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Perceived risk of infection while traveling during the COVID-19 pandemic: Insights from Columbus, OH



Basar Ozbilen^{a,*}, Kristina M. Slagle^b, Gulsah Akar^a

^a City and Regional Planning, Knowlton School, The Ohio State University, United States

^b School of Environment and Natural Resources, The Ohio State University, United States

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ABSTRACT

The COVID-19 outbreak caused major disruptions on individuals' out-of-home activities. Worldwide mandates to slow down the spread of the disease resulted in significant reductions in travel. This study analyzes the changes in individuals' travel outcomes and their risk perceptions related to exposure and specific travel modes during the COVID-19 pandemic. We use data collected through an online survey with residents of Columbus, OH from April 30 to May 7, 2020. Employing multiple generalized estimating equations (GEEs) with a logit link function, we analyze the perceived risk of infection while traveling with different modes controlling for socio-demographics. The findings show that on average individuals are more likely to find shared modes (i.e., transit, ride-hailing, carsharing) riskier as compared to individual ones (i.e., walking, autos) when it comes to COVID-19 exposure. This study also suggests that the associations between perceptions related to exposure and various travel modes vary across groups with (1) different primary mode preferences (auto users vs non-auto users (e.g., transit users, bicyclists, etc.)), and (2) different socio-demographics. For example, auto users are more likely to find shared modes such as ride-hailing or transit riskier as compared to personal car. The conclusions present recommendations for future transportation policies in the post-COVID era. These include building upon the emerging positive perceptions towards non-motorized modes as an opportunity to promote sustainable transportation as well as formulating viable solutions to address the high-risk perceptions associated with transit.

1. Introduction

The World Health Organization (WHO) declared COVID-19 (also referred to as the novel coronavirus) as a pandemic in March 2020 (WHO, 2020). Since then the COVID-19 outbreak caused major disruptions in the world. Given that the novel coronavirus can survive on surfaces for several days, and can drift around in the air for up to three hours (Harvard Medical School, 2020), decision-makers from all over the world mandated social distancing measures, such as stay-at-home orders, cancellation of events, and closing of non-essential businesses, to slow down the spread of the disease (BBC, 2020; De Vos, 2020). These mandates led to reductions in auto travel as well as transit capacity and use in general (Budd & Ison, 2020; de la Graza, 2020; Goldbaum, 2020). Some cities took this as an opportunity to redistribute the street space to create more bicycle- and pedestrian-friendly environments that meet the social distancing requirements (De Vos, 2020; Kraus & Koch, 2020; NACTO, 2020).

To better understand the associations between COVID-19, transportation, and built environment, researchers from around the world conducted a number of studies within a short period of time (e.g., Hadjidemetriou et al., 2020; Hamidi et al., 2020; Knittel & Ozaltun, 2020; Shamshiripour et al., 2020). A significant portion of these studies focus on the impacts of COVID-19 and social distancing measures on travel behavior. These studies reveal reductions in travel, particularly with the shared modes that may increase the risk of contact with other users (de Haas et al., 2020; Gao et al., 2020; Klein et al., 2020; Sadik-Khan and Solomonow, 2020; Wang et al., 2020a). Transit demand decreased substantially in many metropolitan areas in different countries (Transit App, 2020). Studies show that transit ridership may not be fully recovered even after the COVID-19 restrictions are lifted (Thigpen, 2020; Wang et al., 2020a). Studies also report that individuals walked and bicycled more than they used to during this period (de Haas et al., 2020; Li et al., 2020a; Handy, 2020; Riggs, 2020). Non-auto travel modes such as walking and bicycling promote sustainable development, positive health outcomes, and transport

* Corresponding author.

E-mail address: ozbilen.1@osu.edu (B. Ozbilen).

equity (Hilland et al., 2020; Litman, 2019; Schiller et al., 2010; Singleton, 2019). Therefore, the increase in non-motorized travel demand can be considered as a positive outcome of this pandemic.

Transportation mode choice is associated with a number of factors, namely socio-demographics, built environment characteristics, travel attitudes, intrinsic values of mobility, and risk perceptions (Akar et al., 2013; Cao et al., 2010; Deka et al., 2018; Ewing & Cervero, 2010; Mokhtarian et al., 2015; Namgung & Akar, 2015; Park et al., 2018). The latter two are particularly important during the COVID-19 era. Intrinsic values of mobility are the perceived benefits of travel itself, such as enjoying the scenery while traveling or exercising while walking/bicycling (Handy & Lee, 2020; Shliselberg & Givoni, 2018). Given that people reduced their travel significantly during the pandemic, we hypothesize they may have missed certain positive aspects of their daily travel. Understanding what individuals miss (or do not miss) regarding their travel can help clarify individual travel mode choices and set informed transportation policies for the post-COVID era.

