Understanding Public Perceptions of Congestion Pricing – A U.S. Perspective

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ABSTRACT
Despite theoretical and practical advantages of congestion pricing as a policy instrument to reduce traffic congestion, implementation of such policies in the real world faces public opposition, as seen in the context of New York City's recent congestion pricing program. At the same time, there has not been adequate investigation of public perceptions – especially the perceived (un)fairness of congestion pricing – that underlie such opposition in the United States. To that end, this study examines demographic, employment, built environment, and attitudinal factors affecting individuals' perceived fairness of congestion pricing, using data from the first wave of the Transportation Heartbeat of America (THA) Survey conducted from October 2024 through January 2025. Results suggest that more than 65 percent of Americans believe congestion pricing is unfair, and the percentage is higher for those who view travel as a positive experience, prefer a suburban lifestyle, commute frequently over long distances, own multiple vehicles, and are middle-aged. In contrast, those who feel a strong burden from traffic congestion, live in the New York City area, and have high formal educational attainment perceive congestion pricing as relatively more fair. These findings highlight the important role of personal attitudes and socio-demographic factors in shaping fairness perceptions of congestion pricing, and offer insights for the design and implementation of publicly acceptable congestion pricing policies.

Keywords: Transportation system fairness, Transportation policy, Congestion pricing, Attitudes, Lifestyle factors, GHDM model

1. INTRODUCTION

Congestion pricing is a transportation policy instrument that is often viewed as a mechanism to reduce traffic congestion, improve traffic flow, reduce vehicular travel and associated emissions, and raise revenue for transportation infrastructure and public transit systems (Federal Highway Administration, 2008). Congestion pricing generally involves charging drivers a fee for using roads or entering certain areas (such as downtowns or central business districts) during peak traffic hours. The goal is to reduce traffic congestion by encouraging people to travel at non-peak hours, use alternative routes, visit alternative destinations, or switch to alternative modes of transportation such as public transit. Congestion pricing mechanisms may take several forms, including *cordon pricing,* where a fee is charged to enter a specific area (usually a downtown zone) such as in London or Stockholm – and more recently, New York City; *area-wide pricing* where charges are levied during peak hours for driving anywhere within a defined zone; *variable tolls* on congested corridors with toll rates changing based on traffic congestion levels, with higher prices during rush hours; and *distance-based pricing* where charges are based on how far a driver travels in a congested area (De Palma and Lindsey, 2011).

Although there has been interest in the concept of congestion pricing in the United States for many years, the policy is seeing particularly renewed interest in light of the recent implementation of the New York City congestion pricing policy. Launched in January 2025, the New York City implementation marked the first such initiative in the United States and has generated considerable controversy, with supporters lauding its potential to reduce congestion and emissions and raise much needed revenue for public transit, and detractors criticizing the policy for its regressive nature and potential loss of patronage for businesses and offices in the priced zone. In fact, this was not the city's first attempt at introducing congestion pricing, as a previous effort in 2007 was ultimately abandoned due to insufficient public support (Schaller, 2010).

In the U.S., in particular, it has been difficult to implement pricing-based policies because of the real or perceived lack of broad support for such measures. Individual support for congestion pricing or similar policies is influenced by various factors, with perceptions of fairness appearing to be consistently significant and important (Jakobsson et al., 2000; Sun et al., 2016). While people generally recognize and value congestion relief and environmental benefits that may result from the implementation of a pricing policy, whether or not the pricing policy is considered fair tends to be more complex and nuanced (Oberholzer-Gee and Weck-Hannemann, 2002). On the one hand, people may view congestion pricing as unfair if it disadvantages them personally; on the other hand, they may also consider it fair if they perceive the policy as bringing about broader societal benefits even at their own personal expense (Jakobsson et al., 2000).

Because of the potential for pricing-based policies to bring about a variety of desired transportation and societal outcomes, it is not surprising that there has been considerable interest in the study of perceptions of fairness towards pricing-based policies (besides examining the potential or actual impacts of such policies). For example, Schuitema et al. (2011) found that transportation pricing policies were perceived as more fair when they were seen as protecting the environment for future generations and affecting everybody equally. Eliasson (2016) attempted to draw a distinction between consumer and citizen perspectives in examining perceptions of fairness of congestion pricing policies. Consumer perspective reflected the economic welfare accrued to society due to the implementation of the congestion pricing policy, while the citizen perspective reflected the extent to which the policy aligned with individual social values and perceptions of fairness, independent of their personal economic interests. Other studies have examined fairness in broader terms beyond mere economic aspects. For example, Selmoune et al. (2022) emphasized that the concept of fairness should be expanded to consider potential for evasion of payment, accommodation of special groups such as persons with disabilities, and broad stakeholder engagement to ensure all voices are heard in policymaking. Krabbenborg et al. (2020) found that one of the key aspects in the assessment of fairness is the extent to which effective transportation alternatives are available to the public. While people appreciate the problems that congestion pricing aims to solve, they view it as a policy that favors high-income groups and would rather see effective transportation alternatives, such as public transit, expanded to realize similar benefits or outcomes. Beyond fairness considerations, studies have examined issues related to transparency, perceived effectiveness, equity considerations, and general attitudes toward congestion pricing. Axsen and Wolinetz (2021) conducted a review of road pricing research and highlighted the importance of providing detailed information about pricing structures, including exemptions and billing procedures, in addressing implementation concerns. Schade and Schlag (2003) found that, although road pricing does not garner broad support among drivers, factors such as social norms, equity perceptions, and perceived effectiveness (in delivering benefits) are positively related to acceptance. Some studies also have shown that latent attitudinal factors, such as being pro-environment and pro-taxation, affect support for congestion pricing (Hess and Börjesson, 2019) and that distrust related to fairness plays a greater role in determining acceptance than doubts about the potential effectiveness of the policy in delivering benefits (Wang et al., 2019).

In contrast to the studies above that focus on fairness perceptions, effectiveness, equity considerations, and general attitudes, prior research has also examined factors that affect acceptance towards congestion pricing. Gu et al. (2018) reviewed acceptance of congestion pricing policies in cities that both implemented and rejected such policies. They found four key factors that affect public acceptance, including privacy, equity, simplicity, and uncertainty. Similarly, De Borger and Proost (2012) and Milenković et al. (2019) showed that investing revenue from the congestion pricing policy to improve public transportation positively impacts acceptance of the pricing policy, while Zheng et al. (2014) showed that the presence and availability of good public transportation service (as an alternative to driving) is also positively correlated with congestion pricing acceptance. In other words, ensuring that travelers have reasonable alternatives to driving (if they wish to avoid paying the congestion price) would help enhance acceptance of congestion pricing policies. Souche et al. (2012) emphasized the need to ensure that accommodations were made for special groups to enhance acceptability of pricing policies. These included exemptions for emergency vehicles and travelers with disabilities, along with reduced rates for low-income travelers and carpool users. Recent research has also found that, even when there is initial resistance to pricing based policies, acceptance tends to increase after implementation (Veitch and Rhodes, 2024) – with the use of the revenue derived playing a significant role in shaping post-implementation perceptions. A similar trend has been seen in the case of the New York congestion pricing policy. Public opinion appears to be shifting, with polls showing increased support for the program after its implementation. A Siena College poll in December, before the program launched, found only 32% of New York City voters in favor, while 52% were in opposition. By March 2025, support rose to 42%, with 33% opposing (NBC New York, 2025).

It is clear that public perceptions of congestion pricing are critical determinants of the potential acceptance and effectiveness of congestion pricing policies. Because of the limited experience with congestion pricing in the U.S., there is also limited evidence of public perceptions of such policies. This study aims to fill this critical gap to help inform the design and implementation of pricing policies in the United States, with a focus on congestion pricing – similar to that implemented in New York City. This research extends the body of literature by providing a comprehensive understanding of fairness perceptions of congestion pricing in the United States based on a recent nationwide survey conducted in late 2024 and early 2025. The study also explicitly accounts for attitudes and lifestyle preferences in assessing the factors that influence perceptions of fairness of congestion pricing measures. Using a Generalized Heterogeneous Data Model (GHDM) framework, the model system presented in this paper provides a systematic approach to assess the impacts of socio-economic, demographic, and attitudinal factors on public perceptions of congestion pricing fairness. Through this effort, the study provides insights on strategies that cities and communities contemplating such measures could use to enhance public support for pricing policies.

The remainder of this paper is organized as follows. The next section provides a detailed description of the survey and data set used in this study. The third section presents the modeling framework and methodology, while the fourth section presents model estimation results in detail. The fifth section presents average treatment effects to illustrate the impacts of different variables and latent factors on perceptions of congestion pricing. Finally, the sixth section offers concluding thoughts.

