Final Project Report

Assessing the Impact of Ridehailing Service Use on Bus Ridership: A Joint Modeling Framework Accounting for Endogeneity and Latent Attitudes

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

TOMNET Transportation Center

Teaching Old Models New Tricks

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This project involves the use of machine learning methods to impute attitudes into the Georgia subsample of the 2016-17 National Household Travel Survey, training the algorithms on the responses to a 2017 attitudinal survey administered to a separate statewide sample in Georgia. The “common variables” needed to train the learning function will include socio-economic/demographic and other variables found in both samples but will be augmented by (1) land use-related variables (obtained from multiple external sources) associated with respondents’ residential neighborhoods, and (2) (for the first time) lifestyle-oriented targeted marketing variables associated with the household/respondent that are purchased from a commercial provider. The project evaluates the effectiveness of targeted marketing variables for this purpose. The objectives of this project are (1) to impute attitudes into the Georgia subsample of the 2016-17 NHTS, training the imputation functions using attitudinally-rich data collected in Fall 2017 from a sample that is (reasonably) representative of the urban and small-town population of the state of Georgia; and (2) to augment the set of “common variables” available for training the imputation process with information from targeted marketing databases. Achievement of both objectives involves testing the efficacy of the imputed attitudes for predicting travel-related choices of interest, using a variety of comparisons.</td></tr>
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EXECUTIVE SUMMARY

Transit ridership has been on the decline for several years. One key contributing factor is the rise of ridehailing service usage and its impact on transit use. This report attempts to provide a comprehensive and holistic assessment of the impacts of ridehailing service use on transit ridership while controlling for a host of socio-economic, demographic, and attitudinal factors. Using detailed survey data collected in four automobile-centric metropolitan areas of the US, this report jointly models the frequency of using ridehailing services and the extent to which an individual has changed bus use due to ridehailing. The results indicate that ridehailing use frequency is significantly associated with a decrease in bus use, suggesting that ridehailing serves as a substitute for bus use (more than it serves as a complement). The findings suggest that transit agencies need to explore pathways towards leveraging ridehailing services to better complement transit usage.

1.INTRODUCTION

Transit has been experiencing a decline in ridership over the past decade in the United States (Boisjoly et al., 2018). While the COVID-19 pandemic has undoubtedly played havoc with transit ridership during 2020 and 2021, the fact remains that transit ridership was on the decline even prior to the onset of the pandemic (Graehler et al., 2019). As transit agencies look to the future and contemplate how they can enhance their service to stem the tide, there is a critical need to better understand the contribution of various factors to the decline in transit ridership. Transit remains a mode of transportation that is critical to the movement of people, particularly serving those who may not have access to (or be able to use) an automobile. During the pandemic, it became apparent that transit is a critical mode of transportation helping essential frontline workers to get to and from their jobs.

There are a number of reasons that have likely contributed to the decline in transit ridership over the past decade in particular. In most markets across the US, transit is not competitive when compared to the private automobile. As such, except for small shares of individuals, many travelers naturally gravitate toward the use of the automobile for meeting mobility needs. With rising incomes and greater employment opportunities available following the great recession, it is to be expected that individuals would acquire private automobiles for transportation purposes. During the years preceding the pandemic, the nation saw record numbers of new and used vehicles being bought and sold in the US (Woodall, 2016), clearly suggesting that the appetite for automobile-oriented private mobility continues unabated. Other reasons that contribute to transit decline include the continued sprawl of land use patterns (both residential and employment) that render transit use challenging, reconfiguration of transit service in efforts to attract choice riders (which often occurs at the expense of serving more captive riders), and the affordability and reliability of the personal automobile mode (Taylor et al., 2009; Chakraborty and Mishra, 2013; Boisjoly et al., 2018).

In addition to the reasons for transit decline noted in the prior paragraph (which have existed for decades now), a more recent phenomenon that may have adversely impacted transit ridership is the rise of ridehailing services (e.g., Uber and Lyft) that provide on-demand curb-to-curb mobility through the convenience of a smartphone app. The app allows users to summon rides and automates the process of tracking and paying for rides. These services have gained considerable traction over the past decade in cities around the world thanks to their convenience and affordability (relative to traditional taxi transportation).

Ridehailing services may impact transit patronage in a number of ways. An individual may utilize ridehailing services instead of transit, thus creating a substitution effect with transit losing riders to ridehailing services. An individual may use ridehailing services to connect to and from transit stations/stops, essentially creating first- and last-mile connectivity that would enable convenient transit access and egress. In this scenario, transit would gain ridership thanks to the availability of ridehailing services. And finally, ridehailing services may not impact transit ridership at all; it could take the place of another mode of transportation or simply generate a net new trip that would not have been undertaken otherwise. There may be other ways in which ridehailing services and transit interact with one another, especially with a number of transit agencies establishing partnerships with ridehailing service providers (e.g., APTA, 2020; Shaheen and Cohen, 2020), but the fact remains that the relationship generally boils down to one of substitution, complementarity, or no-effect.

Explorations of the relationship between ridehailing service and transit use have been undertaken and documented in the literature. Some studies point to instances where ridehailing has served to enhance transit connectivity and usage, but in most instances, it is clear that ridehailing is a transit substitute. Ridehailing also substitutes for the use of other modes (most notably, traditional taxi and personal automobile), but most survey research to date clearly shows that ridehailing serves as a substitute for transit. However, past studies exploring the relationships between ridehailing and transit use have largely been descriptive in nature (e.g., Rayle et al., 2016; Clewlow and Mishra, 2017; Young and Farber, 2019) or have relied on models that do not fully account for the complex relationships that govern the impact of ridehailing on transit use (e.g., Hall et al., 2018; Gehrke et al., 2019; Dong, 2020).