Risk perceptions related to individual health, crime, and traffic safety can affect individuals' preference or avoidance of specific travel modes (Hilland et al., 2020; Hotle et al., 2020; Ma et al., 2019; Wang & Akar, 2019). Studies focusing on risk perceptions, COVID-19, and travel outcomes state that perceived risk of infection is negatively associated with out-of-home activity participation and trip frequency (Parady et al., 2020; Wise et al., 2020). Considering COVID-19 is far more lethal than seasonal flu or pneumonia, we may expect the perception of people towards infection to be one of the most important factors that impacts travel behavior (Basu, 2020). We may expect these tendencies to remain as we continue living under these unusual circumstances. These arguments call for novel studies focusing on the perceived risk of infection specific to COVID-19 and travel outcomes. Such studies will enable transportation planners to explore potential mobility challenges, and formulate strategies to promote safe mobility for all during the pandemic. The unique contribution of this study is that it provides a thorough analysis of the above-mentioned factors, namely intrinsic values of mobility and perceived risk of exposure while traveling that can affect the travel behavior of individuals during the pandemic. Particularly, the multivariate analysis enables us to disentangle the effects of perceptions of infection risk while traveling with various transportation options, controlling for socio-demographics.

The present study analyzes the changes in individuals' travel outcomes during the pandemic, intrinsic values of mobility, and individuals' infection risk perceptions related to COVID-19 while using specific travel modes based on data from Columbus, OH. In the next section, we present the data, sample characteristics, and explanatory analyses. Following, we present the methodology and model estimations, as well as policy implications for both researchers and practitioners in transportation planning and urban design fields. The conclusion presents recommendations for current and future transportation policies regarding COVID-19.

2. Data and explanatory analysis

This study focuses on travel behavior of residents of Columbus, OH during the COVID-19 outbreak. Columbus is the state capitol of Ohio, and the 14th largest city in the U.S. (The City of Columbus, 2021). The Central Ohio region is growing in population, with 3 million residents expected by 2050—most of that coming from growth in the Columbus MSA (MORPC, 2018). With this growth in mind, in 2016 the city began investing in improvements in daily mobility and accessibility for Columbus residents. Results presented here are part of a larger effort to assess the impacts of these improvements over time.

Considering the extensive impacts of the pandemic on the daily travel of individuals, our team designed this survey to explore the effects

of the COVID-19 outbreak on travel frequencies, mode choices, and attitudes. The survey questions were developed and distributed on the Qualtrics survey platform during the stay-at-home orders in Ohio. The State of Ohio went under a stay-at-home order from March 23 to May 29, 2020. The participants were recruited through the Qualtrics Panel, which is an online sample recruitment service. The survey was distributed among those who are 18 and older, and who live in Columbus Metropolitan Area (the city of Columbus and the surrounding suburbs). Our data collection took place from April 30 to May 7, 2020. The survey included questions about pre-COVID travel preferences and experiences, travel patterns during the stay-at-home order, risk perceptions associated with COVID-19 regarding different modes, future expectations in the post-COVID era, and personal and household characteristics. To ensure the quality of the collected data, we included an attention check question in the survey. In addition, the Qualtrics team monitored the response time to flag the respondents who did not spend an adequate amount of time answering the questions. Lastly, we screened initial survey results and recruited additional participants to replace the low-quality responses via Qualtrics Panel service.

The results we present here are based on 436 valid responses. The sample size is an outcome of the intention to collect the complete dataset while the stay-at-home orders were still in effect (the state of Ohio began to ease some of the restrictions on businesses and offices starting from May 4, 2020 and gradually lifted all stay-at-home restrictions on May 29, 2020 (for details please see Ohio Department of Health, 2020)). Table 1 presents the main sample characteristics at the person (i.e., age, gender, race, etc.) and household levels (i.e., annual household income, household vehicle ownership).

We grouped the survey respondents into two categories based on their pre-COVID primary travel modes: auto users and non-auto users. As expected, auto was the dominant mode of transportation in the pre-COVID period with an 89% share (387 individuals). Non-auto modes such as transit, walking, and bicycling (including individual bikes and bike-share) consisted of 9% of the total sample (40 individuals). Very few individuals reported using Uber/Lyft and taxi as their primary travel mode (7 individuals). Because of their small sample size, we have excluded Uber/Lyft and taxi users from the disaggregate level analyses.

In order to understand the changes in individuals' travel, we asked the respondents whether their daily travel for work and non-work purposes increased, decreased, or stayed the same during the stay-at-home order. Fig. 1 presents the changes in daily trips as reported by the respondents. While most respondents reported decreases in both work and non-work trips due to the COVID-19 outbreak, we find more individuals reported decreases in non-work travel.

Among those reporting decreases in their daily travel, 66% stated that they are willing to reduce their travel for out-of-home activities after the stay-at-home order restrictions are lifted, while only 15% reported their desire to go back to their previous activity and travel patterns (see Fig. 2). Therefore, we may expect to see a decrease in travel demand even after the restrictions are lifted.