2. DATA DESCRIPTION

This section presents a summary of the survey and data set used in this study. An overall description of the survey and sample is presented first, while a more detailed description of endogenous variables and latent attitudinal factors is presented second.

2.1. Survey Overview and Sample Characteristics

The data used in this study is derived from the first wave of the Transportation Heartbeat of America (THA) Survey, conducted from October 2024 through January 2025 in the United States. The THA Survey is a nationwide survey aimed at obtaining detailed information about people's socio-economic and demographic characteristics, traveler behavior and values, mobility patterns and choices, activity-travel demand, attitudes and perceptions, and lifestyle preferences and personality traits. The survey was administered to a nationwide online survey panel assembled by a commercial firm, with specific sample quotas specified for a wide array of socio-economic and demographic variables to ensure that the respondent sample captured the variation in attributes that exists in the population as a whole. A total of 8,212 responses were obtained for the nationwide THA survey.

Following the collection of the survey data, built environment variables, including population density, employment density, and network density, were appended to the survey records using information from the Smart Location Database 3.0 provided by the Environmental Protection Agency (EPA, 2021). As the built environment data is provided at the census block group level and the THA survey collected residential locations at the zip code level, the area-weighted average of the census block group level data is used to append built environment measures to the survey records. This exercise resulted in the loss of a few survey data records (due to inability to match geographies), resulting in a final sample size of 8,030 respondents.

Table 1 shows the socio-economic and demographic characteristics of the final sample used in this study, along with the distributions of the endogenous variables of interest. In general, the sample exhibits distributions across attributes suitable for undertaking a multivariate econometric modeling exercise such as that undertaken in this study. There is a slightly larger percent of women compared to men. All age groups are well represented in the data set, with 21.3 percent aged 65 years or older. About 44 percent of respondents are non-workers, and 46 percent are full-time workers. About one-third of the sample has an educational attainment of high school or less, while 14.8 percent have a graduate degree. About 65 percent of the sample is White, while 15.4 percent is Black; nearly 80 percent classify as non-Hispanic. In terms of income, 17.1 percent report annual household income less than $25,000, while 11.1 percent report household incomes of $150,000 or more, thus depicting a healthy range of variation in household income. While just under 20 percent of respondents report a household size of one person, it is found that 47.8 percent report residing in households with three or more persons. Two-thirds of respondents reside in stand-alone homes, and just under 60 percent report owning their home. Just over 50 percent of respondents reside in households with two or more cars, while 8.5 percent reside in households with zero cars. Close to 20 percent of respondents reside in rural areas. In general, the sample depicts variation appropriate for estimating multivariate statistical and econometric model systems.

TABLE 1 Socio-Economic and Demographic Characteristics of the Sample

Individual Demographics (N=8,030)		***Household Characteristics (N=8,030)***	
Variable	**%**	**Variable**	**%**
Gender		**Household annual income**	
Woman	53.3	Less than $25,000	17.1
Man	46.7	$25,000 to $49,999	22.0
Age category		$50,000 to $99,999	30.5
18 to 24 years	12.6	$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	21.3	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	66.6
Non-worker	43.5	Attached home/apartment	27.1
Education attainment		Other	6.3
High school or less	33.0	**Home ownership**	
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	65.4	Two	34.1
Other	11.6	Three or more	16.8
Ethnicity		**Location**	
Hispanic	20.1	Urban	80.4
Non-Hispanic	79.9	Rural	19.6
Main Outcome Variable			
"Congestion pricing (charging drivers at busy times) is unfair."			
Strongly disagree			4.5
Somewhat disagree			7.5
Neutral			23.5
Somewhat agree			30.4
Strongly agree			34.1

2.2. Endogenous Variables and Attitudinal Indicators

The endogenous variable of this study is *Congestion Pricing Unfairness*. This variable is derived from the survey question that asked respondents to rate, on a five-point Likert scale, the extent to which they agree with the following statement: *Congestion pricing (charging drivers at busy times) is unfair*. The distribution of responses to this statement is shown in the bottom panel of Table 1. The distribution shows that about 65 percent of respondents somewhat agree or strongly agree with this statement, indicating that a majority of respondents feel that congestion pricing is unfair. While 23.5 percent indicate that they are neutral about congestion pricing, a total of 12 percent somewhat disagree or strongly disagree with this statement – thus indicating that only a small minority of respondents feels that congestion pricing is not unfair. This finding is quite consistent with the strong public opposition to congestion pricing reported in other surveys (e.g., Siena College Research Institute, 2024).

The THA survey also included a battery of attitudinal statements designed to gather deep insights about respondent attitudes, perceptions, lifestyle preferences, personality traits, and opinions about various aspects of transportation systems, services, and policies. These attitudinal statements, measured using 5-level Likert scales, were used to construct a set of latent constructs that are treated as endogenous in the modeling framework. By including a set of attitudinal constructs in the model framework, it is possible to explicitly account for such factors and more accurately assess the influence of socio-economic and demographic variables on the key behavioral endogenous variable of interest. The latent constructs were identified through an exploratory factor analysis (EFA) followed by a confirmatory factor analysis (CFA). After extensive testing of alternative specifications and factor constructs, three final constructs were developed and retained based on their statistical significance, behavioral intuitiveness, relevance to the key endogenous variable of interest, interpretability, and consistency with prior literature on factors influencing public opinion toward congestion pricing (Hamilton et al., 2014; Hess and Börjesson, 2019). The final constructs used in this study, as depicted in Figure 1, are: *Congestion Burden Perception (CBP)*, *Positive Travel Engagement (PTE)*, and *Suburban Lifestyle (SL)*.

While CBP and PTE are indicated by three attitudinal statements each, SL is indicated by two attitudinal statements. The distributions of responses to these attitudinal statements are shown in Figure 1. The CBP factor captures perceptions of traffic congestion as a burden and efforts made to avoid congestion; PTE represents a positive outlook toward travel experiences and making productive use of travel time; and SL reflects a preference for lower-density, privacy-oriented residential environments. As the distributions shown in Figure 1 are self-explanatory, a detailed discussion of each attitudinal statement is not provided here in the interest of brevity. In general, it is found that a majority of respondents make efforts to adjust their schedule to avoid traffic congestion, and only 40 percent somewhat agree or strongly agree that they would be willing to pay more money to have a faster trip. About two-thirds of respondents indicate that they somewhat or strongly agree that they enjoy the act of traveling itself, indicating that travel may not be perceived as all that burdensome by many. About 62 percent somewhat or strongly agree that apartment living does not provide enough privacy. These attitudinal factors provide a rich basis for reflecting the influence of attitudes and perceptions in the joint econometric model system formulated and estimated in this study.

