Rider-to-rider discriminatory attitudes and ridesharing behavior

Rider-To-Rider Discriminatory Attitudes and Ridesharing Behavior

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ABSTRACT

Using online survey data from N = 2,041 Uber and Lyft users in the United States collected in 2016 and 2018, this paper establishes the validity, reliability, and invariance of a measure of rider-to-rider race and social class discrimination. This measure is then incorporated into three structural models that investigate associations between rider-to-rider discriminatory attitudes and four aspects of ridesharing behavior. We find no significant relationship between rider-to-rider discriminatory attitudes and whether a TNC user has ever used a ridesharing service (such as uberPOOL or Lyft Line). However, among those who have used ridesharing services before, rider-to-rider discriminatory attitudes are strongly negatively predictive of an individual's level of satisfaction with the sharing option, and marginally negatively predictive of an individual's percentage of shared TNC trips. Furthermore, among those who have *not* yet used ridesharing services, rider-to-rider discriminatory attitudes are strongly negatively predictive of willingness to consider using uberPOOL or Lyft Line in the future. Together, these findings suggest that rider-to-rider discriminatory attitudes may discourage sustained and frequent use of ridesharing services among TNC users. Further research is required to identify strategies for addressing discriminatory attitudes in the ridesharing context and overcoming reluctance to sharing.

Keywords: dynamic ridesharing; race; class; discrimination; Transportation Network Companies (TNCs)

1. INTRODUCTION

In the 2010s transportation network companies (TNCs) like Uber and Lyft have replaced, supplemented, and disrupted traditional modes of transportation. Their core *ridehailing* or *ridesourcing* services like UberX and Lyft Classic pair a single rider (or rider party) with a driver, while cost-reducing dynamic *ridesharing* services such as uberPOOL and Lyft Line (recently rebranded as Lyft "Shared") pair multiple riders (or rider parties) with a driver. These ridesharing services have made TNCs more price competitive with public transit and have expanded urban mobility options. As they continue to expand, flexible, dynamic, and affordable ridesharing services may play an enormous role in the urban transportation of the future. Due to the enormous scale and unregulated nature of these new mobility marketplaces and the uncertainty surrounding how they will transform urban mobility in the future, it is critical that we understand who has access to these platforms and who may be excluded from their services.

To address one aspect of exclusion from ridesharing services, recent studies have investigated discriminatory outcomes enabled by these new mobility platforms. Many of these initial investigations have focused on the core ridehailing services offered by TNCs that match a single rider party with a driver. In such situations, discrimination can occur in either direction between rider and driver. In the most comprehensive and telling study to date, Ge et al. (2016) explored driver-to-rider discrimination in ridehailing, finding that the decisions of individual Uber and Lyft drivers lead to discriminatory outcomes for riders. Through two field experiments, the researchers observed a significant difference in wait times and cancellations for otherwise identical riders with African American-sounding and Caucasian-sounding names. Brown (2018) has argued that TNC services have nearly eliminated racial and ethnic differences in service quality, relative to the taxicab industry. Specifically, Brown used an audit study of ridehailing and taxi services to assess how wait times and cancellation rates vary by rider race, ethnicity, and gender in Los Angeles County. The study found significant evidence of discrimination against black riders by taxi drivers, but dramatically lower racial and ethnic service gaps in ridehailing. In her study of Lyft use in Los Angeles County, Brown also found that riders are less likely to share rides in racially or ethnically diverse neighborhoods – a highly relevant finding for the current study of discrimination and behavior in ridesharing.

Other recent studies have highlighted the theoretical case for rider-to-driver discrimination in TNCs. Rosenblat et al. (2017) used a review of consumer behavior in online marketplaces and performance evaluations in managerial settings to argue that racial and gender bias is likely to influence TNC driver evaluations, which could lead to discriminatory termination practices by Uber. Recent research has also explored how driver earnings vary according to driver characteristics. In particular, a 2018 paper published analyzed earnings data for more than one million Uber drivers to find a 7% gender earnings gap among drivers (Cook, et al., 2018).

While existing research has largely focused on discrimination between riders and drivers in core ridesourcing services, as the proportion of dynamic *ridesharing* services increases, rider-to-rider discrimination may emerge as an additional critical issue. Recent research provides initial evidence that some TNC users harbor discriminatory attitudes towards fellow passengers of different social class and race, that fear of negative social interactions may reduce users' willingness to request shared rides, and that these riders prefer to have early information about potential fellow passengers (Sarriera, et al., 2017). Additionally, it has been shown that discriminatory attitudes toward fellow passengers of differing class and/or race in the shared ride are correlated with characteristics such as gender, parental status, race, geography, and income

(Middleton & Zhao, 2018). This paper also found that users' general social dominance orientation[1] strongly influences his/her discriminatory attitudes in ridesharing, supporting the claim that behavior in shared mobility platforms reflects long-standing social dominance attitudes.

The present paper expands upon research from Sarriera et al. (2017) and Middleton and Zhao (2018) by considering the associations between rider-to-rider discriminatory attitudes and user behavior in the context of ridesharing. While previous research has explored the association of rider-to-rider discrimination in the traditional carpooling context, finding that individuals are more likely to carpool when surrounded by neighbors of the same race (Charles & Kline, 2006), our work represents the first research into the relationship between users' willingness to share rides and their discriminatory attitudes in the context of *dynamic* ridesharing, in which the characteristics of fellow passengers is not known beforehand. In particular, this paper uses two surveys of TNC users ($N = 2{,}041$) in the United States collected in 2016 and 2018 to estimate three structural equation models that explore how an individual's discriminatory attitude is associated with four aspects of ridesharing behavior: 1) whether the TNC user has ever used a ridesharing service; 2) the proportion of the individual's total TNC trips that are shared, 3) the individual's level of satisfaction with ridesharing services, and 4) willingness to use ridesharing in the future. For each association of rider-to-rider discriminatory attitudes and ridesharing behavior, we also explore whether there is any change in the structural relation between 2016 and 2018.

This paper is organized as follows. Section 2 introduces the survey data used in this research, including collection methods and descriptive statistics. Section 3 presents the analytical methods used in this research, including both measurement and structural models. Section 4 discusses findings. Section 4.1 explores the convergent and divergent validity of our measure of rider-to-rider discrimination in ridesharing and Section 4.2 establishes the measure's invariance across the two survey years. Section 4.3 presents the results of three structural models that relate our measure of rider-to-rider discrimination to four aspects of ridesharing behavior. Finally, Section 5 discusses the behavior and policy implications of these findings.

2. DATA

2.1 Survey Collection and Screening

This study builds on data collected for two prior studies. An initial survey of Uber and Lyft users was conducted in June and July 2016 through Amazon Mechanical Turk, a crowdsourcing service that allows researchers to compensate human workers to answer questions or perform other tasks (Sarriera et al., 2017). A follow-up survey of different Uber and Lyft users was conducted in March and April 2018 through Mechanical Turk. In both survey waves, respondents were screened for eligibility for the study, having to self-report that 1) uberPOOL/Lyft Line is available in their city, and 2) they had used Lyft or Uber in the past 30 days. Respondents that reported zero Uber or Lyft trips in the past month were omitted from further analysis.

To screen valid responses, the researchers embedded two basic attention check questions (e.g., "Please select 'Agree' for this question") in the survey and applied six additional tests of quality and logical consistency to the completed responses. Responses meeting any of the following criteria were flagged and responses with two or more flags were omitted from further analysis.

[1] Social dominance orientation refers to an individual's preferences for group-based discrimination, social hierarchy, and domination over lower-status groups, measured according to scales established in social psychology literature (Ho, et al., 2016).

1. Completion time in the fifth percentile for the respective survey year (roughly less than 3.5 minutes)
2. Reported number of shared trips greater than reported number of total TNC trips
3. Inconsistent social dominance orientation preferences (i.e., strong agreement with two or more opposing statements in the social dominance orientation scale)
4. Inconsistent ridesharing preferences (i.e., strong agreement with two or more opposing statements related to discriminatory attitudes in the ridesharing discrimination scale)
5. Ridesharing not actually available in home ZIP code

According to our review of uberPOOL and Lyft Line services, ridesharing is currently available in the following markets: Seattle; Portland; San Francisco/San Jose; Los Angeles; San Diego; Las Vegas; Denver; Austin; Atlanta; Miami; Chicago; Nashville; Washington, DC; New Jersey; New York City; Boston; Philadelphia.[2] However, ridesharing may be available intermittently in other markets, and it is possible that respondents have used these services while traveling. For these reasons, we determined that the availability of ridesharing in a respondent's home ZIP code alone was not adequate cause for eliminating responses.