Respondents reporting reductions in their daily trips were asked to select three positive aspects of their previous travel experience that they miss during the stay-at-home order (Fig. 3). The three aspects that auto users missed the most were 'feeling of independence', 'looking at the scenery', and 'other activities while traveling such as reading, listening to music, etc.'. While the top aspect 'feeling of independence' remains the same for non-auto users, the other two aspects they missed the most were 'getting physical exercise' and 'interacting with fellow passengers'. Given that recent studies show increases in walking and bicycling during the pandemic, we believe these two attributes that are related to these non-auto modes will be even more important in the post-COVID era. Additionally, while 12% (39 individuals) of auto users did not miss any aspect of their previous travel experience, all non-auto users missed at least one attribute of their daily travel. This shows that while travel has an intrinsic value for all non-auto users

Table 1
Main Sample Characteristics.

Categories	Variable	Values	Mean/% ¹	S.D.	
<i>Person-level characteristics</i>	Age		42.10	15.94	
	Gender	Male		31.19	
		Female		67.20	
		Other		0.69	
		Prefer not to say		0.92	
	Race	Non-Hispanic White		80.28	
		Non-Hispanic Black		9.17	
		Others		9.40	
		Prefer not to say		1.15	
	Education	Less than undergraduate		41.74	
Undergraduate			40.60		
Graduate			16.51		
Prefer not to say			1.15		
Employment Status	Working		51.61		
	Unemployed		30.28		
	Retired or disabled		15.37		
	Prefer not to say		2.75		
<i>Household-level Characteristics</i>	Annual Household Income (in U.S. dollars)	Less than \$45,000		32.11	
		\$45,000-\$89,999		31.19	
		\$90,000-\$149,999		22.02	
		\$150,000 or more		7.57	
		Prefer not to say		7.11	
Household Vehicle Ownership	Yes		91.97		
	No		8.03		
# of obs.	436				

Notes: ¹ For continuous variables, we report the mean values. We report the percentages for categorical variables.

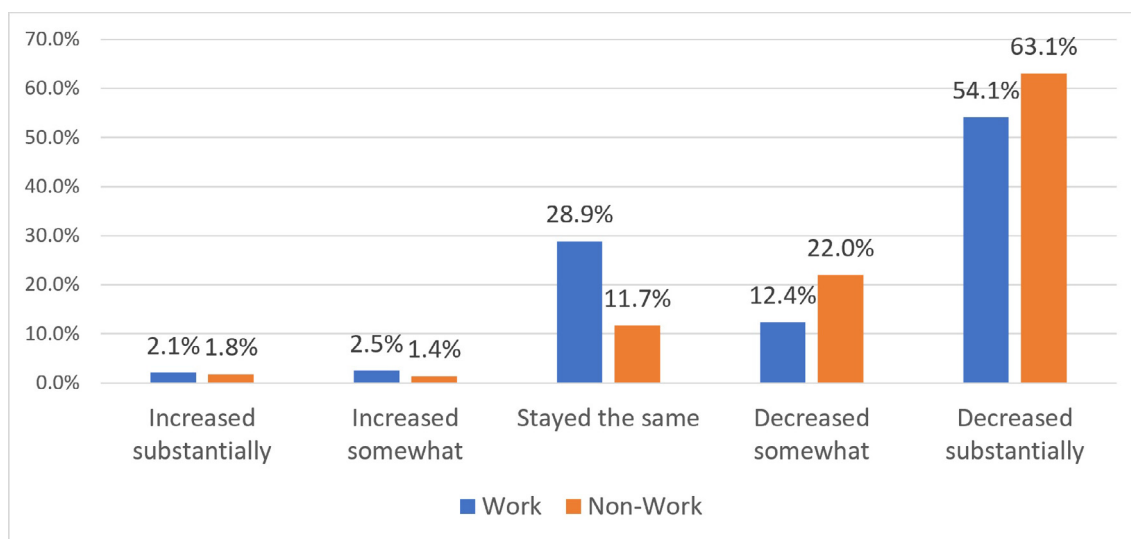


Fig. 1. Change in travel after the stay-at-home order (N = 436).

in our sample, 12% of auto users do not attribute any intrinsic value to their auto trips.

We asked respondents what they think about the perceived risk of becoming infected with COVID-19 while using different transportation modes. The risk perception rating was based on a 5-point Likert scale (1 = extremely unlikely; 2 = unlikely; 3 = neutral; 4 = likely; 5 = extremely likely). Individuals rated shared modes (transit, ride-hailing, carshare, and bicycle/scooter share) riskier than individual modes (autos, walking, and bicycling; Fig. 4).