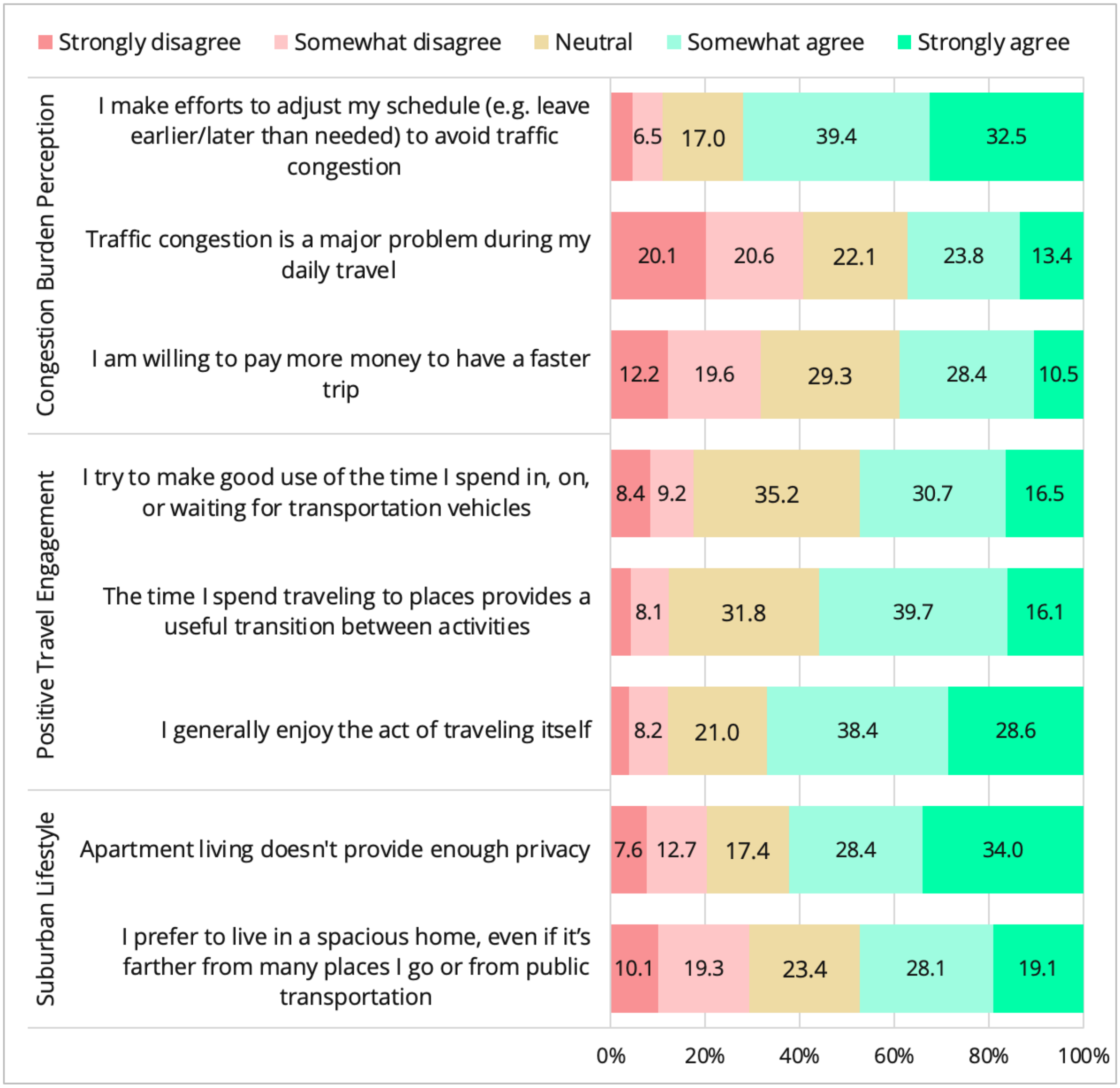

Figure 1. Agreement with Attitudinal Indicators Defining Latent Constructs (N=8,030)

3. MODELING FRAMEWORK

This section presents the model structure and framework adopted in this study. A qualitative depiction of the modeling methodology is presented first, followed by the details of the formulation and estimation methodology.

3.1. Model Structure

A simplified representation of the overall model structure adopted in this study is depicted in Figure 2. The main outcome variable, *Congestion Pricing Unfairness*, which is an ordered-response outcome, appears on the right hand side of the figure. Individual attributes that may be considered exogenous in nature for purposes of this study, such as socio-economic, demographic, and other characteristics, are depicted on the left hand side of the figure. The exogenous variables influence the main outcome variable (congestion pricing unfairness) directly and indirectly through the three stochastic latent constructs – Congestion Burden Perception (CBP), Positive

Travel Engagement (PTE), and Suburban Lifestyle (SL). These latent constructs are positioned in the middle of the figure between the exogenous variables and the main outcome variable. For simplicity of representation, the mappings of the latent constructs to their respective attitudinal indicators are not shown in the figure. The model structure accounts for correlations across the latent constructs as depicted by the curved double-arrows.

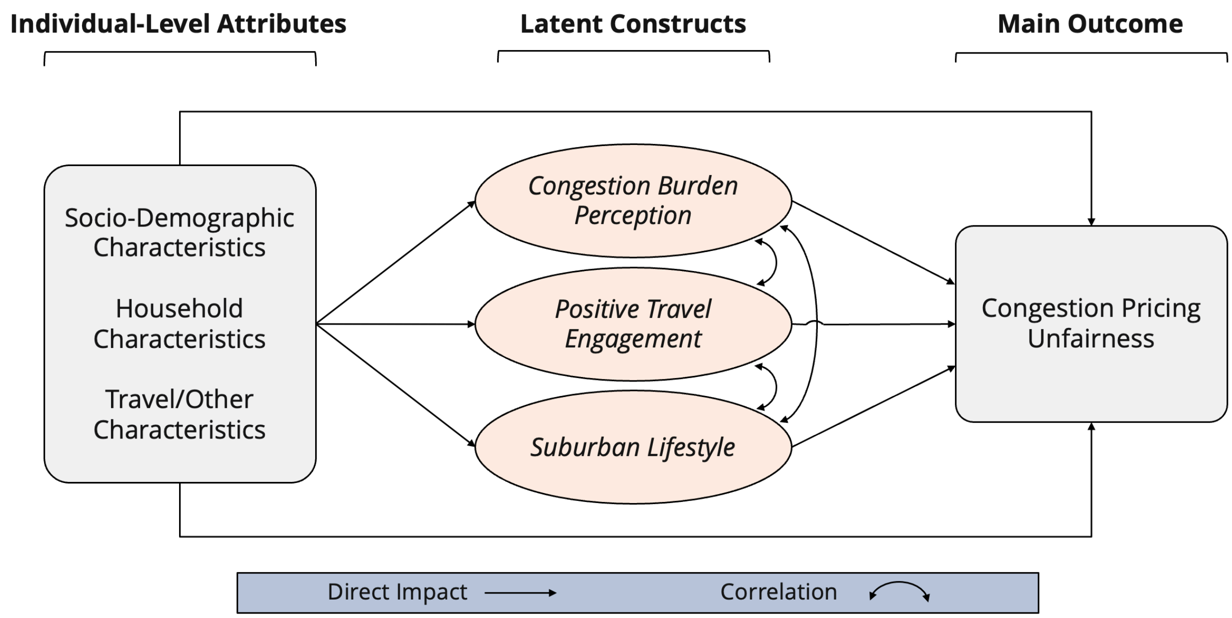

Figure 2. Model Framework

The model system is estimated using the Generalized Heterogeneous Data Model (GHDM) framework and methodology developed by Bhat (2015). The GHDM framework enables the analysis of how exogenous variables influence the outcome variable both directly and indirectly through three latent constructs. In this application, all attitudinal indicators associated with the three latent constructs, as well as the main outcome variable of interest, are ordinal in nature. While a detailed discussion of the methodology and technical aspects of the estimation process can be found in Bhat (2015), a concise description of the model estimation as applied in this study is presented below.

3.2. Model Estimation Methodology

Consider the case of an individual $q \in \{1,2,...,Q\}$. Let $l \in \{1,2,...,L\}$ be the index of the latent constructs (in this study $L=3$), and let z_{ql}^* be the value of the latent variable l for the individual q. All latent constructs for individual can be expressed in matrix form as,

$$\boldsymbol{z}_q^* = \boldsymbol{w}_q \boldsymbol{\alpha} + \boldsymbol{\eta}_q \tag{1}$$

where $\boldsymbol{z}_q^*$ $(L \times 1)$ is a column vector of all the latent variables, $\boldsymbol{w}_q$ $(L \times D)$ is a matrix of the explanatory variables of latent variables, and $\boldsymbol{\alpha}$ $(D \times 1)$ is a vector of its coefficients. $\boldsymbol{\eta}_q (L \times 1)$ is the unexplained error term vector and is assumed to follow a multivariate normal distribution centered at the origin and having a correlation matrix of $\boldsymbol{\Gamma}$ $(L \times L)$, i.e., $\boldsymbol{\eta}_q \sim MVN_L(\boldsymbol{0}_L, \boldsymbol{\Gamma})$, where

$\mathbf{0}_L$ is a vector of zeros. The variance of all the elements in $\boldsymbol{\eta}_q$ is fixed as unity because it is not possible to uniquely identify a scale for the latent variables.