Of 1,222 eligible respondents who completed the 2016 survey and passed the basic attention checks, 207 failed the additional consistency and quality checks. This yielded a final sample size of n_{2016} = 1,015 respondents. Similarly, of the 1,446 respondents who completed the 2018 survey and passed the attention checks, 420 failed the tests of additional consistency and quality. This yielded a final sample size of n_{2018} = 1,026 respondents.

2.2 Sample Demographics

Our sampling frame consists of adult users of TNC services in the U.S. TNC users in the U.S. have been found to be younger, more highly educated, from households with higher annual income, and more urban compared to the general U.S. population (Smith, 2016; GlobalWebIndex, 2017). Even compared with U.S. urban populations, users of TNCs are more likely to be young, highly educated and higher income (Clewlow & Mishra, 2017). Data suggests that such user sociodemographics (particularly gender and age distribution) are similar across different ridehailing platforms (i.e. Uber or Lyft) (VertoWatch, 2018).

To compare our sample sociodemographics to those of general TNC users in the U.S., we take advantage of the recently released 2017 National Household Travel Survey (NHTS), which added a new question regarding use of ridehailing applications (USDOT FHWA, 2017). Subsetting the NHTS data only to those who are 18 years of age or older, we find that only 10% of the adult population reports having used a ridehailing application at least once. For these users, we then calculate the weighted percentage of respondents by gender, age, race and ethnicity, annual household income, and education attainment and compare the results to our sample sociodemographics (Table 1). Compared to TNC users in the NHTS data, our sample is fairly representative in terms of gender, race and ethnicity, and educational attainment, but overrepresents young and lower income respondents. These discrepancies are likely due to convenience sampling from Mechanical Turk, whose worker pool has been shown to overrepresent younger respondents (particularly between the ages of 21-35 years old), and those with lower incomes (Ipeirotis, 2010). Additionally, we find that there is little difference in the sample sociodemographics across the two survey years except for age and student status. Our 2018 survey,

[2] uberPOOL and Lyft Line were launched in each of these markets before the initial survey of Uber and Lyft users in June and July 2016. No changes in service areas were announced between the initial survey in 2016 and the second survey in 2018. As such, we apply the same ZIP code-based service area for both survey years.

while still overrepresenting young respondents, has slightly greater representation of TNC users in older age groups but fewer students.

Table 1. Demographics of survey respondents n_{2016} = 1,015 and n_{2018} = 1,026 compared with weighted 2017 NHTS respondents who have used a ridehailing application at least once and are 18 years of age or older.

Characteristic	Study Samples 2016	Study Samples 2018	NHTS 2017
Male	58.6	53.7	52.3*
Age			
18-24	28.1	12.5	17.1*
25-34	50.4	53.0	35.1*
35-44	15.8	21.2	21.4*
45-54	3.8	7.5	13.5*
55 and older	1.9	5.8	12.8*
Race/Ethnicity			
White	70.0	64.2	71.5
Black	8.5	9.7	10.6
Asian	10.2	12.7	8.4
Hispanic	7.8	6.7	18.2
Annual Household Income			
Less than $35,000	21.1	18.6	16.3
$35,000 to $74,999	49.3	47.4	21.1
$75,000 to $149,999	23.1	28.0	33.0
$150,000 or more	6.5	6.0	28.1
Educational Attainment			
HS education	6.6	6.5	8.2
Some college	28.3	24.9	20.8
College degree	48.0	49.4	36.8
Graduate degree	17.1	18.4	32.5
Employment Status			
Unemployed	6.4	6.8	--
Student	12.9	4.8	--
Uses sharing	75.5	74.2	--
Sharing available in home zip code	64.7	63.5	--

Note: * = missing data imputed by NHTS; -- = not available

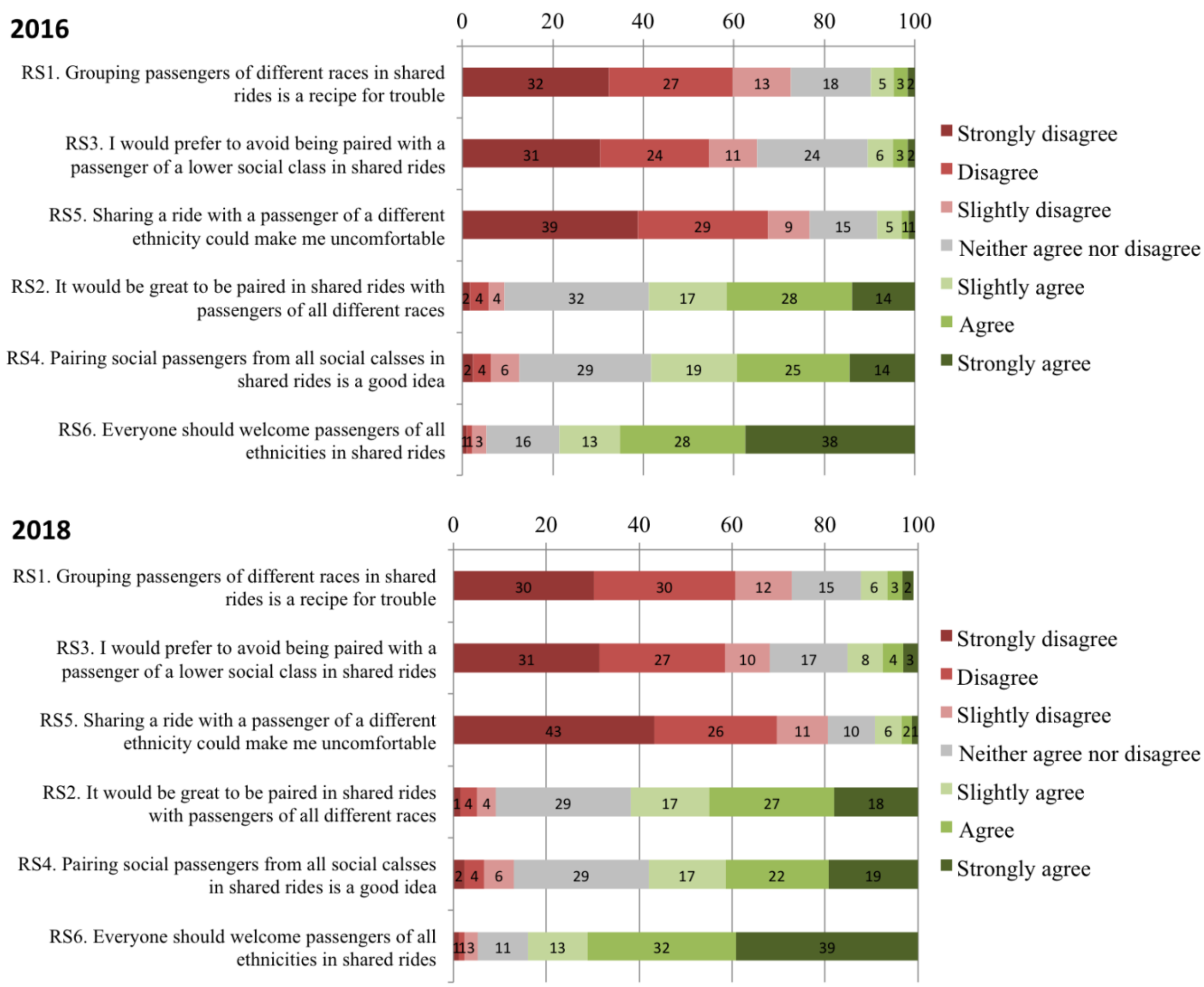
2.3 Study Variables

In addition to basic demographics, the two surveys posed questions in the following categories: general travel behavior; opinion on and experience with uberPOOL and Lyft Line; generic attitude toward social dominance; and specific preferences with respect to being paired with people of different backgrounds in shared rides. Six of these attitudinal questions assess the existence of and potential for race- and class-based rider-to-rider discrimination through stated preferences.