We also checked the mean risk perception scores overall and for auto-users and non-auto users to understand whether the overall

results regarding most risky and least risky options are consistent between two groups¹. Both auto and non-auto users rated bus, Uber-Lyft-Taxi, and carshare as the top three most risky modes (all rated above 3; Table 2). For the least risky modes, the results differ slightly

¹ We conducted t-tests to compare the two groups' mean scores of COVID-19 exposure risk while using different transportation modes. We observed statistically significant differences for "My Car" and "Walking" options at the 5% level between auto-users and non-auto users. The comparison of mean scores regarding other 8 options did not provide significant t-test results. Therefore, we did not present these results in the table. Instead, we evaluated the mean scores of each group within itself in a descriptive way.

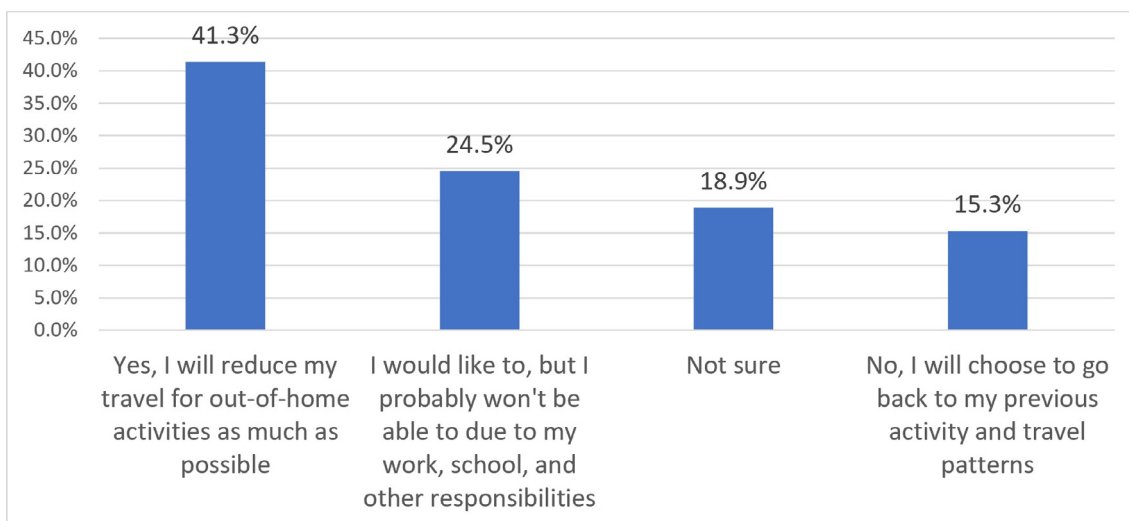


Fig. 2. Responses to the survey question: “Do you think you will continue to reduce your travel after the stay-at-home order restrictions are lifted?” (N = 392).

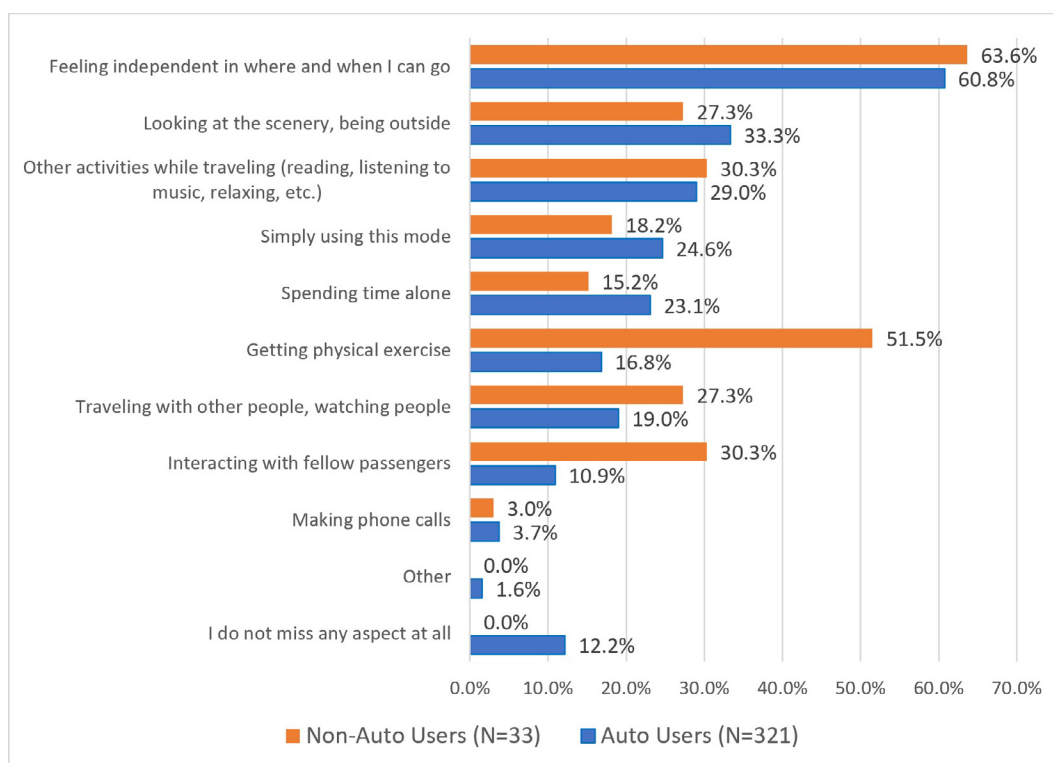


Fig. 3. Responses to the survey question: “What aspects of your experience with your primary travel mode are you missing during the stay-at-home order?” (Auto users vs non-auto users; N = 354).