Next, let $j \in \{1,2,...,J\}$ denote the index of the outcome variables (including the eight attitudinal indicators and one main outcome variable, so in this study $J = 9$). Let y_{qj}^* be the underlying continuous measure associated with the outcome variable y_{qj}. Then,

$$y_{qj} = k \text{ if } \psi_{jk} < y_{qj}^* \leq \psi_{j(k+1)}, \tag{2}$$

where $k \in \{1,2,...,K_j\}$ denotes the ordinal category assumed by y_{qj} and ψ_{jk} denotes the lower boundary of the k^{th} discrete interval of the continuous measure associated with the j^{th} outcome. $\psi_{jk} < \psi_{j(k+1)}$ for all *j* and all *k*. Since y_{qj}^* may take any value in $(-\infty,\infty)$, we fix the value of $\psi_{j1} = -\infty$ and $\psi_{j(K_j+1)} = \infty$ for all *j*. y_{qj}^* is expressed as a function of explanatory variables and latent constructs:

$$y_{qj}^* = \boldsymbol{x}_{qj}^{\mathrm{T}}\boldsymbol{\beta} + \boldsymbol{z}_q^{*\mathrm{T}}\boldsymbol{d}_j + \xi_{qj}, \tag{3}$$

where $\boldsymbol{x}_{qj}$ is an $(E \times 1)$ vector of explanatory variables not including a constant. $\boldsymbol{\beta}$ $(E \times 1)$ is a column vector of the coefficients associated with $\boldsymbol{x}_{qj}$ and $\boldsymbol{d}_j$ $(L \times 1)$ is the vector of coefficients of the latent variables $\boldsymbol{z}_q^*$ for outcome *j*. ξ_{qj} is a stochastic error term that captures the effect of unobserved variables on y_{qj}^*. ξ_{qj} is assumed to follow a standard normal distribution. Jointly, the continuous measures of the eight indicator variables and the single main outcome variable (for a total of *J*=9 ordinal variables) may be expressed as,

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\boldsymbol{z}_q^* + \boldsymbol{\xi}_q, \tag{4}$$

where $\boldsymbol{y}_q^*$ $(J \times 1)$ and $\boldsymbol{\xi}_q$ $(J \times 1)$ are the vectors formed by vertically stacking y_{qj}^* and ξ_{qj}, respectively, of the *J* ordinal variables. $\boldsymbol{x}_q$ $(J \times E)$ is a matrix formed by vertically stacking the vectors $\left(\boldsymbol{x}_{q1}^{\mathrm{T}}, \boldsymbol{x}_{q2}^{\mathrm{T}}, ..., \boldsymbol{x}_{qJ}^{\mathrm{T}}\right)$ and $\boldsymbol{d}$ $(J \times L)$ is a matrix formed by vertically stacking $\left(\boldsymbol{d}_1^{\mathrm{T}}, \boldsymbol{d}_2^{\mathrm{T}}, ..., \boldsymbol{d}_J^{\mathrm{T}}\right)$. $\boldsymbol{\xi}_q$ follows a multivariate normal distribution centered at the origin with an identity matrix as the covariance matrix (independent error terms), i.e., $\boldsymbol{\xi}_q \sim MVN_J(\boldsymbol{0}_J, \mathbf{I}_J)$. Note, however, that correlations are engendered across the attitudinal indicator variables and the main outcome through the latent stochastic constructs. Further, because of the ordinal nature of the outcome variables, the scale of $\boldsymbol{y}_q^*$ cannot be uniquely identified. Therefore, the variances of all elements in $\boldsymbol{\xi}_q$ are fixed to one.

Substituting Equation (1) in Equation (4), $\boldsymbol{y}_q^*$ can be expressed in the reduced form as

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\left(\boldsymbol{w}_q\boldsymbol{\alpha} + \boldsymbol{\eta}_q\right) + \boldsymbol{\xi}_q, \tag{5}$$

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\boldsymbol{w}_q\boldsymbol{\alpha} + \boldsymbol{d}\boldsymbol{\eta}_q + \boldsymbol{\xi}_q. \tag{6}$$

On the right side of Equation (6), $\boldsymbol{\eta}_q$ and $\boldsymbol{\xi}_q$ are random vectors that follow the multivariate normal distribution, and the other variables are non-random. Therefore, $\boldsymbol{y}_q^*$ also follows the multivariate normal distribution with a mean of $\boldsymbol{b} = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\boldsymbol{w}_q\boldsymbol{\alpha}$ (all elements of $\boldsymbol{\eta}_q$ and $\boldsymbol{\xi}_q$ have a mean of zero) and a covariance matrix of $\boldsymbol{\Sigma} = \boldsymbol{d}\boldsymbol{\Gamma}\boldsymbol{d}^{\mathrm{T}} + \mathbf{I}_J$, i.e.,

$$\boldsymbol{y}_q^* \sim MVN_J(\boldsymbol{b}, \boldsymbol{\Sigma}). \tag{7}$$

The parameters that are to be estimated are the elements of $\boldsymbol{\alpha}$, strictly upper triangular elements of $\boldsymbol{\Gamma}$, elements of $\boldsymbol{\beta}$, elements of $\boldsymbol{d}$ and ψ_{jk} for all j and $k \in \{2,3,4,...,K_j\}$. Let $\boldsymbol{\theta}$ be a vector of all the parameters that need to be estimated. The maximum likelihood approach can be used for estimating these parameters. The likelihood of the q^{th} observation will be,

$$L_q(\boldsymbol{\theta}) = \int_{v_1=\psi_{1y_{q1}}-b_1}^{v_1=\psi_{1(y_{q1}+1)}-b_1} \int_{v_2=\psi_{2y_{q2}}-b_2}^{v_2=\psi_{2(y_{q2}+1)}-b_2} \cdots \int_{v_J=\psi_{Jy_{qJ}}-b_J}^{v_J=\psi_{J(y_{qJ}+1)}-b_J} \phi_J(v_1, v_2, \ldots, v_J \mid \boldsymbol{\Sigma}) dv_1 dv_2 \ldots dv_J , \tag{8}$$

where, $\phi_J(v_1, v_2, \ldots, v_J \mid \boldsymbol{\Sigma})$ denotes the probability density of a J dimensional multivariate normal distribution centered at the origin with a covariance matrix $\boldsymbol{\Sigma}$ at the point $(v_1, v_2, \ldots, v_J)$. 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 (2018) was used for approximating this integral. The estimation of parameters was carried out using the *maxlik* library in the GAUSS matrix programming language.

4. MODEL ESTIMATION RESULTS

This section presents detailed model estimation results. The results for the latent construct model component are presented first, while the results for the main outcome model are presented second.

4.1. Latent Construct Model Component

The results of the latent construct model component are presented in Table 2. The top half of the table shows the effects of exogenous variables on the three latent constructs used in this study, while the bottom half of the table presents the factor loadings for each latent construct. Focusing on the bottom half of the table, it can be observed that the factor loadings are statistically significant and intuitive in sign and magnitude, thus signifying that the attitudinal statements are appropriate indicators of the latent constructs conceived for this study. Just above the factor loadings is the correlation matrix, which shows that significant error correlations are found among the three latent constructs.

The remainder of this subsection is devoted to a discussion of exogenous variable effects on the three latent attitudinal constructs. Women are found to exhibit lower levels of congestion burden perception, presumably because they drive fewer miles than men (Hu, 2021) and hence do not perceive congestion as burdensome. They also have a lower positive travel engagement, likely arising from greater modal constraints and their shouldering household obligations and childcare responsibilities to a greater degree than men (Hu, 2021) (thus limiting their travel flexibility and enjoyment). Compared to the youngest age group, those in the middle age groups of 24-44 years and 45-64 years are more suburban lifestyle oriented, consistent with the notion that households with adults in these age groups are more likely to have children and seek open space, larger homes, and good schools (Coogan et al., 2018). Older individuals perceive congestion burden less, presumably because they have greater schedule flexibility (Fournier and Christofa, 2021), with those aged 65 years and over exhibiting the lowest level of congestion burden perception. Older age groups also depict lower positive travel engagement when compared with younger age groups, most likely because of intense activity-travel schedules (particularly for those 45-64 years, who are in their peak travel years) and the onset of mobility limitations (particularly for those 65 years and over) (Ravensbergen et al., 2021).

Non-Hispanic Black individuals report a more positive travel engagement; they are more likely to use transit than other groups (American Public Transportation Association, 2017) and are able to put their travel time to good use. White individuals exhibit a lower level of congestion burden perception, presumably because they tend to reside more so in suburban and rural areas where congestion levels are lower. Individuals with low educational attainment are more likely to be dependent on alternative modes of transportation and work in service jobs with fixed schedules, thus reducing the positivity of their travel engagement. Higher educated individuals, on the other hand, are able to perceive a lower congestion burden because they have more flexible schedules (Anderson et al., 2024); at the same time, they prefer urban living for the amenities that such environments provide (Nijman and Wei, 2020).

Income effects show that higher income levels are associated with higher levels of congestion burden perception, positive travel engagement, and suburban lifestyle orientation. The first may be explained by the more intense work and commuting schedules and higher value of time (thus perceiving congestion as a burden) associated with those with higher incomes, the second possibly due to higher levels of vehicle ownership and the ability to use premium transit or ridehailing services that facilitate multitasking during travel (Singleton, 2020), and the third presumably due to higher income individuals seeking nicer suburban locations with large homes for their residence. The presence of children further reinforces the suburban lifestyle orientation where households are seeking good schools, open space, and larger homes (Coogan et al., 2018). At the same time, the presence of children appears to amplify the congestion burden perception, possibly a result of these households being time and schedule constrained (Bai et al., 2021) and feeling the ill-effects of congestion more so than others. For similar reasons, single adults eschew the suburban lifestyle orientation, while individuals in multi-adult households tend to embrace it. Overall, the model estimation results are consistent with expectations and behaviorally intuitive.