Figure 1 summarizes respondents' level of agreement to these preferences according to a seven-point Likert scale from "strongly disagree" to "strongly agree." Figure 1 reveals that, in general, a small but significant minority explicitly expressed discriminatory attitudes (i.e., 5.9 to 15.9 percent depending on the specific survey statement and year). Looking at the average across all 6 items, 9.5% of individuals in both survey years expressed explicit agreement with discriminatory statements. Stated preferences are likely to under represent the prevalence of discriminatory attitudes due to social desirability bias (Pager & Shepherd, 2008). However, despite the limitations of measuring discriminatory attitudes through such stated preference surveys, these descriptive statistics suggest that such attitudes do indeed exist within the population of ridehailing users.

Both surveys also asked eight additional Likert-scale questions (see Appendix Table A) used in our measurement models to create a social dominance orientation factor. This social dominance orientation is a well-established measure of respondents' general attitudes towards the relative status of different social groups in general (e.g., "Some groups of people must be kept in their place") (Ho, et al., 2015).

Figure 1. Ride sharing preferences of respondents, from "strongly disagree" to "strongly agree", n_{2016} = 1,015 and n_{2018} = 1,026.



The survey also collected information on respondent's current use of private and shared ridehailing services, which provide the behavioral outcome variables tested in the structural models in Section 3.2. In particular, the survey asked users the following:

I. Have you ever used uberPOOL or Lyft Line? [Yes / No]

2. *For those who answered yes to 1:* Overall, what do you estimate as the percentage of your total Uber or Lyft trips taken with uberPOOL or Lyft Line? [slider bar from 0 – 100%]
3. *For those who answered yes to 1:* Thinking about the service you use most frequently (i.e., Lyft or Uber), how satisfied are you with uberPOOL or Lyft Line specifically? [Integer scale from 1 to 10]
4. *For those who answered no to 1:* Would you ever consider using uberPOOL or Lyft Line in the future?. [Yes / No]

3. METHODS

We adopt a structural equation modeling (SEM) framework to answer our research questions. SEM allows the researcher to quantitatively test whether a theoretical or hypothesized model depicting the relationships among different variables is supported by sample data. The overall fit of the model can be quantified by comparing the estimated variance-covariance matrix implied by the model with the variance-covariance matrix of the sample data. For directed relationships among variables, the path parameter is estimated as a regression coefficient. Therefore, estimated coefficients can be interpreted as multivariate linear or logistic regression coefficients (depending on whether the outcome variable is continuous or categorical).

SEM has several advantages over traditional regression approaches. First, the "measurement model" component of an SEM estimates latent constructs from a series of observed variables. Measurement models can be used to establish the validity of the latent variables, which are generally more reliable measures than their individual indicators. When estimated simultaneously with the structural component of the SEM (the specified paths among the variables), the model explicitly accounts for measurement error in these latent factors (which traditional regression ignores for all independent variables). Second, SEM works by reproducing not just the mean and variance structures among the variables (as traditional regression), but also the covariances. This allows it to explore more complex, multivariate relationships among variables that are correlated with one another.

For this study, SEM was chosen because it enabled us to group observed responses to multiple indicators into two latent factors (i.e. rider-to-rider discrimination and social dominance orientation) and explore their relations with key behavioral outcomes of interest. First, a series of measurement models are estimated to establish the unidimensionality, convergent and divergent validity, and invariance across survey years of our measure of passenger-to-passenger discriminatory attitudes in ridesharing. Second, a series of structural models explore the association of discriminatory attitudes with ridesharing behavior. All models are estimated using Mplus version 8.1 using Maximum Likelihood with Robust Standard Errors (MLR) estimation to correct for the non-normality of exogenous variables (Muthén & Muthén, 1998-2017).

3.1 Measurement Models

We estimate a confirmatory factor analysis (CFA) model to identify a reliable measure of rider-to-rider discrimination on the pooled sample from both 2016 and 2018 survey implementations. We compare the overall model fit to established standards: a chi-square test statistic that is not statistically different from zero, CFI and TLI > 0.90, and RMSEA and SRMR < 0.08 (Kline, 2016; Hu & Bentler, 1999). We demonstrate the convergent validity of a 6-item measure of rider-to-rider discrimination by showing that all items have standardized factor loadings > 0.7 and $R^2 > 0.50$, suggesting that the majority of the variation in the response patterns on the observed indicators is explained by the latent construct of rider-to-rider discrimination (Kline, 2016). We then demonstrate the divergent validity of the rider-to-rider discrimination measure by estimating a CFA that correlates rider-to-rider discrimination with the social dominance scale to show that these are related, but distinct constructs.

Comfortable with the convergent and divergent validity of the measure of rider-to-rider discrimination, we perform a multigroup analysis to determine whether the factor structure of rider-to-rider discrimination is invariant across the two sample years (2016 and 2018). We estimate a CFA model for the rider-to-rider discrimination measure that allows all estimated parameters (factor loadings, variances, and covariances) to differ across respondents from the two survey years. We perform a Satorra-Bentler scaled chi-square difference test to determine whether there is better fit between the initial model, which assumes the same factor structure across survey years, and the unconstrained model, which allows the factor structure to differ across the two years (2001).

3.2 Structural Models

After we have determined the reliability and invariance of the structure of the rider-to-rider discrimination measure, we incorporate the latent construct into structural models to explore its relation with ridesharing behavior (see Table 2). Controlling for individual-level covariates (including age, gender, race/ethnicity, educational attainment, and income) as well as frequency of TNC use, we estimate three structural equation models to explore the association of rider-to-rider discriminatory attitudes with ridesharing behavior.

Model 1 investigates the (logistic) direct path from discriminatory attitudes to whether the respondent have used ridesharing (0/1) for the entire pooled sample of $N = 2{,}041$. For the subset of respondents who have used sharing ($n = 1{,}527$), Model 2 estimates direct paths from discriminatory attitudes to the respondent's estimated percentage of TNC trips that are shared (0-100%) and satisfaction with shared trips (on a 1-10 scale). For those respondents who have not used sharing ($n = 514$), Model 3 investigates a (logistic) direct path from rider-to-rider discriminatory attitudes to whether the respondent would be willing to share in the future (0/1). All models are estimated using the pooled sample of respondents from 2016 and 2018, with an additional moderation analysis performed to test for statistical difference in structural associations across these two survey years.

Table 2. Summary of the structural models of the study.

	Dependent variable(s)	Descriptive statistics	Respondents
Model 1	Have you ever used uberPOOL or Lyft Line? (0/1)	Mean = 0.748	All ($N = 2{,}041$)
Model 2	Percentage of TNC trips that are shared in the past month (0-100%)	1st quartile = 10.0 Median = 28.0 Mean = 37.1 3rd quartile = 55.0	Those who have shared ($n = 1{,}527$)
	Satisfaction with shared trips (0-10)	1st quartile = 6.0 Median = 7.0 Mean = 7.2 3rd quartile = 8.5	
Model 3	Would you share in the future? (0/1)	Mean = 0.531	Those who have not shared ($n = 514$)

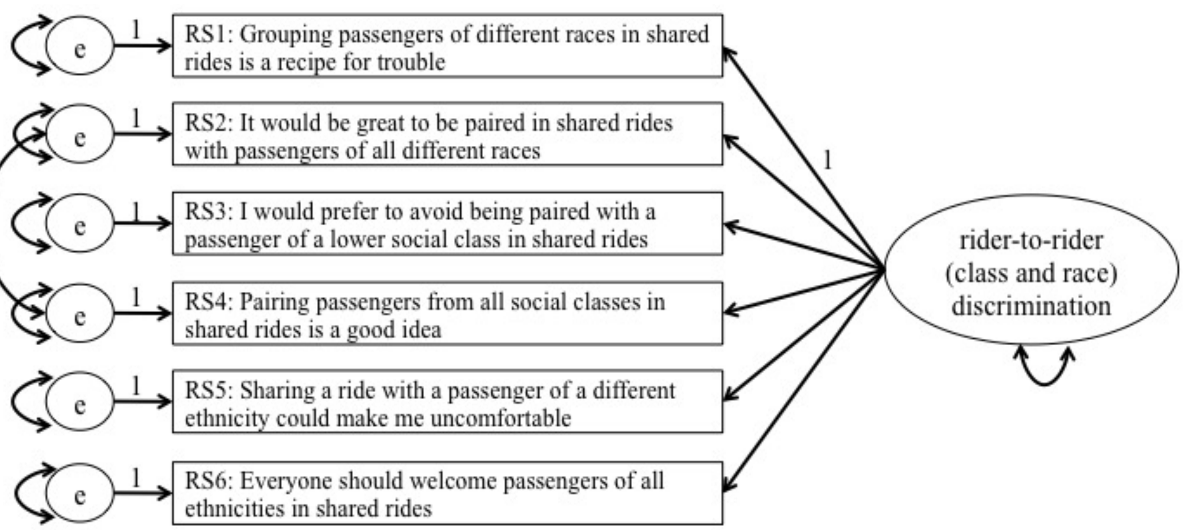
In each model, we assume that rider-to-rider discriminatory attitudes predict behavior in accordance with the Theory of Planned Behavior (Ajzen 1995). While limited by cross-sectional data, we can use the social dominance orientation factor as an instrumental variable for our measure of rider-to-rider discrimination to estimate its directed path to the behavioral outcomes of interest (Bollen & Nobel, 2011). However, it is likely that these relationships are bi-directional, since behavior can also reinforce attitudes (Kroesen, Handy, & Chorus, 2017). Future work using longitudinal or experimental data would be needed to explore the relative magnitudes of our measured paths from discriminatory attitudes to ridesharing behavior with those from behavior back to discriminatory attitudes.