This report attempts to provide a more comprehensive assessment of the impacts of ridehailing service use on transit ridership while controlling for a host of socio-economic, demographic, and attitudinal factors. Using detailed survey data collected in four automobile-centric metropolitan areas of the US, namely, Phoenix, Austin, Atlanta, and Tampa, this study simultaneously models the frequency of using ridehailing services and the extent to which an individual has changed use of bus services due to ridehailing service usage. The frequency of ridehailing use and the change in bus usage are treated as endogenous variables, with the frequency of ridehailing use directly affecting bus use change. In addition, the simultaneous equations model incorporates latent attitudinal constructs that capture modal and lifestyle proclivities of the survey respondents, thus accounting for the effects of attitudes that are likely to influence the nature of the relationships of interest. The model is estimated in a single step using the Generalized Heterogeneous Data Model (GHDM) framework developed by Bhat (2015); this methodological framework enables the efficient estimation of joint model systems that incorporate error correlations across endogenous variables, thus accounting for the presence of correlated unobserved attributes that may be simultaneously affecting multiple endogenous variables. The study focuses exclusively on bus use change because metropolitan areas differ considerably with respect to the presence and nature of rail service in their transportation ecosystem. Bus use may increase (complementarity), decrease (substitution), or experience no change as a result of ridehailing service use.

The remainder of this report is organized as follows. The next section provides a detailed description of the data set and dependent variables of interest. The third section presents the modeling framework and the modeling methodology adopted in this report. The fourth section presents model estimation results. The fifth section offers a discussion of the implications of the findings and presents concluding thoughts.

2.DATA DESCRIPTION

This section presents a brief description of the dataset used in this study. An overview of the survey and the sample characteristics is presented first; a more in-depth examination of the endogenous variables and attitudinal statements of interest in this study is presented second.

2.1. Characteristics of the Sample

In the Fall of 2019, a comprehensive survey was administered in four major metropolitan areas of the United States: Phoenix, Austin, Atlanta, and Tampa. All four areas are located in warmer climates of the country and are characterized by dispersed land use patterns and rather poor levels of transit service (and very low transit mode shares). The survey was aimed at collecting rich information about people’s attitudes and perceptions towards emerging mobility services and transportation technologies besides their socio-economic, demographic, and routine mobility characteristics. The same survey instrument was administered in all four metropolitan regions, thus ensuring consistency in data collection. The sampling methodology had to be customized to some degree in each region to maximize response rate. Respondents were recruited by sending invitations to hundreds of thousands of e-mail addresses and several thousand mailing addresses. The random set of addresses was obtained from a commercial vendor. Individuals who completed the survey and provided all requisite information were provided a $10 gift card as an incentive and token of appreciation. The complete sample across all four areas comprised 3,465 individuals. Full details about the survey and the sample are contained in a series of reports (Khoeini et al., 2021).

The analysis in this report is focused on understanding the relationship between ridehailing service use (frequency) and change in bus use. As such, the analysis sample includes only the subset of individuals who actually use ridehailing services. All non-users and those who indicated their bus use changed, but not due to ridehailing use, were eliminated from the analysis sample. In addition, records with missing or obviously erroneous data were excluded from the analysis sample. The final resulting analysis sample comprised 1,336 respondents. Table 1 shows the characteristics of this subsample of respondents.

The sample characteristics show a level of variability that is appropriate for model development and estimation. Even though the sample characteristics may not perfectly mirror population census distributions, that does not present a problem in the context of a modeling effort of the kind undertaken in this report. Females are over-represented, comprising just over 60 percent of the sample. The lowest age group depicts the highest presence in the sample, with 37.7 percent of the analysis sample falling into the 18-30-year age group. All other age groups are well represented in the sample. Nearly 93 percent of the respondents have a driver's license, nearly 59 percent are full or part-time workers, and about 14 percent are neither workers nor students. The sample depicts a high level of educational attainment with a little over 38 percent having a bachelor's degree and about 29 percent having a graduate degree. About 73 percent of the sample respondents are White, 12.4 percent are Asian or Pacific Islander, and 8.7 percent are Black.

The income distribution shows a rich variation with a healthy representation of individuals in every income bracket. In terms of household size, 42.3 percent of individuals reported living in households with three or more people while 22.3 percent constituted single person households. A little over 60 percent reside in stand-alone homes and nearly 30 percent reside in condo/apartment units. Nearly 60 percent own their home, while 35 percent are renters. Just about 5.5 percent of individuals report living in households with no vehicles; nearly 25 percent are in households with one vehicle; and 30.5 percent are residing in households with three or more vehicles. This distribution suggests that this is a sample with a high level of household vehicle availability. The sample is composed more heavily of individuals from the Austin and Atlanta areas due to a higher level of ridehailing service use in those areas.

2.2. Endogenous Variables and Attitudinal Indicators

Table 1 also depicts distributions on the behavioral endogenous variables of interest. Both frequency of ridehailing service usage and change in bus use after adoption of ridehailing service are ordered dependent variables with three categories each. It is found that about two-thirds of the sample uses ridehailing services rarely (less than monthly); just over one-quarter of the sample uses ridehailing services monthly; and only 6.7 percent use these services weekly. In terms of change in bus usage, only 4.2 percent report an increase in bus use due to adoption of ridehailing services. On the other hand, 18.5 percent report a decrease in bus usage. Most individuals (77.3 percent) report no change in bus use due to ridehailing service usage.

Table 1: Socio-Economic and Demographic Characteristics of the Sample

Individual characteristics (N = 1,336)		*Household characteristics (N = 1,336)*	
Variable	**%**	**Variable**	**%**
Gender		**Household annual income**	
Female	60.4	Less than $25,000	12.9
Male	39.6	$25,000 to $49,999	11.8
Age category		$50,000 to $74,999	16.3
18-30 years	37.7	$75,000 to $99,999	12.8
31-40 years	15.8	$100,000 to $149,999	21.2
41-50 years	15.3	$150,000 to $249,999	15.9
51-60 years	15.7	$250,000 or more	9.1
61-70 years	10.5	**Household size**	
71+ years	5.0	One	22.3
Driver's license possession		Two	35.4
Yes	92.6	Three or more	42.3
No	7.4	**Housing unit type**	
Employment status		Stand-alone home	61.1
Student (part-time or full-time)	12.9	Condo/apartment	29.7
Worker (part-time or full-time)	58.8	Other	9.1
Both worker and student	14.1	**Homeownership**	
Neither worker nor student	14.1	Own	59.7
Education attainment		Rent	35.0
High school or less	7.2	Other	5.3
Some college or technical school	25.6	**Vehicle ownership**	
Bachelor's degree(s)	38.4	Zero	5.5
Graduate degree(s)	28.8	One	24.7
Race		Two	39.3
Asian or Pacific Islander	12.4	Three or more	30.5
Black or African American	8.7	**Location**	
Multi race	3.7	Atlanta, GA	34.2
Native American	0.6	Austin, TX	42.4
Other	1.5	Phoenix, AZ	16.7
White or Caucasian	73.2	Tampa, FL	6.7
Endogenous Variables			
Frequency of ridehailing service usage		**Change in bus use due to ridehailing service**	
Weekly	6.7	Increase	4.2
Monthly	25.8	No change	77.3
Rarely	67.4	Decrease	18.5