TABLE 2 Determinants of Latent Variables and Loadings on Indicators (N = 8,030)

Explanatory Variables (base category)		Structural Equations Model Component					
		Congestion Burden Perception		Positive Travel Engagement		Suburban Lifestyle	
		Coef	t-stat	Coef	t-stat	Coef	t-stat
Individual characteristics							
Gender (not woman)	Woman	-0.341	-8.14	-0.186	-5.52	na	na
Age (18 to 24 years)	25 to 44 years	na	na	na	na	0.205	4.52
	45 to 64 years	-0.437	-8.85	-0.233	-6.20	0.142	3.29
	65 years or older	-0.907	-13.75	-0.460	-9.61	na	na
Race and Ethnicity (All race/ethnicity combinations except non-Hispanic Black and White)	Non-Hispanic Black	na	na	0.347	7.47	na	na
	Non-Hispanic White	-0.361	-8.46	na	na	na	na
Education (some college or technical school)	High school or lower	na	na	-0.151	-4.26	na	na
	Bachelor's or higher	0.247	5.60	na	na	-0.189	-4.86
Household characteristics							
Household income (less than $50,000)	$50,000-$99,999	0.397	8.00	0.199	5.02	0.264	6.07
	$100,000 or more	0.860	14.76	0.251	5.98	0.425	8.63
Presence of children (none)	One or more	0.168	3.67	na	na	0.118	2.78
Number of adults (three or more)	One	na	na	na	na	-0.216	-4.40
	Two	na	na	na	na	0.186	4.67
Correlations between latent constructs							
Congestion Burden Perception		1	na	0.588	23.74	0.397	14.76
Positive Travel Engagement				1	na	0.304	13.95
Suburban Lifestyle						1	na
Attitudinal Indicators							
I am willing to pay more money to have a faster trip		0.631	27.36				
Traffic congestion is a major problem during my daily travel		0.403	26.30				
I make efforts to adjust my schedule (e.g. leave earlier/later than needed) to avoid traffic congestion		0.142	10.46				
I generally enjoy the act of traveling itself				0.441	25.09		
The time I spend traveling to places provides a useful transition between activities				0.839	31.96		
I try to make good use of the time I spend in, on, or waiting for transportation vehicles				0.602	32.51		
I prefer to live in a spacious home, even if it's farther from many places I go or from public transportation						0.897	16.92
Apartment living doesn't provide enough privacy						0.409	20.48

Note: Coef = coefficient; "na" = not applicable.

4.2. Model of Congestion Pricing Unfairness

The estimation results for the model of congestion pricing unfairness are presented in Table 3. The coefficients refer to the effects of exogenous variables on the underlying latent propensity determining the level of unfairness associated with congestion pricing. Technically, in ordered-response models, even the sign of the coefficients does not unambiguously indicate the effect on each ordinal category, except for the two extreme ordinal unfairness categories of "strongly agree" and "strongly disagree". But, for presentation simplicity, this issue will be overlooked, with the understanding that the terminology of individuals feeling "more unfair" (about congestion pricing) really implies the high probability of choosing the "strongly agree" ordinal category, and any reference to feeling "less unfair" implies a high probability of choosing the "strongly disagree" ordinal category. With that, the results in Table 3 show the significant influence of the stochastic latent constructs on the perception of congestion pricing unfairness. In particular, those with a higher congestion burden perception feel that congestion pricing is less unfair (i.e., more fair) as evidenced by the negative, significant coefficient. This is intuitive, as those who feel the burden of congestion may feel that congestion pricing is a fair way to alleviate congestion and make those who travel during congested periods pay their fair share. On the other hand, employed individuals who feel a higher congestion burden believe that congestion pricing is unfair. As employed individuals often need to adhere to fixed (peak period) commuting schedules, they may feel unfairly penalized by a congestion pricing scheme (because they do not have the flexibility to travel during uncongested periods). Those with a higher positive travel engagement and a suburban lifestyle orientation are more likely to perceive congestion as unfair; as both these groups are likely to travel more (in frequency and distance) than other groups, it is not surprising that they would consider a congestion pricing scheme as punitive. These results signify that latent attitudinal factors are important determinants of perceptions (and hence acceptability) of congestion pricing schemes.

In terms of individual characteristics, those in the youngest age group perceive congestion pricing as less unfair (more fair), presumably because they use alternative modes more than others and drive less (Song et al., 2023). Higher educated individuals also perceive congestion pricing as more fair (less unfair), likely due to awareness of the benefits of congestion pricing and a more pro-tax, pro-environment, pro-pricing approach to life (Hess and Börjesson, 2019). Black women also consider congestion pricing more fair; this demographic is more likely to use alternative modes of transportation (Pew Research Center, 2024) and may view congestion pricing as a fair way to make automobile users pay for traveling during congested periods and generate revenue to improve transit services. Individuals in high-income households (earning $100,000 or more per year) are also more likely to consider congestion pricing less unfair (or more fair). This is because they are more able to afford to pay when they do have to travel in peak periods, and are more able to adjust their schedules when they do not have to travel in congested periods (Ray and Pana-Cryan, 2021). On the other hand, individuals in households with high vehicle ownership tend to consider congestion pricing as more unfair, presumably due to their dependence on and high use of the automobile to fulfill travel needs.

As expected, commute characteristics and location matter. Those who commute long distances (50 miles or longer round trip) perceive congestion pricing as unfair, as this price is added on to their already high commuting costs. Similarly, those who commute to the workplace three or more days per week are also likely to feel disproportionately impacted by a congestion pricing scheme that they are not able to escape through schedule adjustments; hence frequent commuters also deem a congestion pricing scheme as more unfair compared to those who are able to work from home at least a part of the week. Interestingly, those in urban environments within New York State consider congestion pricing less unfair (or more fair), signifying that the congestion pricing experiment in New York City is being viewed positively for its (potential) benefits on relieving congestion and generating revenue for enhancing transit service (NY1, 2025). It appears that context matters, greater awareness of the benefits of congestion pricing and the intended use of the revenue matters, and actual experience (in which the benefits are seen firsthand) matters. Finally, ridehailing drivers in New York consider the scheme more unfair, as they feel unduly penalized by the scheme (CBS New York, 2022). Indeed, it has been found that ridehailing use in New York City has decreased after the implementation of congestion pricing (Zhang and Wu, 2025). Women in low density areas appear to perceive congestion pricing as more fair (than others), presumably because they do not travel during congested periods as much as their male counterparts (Zhang and Song, 2024). They may view congestion pricing as an appropriate mechanism for managing traffic congestion and pricing transportation infrastructure use during congested periods.

Model goodness-of-fit measures are furnished in the bottom portion of Table 3. The performance of the GHDM, which utilizes the information provided through the latent construct indicators to develop the latent constructs, is compared against that of an independent ordered probit (IOP) model that does not include latent constructs in the model specification (but includes all the exogenous variables affecting the latent constructs). The GHDM is assessed on a number of goodness-of-fit metrics, including log-likelihood measures and predictive log-likelihood at convergence, predictive adjusted likelihood ratio index, predictive Bayesian Information Criterion (BIC), and average probability of correct prediction. The GHDM is found to offer a statistically superior goodness-of-fit across all measures, thus validating the use of the GHDM with correlated stochastic latent constructs embedded in the model specification. This model accounts for error correlations among endogenous latent constructs and explicitly captures the influence of latent attitudinal factors (as extracted through the attitudinal indicators) in shaping perceptions of congestion pricing fairness.