4. RESULTS

4.1. Measurement Models

Our survey contains 6 Likert-format statements designed to capture both race and class discrimination from rider-to-rider using the pooled dataset from both the 2016 and 2018 survey implementations (*N* = 2,041). We estimate a CFA model with the 6 items loading onto one factor. An investigation of modification indices suggests that adding a correlation between the error terms of two items would significantly improve model fit. We introduce one correlation between two statements (RS2 and RS4) that express a preference for social mixing in pairing ridesharing passengers (by race and by class, respectively). We propose a final 6-item CFA model of rider-to-rider discrimination as depicted in Figure 2).

Figure 2. Confirmatory factor analysis model for the measure of rider-to-rider discrimination.



The CFA model results for the factor structure presented in Figure 2 are given in Table 3. We find that this 6-item single-factor measure of rider-to-rider discrimination meets established standards of model fit: $\chi^2(8, N = 2{,}041) = 131.086$, $p < .01$, RMSEA = 0.087, CFI = 0.963, TLI = 0.930, SRMR = 0.026. Given the large sample size, we overlook the statistically significant chi-square test statistic and note that the CFI and TLI are well above the established threshold of 0.90 for moderate model fit, the RMSEA is around the threshold of 0.08 and SRMR is well below 0.08 (Kline, 2016; Hu & Bentler, 1999). The convergent validity of the measure is well established, with all items having standardized factor loadings > 0.6 and R^2 values close to or above 0.50. This suggests that the latent variable of rider-to-rider discrimination explains much of the variance in the response patterns to each of the 6 items that constitute the measure.

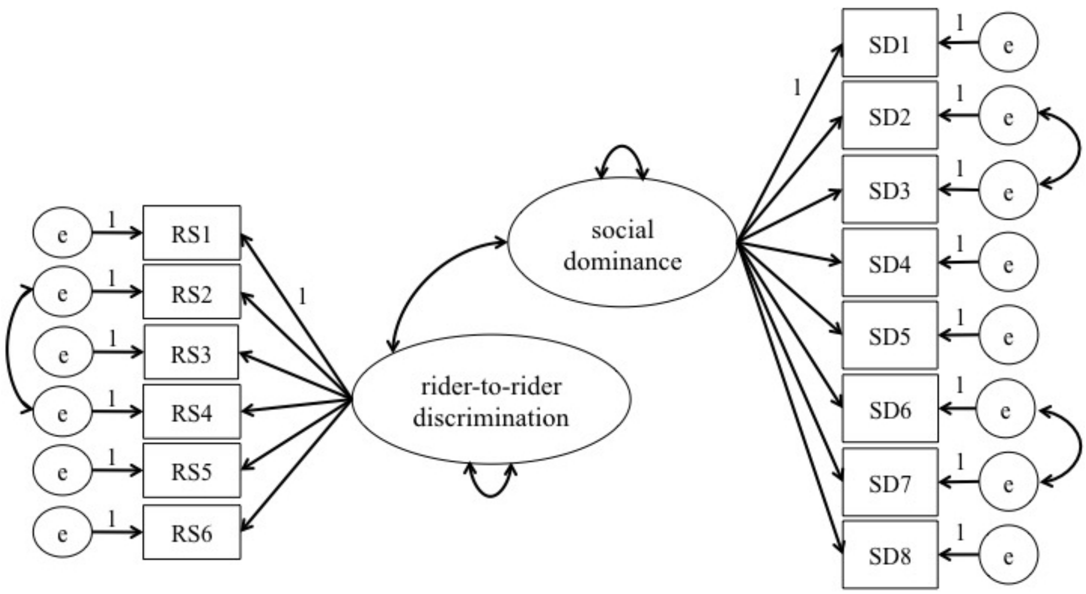
Table 3. Confirmatory factor analysis results for the measure of rider-to-rider discrimination.

Item	Survey statement	*b*	*S.E.*	*p*	*β*	R^2
RS1	Grouping passengers of different races in shared rides is a recipe for trouble	1.000	—	—	0.741	.550
RS2	It would be great to be paired in shared rides with passengers of all different races [rev]	0.834	0.028	.000***	0.673	.453
RS3	I would prefer to avoid being paired with a passenger of a lower social class in shared rides	1.035	0.036	.000***	0.728	.530
RS4	Pairing passengers from all social classes in shared rides is a good idea [rev]	0.870	0.031	.000***	0.663	.440
RS5	Sharing a ride with a passenger of a different ethnicity could make me uncomfortable	1.074	0.029	.000***	0.839	.704
RS6	Everyone should welcome passengers of all ethnicities in shared rides	0.967	0.032	.000***	0.827	.684

Significance: * = 10%, ** = 5%, *** = 1%
Note: [rev] = reverse-coded item; b = unstandardized factor loading; S.E. = standard error; p = two-tailed p-value (μ = 0); β = STDYX standardized factor loading
Overidentified model fit: $\chi^2(8, n = 2{,}041) = 131.086$, $p < .01$, RMSEA = 0.087, CFI = 0.963, TLI = 0.930, SRMR = 0.026.

To explore the divergent validity of our measure of rider-to-rider discrimination, we run a second CFA model that simultaneously estimates the rider-to-rider discrimination factor along with the social dominance scale and allows them to correlate (see Figure 3). The overidentified model demonstrates adequate model fit: $\chi^2(73, N = 2{,}041) = 454.947$, RMSEA = 0.051, CFI = 0.967, TLI = 0.959, SRMR = 0.027 (see Table A in the *Appendix*). Factor loadings for the rider-to-rider discrimination and social dominance scale items are consistent with those estimated in the individual measurement models. Of particular interest for divergent validity is the correlation of the rider-to-rider discrimination measure with the social dominance scale. We find that this correlation is positive, moderate in magnitude, and statistically significant ($b = 1.001$, $S.E. = 0.060$, $p < .01$, $\beta = 0.615$). This result suggests that our measure of rider-to-rider discrimination, while related to the social dominance scale, captures discriminatory attitudes specific to the ridesharing context.

Figure 3. Confirmatory factor analysis model for correlated measures of rider-to-rider discrimination and social dominance orientation.



Note: Variances of all error terms were estimated, but are not pictured

4.2 Measurement Invariance: Comparison across Survey Years

We perform a multigroup analysis to determine whether the factor structure for the rider-to-rider discrimination measure is invariant across the two survey years. We estimate the rider-to-rider discrimination measurement model specified in Figure 2 allowing all estimated path parameters and variances to differ between the 2016 and 2018 samples. This unconstrained model exhibited slightly worse overall fit—$\chi^2(26, N = 2{,}041) = 181.638$, p < .01 with an MLR scaling correction factor of 1.35[3]—than the constrained model where all parameters are equal across respondents in the two survey years. Performing a Satorra-Bentler scaled chi-square difference test, we find that the scaled chi-square difference of χ^2_D (18) = –35.59, $p < .01$ is statistically significant. We reject the null hypothesis that the models are equivalent and conclude that the constrained model, with the lower chi-square value, fits the data significantly better than the unconstrained model. Therefore, we conclude that there is no significant difference in the structure of the rider-to-rider discrimination measure between respondents in the 2016 and 2018 survey implementations.