between two groups. Both groups rated ‘my car’ as the least risky option, as expected. However, while auto users rated bicycle and walking as their second and third least risky modes, non-auto users rated bicycle and scooter as their second and third least risky modes. Unexpectedly, non-auto users attributed more risk to some of the non-auto options, namely walking, bicycle, and scooter. This is surprising because we anticipated auto users to attribute higher risk ratings to all non-auto options as compared to non-auto users.

Our explanatory analyses demonstrate important changes in the daily travel patterns as well as individual attitudes on travel. While these are helpful, we conduct further analysis to draw solid conclu-

sions. In order to test the associations between the infection risk perceptions and various travel options, we introduce a multivariate analysis in the next section.

We estimate a generalized estimating equation (GEE) model with the perception of exposure risk as the dependent variable. Since our primary aim is understanding whether respondents find travel risky or not in terms of COVID-19 exposure, we dichotomized this variable to a binary scale of likely (includes likely and extremely likely) vs not likely (includes extremely unlikely, unlikely, and neutral). Aggregation of the response categories in Likert scale to two categories representing positive and negative perceptions is a common application,

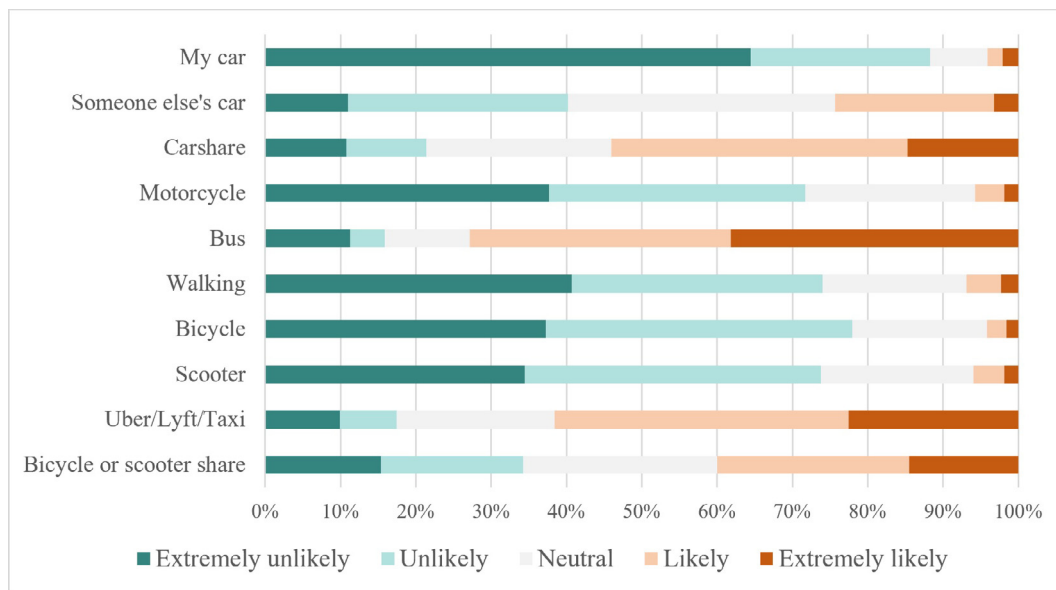


Fig. 4. Risk of becoming infected with COVID-19 while using different transportation modes (Full sample; N = 435).

Table 2
COVID-19 risk perceptions associated with different transportation modes – from least to most risky (Auto users vs non-auto users).

Transportation Mode	Combined (N = 426)		Auto Users (N = 387)		Non-Auto Users (N = 39)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
My car	1.52	(0.87)	1.49	(0.85)	1.87	(1.06)
Bicycle	1.90	(0.89)	1.88	(0.87)	2.08	(1.01)
Walking	1.95	(1.00)	1.90	(0.96)	2.39	(1.23)
Motorcycle	1.98	(0.96)	1.96	(0.95)	2.13	(1.01)
Scooter	1.99	(0.93)	1.97	(0.90)	2.18	(1.12)
Someone else's car	2.78	(1.01)	2.78	(0.99)	2.72	(1.21)
Bicycle/Scooter share	3.05	(1.28)	3.04	(1.27)	3.10	(1.37)
Carshare	3.38	(1.17)	3.40	(1.16)	3.13	(1.30)
Uber-Lyft-Taxi	3.58	(1.19)	3.60	(1.19)	3.33	(1.24)
Bus	3.87	(1.27)	3.88	(1.26)	3.74	(1.39)

particularly in health-related research (Daoud et al., 2018; Pae & Akar, 2020). Our analysis focuses on mode specific dummies and auto user status. Individual and household level characteristics such as age, gender, income, etc. are included as control variables.