TABLE 3 Estimation Results of Congestion Pricing Unfairness Model (N = 8,030)

Explanatory Variables (base category)		**Congestion Pricing Unfairness** *Ordered (5-level): strongly disagree (1) to strongly agree (5)*	
		Coefficient	t-stat
Latent constructs			
Congestion Burden Perception		-0.096	-3.39
Congestion Burden Perception × Employed		0.145	5.15
Positive Travel Engagement		0.164	6.59
Suburban Lifestyle		0.100	4.88
Individual characteristics			
Age (25 years or older)	18 to 24 years	-0.080	-1.98
Education (some college or lower)	Bachelor's degree(s) or higher	-0.099	-3.37
Interaction term	Black × Woman	-0.152	-2.72
Household characteristics			
Household income (<$100,000)	$100,000 or more	-0.081	-2.44
Number of vehicles (zero or one)	Two or more	0.102	3.73
Commute, location, and other characteristics			
Commute distance (two-way commute less than 50 miles)	Two-way commute 50 miles or longer	0.181	2.12
Commute frequency (less than 3 days per week)	3 or more days per week	0.092	3.22
Interaction terms	Urban area × New York State	-0.171	-2.88
	Ridehailing driver × New York State	0.181	1.45
	Woman × Live in a low population density area (< 1.96 people/acre)	-0.081	-2.25
Thresholds			
1|2		-1.732	-47.96
2|3		-1.195	-36.20
3|4		-0.369	-11.88
4|5		0.439	14.26
Data Fit Measures		**GHDM**	**IOP**
Log-likelihood at convergence		-87702.86	-12123.63
Log-likelihood at constants		-92224.55	-12359.41
Number of non-constant parameters		85	9
Predictive log-likelihood at convergence		-11204.89	-12123.63
Constants-only predictive log-likelihood		-12359.41	
Predictive adjusted likelihood ratio index		0.206	0.051
Predictive Bayesian Information Criterion (BIC)		22727.8	24298.02
Average probability of correct prediction		0.357	0.221

5. AVERAGE TREATMENT EFFECTS

This section presents a discussion of average treatment effects (ATEs) to illustrate the sensitivity of the main outcome variable to changes in exogenous variables. The notion of an average treatment effect (ATE), which is widely used in econometrics to measure the potential impact of treatments, represents the mean causal effect of a treatment on an outcome across the entire population. This is defined as the expected difference in potential outcomes between a control state and a treatment state.

As illustrated in the model structure (Figure 2), exogenous variables influence perceptions of congestion pricing fairness through multiple pathways: directly and indirectly via three latent constructs. Thus, the total ATE of a variable on the main outcome of interest (congestion pricing fairness perception) can arise through four possible pathways — a direct effect and effects through one or more of the three latent constructs. The total ATE effect and the partitioning of this total ATE effect to different pathways are shown in Table 4 (see the last five columns of Table 4). The total ATE effect represents the overall effect on the dependent outcome because of a change of an exogenous variable from a base state to a treatment state (these states are identified in the second and third columns of the table). For the ATE computations, and for presentation simplicity, we combined the "somewhat agree" and the "strongly agree" categories of the dependent outcome into a single "agree" category, and examined the effects of exogenous variables on this combined "agree" category. For instance, the first numeric entry of "-1.5" under the "Total ATE" column in Table 4 indicates that, in a group of 100 women, there would be 1.5 fewer individuals who would "agree" that congestion pricing is unfair relative to in a group of 100 men (equivalently, in a group of 200 women, there would be three fewer individuals who would "agree" that congestion pricing is unfair relative to in a group of 200 men). Other entries in the "Total ATE" column may be similarly interpreted.

The main column entitled "Contribution through Latent Constructs and/or Direct Effect" presents the relative magnitude and direction of each pathway effect leading up to the total ATE in the final column. Specifically, the absolute values of the relative contributions in each sub-column of this main column add up to 100 percent, with the sign indicating the direction of impact (of the specific pathway) on the outcome variable. For example, in the case of the education variable, the direct pathway accounts for 65.4 percent of the total ATE effect, operating in the negative direction. Meanwhile, the indirect pathways through the congestion burden perception (CBP) and suburban lifestyle (SL) latent constructs account for 5.1 percent and 12.7 percent of the total effect, respectively, again in the negative direction. However, these effects are moderated by the indirect effect through the positive travel engagement (PTE) latent construct, which accounts for 16.8 percent of the total effect, but in a positive direction (consistent with the result described in the previous section that those with high positive travel engagement propensity are likely to perceive congestion pricing as more unfair than those with low travel engagement propensity, combined with the positive effect of high educational attainment relative to low educational attainment on PTE).

In some cases, an explanatory variable may not necessarily have a direct effect on the outcome variable. For example, the employment status variable itself affects neither the congestion burden perception (CBP) latent factor nor the outcome variable directly. However, employment status modifies commute characteristics, thereby affecting the relationship between the CBP latent factor and the outcome. Thus, the employment variable row reflects the influence of employment status on congestion pricing fairness perception through these indirect mechanisms.

TABLE 4 Average Treatment Effects (ATEs) for Congestion Pricing Unfairness

Variable	Base State	Treatment State	Contribution through Latent Constructs or Direct Effect (%)				Total ATE
			CBP	PTE	SL	Direct effect	
Individual characteristics							
Gender	Man	Woman	13.1	-37.7	0.0	49.2*	-1.5
Age	18 to 24 years	25 to 44 years	0.0	0.0	19.6	80.4	3.8
		45 to 64 years	9.1	-24.9	9.5	56.5	2.6
		65 years or older	14.8	-39.8	0.0	45.4	1.3
Education	High school or lower	Bachelor's degree or higher	-5.1	16.8	-12.7	-65.4	-3.7
Race and ethnicity	All other racial/ethnic groups**	Non-Hispanic White	100.0	0.0	0.0	0.0	0.4
		Non-Hispanic Black	0.0	40.6	0.0	-59.4*	-1.0
Employment	Unemployed	Employed	44.8	0.0	0.0	55.2	2.0
Commute conditions of employed	Not long (two-way commute < 50 miles) and infrequent (< 3 days/week)	Long-distance (two-way commute ≥ 50 miles)	0.0	0.0	0.0	100.0	6.5
		Frequent (≥3 days/week)	0.0	0.0	0.0	100.0	3.4
Household characteristics and others							
Income	Lower than $50,000	$100,000 or higher	-13.8	21.8	22.4	-42.0	-0.9
		$50,000 - $100,000	-16.7	46.1	37.2	0.0	1.7
Presence of children	None	One or more	-30.2	0.0	69.8	0.0	0.3
Number of adults	Three or more	One	0.0	0.0	100.0	0.0	-0.8
		Two	0.0	0.0	100.0	0.0	0.7
Vehicle ownership	Zero or one	Two or more	0.0	0.0	0.0	100.0	3.8
Urban × New York State	No	Yes	0.0	0.0	0.0	100.0	-6.4
Ridehailing driver in New York State	No	Yes	0.0	0.0	0.0	100.0	6.4

(*) The direct effects for non-Hispanic Black and woman are caused by their corresponding interaction terms.
(**) The reference group includes Hispanic (any race) and non-Hispanic individuals of other races (e.g., Asian, Native American, Pacific Islander, multiracial).

Table 4 shows that, in most cases, the direct effects dominate over the latent construct effects. The results in the table also illustrate how the indirect effects through latent constructs may counteract when direct effects are absent. For example, consider the variable corresponding to the presence of children. This variable has no direct effect on the outcome variable. However, it has a positive effect on congestion burden protection (CBP), which in turn has a negative effect on perception of unfairness of congestion pricing. At the same time, the presence of children has a positive effect on suburban lifestyle (SL) propensity, which in turn has a positive effect on perceptions of congestion pricing unfairness. Hence, the effect of presence of children is negative through CBP, but positive through SL – with a net positive total effect amounting to a modest total ATE value of 0.3.

The ATE results provide important insights into population groups that hold skeptical opinions on the fairness of congestion pricing, and reveal the pathways through which latent constructs contribute to their perception. Policy actions can be tailored toward these groups directly, as well as by influencing the underlying attitudes within these groups, to more effectively improve their perceptions of the fairness of congestion pricing. Based on the ATE results, the most negative perceptions of congestion pricing fairness are found among (a) employed individuals who commute long distances (two-way commutes of more than 50 miles) and/or commute frequently (three or more times a week), (b) ridehailing drivers in New York State, and (c) those in multi-vehicle households. Their views are solely through direct effects, meaning their perceptions are not mediated by the three latent attitudinal constructs included in the model but rather by automobile dependence and perceived exposure to pricing costs. To improve perceptions among these strong opposition groups, discounts or caps on frequent fee payments could be offered, even though this results in partially offsetting the effects of congestion pricing. In New York City's currently implemented Congestion Relief Zone (CRZ) toll system, passenger and small commercial vehicles only pay once per day regardless of how many times they enter and exit, and the low-income discount plan provides a 50 percent discount for low-income vehicle owners who enter the toll zone more than 10 times per month (MTA, 2025). This program could be partially expanded beyond low-income groups to include people who work within the toll zone, though under more stringent eligibility criteria. For example, partial discounts could be provided to those who enter the zone more than 15 times per month to mitigate the financial burden of frequent toll payments. For ridehailing drivers, while New York City charges per trip to/from/within/through the zone instead of per zone entry, implementing a monthly flat-rate fee could make ridehailing drivers' expenses more predictable. However, it is obvious that spending caps or discounts for frequent travelers undermine the policy's primary goal to reduce vehicle traffic. Therefore, the level of such discounts and caps should be carefully calibrated based on the region's policy objectives and level of public support.

