashion.

In most instances, the average treatment effects are rather modest. There are, however, a few instances where the ATEs are more pronounced. For example, in the case of age, a shift from 18-24 years of age to 65 years or older is associated with an ATE of 0.448 for not experiencing any transportation insecurity overall. This means that a 1000-person sample of 65+ year-old individuals would have about 448 fewer instances of experiencing transportation security overall than a corresponding 1000-person sample of 18–24-year-old individuals. This is quite a substantial shift, suggesting that those in the youngest age group experience considerable transportation insecurity. The ATEs are all positive in that row, indicating that 65+-year-old individuals are also better off in terms of being less likely to experience all of the specific types of transportation insecurity compared with 18–24-year-old individuals.

At the bottom of the table, the influence of the latent constructs may be discerned. An increase of a unit on the transportation limitations perception scale is associated with an ATE of -0.053, suggesting that if 1000 people experienced a unit increase in this latent construct (perceived transportation limitations), 53 additional instances of transportation insecurity experience would result. It is clear, then, that policies aimed at reducing transportation limitations (especially for transportation disadvantaged groups) could go a long way in reducing the incidence of transportation insecurity experiences. On the other hand, a unit increase in the positive travel engagement construct would be associated with 78 fewer instances of individuals experiencing transportation insecurity overall (in a sample of 1000 individuals) as evidenced by the ATE value of 0.078. In the same row, it is seen that a unit increase in positive travel engagement would be met with a mix of changes in the proportion of individuals experiencing specific types of insecurity. For example, in a sample of 1000 individuals, there would be 132 more individuals "never or rarely" skipping trips (by virtue of an increase in positive travel engagement), but 103 fewer individuals "never or rarely" being unable to leave home, 173 fewer individuals "never or rarely" having impacted relationships, 159 fewer individuals "never or rarely" arriving late, and 183 fewer individuals "never or rarely" rescheduling appointments. The results show that being sensitive to traffic congestion and having positive perceptions about travel lead to the highest impacts on transportation insecurity experience overall, with congestion sensitivity leading to higher stated experiences of transportation insecurity and positive travel perceptions leading to lower stated experiences of transportation insecurity. Also, positive travel perception, as a latent construct, appears to consistently be a strong determinant (relative to other latent constructs) in affecting the experience of each type of insecurity.

TABLE 4 Average Treatment Effects (ATEs)

Variable	Base	Treatment	Any Transportation Insecurity Experience	Skipped Trip	Unable to Leave Home	Impacted Relationships	Arrived Late	Rescheduled Appointment
Individual Characteristics								
Gender	Male	Female	0.075	-0.068	-0.055	0.035	0.029	0.019
Age	18 to 24 years	65 years or older	0.448	0.104	0.165	0.150	0.285	0.198
Race	White	Non-White	0.041	0.084	0.051	-0.001	-0.021	-0.007
Ethnicity	Not Hispanic	Hispanic	0.003	-0.021	-0.007	0.022	-0.015	0.023
Education	Less than high school	Graduate degree(s)	0.000	-0.001	0.149	-0.049	-0.064	0.074
Employment status	Not employed	Employed	0.102	0.152	0.076	-0.027	-0.052	-0.039
Retirement status	Not retired	Retired	0.027	0.013	-0.003	-0.019	-0.023	-0.024
Household Characteristics								
Household income	Less than $25,000	$200,000 or more	0.244	0.075	0.069	-0.056	-0.090	0.061
Presence of children	None	One or more	-0.018	0.005	-0.005	-0.024	-0.028	-0.096
Household composition	Multi-adult family	Single adult	0.068	0.052	0.061	0.015	0.009	0.020
Home type	Single-family home	Apartment	0.023	0.022	0.084	0.033	0.031	0.034
Tenure type	Own	Rent	-0.023	-0.061	-0.055	0.030	-0.021	0.034
Vehicle ownership	Vehicle deficient	Vehicle sufficient	0.060	0.036	0.039	0.059	0.041	0.059
Built Environment Characteristics								
Location	Urban	Rural	0.006	0.044	0.051	--	--	--
Land-use diversity	Current values	50% increase	0.059	0.042	--	--	0.035	--
Car network density	Current values	50% increase	--	-0.027	--	--	--	--
Transit accessibility	Current values	50% increase	-0.007	--	0.003	0.008	-0.005	--
Latent Constructs								
Perceived Transportation Limitations	Current value	1 Unit Increase*	-0.053	-0.096	-0.153	-0.116	-0.085	-0.125
Safety Consciousness	Current value	1 Unit Increase*	0.063	-0.056	--	--	0.042	-0.033
Congestion Sensitivity	Current value	1 Unit Increase*	-0.086	0.054	0.082	--	-0.066	--
Positive Travel Engagement	Current value	1 Unit Increase*	0.078	0.132	-0.103	-0.173	-0.159	-0.183

*Since the latent constructs are unitless, a "1 unit increase" refers to a change normalized to the scale of the error components, which is fixed to 1 for identification purposes.