One of the key objectives of the modeling exercise undertaken in this report is to explicitly account for latent attitudinal constructs that may impact the endogenous variables of interest. The latent attitudinal constructs are endogenous variables themselves as well and are influenced by exogenous socio-economic and demographic characteristics. Three latent constructs are considered in this study. They are *pro-environment attitude*, *mobility service perception*, and *transit-oriented lifestyle*. Each latent construct is captured using three attitudinal variables or indicators in the data set. These indicators are highly correlated with one another and constitute an important dimension of the latent construct. Figure 1 depicts the three stochastic latent constructs and their corresponding attitudinal indicators. In the interest of brevity, each and every attitudinal statement is not described in detail here as the distributions depicted in the figure are self-explanatory.

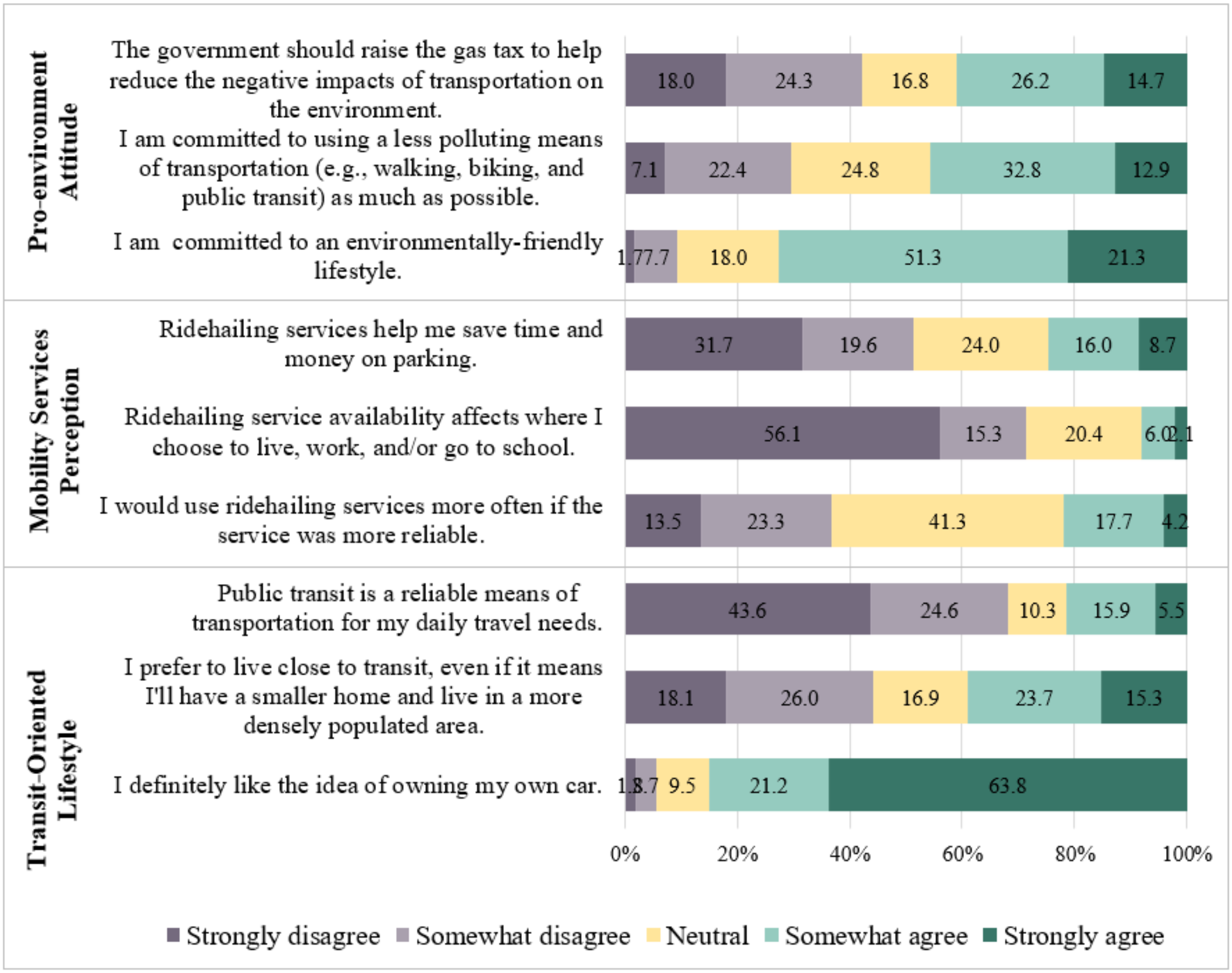

Figure 1: Distribution of Attitudinal Indicators of Latent Variables (N = 1336)

Figure 2 presents a bivariate descriptive chart of the two dependent variables. The pattern suggests a relationship between the two dimensions of interest, but a multivariate modeling framework is needed to truly capture the relationship between these two behavioral phenomena while controlling for other socio-economic, demographic, and attitudinal variables. As expected, the greatest change in bus use occurs among those who use ridehailing services very frequently (weekly basis). The number of individuals who indicate that they use ridehailing weekly is small

(N=90); within this group, nearly nine percent indicated that they increased bus use, but 40 percent indicated that they decreased their bus use as a result of ridehailing service usage. Among those who use ridehailing services more sparingly, nearly 80 percent report no change in bus use due to ridehailing. Only four percent increased bus use, while the remainder (16 percent of rare users and 19.4 percent of monthly users) decreased bus use. Clearly, frequency of ridehailing service usage does have implications for change in bus use, and the percentage of individuals decreasing bus use greatly exceeds the percent of individuals increasing bus use (due to ridehailing service usage). This is the first indication that ridehailing substitutes for, and takes away, bus ridership (more than it complements and adds to bus ridership).