For other population groups, the ATE analysis reveals attitudinal pathways that mediate the effects of their characteristics, suggesting that tailored policy strategies could enhance fairness perceptions. For employed individuals (relative to those unemployed), fairness perceptions are influenced not only directly (by commute conditions), but also indirectly through heightened sensitivity to CBP. To enhance fairness perceptions among this group, policies should emphasize that congestion pricing can deliver tangible congestion-relief benefits and support reinvestment in multimodal infrastructure that improves travel reliability and options. As one implementation strategy, congestion pricing revenue could fund a monthly discount transit pass program for employees working within the congestion pricing zone, encouraging mode shift to public transportation. For example, Colorado's EcoPass program in Denver allows employers to purchase unlimited transit passes for their employees, incentivized through tax credits on program expenditures (Regional Transportation District, 2025). Another strategy is to ensure that congestion relief projects, especially when under construction, clearly display congestion pricing revenue as their funding source, enabling the public to readily recognize that congestion pricing actively contributes to alleviating their congestion burdens.

Furthermore, two other groups show distinct attitudinal patterns involving lifestyle orientations. For middle-income households ($50,000-$100,000), the ATE decomposition reveals offsetting attitudinal influences with no direct effect. The negative contribution through CBP indicates that frustration with traffic congestion can enhance acceptance of congestion pricing, while the positive contributions through PTE and SL reflect opposition among those who enjoy traveling and maintain auto-oriented suburban lifestyles. Another group whose perceptions are also influenced by lifestyle orientations is adults in prime working ages (25–44), who exhibit moderately higher unfairness perceptions than other age groups, partly driven by stronger SL preferences. Messaging directed toward both middle-income households and adults in prime working ages should therefore highlight how congestion pricing revenues can be used to improve accessibility, reliability, and quality of transportation services for suburban and auto-dependent travelers – framing the policy as a practical mobility improvement rather than a financial penalty. Based on attitudinal indicators, these groups demonstrate a strong preference for suburban living, despite the limited accessibility of public transportation. Therefore, rather than focusing exclusively on public transportation improvements, promises of transportation services that better serve suburban dwellers are better suited to gain support from suburban residents. Carpool-related investments can serve as an alternative strategy, such as expanding carpool infrastructure (e.g., carpool lanes) or providing subsidies for carpools from suburban areas. Another option is offering congestion toll discounts for carpool vehicles or vehicles with multiple passengers. This provides suburban residents with an alternative to avoid tolls without relying on transit services. A relevant example is Seoul's Namsan Tunnel, where the toll is waived for vehicles with three or more passengers entering downtown to encourage carpooling (Son and Hwang, 2002). This approach works well in systems with fixed toll booths where occupancy can be visually verified on-site. For systems without fixed toll booths (such as the CRZ toll in New York City), a pre-registration system could be implemented where carpool vehicles receive discounts that are verified through post-travel enforcement.

6. DISCUSSION AND CONCLUSIONS

Congestion pricing policies are viewed as strategies for mitigating congestion, reducing automobile-traffic induced externalities, and raising revenue to enhance multimodal mobility options. However, congestion pricing schemes often face considerable headwinds with low public support and limited societal willingness to embrace pricing-oriented transportation control and revenue generation measures. In the United States, only New York City has been able to implement a congestion pricing scheme successfully, although it too faces considerable opposition from certain groups who feel adversely impacted by the pricing scheme.

This study is aimed at shedding light on the factors that contribute to perceptions of unfairness of congestion pricing. The focus in this paper is on the notion of *unfairness* perceptions because it is these perceptions of *unfairness* that present challenges in garnering public support for such pricing schemes. The study objective is accomplished by analyzing data derived from the Transportation Heartbeat of America (THA) survey, a nationwide survey conducted in the United States in late 2024 and early 2025. The survey yielded a data set with more than 8,000 responses, providing rich information about socio-economic, demographic, travel behavior, and attitudinal characteristics. The survey also included a specific question probing the degree to which respondents feel that a congestion pricing scheme is unfair. This question served as the basis for the study.

The survey confirms that there is a widely held belief that congestion pricing is unfair. About 64.5 percent of respondents indicated that they strongly or somewhat agree that congestion pricing is unfair. Only 12 percent of respondents indicated that they strongly or somewhat disagree that congestion pricing is unfair. The descriptive statistical analysis was followed by an econometric model estimation effort in which the dependent variable was treated as an ordered response and the model structure included a series of correlated latent attitudinal constructs. This econometric model structure offered the ability to unravel the influences of different attitudinal constructs and socio-economic and demographic characteristics on perceptions of unfairness of congestion pricing.

It is found that middle aged individuals who are in their lifecycle stage of peak travel tend to feel more strongly that congestion pricing is unfair. Younger age individuals, on the other hand, feel that congestion pricing is more fair. Individuals who have higher educational attainment, live in higher income households, and live in urban areas of New York state are more likely to feel that congestion pricing is fair. Those who own more household vehicles, commute long distances, and commute more days of the week tend to feel more strongly that congestion pricing is unfair - consistent with the greater levels of automobile-oriented travel that these individuals undertake. Interestingly, ridehailing drivers in New York feel that congestion pricing is unfair as it adversely impacts their revenue. Among attitudinal constructs, those who perceive and are more sensitive to the burdens of traffic congestion tend to feel that congestion pricing is fair, presumably because they are seeking congestion relief. Those who have a positive travel engagement (i.e., they like traveling) and prefer a suburban lifestyle tend to believe that congestion pricing is unfair, consistent with their higher levels of automobile travel.

Average Treatment Effects (ATEs) are also computed to translate the model estimation results into more tangible and policy-relevant insights. The ATE analysis quantifies both the direct and indirect contributions of individual characteristics through three latent attitudinal factors – Congestion Burden Perception (CBP), Positive Travel Engagement (PTE), and Suburban Lifestyle (SL) – thereby revealing not only which population segments exhibit the highest unfairness perceptions but also the underlying attitudinal pathways that explain the differences from the other groups. From the ATE analysis results, long-distance or frequent commuters and ride-hailing drivers are identified as having a negative view of congestion pricing fairness, likely due to their car-dependence, which leads them to perceive congestion fees as an unavoidable cost. To mitigate the financial burden of frequent tolls, partial discounts or caps on congestion fees could be offered to these individuals. Employed individuals tend to view congestion pricing as unfair because they may feel disproportionately penalized by congestion fees, which they cannot avoid by adjusting their schedule or destination. For this group, revenues from congestion pricing could be used to fund monthly discounted transit passes for employees working within the toll zone. Adults aged 25–44 and middle-income households ($50,000–$100,000) form another group having skeptical view on the fairness of congestion pricing due to their preference for suburban lifestyles. Facilitating carpooling from suburban areas through dedicated carpool lanes or discounted fees for high-occupancy vehicles may help increase support for congestion pricing among these groups.

The findings suggest that garnering overall support for congestion pricing schemes may prove to be challenging, as many in the U.S. are automobile-dependent and live in suburbs necessitating travel over long distances. However, as the recent New York City experience shows, realizing congestion relief benefits for real while simultaneously deriving revenue for improving alternative transportation mode services (e.g., transit) could help enhance public support for such pricing schemes. In other words, raising awareness about the pricing scheme, ensuring that the implementation (collection) methods and use of revenue are clear and transparent to the public, and providing firsthand experience of the benefits of a pricing scheme (even on a trial basis) could go a very long way in garnering public support for a congestion pricing scheme. The congestion pricing scheme needs to appeal to all. It needs to provide benefits to automobile travelers in the form of congestion relief, and it needs to provide benefits to those who want to use alternative modes of transportation (and avoid paying the congestion charge). The heterogeneity in perceptions of congestion pricing unfairness found in this study points to the need to ensure that the congestion pricing scheme appeals to a broad section of society. Providing incentives for using alternative modes of transportation and fuel efficient vehicles and accommodating exceptions or differential pricing levels for transportation disadvantaged populations could also help enhance public support for congestion pricing. However, experience to date suggests that context matters and congestion pricing is unlikely to see much support in most contexts of the United States; this is simply because congestion levels in a post-pandemic era in most cities are not so egregious that they would have the public believe such a pricing scheme is warranted and necessary in their locales.

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REFERENCES

American Public Transportation Association. *Who Rides Public Transportation 2017*. American Public Transportation Association, Washington, DC, 2017.

Anderson, S. M., K. E. Asmussen, S. Saxena, I. Batur, R. M. Pendyala, and C. R. Bhat. An Investigation of Dissonance in Telework Frequency. *Transportation Research Part C: Emerging Technologies*, 2024. 166:104712.

Axsen, J., and M. Wolinetz. Taxes, Tolls and ZEV Zones for Climate: Synthesizing Insights on Effectiveness, Efficiency, Equity, Acceptability and Implementation. *Energy Policy*, 2021. 156:112457.