Given that the factor structure for the rider-to-rider discrimination measure is invariant across the two survey years, we can compare the estimated factor scores across these subsamples (see Table 4). Factor scores are essentially optimally-weighted averages of the individual item scores standardized to have a mean of zero across all individuals. Therefore, negative values indicate below-average rider-to-rider discriminatory attitudes while positive values indicate above-average discriminatory attitudes. Performing a Welch two sample t-test to compare the means ($\mu_{2016} = 0.030$ and $\mu_{2018} = -0.029$), we find that there is no statistical difference in the means across the two survey years ($t = 1.247$, *d.f.* = 2038, $p = .213$). Therefore, there is no evidence of any difference in average rider-to-rider discriminatory attitudes between 2016 and 2018. However, we do find that there is a statistically significant difference in the average rider-to-rider discriminatory attitude between those who have and have not used shared service ($t = 2.173$, *df* =

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[3] Additional fit statistics for the unconstrained model: RMSEA = 0.077, CFI = 0.954, TLI = 0.947, SRMR = 0.035.

948, $p = .030$). Across both survey years, we find that those who have used sharing report higher average discriminatory attitudes towards fellow passengers of a different race or class ($\mu_{\text{have shared}} = 0.029$) than those who have not shared ($\mu_{\text{have not shared}} = -0.085$).

Table 4. Rider-to-rider discrimination factor scores for key subsamples.

Sample	1st quartile	Median	Mean	3rd quartile	Welch two sample t-test
All (N = 2,040)	-0.867	-0.269	0.000	0.738	
2016 (n = 1,015)	-0.815	-0.259	0.030	0.818	$t = 1.247, p = .213$
2018 (n = 1,026)	-0.867	-0.292	-0.029	0.608	
Have shared (n = 1,527)	-0.867	-0.260	0.029	0.840	$t = 2.173, p = .030$
Have not shared (n = 514)	-0.867	-0.309	-0.085	0.487	

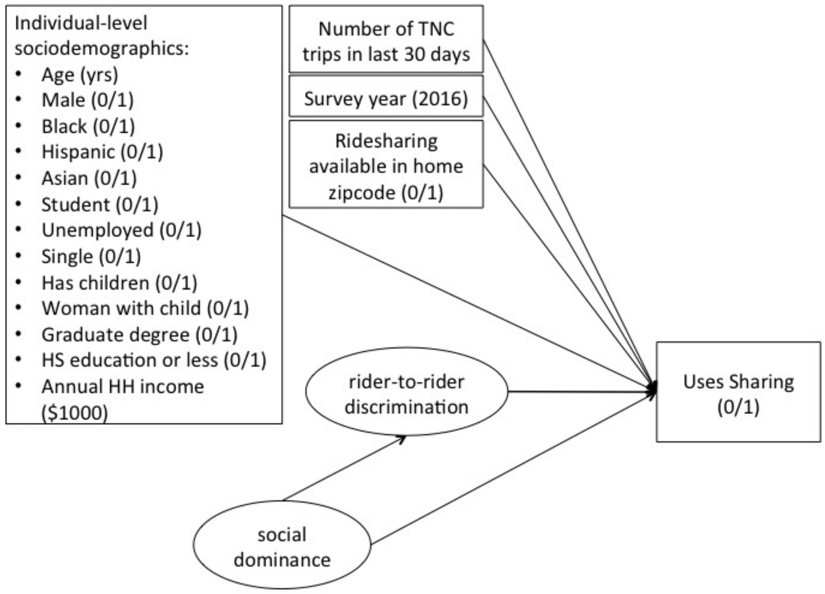
Note: Factor scores are standardized to have a mean of zero across all individuals. A negative value indicates below-average rider-to-rider discriminatory attitudes. Positive values indicate above-average discriminatory attitudes.

4.3 Structural Models

Having established a unidimensional, reliable, and survey year-invariant measure of rider-to-rider discrimination, we estimate three structural models to explore its relations with ridesharing behavior (see Table 2). Model 1 is estimated for all respondents and explores the association of rider-to-rider discrimination with whether the respondent has used a shared service (uberPOOL or Lyft Line), as in Figure 4. Within the sample, 74.8% of respondents have used a shared service (see Table 2). Model 2 is estimated for the subset of respondents who have used the sharing option and explores the association of rider-to-rider discrimination with the percentage of TNC trips that are shared in the past 30 days (mean = 37.1%) and satisfaction with these shared trips (mean = 7.2 out of 10), as in Figure 5. Model 3 is estimated for the subset of respondents who have not ever used a shared service and explores the association of rider-to-rider discrimination with whether the respondent would be willing to use a shared ride in the future as in Figure 6. Of the 514 people in the sample who have not used the ridesharing service, 53% expressed willingness to share in the future (see Table 2).

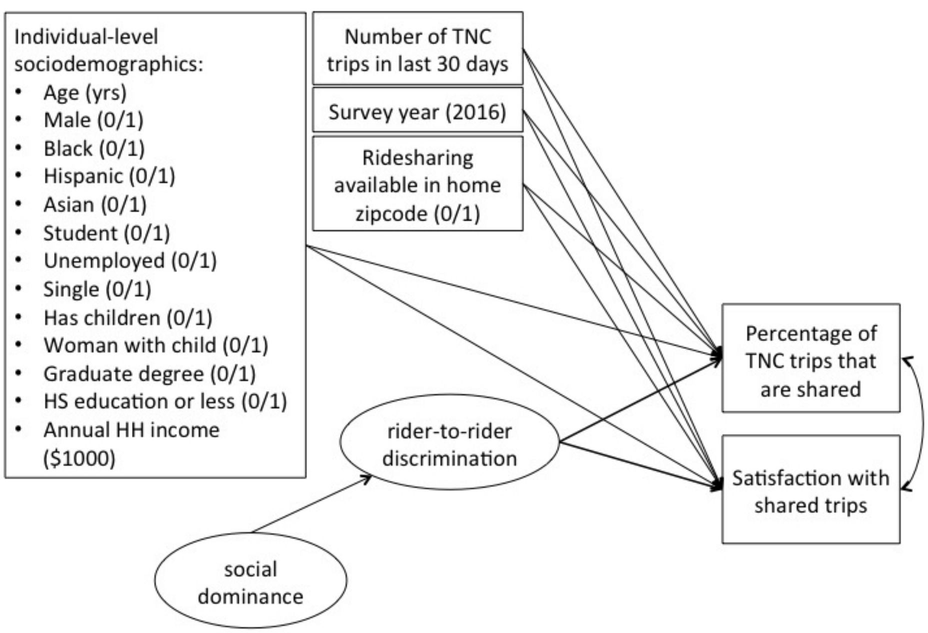
A mediation analysis found that the relations between social dominance orientation and the behavioral outcomes of interest in Models 2 and 3 are fully mediated by our measure of rider-to-rider discrimination (MacKinnon, Fairchild, & Fritz, 2007; Zhao, Lynch & Chen, 2010). Therefore, we can use social dominance orientation as an instrumental variable to explore the direct paths from rider-to-rider discrimination to percentage of TNC trips that are shared and satisfaction with shared trips in Model 2 (see Figure 5) and to willingness to share in the future in Model 3 (see Figure 6) (Bollen & Nobel, 2011). This model specification is further defended by theoretical time precedence, which suggests that an individual's social dominance orientation is likely to be formed long before they use TNC services or manifest rider-to-rider discrimination.

Figure 4. Analytic structure for Model 1 with rider-to-rider discrimination predicting whether respondent has used a shared service.