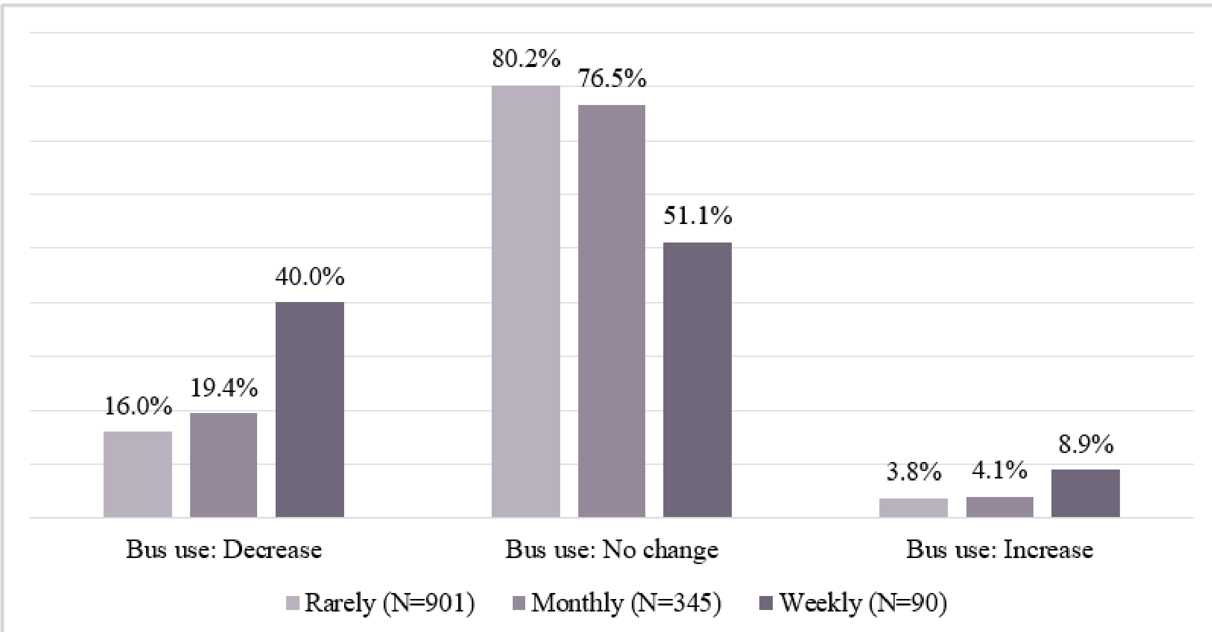

Figure 2: Bus Use Change by Ridehailing Services Usage Frequency (N = 1336)

3. MODELING FRAMEWORK

This section presents the modeling framework and methodology. The modeling framework should be capable of accounting for multiple endogenous variables and the influence of latent attitudinal constructs (which are endogenous themselves). The overall model structure is presented first, while the model formulation and estimation methodology are presented second.

3.1. Model Structure

A simplified representation of the model structure is depicted in Figure 3. The analytic framework centers on developing a joint model of ridehailing service use frequency and bus use change. The determinants of the main outcome variables include individual-level variables spanning socio-economic, demographic, and household characteristics as well as attitudinal/lifestyle factors that are also known as psycho-social factors. The factors are not directly observable but are treated as latent stochastic constructs revealed through an individual's responses to a set of attitudinal statements.

Exogenous variables include socio-economic and demographic variables together with select travel or mobility routines that may be treated as exogenous for purposes of this study. There is a direct effect between the two endogenous variables, with the frequency of ridehailing service use affecting change in bus use. Exogenous variables can directly influence the behavioral outcomes of interest. At the same time, they may also influence the endogenous variables through an intermediate set of latent attitudinal constructs. The three latent attitudinal constructs influence the endogenous variables and are themselves influenced by exogenous variables. As they are stochastic in nature, error correlations may be computed for the latent constructs; and by virtue of their stochasticity, they are able to engender an implied correlation between the two endogenous variables themselves. It is desirable to estimate the entire model structure in one step for purposes of parameter efficiency and representation of jointness in the behavioral outcomes of interest. The Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015) offers a computationally efficient and robust approach for parameter estimation. The estimation methodology is presented briefly in the next subsection.