Bai, B., N. Gopalan, N. Beutell, and F. Ren. Impact of Absolute and Relative Commute Time on Work–Family Conflict: Work Schedule Control, Child Care Hours, and Life Satisfaction. *Journal of Family and Economic Issues*, 2021. 42:586–600.

Bhat, C. R. A New Generalized Heterogeneous Data Model (GHDM) to Jointly Model Mixed Types of Dependent Variables. *Transportation Research Part B: Methodological*, 2015. 79:50–77.

Bhat, C. R. New Matrix-Based Methods for The Analytic Evaluation of The Multivariate Cumulative Normal Distribution Function. *Transportation Research Part B*, 2018. 109:238–256.

CBS New York. Taxi, ride-hail drivers stand together to protest controversial Manhattan congestion pricing plan. August 24, 2022. https://www.cbsnews.com/newyork/news/taxi-lyft-uber-drivers-protest-congestion-pricing/ Accessed October 23, 2025.

Coogan, M., G. Spitz, T. Adler, N. McGuckin, R. Kuzmyak, and K. Karash. Understanding Changes in Demographics, Preferences, and Markets for Public Transportation. *Transportation Research Board*, 2018.

De Borger, B., and S. Proost. A Political Economy Model of Road Pricing. *Journal of Urban Economics*, 2012. 71(1):79–92.

De Palma, A., and R. Lindsey. Traffic Congestion Pricing Methodologies and Technologies. *Transportation Research Part C: Emerging Technologies*, 2011. 19(6): 1377–1399.

Eliasson, J. Is Congestion Pricing Fair? Consumer and Citizen Perspectives on Equity Effects. *Transport Policy*, 2016. 52:1–15.

EPA. Smart Location Database Version 3.0 [Dataset]. *U.S. Environmental Protection Agency*, 2021. https://www.epa.gov/smartgrowth/smart-location-mapping.

Federal Highway Administration. *Congestion Pricing: A Primer: Overview.* Technical Report No. FHWA-HOP-08-039. 2008. https://rosap.ntl.bts.gov/view/dot/748

Fournier, N., and E. Christofa. On the Impact of Income, Age, and Travel Distance on the Value of Time. *Transportation Research Record: Journal of the Transportation Research Board*, 2021. 2675(3):122–135.

Gu, Z., Z. Liu, Q. Cheng, and M. Saberi. Congestion Pricing Practices and Public Acceptance: A Review of Evidence. *Case Studies on Transport Policy*, 2018. 6(1):94–101.

Hamilton, C. J., J. Eliasson, K. Brundell-Freij, C. Raux, S. Souche, K. Kiiskilää, and J. Tervonen. Determinants of Congestion Pricing Acceptability. *Centre for Transport Studies*, 2014. 11.

Hess, S., and M. Börjesson. Understanding Attitudes towards Congestion Pricing: A Latent Variable Investigation with Data from Four Cities. *Transportation Letters*, 2019. 11(2):63–77.

Hu, L. Gender Differences in Commuting Travel in the US: Interactive Effects of Race/Ethnicity and Household Structure. *Transportation*, 2021. 48(2):909–929.

Jakobsson, C., S. Fujii, and T. Gärling. Determinants of Private Car Users' Acceptance of Road Pricing. *Transport Policy*, 2000. 7(2):153–158.

Krabbenborg, L., E. Molin, J. A. Annema, and B. Van Wee. Public Frames in the Road Pricing Debate: A Q-Methodology Study. *Transport Policy*, 2020. 93:46–53.

Milenković, M., D. Glavić, and M. Maričić. Determining Factors Affecting Congestion Pricing Acceptability. *Transport Policy*, 2019. 82:58–74.

MTA. Congestion Relief Zone Toll: Discounts and Exemptions. 2025. https://www.mta.info/fares-tolls/tolls/congestion-relief-zone/discounts-exemptions. Accessed Nov. 18, 2025.

NBC New York. NYC Congestion Pricing Has More Support than Ever as Trump Deadline Looms, New Poll Finds. NBC New York, March 10, 2025. https://www.nbcnewyork.com/news/local/nyc-congestion-pricing-support-grows/6165502/ Accessed July 30, 2025.

Nijman, J., and Y. D. Wei. Urban Inequalities in the 21st Century Economy. *Applied Geography*, 2020. 117:102188.

NY1 New poll shows how New Yorkers feel about eliminating congestion pricing. NY1, March 10, 2025. https://www.ny1.com/nyc/all-boroughs/traffic_and_transit/2025/03/10/congestion-pricing-disapproval-falls--city-voters-approve. Accessed July 4, 2025.

Oberholzer-Gee, F., and H. Weck-Hannemann. Pricing Road Use: Politico-Economic and Fairness Considerations. *Transportation Research Part D: Transport and Environment*, 2002. 7(5):357–371.

Pew Research Center. 1 in 10 Americans Rarely or Never Drive a Car. Pew Research Center, Nov, 2024. https://www.pewresearch.org/short-reads/2024/11/14/1-in-10-americans-rarely-or-never-drive-a-car/ Accessed July 29, 2025

Ravensbergen, L., K. B. Newbold, R. Ganann, and C. Sinding. 'Mobility Work': Older Adults' Experiences Using Public Transportation. *Journal of Transport Geography*, 2021. 97:103221.

Ray, T. K., and R. Pana-Cryan. Work Flexibility and Work-Related Well-Being. *International journal of environmental research and public health*, 2021. 18(6):3254.

Regional Transportation District. EcoPass. 2025. https://www.rtd-denver.com/fares-passes/pass-programs/ecopass. Accessed November 13, 2025.

Schade, J., and B. Schlag. Acceptability of Urban Transport Pricing Strategies. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2003. 6(1):45–61.

Schaller, B. New York City's Congestion Pricing Experience and Implications for Road Pricing Acceptance in the United States. *Transport Policy*, 2010. 17(4):266–273.

Schuitema, G., L. Steg, and M. Van Kruining. When Are Transport Pricing Policies Fair and Acceptable? *Social Justice Research*, 2011. 24:66–84.

Selmoune, A., Q. Cheng, L. Wang, and Z. Liu. Influencing Factors in Congestion Pricing Acceptability: A Literature Review. *Journal of Advanced Transportation*, 2020. 2020:1–11.

Siena College Research Institute. Siena College Poll: NYers Say Trump Manhattan Trial is 'Legitimate,' 54-30%, Including More Than 3/4 of Dems and Plurality of Inds; 2/3 of Reps Call it 'Witch Hunt' [Press release]. Apr. 22, 2024. https://scri.siena.edu/wp-content/uploads/2024/04/SNY-April-2024-Poll-Release-FINAL.pdf.

Singleton, P. A. Multimodal Travel-Based Multitasking during the Commute: Who Does What? *International Journal of Sustainable Transportation*, 2020. 14(2):150–162.

Son, B., and K. Y. Hwang. Four-year-old Namsan Tunnel Congestion Pricing Scheme in Seoul. *IATSS Research*, 2002. 26(1):28–3.

Song, Y., Y. Fan, Y. Zhang, and A. McDonnell. Advancing Equity in Accessibility and Travel Experiences: The Role of Gender and Identity. *Minnesota Department of Transportation*, 2023.

Souche, S., C. Raux, and Y. Croissant. On the Perceived Justice of Urban Road Pricing: An Empirical Study in Lyon. *Transportation Research Part A: Policy and Practice*, 2012. 46(7): 1124–1136.

Sun, X., S. Feng, and J. Lu. Psychological Factors Influencing the Public Acceptability of Congestion Pricing in China. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2016. 41:104–112.

Veitch, E., and E. Rhodes. A Cross-Country Comparative Analysis of Congestion Pricing Systems: Lessons for Decarbonizing Transportation. *Case Studies on Transport Policy*, 2024. 15:101128.

Wang, Yacan, Yu Wang, L. Xie, and H. Zhou. Impact of Perceived Uncertainty on Public Acceptability of Congestion Charging: An Empirical Study in China. *Sustainability*, 2019. 11(1):129.

Zhang, Y., and M. Wu. Impact of Tolling on Ride-Hailing Ridership in NYC. *Preprint*, SSRN 5315875, 2025.

Zhang, Y., and Y. Song. Gender Differences in Travel and Everyday Life: A Data-Driven Approach to Address the Intersectional Nature of Gender as a Social Construct. *Travel Behaviour and Society*, 2024. 36:100797.

Zheng, Z., Z. Liu, C. Liu, and N. Shiwakoti. Understanding Public Response to a Congestion Charge: A Random-Effects Ordered Logit Approach. *Transportation Research Part A: Policy and Practice*, 2014. 70:117–134.