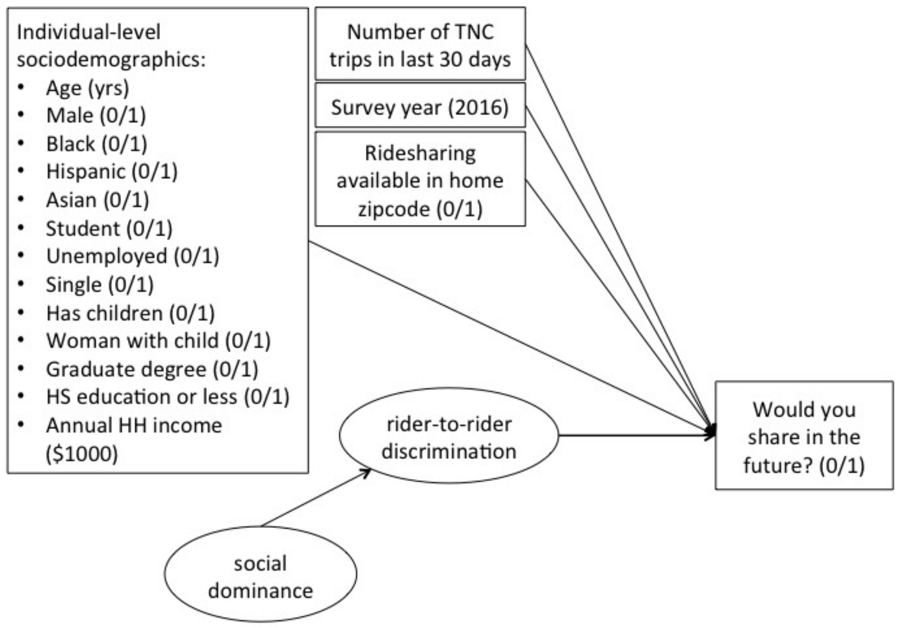
Note: Variances and covariances of all exogenous variables are also estimated. The measurement components for discrimination in ridesharing and social dominance are simultaneously estimated as in Figure 3.

Figure 5. Analytic structure for Model 2 with rider-to-rider discrimination predicting ridesharing percentage of and satisfaction with shared trips.



Note: Variances and covariances of all exogenous variables are also estimated. The measurement components for discrimination in ridesharing and social dominance are simultaneously estimated as in Figure 3.

Figure 6. Analytic structure for Model 3 with rider-to-rider discrimination predicting willingness to share in the future.



Note: Variances and covariances of all exogenous variables are also estimated. The measurement components for discrimination in ridesharing and social dominance are simultaneously estimated as in Figure 3.

Model 1. Model 1 specifies rider-to-rider discriminatory attitudes predicting whether the respondent has used a shared TNC service like uberPOOL or Lyft Line using a logistic function (as in Figure 4). Estimated structural parameters for Model 1 are presented in Table 5. The results indicate that younger, employed, non-student TNC users are more likely to have used shared services, while all other sociodemographic characteristics are not predictive. These results are in line with previous research that suggests younger people (Sarierra, et al., 2017) and employees rather than students (Deakin, Frick, & Shivley, 2010) are more likely to be users of dynamic ridesharing services. While further research is needed to fully understand why students are less likely to be users of dynamic ridesharing, literature suggests that students travel in less predictable patterns that are distributed more evenly across the day, which makes scheduling ridesharing more difficult (Deakin, Frick, & Shivley, 2010). Furthermore, those who commute by public transit and non-motorized modes—like students—are less likely to try or to regularly use a dynamic ridesharing service than those who commute by car (Deakin, Frick, & Shivley, 2010).

We find that the direct path from rider-to-rider discrimination to use of sharing (0/1) is not statistically significant from zero ($b = 0.001$, S.E. = 0.067, $p = .998$), but that an individual's social dominance orientation is positively predictive of whether he/she has used sharing ($b = 0.168$, S.E. = 0.052, $p = .001$, $\beta = 0.125$). This is a somewhat unintuitive finding that TNC users with greater tendency toward group-based discrimination, social hierarchy, and domination over lower-status groups are more likely to have used a shared service.

While our measure of rider-to-rider discrimination is not found to be significant, frequent use of TNCs ($b = 0.061$, *S.E.* = 0.015, $p < .01$) and availability of shared services in the metropolitan area of the respondent's home zip code ($b = 0.615$, *S.E.* = 0.110, $p < .01$) are found to be strongly significant and positive predictors of whether the respondent has used sharing. The overall variance explained by the model is moderate (pseudo $R^2 = .125$), suggesting that factors not captured in the study variables contribute to whether a TNC user uses shared services. However, these results together suggest that whether a TNC user uses shared service may be dominated more by utilitarian factors and familiarity with the service rather than rider-to-rider discriminatory attitudes or other personal characteristics. This conforms with previous research that suggests that considerations such as travel time and cost, service availability, and convenience dominate predictions of whether TNC users use ridesharing services (Sarriera, et al., 2017).

Table 5. Direct logistic path parameter estimates for Model 1 predicting use of sharing (0/1), *n* = 2,041.

Predictor	*b*	*S.E.*	*p*	*β*	log-odds
Age	-0.039	0.006	.000***	-0.191	0.961
Male (0/1)	0.026	0.132	.842	0.007	1.027
Income ($1000)	-0.001	0.001	.661	-0.013	0.999
Unemployed (0/1)	-0.357	0.212	.092*	-0.046	0.700
Student (0/1)	-0.454	0.196	.020**	-0.066	0.635
HS degree or less (0/1)	0.194	0.319	.544	0.018	1.214
Graduate degree (0/1)	0.015	0.143	.915	0.003	1.015
Black (0/1)	-0.015	0.193	.939	-0.002	0.985
Hispanic (0/1)	-0.275	0.205	.179	-0.037	0.760
Asian (0/1)	-0.158	0.173	.361	-0.026	0.853
Single (0/1)	0.000	0.120	.998	0.000	1.000
Has children (0/1)	-0.132	0.174	.448	-0.031	0.876
Woman with child (0/1)	0.332	0.235	.158	0.062	1.393
Survey year (2016)	0.023	0.112	.838	0.006	1.023
Sharing available in home zip code (0/1)	0.615	0.110	.000***	0.152	1.849
Number of TNC trips in past 30 days	0.061	0.015	.000***	0.191	1.063
Rider-to-rider discrimination	0.001	0.067	.988	0.001	1.001
Social dominance orientation	0.168	0.052	.001***	0.125	1.183

Significance: * = 10%, ** = 5%, *** = 1%
Note: b = unstandardized coefficient; S.E. = standard error; p = two-tailed p-value (μ = 0); *β* = STDYX standardized coefficient
Overidentified model fit: AIC = 91722, BIC = 92087, sample-size adjusted BIC = 91880. Additional fit statistics are not available when using MLR estimation with a binary outcome in Mplus version 8.1.

A moderation analysis was conducted to test whether the direct path from rider-to-rider discrimination to whether the respondent has used uberPOOL or Lyft Line differed across the two survey years. The moderator was found to be an insignificant predictor of use of shared service (b = -0.043, *S.E.* = 0.106, p = .686), suggesting that our findings are robust across the 2016 and 2018 samples.

Model 2. For the subset of respondents who have used shared service, Model 2 estimates rider-to-rider discrimination as predictive of the respondent's reported percentage of TNC trips that are shared (0-100%) and satisfaction with shared trips (1-10) (Figure 5). The structural parameter estimates for Model 2 are presented in Table 6.

The results of Model 2 indicate that students, respondents with graduate degrees, Asians, and those who are single have a higher percentage of shared TNC trips, while all other sociodemographic characteristics are not significant. While Model 1 found that students are less likely to have used dynamic ridesharing services, Model 2 suggests that students who do use ridesharing services tend to use them for a greater percentage of their TNC trips. Exploration of the socio-demographics among students in our survey who share and those that do not and among students with high shares of TNC trips and those with lower shares did not yield any clear explanation for these findings. Further research could explore whether different travel behaviors rather than socio-demographics among students explains this apparent bimodal distribution.

We find that the direct path from rider-to-rider discrimination to percentage of TNC trips that are shared is negative as hypothesized, but is only marginally statistically significant (*b* = -1.192, *S.E.* = 0.766, *p* = .120, *β* = -0.043). We also find that respondents in the more recent 2018 survey, those with sharing available in their home zip code, and those who took more TNC trips in the last 30 days reported higher percentages of shared TNC trips. Although the overall variance explained in the percentage of TNC trips that are shared is very low (R^2 = .070), taken together, these results suggests that expanding familiarity with and availability of shared TNC services are more predictive of greater percentage of shared trips among TNC users than rider-to-rider discriminatory attitudes.

Considering satisfaction with shared trips, Model 2 finds that those with higher income are generally less satisfied with sharing, even after controlling for satisfaction with TNC trips in general. This suggests a non-zero willingness-to-pay for a private TNC trip. We find that the direct path from rider-to-rider discrimination to satisfaction with shared trips is statistically significant and negative as hypothesized (*b* = -0.130, *S.E.* = 0.041, *p* = .002, *β* = -0.078). Although the overall variance explained is moderate (R^2 = .350), Model 2 suggests that greater rider-to-rider discriminatory attitudes are predictive of a lower level of satisfaction with shared trips.