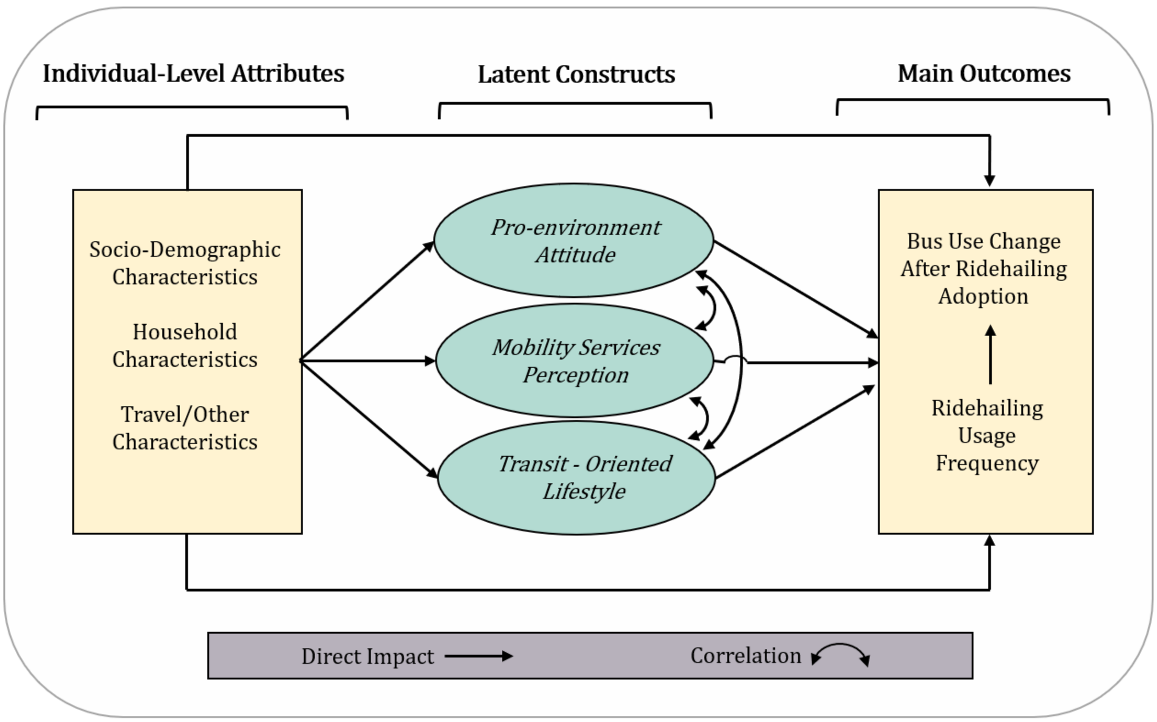

Figure 3: Modelling Framework

3.2. Model Estimation Methodology

As the outcomes as well as the indicators are ordinal in nature, the GHDM model for this study is formulated for exclusively ordinal outcomes. Consider the case of an individual $q \in \{1,2,\ldots,Q\}$. Let $l \in \{1,2,\ldots,L\}$ be the index of the latent constructs and let z_{ql}^* be the value of the latent variable $\boldsymbol{l}$ for the individual q. z_{ql}^* is expressed as a function of its explanatory variables as,

$$z_{ql}^* = w_{ql}^T \alpha + \eta_{ql} \tag{1}$$

where w_{ql} $(D \times 1)$ is a column vector of the explanatory variables of latent variable l and α $(D \times 1)$ is a vector of its coefficients. η_{ql} is the unexplained error term and is assumed to follow a standard normal distribution. Equation (1) can be expressed in matrix form as,

$$z_q^* = w_q \alpha + \eta_q \tag{2}$$

where z_q^* $(L \times 1)$ is a column vector of all the latent variables, w_q $(L \times D)$ is a matrix formed by vertically stacking the vectors $(w_{q1}^T, w_{q2}^T, \ldots, w_{qL}^T)$ and η_q $(D \times 1)$ is formed by vertically stacking $(\eta_{q1}, \eta_{q2}, \ldots, \eta_{qL})$. η_q follows a multivariate normal distribution centered at the origin and having a correlation matrix of $\boldsymbol{\Gamma}$ $(L \times L)$, i.e., $\eta_q \sim MVN_L(0_L, \boldsymbol{\Gamma})$, where 0_L is a vector of zeros. The variance of all the elements in η_q is fixed as unity because it is not possible to uniquely identify a scale for the latent variables. Equation (2) constitutes the structural component of the framework.

Let$j \in \{1,2,\ldots,J\}$ denote the index of the outcome variables (including the indicator variables). Lety_{qj}^*be the underlying continuous measure associated with the outcome variabley_{qj}. Then,

$$y_{qj} = k \text{ if } t_{jk} < y_{qj}^* \leq t_{j(k+1)} \tag{3}$$

where $k \in \{1,2,\ldots,K_j\}$ denotes the ordinal category assumed by y_{qj} and t_{jk} denotes the lower boundary of the k^{th} discrete interval of the continous measure associated with the j^{th} outcome. $t_{jk} < t_{j(k+1)}$ for all j and all k. Since y_j^* may take any value in $(-\infty, \infty)$, we fix the value of $t_{j1} = -\infty$and $t_{j(K_j+1)} = \infty$ for all j. Since the location of the thresholds on the real line is not uniquely identifiable, set $t_{j2} = 0$. y_j^* is expressed as a function of its explanatory variables and other observed dummy variable endogenous outcomes (only in a recursive fashion, if specified),

$$y_{qj}^* = x_{qj}^T \beta + z_q^{*T} d_j + \xi_{qj} \tag{4}$$

where $\boldsymbol{x_{qj}}$is an $(E \times 1)$ vector of size of explanatory variables including a constant as well as including the possibility of other dummy variable endogenous outcome variables.$\boldsymbol{\beta}$ $(E \times 1)$ is a column vector of the coefficients associated with $\boldsymbol{x_{qj}}$ and d_j $(L\times1)$ is the vector of coefficients of the latent variables 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 J outcome variables may be expressed as,

$$y_q^* = x_q \beta + d z_q^* + \xi_q \tag{4}$$

where y_q^* $(J \times 1)$ and ξ_q $(J \times 1)$ are the vectors formed by vertically stacking y_{qj}^* and ξ_{qj}, respectively, of the J dependent variables. x_q $(J \times E)$ is a matrix formed by vertically stacking the vectors $\left(x_{q1}^T, x_{q2}^T, \ldots, x_{qJ}^T\right)$ and d $(J \times L)$ is a matrix formed by vertically stacking $\left(d_1^T, d_2^T, \ldots, d_J^T\right)$. $\boldsymbol{\xi_q}$ follows a multivariate normal distribution centered at the origin with an identity matrix as the covariance matrix (independent error terms). $\xi_q \sim MVN_J(0_J, \boldsymbol{I}_J)$. It is assumed the terms in $\boldsymbol{\xi_q}$ are independent because it is not possible to uniquely identify all correlations between the elements in $\eta_q$and all correlations between the elements in $\boldsymbol{\xi_q}$. Further, because of the ordinal nature of the outcome variables, the scale of y_q^* cannot be uniquely identified. Therefore, the variances of all elements in $\boldsymbol{\xi_q}$ is fixed to one. The reader is referred to Bhat (2015) for further nuances regarding the identification of coefficients in the GHDM framework.