5. DISCUSSION AND CONCLUSIONS

Transportation is vital to quality of life and wellbeing. Transportation makes it possible for people to access jobs and opportunities, fulfill activities, and interact with friends, family, and society at large. For this reason, the notion of transportation insecurity is important and has received considerable attention in recent years. Those who experience transportation insecurity (regardless of reason) may not be able to fully participate in society and access opportunities and destinations, thus diminishing their quality of life and social interactions. This study aims to shed deep insights into the prevalence and impacts of transportation insecurity in the United States.

The analysis is conducted using data collected from the Transportation Heartbeat of America (THA) survey administered nationwide in late 2024 and early 2025. The data set includes more than 8,000 responses from across the nation and contains detailed socio-economic, demographic, travel and mobility, and attitudinal information for the respondents. The survey included specific questions probing whether individuals experienced any transportation insecurity and the ways in which the transportation insecurity manifested itself in terms of outcomes. Thus, the survey gathers information on five important outcomes related to transportation insecurity, namely, the need to skip trips, being unable to leave home, having relationships with others adversely affected, arriving late at destinations, or needing to reschedule appointments.

The simple descriptive analysis of the data shows that more than one-half of the sample experienced transportation insecurity of some sort. This suggests that transportation insecurity is quite prevalent, potentially impacting quality of life and wellbeing for a sizable fraction of the population. Among the outcomes for those who experienced transportation insecurity, a higher fraction reported skipping trips and arriving late, while a smaller fraction reported experiencing adverse impacts on relationships with others. The analysis then involved estimating a multivariate econometric model system of the endogenous variables together with latent attitudinal constructs. The model takes the form of a multivariate ordered probit with six outcome variables and four latent attitudinal constructs.

Both model estimation results and average treatment effects reveal that socio-economic, demographic, and attitudinal factors shape transportation insecurity outcomes. Most notably, those who perceive having transportation limitations are more likely to experience transportation insecurity outcomes of all types. Sensitivity to congestion is associated with a higher probability of experiencing transportation insecurity, with late arrival being the way that congestion usually manifests itself. Those who enjoy traveling experience lower prevalence of transportation insecurity, but are more likely to arrive late, have to reschedule appointments, and have relationships impacted, presumably because they are attempting to travel more than their schedules can accommodate

An interesting finding is that the incidence of transportation insecurity decreases with age, with older individuals (65 years or older) being the least likely to experience transportation insecurity. This trend is seen across the board for all insecurity outcomes, indicating that older adults are more adept at navigating challenges associated with transportation to limit the impacts on their social interactions. Similarly, the level of transportation insecurity decreases with increasing income; however, those in the highest income groups show a higher probability of experiencing situations where relationships are impacted and trips have to be skipped (likely due to busy lifestyles). Presence of children is associated with a higher probability of experiencing transportation insecurity and having to reschedule appointments. Renters experience a higher probability of transportation insecurity overall (compared with homeowners), and for multiple outcomes; higher levels of vehicle ownership, on the other hand, are associated with a lower probability of transportation insecurity experiences. A diverse land-use environment also reduces the probability of experiencing transportation insecurity.

Overall, the study findings show that transportation insecurity is real and experienced by a majority of individuals; however, there is considerable heterogeneity in transportation insecurity experiences across demographic and attitudinal groups. Notably, our findings highlight that the actual ways that transportation insecurity manifests are widely varied across population groups, as different individuals experience different constraints and adapt to transportation challenges in different ways. Steps to reduce transportation insecurity for all impacted groups would help enhance quality of life and access to opportunities. This need to address transportation insecurity is especially salient for low-income individuals, individuals who experience congestion, younger individuals, individuals in households that are vehicle-deficient (own fewer cars than drivers), live in less diverse land-use environments, and have perceived transportation limitations. Providing and investing in alternative mobility options and specialized (and subsidized) transportation services that cater to the mobility needs of these subgroups would go a long way in reducing transportation insecurity and enhancing quality of life for these transportation disadvantaged groups. Improving the positive travel engagement (latent attitudinal construct) by improving facilities for walking and bicycling, as well as providing comfortable and reliable transit service conducive to multitasking (while traveling) would help enhance the travel environment and reduce transportation insecurity, particularly with respect to foregoing trips completely, but also for reductions of other types of transportation insecurity.

ACKNOWLEDGMENTS
This research was partially supported by the National Center for Understanding Future Travel Behavior and Demand (TBD), which is a University Transportation Center sponsored by the US Department of Transportation under grant numbers 69A3552344815 and 69A3552348320.

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