We excluded 92 individuals from the original dataset, because of their responses (or lack thereof) to specific survey questions (e.g., those who preferred not to share their gender/race/income information, or those who did not provide responses to risk perception questions, etc.). In the final dataset, we had 344 individuals. We examined the correlations between all independent variables included in the analysis. Since all results are modest (all Pearson correlations ≤ 0.5), we proceeded with multivariate analysis.

3. Methodology

The dependent variable in our study is the perception of infection risk, and has two outcomes (likely and not likely). There are six observations from each individual, as each individual rates six distinct travel modes in terms of their infection risk. With a binary outcome variable and repeated observations from each individual, we conduct our multivariate analysis using generalized estimating equation (GEE) approach that is developed by Liang & Zeger (1986), Zeger & Liang (1986). This approach is widely used in health related disciplines such as biostatistics, epidemiology, etc. (Zorn, 2001). Models estimated through GEE are based on the assumption that outcomes

from the same individuals are correlated, while those from different individuals are independent (Kuchibhatla & Fillenbaum, 2003). Since GEE accounts for within-subject correlation, it is important to specify the correct correlation structure prior to running the analysis (Abdel-Aty & Abdalla, 2004; Ballinger, 2004; Zorn, 2001). We specified an exchangeable correlation structure assuming that the within-subject observations are equally correlated (constant correlation), which resulted in a population averaged model.

4. Results and discussion

We use three GEEs with a logit link function (binomial distribution) and an exchangeable correlation structure. While the first GEE estimation presents the main effects of independent variables on the outcome, the second and third ones include interaction effects (see Table 3). We report odds ratios (ORs) and p-values for easier interpretation. OR refers to the odds of the outcome occurring over not occurring for each 1-unit change in the predictor variable. In this study, the outcome variable is the perception of COVID-19 exposure risk while traveling. If OR is greater than 1 for a predictor, the probability of finding travel risky in terms of COVID-19 exposure is higher for each 1-unit increase in this predictor variable. If OR value is less than 1, it refers to otherwise.

The first model in Table 3 presents the estimations for the main effects only. The findings regarding mode specific dummies demon-

Table 3
GEE Estimates for Perception of Infection Risk while Traveling.

	Model 1 (w/o interaction) OR (p-value)	Model 2 (w interaction) OR (p-value)	Model 3 (w interaction) OR (p-value)
Key variables			
Mode specific dummies (base case: My car)			
Bicycle	1.12 (0.80)	0.30 (0.29)	2.14 (0.20)
Walk	2.06 (0.06)	1.84 (0.41)	2.79 (0.08)
Carshare	57.12 (0.00)	11.82 (0.00)	31.72 (0.00)
Uber/Lyft/Taxi	77.08 (0.00)	11.82 (0.00)	31.72 (0.00)
Bus	159.20 (0.00)	31.56 (0.00)	55.59 (0.00)
Auto User	1.77 (0.06)	0.26 (0.07)	1.72 (0.07)
Socio-demographics			
Age	0.99 (0.05)	0.99 (0.05)	0.99 (0.11)
Female	1.17 (0.35)	1.16 (0.38)	1.13 (0.46)
Non-Hispanic White	0.70 (0.10)	0.73 (0.15)	0.26 (0.05)
Has at least an undergraduate degree	0.72 (0.06)	0.71 (0.06)	0.67 (0.02)
Currently working	0.71 (0.04)	0.69 (0.03)	0.74 (0.07)
Annual household income in U.S. dollars (base case: Less than \$45,000)			
\$45,000 – \$89,999	0.90 (0.62)	0.94 (0.75)	0.95 (0.78)
\$90,000 – \$149,999	0.68 (0.09)	0.67 (0.07)	0.68 (0.09)
\$150,000 or more	1.37 (0.32)	1.40 (0.30)	1.44 (0.25)
Expectation about travel after stay-at-home restrictions are lifted (base case: Willing to continue reducing travel)			
Not sure	0.46 (0.00)	0.46 (0.00)	0.45 (0.00)
Will go back to previous travel patterns	0.37 (0.00)	0.35 (0.00)	0.34 (0.00)
Interaction Terms			
Mode specific dummies X			
Auto User (base case: My car X Auto User)			
Bicycle X Auto User	–	5.00 (0.19)	–
Walk X Auto User	–	1.21 (0.83)	–
Carshare X Auto User	–	6.75 (0.02)	–
Uber/Lyft/Taxi X Auto User	–	9.39 (0.01)	–
Bus X Auto User	–	7.09 (0.02)	–
Mode specific dummies X			
Non-Hispanic White (base case: My car X Auto User)			
Bicycle X Non-Hispanic White	–	–	0.18 (0.09)
Walk X Non-Hispanic White	–	–	0.59 (0.51)
Carshare X Non-Hispanic White	–	–	2.51 (0.20)
Uber/Lyft/Taxi X Non-Hispanic White	–	–	3.62 (0.07)
Bus X Non-Hispanic White	–	–	4.40 (0.04)
Constant	0.06 (0.00)	0.28 (0.05)	0.11 (0.00)
Number of individuals	344	344	344
	Wald χ^2	Wald χ^2	Wald χ^2
	(16) = 536.60	(21) = 519.60	(21) = 454.16