Substituting Equation (2) in Equation (5), y_q^* can be expressed in the reduced form as

$$y_q^* = x_q\beta + d\left(w_q\alpha + \eta_q\right) + \xi_q \quad (5)$$
$$y_q^* = x_q\beta + dw_q\alpha + d\eta_q + \xi_q \quad (6)$$

On the right side of Equation (7), $\boldsymbol{\eta}_q$ and ξ_q are random vectors that follow the multivariate normal distribution and the other variables are non-random. Therefore, y_q^* also follows the multivariate normal distribution with a mean of $b = x_q\beta + dw_q\alpha$ (all elements of $\boldsymbol{\eta}_q$ and ξ_q have a mean of zero) and a covariance matrix of $\boldsymbol{\Sigma} = d\boldsymbol{\Gamma}d^T + \boldsymbol{I}_J$.

$$y_q^* \sim MVN_J(b, \boldsymbol{\Sigma}) \quad (7)$$

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 t_{jk} for all j and $k \in \{3,4,\ldots,K_j\}$. 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,

$$L_q(\theta) = \int_{v_1=t_{1y_{q1}}-b_1}^{v_1=t_{1(y_{q1}+1)}-b_1} \int_{v_2=t_{2y_{q2}}-b_2}^{v_2=t_{2(y_{q2}+1)}-b_2} \ldots \int_{v_J=t_{Jy_{qJ}}-b_J}^{v_J=t_{J(y_{qJ}+1)}-b_J} \phi_J(v_1, v_2, \ldots, v_J|\boldsymbol{\Sigma})dv_1dv_2 \ldots dv_J, \quad (8)$$

where, $\phi_J\left(v_1, v_2, \ldots, v_J|\boldsymbol{\Sigma}\right)$ 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 the estimation results for the joint model system. The entire model structure was estimated in one step using the GHDM methodology. The factor loadings, effects of exogenous variables on the latent factors and behavioral dimensions of interest, and the relationship between the endogenous variables are estimated simultaneously, thus recognizing the jointness in the complex interrelationships that characterize ridehailing and bus use.

4.1. Latent Construct Model Components

Table 2 presents estimation results for the latent variable component of the model system. The table presents factor loadings for attitudinal indicators that define the latent constructs as well as model coefficients depicting the influence of exogenous variables on the latent constructs. As noted earlier, there are three latent constructs defined by three attitudinal indicators each. The factor loadings are all intuitive and significant, clearly indicating that they are appropriate indicators for the latent constructs defined in this study.

Table 2: Determinants of Latent Variables and Loadings on Indicators (N = 1336)

Explanatory Variables (base category)	**Structural Equations Model (SEM) Component**					
	Pro-environment Attitude		Mobility Services Perception		Transit-oriented Lifestyle	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
Individual characteristics						
Age (*)						
18-30 years	—	—	0.59	16.47	—	—
18-40 years	-0.14	-6.29	—	—	—	—
31-65 years	—	—	—	—	-0.37	-16.13
Education (*)						
High school or less	—	—	—	—	0.32	9.29
Graduate degree(s)	0.31	13.61	—	—	—	—
Race (White)						
Non-White	—	—	0.66	18.46	—	—
Employment status (not a student)						
Student	0.38	13.91	—	—	—	—
Household characteristics						
Household income (*)						
Up to $25,000	—	—	0.34	8.43	—	—
Up to $50,000	—	—	—	—	0.50	20.98
$100,000 to $150,000	-0.25	-10.73	—	—	—	—
$100,000 or over	—	—	-0.34	-11.13	—	—
Household structure (not a nuclear family)						
Nuclear family	—	—	—	—	-0.39	-15.48
Correlations between latent constructs						
Pro-environment attitude	1	—	0.68	4.61	0.95	7.56
Mobility services perception			1	—	0.80	5.64
Transit-oriented lifestyle					1	—
Attitudinal Indicators	**Loadings of Latent Variables on Indicators (Measurement Equations Model Component)**					
The government should raise the gas tax to help reduce the negative impacts of transportation on the environment.	0.62	22.47				
I am committed to using a less-polluting mean of transportation (e.g., walking, biking, and public transit) as much as possible.	0.91	24.07				
I am committed to an environmentally-friendly lifestyle.	0.45	18.18				
Ridehailing services help me save time and money on parking.			0.66	17.67		
Ridehailing service availability affects where I choose to live, work, and/or go to school.			0.42	17.81		
I would use ridehailing services more often if the service was more reliable.			0.32	17.25		
Public transit is a reliable means of transportation for my daily travel needs.					0.80	26.98
I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area.					0.65	26.01
I definitely like the idea of owning my own car.					-0.58	-22.83

Note: Base categories for attributes (*) are the excluded categories not appearing in the table.

A host of exogenous variables influence the latent attitudinal constructs. It was found that there was no significant gender effect across all three latent constructs. This is somewhat inconsistent with findings reported in the literature (e.g., Lavieri and Bhat, 2019; Sikder, 2019; von Behren et al., 2021), but is a result in this study that proved insensitive to the model specification. Younger individuals are more likely to view mobility services positively, consistent with earlier findings in the literature that have consistently shown that younger individuals use mobility services more than others (e.g., Rayle et al., 2016; Alemi et al., 2018; Sikder, 2019). Older individuals exhibit a higher degree of pro-environment attitude and a lower degree of transit-oriented lifestyle, consistent with the literature (e.g., Cervero, 2007; Wiernik et al., 2013; Lavieri and Bhat, 2019; Sharda et al., 2019). In general, those in the middle age groups are in a lifecycle stage where concerns about employment, household obligations, childcare, and financial security tend to be greater, and hence less emphasis is placed on environmental and transit-oriented lifestyles (Wiernik et al., 2013; McCarthy et al., 2017).