A moderation analysis was conducted to test whether the direct paths from rider-to-rider discrimination to percentage of TNC trips that are shared and satisfaction with shared trips differed across the two survey years. The moderator for the path predicting percentage of TNC trips was found to be insignificant (*b* = 0.352, *S.E.* = 1.522, *p* = .817). Similarly, the moderator for the path predicting satisfaction with shared trips was found to be insignificant (*b* = 0.036, *S.E.* = 0.079, *p* = .654). This suggesting that our findings for Model 2 are robust across our 2016 and 2018 samples.

Table 6. Direct path parameter estimates for Model 2 predicting percentage of TNC trips that are shared and satisfaction with shared trips, *n* = 1,527.

Outcome	Predictor	*b*	*S.E.*	*p*	*β*
Percentage of TNC trips that are shared (0-100%)	Age	-0.104	0.102	.306	-0.029
	Male (0/1)	-0.361	1.887	.848	-0.006
	Household annual income ($1000)	-0.027	0.019	.153	-0.038
	Unemployed (0/1)	-4.899	3.137	.118	-0.037
	Student (0/1)	7.399	3.057	.016**	0.067
	HS degree or less (0/1)	-3.737	4.498	.406	-0.022
	Graduate degree (0/1)	4.488	2.128	.035*	0.055
	Black (0/1)	2.928	2.646	.268	0.027
	Hispanic (0/1)	1.483	3.061	.628	0.012
	Asian (0/1)	7.696	2.479	.002***	0.079
	Single (0/1)	4.518	1.721	.009***	0.071
	Has children (0/1)	3.963	2.668	.137	0.057
	Woman with child (0/1)	1.432	3.604	.691	0.017
	Survey year (2016)	-8.858	1.587	.000***	-0.142
	Sharing available in home zip code (0/1)	5.858	1.680	.000***	0.088
	Number of TNC trips in past 30 days	0.556	0.194	.004***	0.120
	Rider-to-rider discrimination	-1.192	0.766	.120	-0.043
Satisfaction with shared trips (0-10)	Age	0.004	0.004	.409	0.017
	Male (0/1)	0.117	0.097	.229	0.031
	Household annual income ($1000)	-0.002	0.001	.027**	-0.049
	Unemployed (0/1)	-0.174	0.143	.223	-0.022
	Student (0/1)	0.095	0.129	.465	0.014

	HS degree or less (0/1)	-0.128	0.210	.540	-0.012
	Graduate degree (0/1)	-0.153	0.109	.159	-0.031
	Black (0/1)	0.220	0.151	.144	0.034
	Hispanic (0/1)	0.093	0.138	.500	0.013
	Asian (0/1)	0.198	0.113	.080*	0.034
	Single (0/1)	0.085	0.086	.321	0.022
	Has children (0/1)	0.178	0.136	.191	0.042
	Woman with child (0/1)	0.199	0.178	.264	0.038
	Survey year (2016)	-0.193	0.082	.019**	-0.052
	Sharing available in home zip code (0/1)	-0.045	0.083	.586	-0.011
	Number of TNC trips in past 30 days	-0.001	0.007	.866	-0.004
	Satisfaction with TNC trips (0-10)	0.695	0.029	.000***	0.569
	Rider-to-rider discrimination	-0.130	0.041	.002***	-0.078
DRS	Social dominance orientation	0.476	0.029	.000***	0.616

Significance: * = 10%, ** = 5%, *** = 1%

Note: b = unstandardized coefficient; S.E. = standard error; p = two-tailed p-value (μ = 0); β = STDYX standardized coefficient

Overidentified model fit: $\chi^2(338, n = 1{,}527) = 1028.889$, $p < .01$, RMSEA = 0.037, CFI = 0.948, TLI = 0.939, SRMR = 0.047.

Model 3. For the subset of respondents who have not used shared service, Model 3 estimated the structural parameters for rider-to-rider discriminatory attitudes predicting whether the respondent would be willing to use uberPOOL or Lyft Line in the future using a logistic function (Figure 6). The corresponding structural parameter estimates for Model 3 are presented in Table 7. The results indicate that male TNC users and those without children are more willing to use shared service in the future, while all other sociodemographic characteristics are not predictive. We find that the direct path from rider-to-rider discrimination to willingness to share in the future (0/1) is statistically significant and negative as hypothesized (b = -0.409, *S.E.* = 0.101, p = .000, β = -0.246). While the overall variance explained by Model 3 is moderate (pseudo R^2 = .102), we find that rider-to-rider discriminatory attitudes are more predictive of willingness to share than any other variable included in the model.

A moderation analysis was conducted to test whether the direct path from rider-to-rider discrimination to willingness to share in the future differed across the two survey years. The moderator was found to be an insignificant predictor of being willing to use shared services in the future (b = 0.034, *S.E.* = 0.190, p = .860), suggesting that our findings are robust across our 2016 and 2018 samples.

Table 7. Direct logistic path parameter estimates for Model 3 predicting willingness to share in the future (0/1), *n* = 514.

Predictor	*b*	*S.E.*	*p*	*β*	log-odds
Age	-0.007	0.009	.447	-0.040	0.993
Male (0/1)	0.494	0.236	.036**	0.128	1.639
Household annual income ($1000)	0.000	0.002	.835	-0.013	1.000
Unemployed (0/1)	-0.088	0.316	.780	-0.013	0.916
Student (0/1)	-0.387	0.340	.255	-0.059	0.679
HS degree or less (0/1)	-0.559	0.496	.259	-0.052	0.572
Graduate degree (0/1)	-0.216	0.256	.398	-0.044	0.805
Black (0/1)	-0.185	0.350	.598	-0.026	0.381
Hispanic (0/1)	-0.180	0.375	.631	-0.025	0.835
Asian (0/1)	-0.258	0.313	.410	-0.043	0.773
Single (0/1)	0.008	0.214	.968	0.002	1.009

Has children (0/1)	-0.521	0.311	.094*	-0.126	0.594
Woman with child (0/1)	0.590	0.414	.154	0.112	1.804
Survey year (2016)	-0.469	0.195	.016**	-0.122	0.626
Sharing available in home zip code (0/1)	-0.189	0.197	.338	-0.049	0.829
Number of TNC trips in past 30 days	0.014	0.031	.647	0.026	1.014
Rider-to-rider discrimination	-0.409	0.101	.000***	-0.246	0.664

Significance: * = 10%, ** = 5%, *** = 1%
Note: b = unstandardized coefficient; S.E. = standard error; p = two-tailed p-value ($\mu = 0$); β = STDYX standardized coefficient
Overidentified model fit: AIC = 22973, BIC = 23244, sample-size adjusted BIC = 23041. Additional fit statistics are not available when using MLR estimation with a binary outcome in Mplus version 8.1.

5. DISCUSSION

This paper validates a 6-item measure of rider-to-rider race and class discriminatory attitudes and then demonstrates the measure's utility in predicting TNC user behavior in the context of dynamic ridesharing. Using confirmatory factor analysis, we demonstrate our measure's convergent validity and its divergent validity against a well-established measure of social dominance orientation. We show that our measure of rider-to-rider discrimination, while related to social dominance orientation, captures attitudes that are specific to the ridesharing context. We find no statistical difference in either the factor structure or the measured discriminatory attitudes across the two survey years (2016 and 2018). With the reliability and invariance of our measure established, we incorporate our latent factor of rider-to-rider discrimination into three structural models that address associations between an individual's discriminatory attitudes and their ridesharing behavior. This represents the first study in published literature to measure the relation of rider-to-rider discriminatory attitudes and TNC user behavior in the ridesharing context.

We find that rider-to-rider discriminatory attitudes are not significantly predictive of whether an individual has ever used a ridesharing service. In predicting use of ridesharing, discriminatory attitudes are dominated by utilitarian considerations, such as the frequency with which an individual uses TNCs and the availability of shared services in the metropolitan area of the respondent's home. These results match findings from previous literature that relate the choice of whether to use sharing to travel time, cost, service availability, and convenience. For advocates of shared mobility, it may be good news that rider-to-rider discriminatory attitudes do not present a significant barrier to getting individuals in shared vehicles. Nonetheless, whether an individual has ever used the service does not capture long-term behavior patterns.