Notes: Odds ratios (ORs) and p-values are presented. **Bold ORs** are significant at the 10% level.

strate that holding all other variables constant (hereafter this applies to all interpretations), respondents are more likely to find walking riskier as compared to driving their cars. Additionally, respondents are more likely to perceive traveling with shared modes (i.e., carsharing, ride-hailing (Uber-Lyft), taxi, and bus) riskier in terms of COVID-19 transmission as compared to their cars. The change in the ORs shows a clear ranking in perceptions related to exposure risk that is highest for bus and lowest for carshare across the three shared modes. This finding is not surprising considering the substantial reductions in the

use of shared travel modes in the U.S. (de la Graza, 2020; Goldbaum, 2020; Siddiqui, 2020). Additionally, recent studies on COVID-19 demonstrate that the reductions in trips is far more dramatic for shared modes as compared to individual modes around the world (Bucsky, 2020; de Haas et al., 2020; Wang et al., 2020a). Auto users (the respondents whose primary mode of transportation were automobile before the COVID-19 outbreak) are more likely to find travel risky as compared to non-auto users.

The model results suggest that there is a decreasing trend in perception of infection risk with increasing age. As compared to others, those who have at least an undergraduate degree and who are currently working are less likely to find traveling risky in terms of COVID-19 exposure. These findings support earlier evidence on individual behavior changes and exposure risk perceptions during virus outbreaks (e.g., seasonal influenza, SARS, etc.) Previous research shows that (1) individuals who are employed and (2) individuals with higher educational attainment are less likely to take preventative actions and reduce their out-of-home activity and travel during virus outbreaks (Brug et al., 2004; Hotle et al., 2020). We speculate that these negative associations between social and economic factors and exposure risk perception can be explained with the health insurance system tied to the employment in the U.S. (Enthoven & Fuchs, 2006). Those with higher educational attainment and continuous employment can also be the ones with access to better health insurance. They may feel they will have the care they need if infected. However, this claim requires further investigation that will delve into the behavioral differences between these socio-demographic groups in terms of COVID-19 infection risk. Those with an annual household income between \$90,000 and \$149,999 are less likely to find traveling risky as compared to those with less than \$45,000 annual household income. This finding is consistent with recent research on COVID-19 infection risk perceptions of individuals living in households with different income levels (Li et al., 2020b). We find those who are willing to reduce their travel after the stay-at-home orders are also the ones who find travel riskier, as expected.

We also investigated whether there are differences in perceptions of infection risk while traveling with specific modes across individuals with different characteristics. We tested possible interactions between mode specific dummies and other independent variables (second and third columns of Table 3). Since the results of all other variables in these two new models are consistent with the model without interactions, we discuss the effects of the interactions on the outcome only.

The second model demonstrates the effects of interactions between mode specific dummies and auto user status. The results show that auto users are more likely to find shared transportation options such as carshare, Uber, Lyft, taxi, and bus riskier in terms of infection as compared to their cars. This is expected for two reasons. First, auto users are found to be less inclined to use shared options such as ride-hailing or transit because they have negative perceptions towards traveling with strangers (Azimi et al., 2020; Hoffmann et al., 2018). Second, some earlier qualitative studies show that auto users find transit more dangerous in general as compared to driving their own vehicles (Beirão & Sarsfield Cabral, 2007; Gardner & Abraham, 2007).

The third model presents the effects of interactions between mode specific dummies and non-Hispanic White dummy. The results demonstrate that non-Hispanic Whites are more likely to find shared modes, Uber, Lyft, taxi, and bus riskier as compared to their cars in terms of COVID-19 exposure. Given that non-Hispanic Whites ride transit less frequently and are more likely to own private vehicles (Anderson, 2016; National Equity Atlas, 2017), these findings are not unexpected. Non-Hispanic Whites find traveling with bicycle less risky than driving their cars as compared to other racial groups. This difference may be a result of the racial disparities in terms of bicycling in the U.S. Previous empirical studies on bicycling shows that Black and Hispanic individuals are less likely to own a bicycle, more likely to experience environmental barriers such as fewer bicycle facilities, insufficient bike infrastructure, as well as social barriers such as racial profiling or fear

of crime in their neighborhoods (Cox & Brown, 2017; Sallis et al., 2013). More positive perception of bicycling by non-Hispanic Whites may be associated with these variations between racial groups.