As expected, a higher education level is associated with a greater degree of pro-environment attitude, similar to findings reported by Kang et al. (2021) and Blazanin et al., (2021). Students depict a higher level of pro-environment attitude than others. At the same time, those with a lower education level (high school or less) appear more transit oriented than others; this, however, is largely because these individuals are in a lower income bracket and depend more heavily on transit for their mobility (leading to a greater proclivity towards a transit-oriented lifestyle). The household income and structure effects are intuitive as well. Lower income individuals depict a more positive perception of mobility services because they use them for mobility and find them convenient and affordable to do so (at least for short trips). Lower income individuals are also more inclined to be transit oriented. On the other hand, higher income individuals – who tend to own and use cars more than other groups – are less pro-environment and less favorable about mobility services (largely because they do not have a need to use mobility services on any regular basis). These findings are consistent with those reported in the literature (e.g., Cervero, 2007; Sharda et al., 2019). Finally, households that have a nuclear family structure (multiple adults with at least one child) are less likely to score high on the transit-oriented lifestyle, which is consistent with the notion that transit is not very conducive to meeting the complex mobility needs of households with children.

4.2. Bivariate Model of Behavioral Outcomes

Table 3 presents estimation results for the bivariate model of behavioural outcomes. The key finding is that, after controlling for all socio-economic, demographic, and attitudinal effects in a joint behavioural modelling framework, ridehailing usage has a statistically significant negative impact on bus use. An increasing frequency of ridehailing usage has the effect of decreasing bus use. Although there have been efforts to leverage ridehailing to complement and enhance transit usage (Shaheen and Cohen, 2020), the results of this study unequivocally show that ridehailing is taking ridership away from bus service – particularly in automobile-oriented metropolitan areas that are generally characterized by dispersed land use patterns and relatively poor transit service (note that this effect of ridehailing usage frequency on bus use may be considered as a "true" causal effect, after accommodating the spurious unobserved correlation between the two endogenous variables engendered by the stochastic latent constructs).

Table 3: Estimation Results of the Joint Ridehailing Use and Bus Use Change Model (N = 1336)

Explanatory Variables (base category)	Main Outcome Variables			
	Ridehailing Use (rarely, monthly, weekly)		Bus Use Change (decrease, no change, increase)	
	Coef	t-stat	Coef	t-stat
Endogenous variable				
Ridehailing use frequency	—	—	-0.17	-10.59
Latent constructs				
Pro-environment attitude	-0.25	-6.36	—	—
Mobility services perception	0.07	1.29	-0.32	-9.25
Transit-oriented lifestyle	0.46	9.57	0.42	10.99
Individual characteristics				
Age (*)				
31-65 years	—	—	0.25	7.78
Over 65 years	-0.75	-14.85	—	—
Race (White)	—	—		
Non-White	-0.07	-1.57	—	—
Employment (not a student)				
Student	—	—	0.22	7.46
Household characteristics				
Household income (*)				
$50,000 to $100,000	—	—	0.22	7.22
$150,000 or more	0.49	14.50	—	—
Household size (*)				
One	0.22	7.52	—	—
Three or more	—	—	0.20	7.37
Household vehicles (zero or at least two)				
One	—	—	-0.14	-5.26
Travel & built environment characteristics				
Weekly VMT (up to 75 & over 100 mi)				
76 to 100 mi	—	—	-0.31	-7.40
Population density (≥ 3,000 person/sq mile)				
Low density (< 3,000 person/sq mile)	-0.25	-10.51	—	—
Location (Austin, Phoenix, Tampa)				
Atlanta	0.15	5.59	—	—
Thresholds				
1|2	0.44	15.13	-1.08	-26.59
2|3	1.59	45.32	1.69	35.81
Correlation				
Ridehailing use	—	—	0.03	—
Data Fit Measures	**Joint (GHDM) Model**		**Independent (IOP) Model**	
Log-likelihood at convergence	-1838.49		-1850.23	
Log-likelihood at constants	-1925.09			
Number of parameters	82		32	
Likelihood ratio test	0.045		0.039	
Average probability of correct prediction	0.361		0.359	

Note: Base categories for attributes (*) are identified by the excluded categories.

All other effects are as expected and consistent with previous findings in the literature. Pro-environment attitude is associated with a proclivity towards lower level of ridehailing use, a positive perception of mobility services is associated with an inclination towards higher level of ridehailing use and a decreased level of bus use, and a transit-oriented lifestyle is associated with higher levels of ridehailing and increased bus use (suggesting transit oriented individuals use ridehailing to complement transit as opposed to substitution). These findings are similar to those reported in the literature (Rayle et al., 2016; Dong, 2020; von Behren et al., 2021).

Socio-economic and demographic characteristics significantly influence ridehailing use frequency and change in bus usage arising from the use of ridehailing services. Consistent with prior research, those over the age of 65 years are more likely to use ridehailing services sparingly when compared to younger age groups (Rayle et al., 2016; Alemi et al., 2018). Whereas those in the middle age group depict a tendency to increase bus use after adopting ridehailing, the positive coefficient for the 31-65 years group suggests that frequent ridehailing users in this group are more likely to use ridehailing to complement transit than other age groups.

There is a modest race effect with non-whites likely to use ridehailing services on a less frequent basis. This finding is somewhat contradictory to findings reported in the literature where it has been found that minority groups use ride-hailing services to a greater degree than Whites, even after controlling for income (Clewlow and Mishra, 2017; Deka and Fei, 2019). It should be noted that this data set is derived from four automobile-oriented sprawled metropolitan regions; as such, some findings may not be perfectly comparable to those reported in the literature. In a sprawled region, non-whites are likely to find it challenging to use mobility services on a frequent basis due to poor transit services (hence limited opportunities to use mobility services as first-mile/last-mile connectors) and higher costs associated with the need to traverse longer distances. Students on the other hand are likely to use ridehailing services to connect with transit; they report a higher level of transit use after using ridehailing services.