The experience of individuals in these services is instrumental in determining whether they continue to use these services and how frequently. And it is here where discriminatory attitudes play a major role. Subsetting our respondents by those who have and have not used the service, we find that rider-to-rider discriminatory attitudes are significantly associated with other aspects of TNC user's behavior in the ridesharing context. Among those who have used ridesharing services, we find that rider-to-rider discriminatory attitudes are negatively predictive of the percentage of trips shared and of an individual's level of satisfaction with the sharing option. Furthermore, we find that rider-to-rider discriminatory attitudes are negatively predictive of stated willingness to consider using uberPOOL or Lyft Line in the future among those who have *not* yet used these services. We find that these significant relations are robust across the two survey years. Therefore, while rider-to-rider discriminatory attitudes may not be significantly predictive of first-time use of ridesharing services, we find that they are significantly predictive of lower frequency of use and satisfaction with these services as well as lower willingness to adopt them in the future.

These findings suggest that rider-to-rider discriminatory attitudes may persistently present a barrier to the adoption of sharing as a sustained, long-term shift in mobility patterns among both users and non-users of these services.

5.1 Limitations and Future Work

This paper is the first in existing literature to explore the relation between rider-to-rider discriminatory attitudes and behavior in the ridesharing context. With the validated and standard measure of rider-to-rider class and race discriminatory attitude presented in this paper, future research can continue to explore this important issue and address some of the remaining limitations of this initial study. In particular, this paper suggests four avenues for further research.

First, we note that our paper uses self-reported ridesharing behavior. With access to service data or more detailed surveys, further studies could corroborate our findings using revealed rather than stated ridesharing behavior as the outcome. With the participation of TNCs such as Lyft or Uber, researchers could monitor how frequently a sample of passengers use ridesharing services and then model this behavior according to the explanatory variables presented in this paper. Alternatively, without the participation of these companies, researchers could track ridesharing behavior through traditional travel diaries, which would produce a more reliable measure of ridesharing behavior than participants' recollection of the past 30 days.

Second, our paper also relies on self-reported attitudes about discrimination in the context of shared rides. Stated preferences, such as the survey instrument we used to derive our measure of discriminatory attitudes in ridesharing, are likely to under represent discriminatory attitudes due to social desirability bias. However, alternative techniques—such as the implicit association test (IAT)—can circumvent issues with self-reported or explicit measures of discriminatory attitudes and could provide additional evidence that passengers hold the discriminatory attitudes discussed in the analysis above. The IAT, developed in social psychology to measure racial biases that people are unwilling to consciously express on a survey, offers a potential solution to this problem. In particular, IAT associates words and photographs to specific response keys on a keyboard and then measures differential response times to determine the strength of respondents' automatic preferences (Greenwald, Nosek, & Banaji, 2003). Although recent meta-analysis has found evidence that IATs performed no better than explicit measures of bias in measuring and modeling discriminatory attitudes (Oswald et al., 2013), IAT has nonetheless been applied in other transportation behavior research such as predicting users' primary commute mode choice (Moody, et al., 2017) and investigating driver's attitudes towards bicyclists (Goddard 2017). Therefore, future research could apply the IAT to measure implicit preferences for fellow passengers in a shared ride and compare this to our explicit survey measure.

Third, longitudinal data or experimental methods could explore bi-directionality and causality in the relations between ridesharing behavior and discrimination. While this study uses instrumental variables with cross-sectional data to explore the direct path from rider-to-rider discriminatory attitudes to behavior, it might be reasonable to consider whether a path in the opposite direction (with behavior reinforcing attitude) also exists. In fact, the simple descriptive statistics in our sample suggest that the ridesharing context might exacerbate the discriminatory attitudes of passengers using these services. A randomized controlled trial of Lyft and Uber users who have not previously used ridesharing could present the opportunity to test the influence of sharing on rider attitudes and satisfaction. If services like uberPOOL and Lyft Line expand to new markets, such a change in service availability may also present the opportunity for a natural experiment.

Finally, all of the areas for future research discussed above could expand the study's sampling frame to a broader population, including current non-users of TNCs. While the present study was designed to capture existing race and class discrimination in the dynamic ridesharing context, a future study could address the discriminatory attitudes of a much larger population and the extent to which such attitudes present a barrier to TNC use more broadly. Such a study would expand the behavioral outcomes of interest from whether or not TNC users choose to use the sharing option to whether discriminatory attitudes are a barrier to ridehailing or other shared mode use more generally. One challenge to such a study, however, would be ensuring the external validity of discriminatory measures among respondents who are not familiar with TNC services of any kind.

6. CONCLUSION

Promoting sharing in the mobility context is a key component of the global vision for sustainable and livable cities. Proponents of shared mobility suggest that, with widespread adoption, increasing passenger occupancy through ridesharing can takes vehicles off the road, relieve congestion, protect air quality, lower vehicle emissions, and reduce the need for infrastructure investment. However, user attitudes could present a barrier to the rapid and ubiquitous adoption of shared mobility services and retard the realization of their benefits. This paper provides some of the first evidence of one such attitudinal barrier to sharing in the U.S.: rider-to-rider discrimination. While our models suggest that utilitarian considerations are more important than discriminatory attitudes in predicting whether an individual has ever used a ridesharing service, we find that discriminatory attitudes present discourage sustained and frequent user of sharing in two ways. For those who currently use ridesharing services, these attitudes may reduce frequency of sharing and satisfaction with sharing. For those who have not yet used ridesharing services, these attitudes may cause them to avoid sharing altogether. What's more, our findings suggest that those who have used sharing report higher average discriminatory attitudes towards fellow riders of a different race or class than those who have not shared—a concerning trend.

As new standards for the ridehailing industry continue to evolve, policymakers and mobility service providers need to consider how to encourage shared mobility while mitigating the potential for discrimination on these new service platforms. Our findings point to the need for thoughtful dialogue and continued reflection on the associations between discriminatory attitudes and ridesharing behavior, particularly when it comes to sustained, long-term behavioral change. While shared mobility promises more sustainable and livable cities, our research shows that discrimination in the context of sharing may present an obstacle to overcome in pursuit of these goals.

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APPENDIX

Table A. Confirmatory factor analysis results for the correlated rider-to-rider discrimination and social dominance orientation SDO measures.

Item	Survey statement	*b*	*S.E.*	*p*	*β*	R^2
Rider-to-rider discrimination						
RS1	Grouping passengers of different races in shared rides is a recipe for trouble	1.000	—	—	0.742	0.550
RS2	It would be great to be paired in shared rides with passengers of all different races [rev]	0.834	0.028	.000***	0.673	0.453
RS3	I would prefer to avoid being paired with a passenger of a lower social class in shared rides	1.043	0.036	.000***	0734	0.539
RS4	Pairing passengers from all social classes in shared rides is a good idea [rev]	0.868	0.031	.000***	0.662	0.438
RS5	Sharing a ride with a passenger of a different ethnicity could make me uncomfortable	1.070	0.028	.000***	0.836	0.699
RS6	Everyone should welcome passengers of all ethnicities in shared rides	0.965	0.030	.000***	0.826	0.681
Social dominance orientation						
SD1	Some groups of people must be kept in their place	1.000	—	—	0.879	0.773
SD2	Groups at the bottom are just as deserving as groups at the top [rev]	0.771	0.026	.000***	0.663	0.440
SD3	It's probably a good thing that certain groups are at the top and other groups are at the bottom	1.053	0.018	.000***	0.886	0.785
SD4	An ideal society requires some groups to be on top and others to be on the bottom	1.013	0.022	.000***	0.798	0.638
SD5	Groups at the bottom should not have to stay in their place [rev]	0.695	0.026	.000***	0.561	0.315
SD6	Some groups of people are simply inferior to other groups	1.028	0.018	.000***	0.861	0.742
SD7	No one group should dominate in society [rev]	0.828	0.023	.000***	0.750	0.562
SD8	Group dominance is a poor principle [rev]	0.812	0.025	.000***	0.690	0.476

Significance: * = 10%, ** = 5%, *** = 1%
Note: [rev] = reverse-coded item; b = unstandardized factor loading; S.E. = standard error; p = two-tailed p-value (μ = 0); β = STDYX standardized factor loading
Overidentified model fit: $\chi^2(73, N = 2{,}041) = 454.947$, RMSEA = 0.051, CFI = 0.967, TLI = 0.959, SRMR = 0.027.
Correlation of discrimination in ridesharing and social dominance orientation: $b = 1.001$, $S.E. = 0.060$, $p = .00$, $\beta =$ 0.615