5. Conclusions and future directions

This study presents a thorough analysis of COVID-19 impacts on travel behavior with a particular lens on travel changes, intrinsic values of mobility, and the perceived COVID-19 infection risks of travel in Columbus, OH.

The explanatory analyses show that there is a substantial reduction in both work and non-work travel during the stay-at-home orders. Additionally, participant responses on future travel expectations post stay-at-home orders indicate decreases in travel demand may resume even after the restrictions are lifted. The responses to the intrinsic values of mobility questions show that a considerable share of respondents missed multiple aspects of travel during the stay-at-home order such as feeling of independence, looking at the scenery, getting physical exercise, etc. The positive aspects of travel, particularly those that relate to non-motorized travel, should be considered while setting future transportation policies in the post-COVID era. The explanatory analysis of risk perceptions shows individuals perceive shared modes (i.e., transit, ride hailing, carshare, and bike-share) risky when it comes to COVID-19 exposure.

The results of multivariate analysis are mostly consistent with the findings of other studies that focus on COVID-19 impacts on travel. As presented in Table 3, respondents are more likely to find shared modes riskier than their cars, even after controlling for socio-demographics. Additionally, they are more likely to find walking riskier than driving in terms of COVID-19 exposure. Auto users are more likely to find travel riskier as compared to non-auto users. The interaction effects show that there are differences in perceived risk of infection across various modes and respondents with different characteristics. Auto users and non-Hispanic Whites are more likely to find shared modes riskier than their cars in terms of infection as compared to others. These findings show that the relatively higher perception of exposure risk related to shared transportation options can be even stronger for some groups.

Our findings point to a need for new transportation policies in the post-COVID era, as consistent with other recent studies (Budd & Ison, 2020; de Haas et al., 2020). City authorities can use the intrinsic values of non-motorized travel (i.e., feeling independent, getting exercise) as an opportunity to achieve more sustainable transportation outcomes by facilitating bicycle- and pedestrian-friendly environments. Increasing public access to green spaces and pedestrianizing streets can encourage walking, cycling, and exercising. Various cities have already begun implementing these strategies (Diaz, 2020). On the other hand, our findings on individuals finding shared modes riskier than private vehicles pose another great challenge to transportation planners and transit authorities aiming to promote sustainable mobility and reduce car dependency. Transit authorities and transportation planners should formulate viable solutions to address the high-risk perceptions associated with transit. While positive perceptions towards walking and bicycling are encouraging steps towards sustainable mobility, provision of novel transit solutions are particularly important for trips beyond bikeable and walkable distances. Otherwise, individuals with access to autos may prefer driving given their risk perceptions associated with transit. Additionally, it is important to underline that while respondents overall find transit as significantly riskier than their cars, not all people have access to private vehicles. For transportation equity, it is important to take precautions that would reduce the high-risk perception related to transit. At that point, we want to highlight that the COVID relief bill that aims to support already struggling transit agencies may not be adequate to cover huge funding gaps that emerged due to substantial decreases in ridership. For example, New

York City's Metropolitan Transportation Authority is expected to receive only \$4 billion from the stimulus package while they projected a shortfall of \$16 billion through 2024 (Bliss, 2020). Considering the additional negative attitudes towards transit operations during the pandemic, future policymaking should cover these shortfalls to the greatest extent possible for continuous and reliable transit service operations.

It is important to highlight that the survey was conducted during the stay-at-home orders. Individuals' expectations, perceptions, and actions may change with the evolving conditions regarding COVID-19, as well as policy and infrastructure implementations. While the ever-changing nature of the pandemic makes travel outcomes and individual perceptions dynamic, our findings on individual responses in terms of their mobility outcomes during the stay-at-home period set a baseline for future studies. We encourage future researchers to delve into the differences between various socio-demographic groups, given that the effects of the pandemic on travel are not distributed evenly (Brough et al., 2020; Hamidi et al., 2020). Finally, there is a need for additional studies in different geographies to evaluate to what extent our findings are consistent in different cities and countries.

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CRedit authorship contribution statement

Basar Ozbilen: Conceptualization, Data curation, Formal analysis, Writing - original draft, Writing - review & editing. **Kristina M. Slagle:** Conceptualization, Formal analysis, Writing - original draft, Writing - review & editing. **Gulsah Akar:** Conceptualization, Formal analysis, Writing - original draft, Writing - review & editing.

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