A higher income is associated with a proclivity for higher frequency of ridehailing use, a finding that mirrors the literature (e.g., Lavieri and Bhat, 2019; Dong, 2020). The middle-income group appears to show a tendency to increase bus use after ridehailing adoption. This is because they are able to use the service to connect to transit, particularly for commuting; they have enough income to use the service frequently as a first-mile/last-mile connector, but not enough income to undertake the entire commute journey by ridehailing. Individuals living alone show a greater proclivity to use ridehailing services more frequently, while those in larger households show a propensity to increase bus use after ridehailing adoption. The former finding is consistent with that reported by Sikder (2019), and the latter finding reflects the fact that not all individuals in larger households have access to an automobile and are now able to leverage ridehailing services to complement and elevate their bus use.

In one-vehicle households (which are generally vehicle-deficient households where one or more household members often depend on bus service to meet mobility needs), the greater use of ridehailing services is associated with a propensity to reduce bus use. Individuals in these households have clearly substituted the use of bus transit with ridehailing service. The amount of weekly travel influences bus use change. Those who have a large travel footprint (76-100 miles per week), depict a tendency to reduce bus use and substitute bus use with ridehailing services. In the four metro regions covered by this survey sample, meeting such extensive mobility needs using bus service is challenging, and hence ridehailing services are a superior alternative (thus leading to a proclivity to reduce bus use). Lower density living is associated with a higher probability of using ridehailing services less frequently; those in low density neighborhoods are likely to own cars and would find regular use of ridehailing cost prohibitive due to distances that need to be traversed. Respondents from Atlanta report a proclivity to use ridehailing services more frequently, presumably due to high density pockets, severe traffic congestion, and opportunities to connect to major transit (e.g., MARTA rail lines). The error correlation across the dependent variables of interest is very small, suggesting that the inclusion of the direct effect of ridehailing use frequency on bus use change captures the relationship between them quite effectively. Consequently, the remaining error correlation that would arise from the presence of correlated unobserved attributes that affect both endogenous variables is modest.

From a goodness-of-fit standpoint, the joint model is found to offer significantly better fit than a corresponding independent model system in which error correlations engendered through the endogenous treatment of latent attitudinal constructs are ignored (restricted to zero by virtue of treating attitudinal variables as exogenous variables, similar to socio-economic and demographic variables). This shows that modeling latent attitudinal constructs and behavioral outcomes of interest in an integrated framework that recognizes endogeneity is critical to capturing the jointness in attitudes and behaviors.

5. STUDY IMPLICATIONS AND CONCLUSIONS

This study focuses on the interaction between ridehailing service usage and change in bus use that results from the use of ridehailing services. The study utilizes a data set comprising respondents from the metro regions of Phoenix, Atlanta, Austin, and Tampa. The survey specifically asked individuals to convey their attitudes toward ridehailing services, the frequency with which they used ridehailing services, and the extent to which their bus use has changed due to ridehailing usage. In order to better understand and isolate the effect of ridehailing services on bus use change, this study adopts a simultaneous equations modeling framework in which joint relationships among multiple endogenous variables are captured explicitly. The model system accounts for the influence of latent attitudinal factors and treats them as endogenous variables as well.

The findings of this study clearly show that ridehailing usage negatively impacts bus use. Descriptive statistics as well as model estimation results indicate that ridehailing use frequency is significantly associated with a decrease in bus use, suggesting that ridehailing serves as a transit substitute (more than it serves as a complement). Despite attempts to have ridehailing services provide first-mile/last-mile connectivity and serve as a complement to transit, this has not happened – at least in auto-oriented metropolitan regions with dispersed land use patterns and rather limited transit service. After accounting for a host of socio-economic, demographic, and attitudinal factors, the effect of ridehailing is that it takes away from bus ridership.

The results are not surprising. Ridehailing is convenient, flexible, agile, faster (than transit), and personalized – these are many of the traits that render a mode appealing. It is more expensive, but also more affordable than traditional taxi and unlikely to be cost-prohibitive for short trips of a few miles (more than 60 percent of daily trips in the United States are five miles or less). Ridehailing also removes the hassle of driving and parking. It is clear why ridehailing is highly competitive and able to take trips away from public transit. As shared mobility services increasingly make their way into the transportation landscape (potentially shared, electrified, and automated to a greater degree in the future), the future of transit is under threat – and the threat has been exacerbated by the pandemic and the new remote modalities of work, school, and shopping embraced by the public. Transit ridership was already on the decline prior to the pandemic, and this analysis shows that ridehailing contributed significantly to the decline (the survey data pertains exclusively to the pre-pandemic period).

Municipalities and transit agencies need to explore strategies to enhance service and ridership, particularly in auto-oriented regions that have dispersed land use patterns. Partnering with ridehailing services so that first-mile/last-mile connectivity to transit is enhanced, payment systems are integrated, and the cost of ridehailing access/egress segments is highly subsidized would help transit agencies utilize emerging mobility services more effectively to boost ridership. Transit agencies themselves could reconfigure their service to expand coverage and enhance connectivity and accessibility with a focus on key travel corridors, market segments, and destinations. Recent attempts at reconfiguring services have worked to increase ridership in a few areas; examples include the Houston and Seattle metro areas (Descant, 2018) and the Northern Kentucky area (Tindale-Oliver, 2021). In all of these regions, transit services were expanded, routes were redrawn to bring about more direct connections and enhance both speed and reliability, access to destinations and people with mobility limitations was improved, and public input was considered throughout the process of reconfiguration.

Municipalities may need to consider charging an additional fee for ridehailing services and use the revenue obtained to enhance transit services and mobility options for residents. Ridehailing services have already shown to increase congestion (Diao et al., 2021) and this study shows that they take ridership away from transit too. The levying of a fee would help manage the demand for ridehailing services while providing additional revenue for enhancing transit services and access for disadvantaged groups. Transit agencies will be in a better position to provide customized mobility, similar to the RideChoice program currently offered by Valley Metro in the Greater Phoenix region for transportation disadvantaged groups (Valley Metro, 2021). Concerted efforts aimed at increasing awareness about transit options, influencing attitudes and values, and changing perceptions may further help stem the loss of transit ridership.

The future of transit remains uncertain. In the absence of significant investments in service and technology, partnerships with new and emerging mobility providers, and enhancements in service configuration that boost accessibility, it is likely that transit will continue to experience declines in ridership – at least in part due to the rise of ridehailing services.

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