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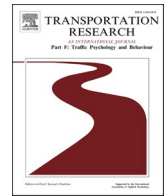
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Perceived risk of using shared mobility services during the COVID-19 pandemic

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ABSTRACT

The COVID-19 pandemic has caused our daily routines to change quickly. The pandemic provokes public fear, resulting in changes in what modes of transport people use to perform their daily activities. It is imperative for transportation authorities to properly identify the different degrees of behavioral change among various social groups. A major factor that can substantially explain individuals' behavioral changes is the personal risk perceptions toward using shared mobility solutions. Thus, this study explores the risk that individuals perceive while using public transit and ridesharing services (as the most widespread forms of shared mobility) during the COVID-19 pandemic. To do so, we designed and implemented a multidimensional travel-behavior survey in the Chicago metropolitan area that comprises socio-demographic information and retrospective questions related to attitudes and travel behavior before and during the pandemic. Utilizing a bivariate ordered probit modeling approach to better account for the potential correlation between unobserved factors, we simultaneously modeled the perceived risk of exposure to the novel coronavirus in case of riding transit and using ridesharing services. A wide range of factors is found to be influential on the perceived risk of using shared mobility services, including the socio-demographic attributes, built environment settings, and the virus spread. Further, our results indicate that the mitigation strategies to increase the ridership of shared mobility services should be adaptive considering the spatial variations.

1. Introduction

The novel coronavirus (SARS-CoV-2) has caused upheaval around the world and has caused our daily routines to change quickly. The World Health Organization (WHO) reported more than 174 million confirmed cases and 3.7 million deaths globally as of June 10, 2021 (WHO, 2021). Governments around the world are striving to fight against the pandemic by substantial diagnosis tests and enacting restrictive guidelines, including stay-at-home orders and social distancing. In the U.S., despite all preventive policies implemented so far, the cases are still increasing at an alarming rate, and the situation is getting worst in various states across the country. On March 14, 2020, the Illinois Department of Public Health (IDPH) announced the first confirmed COVID-19 case in the state (IDPH, 2020). Currently, Illinois is among the six states with the highest number of COVID-19 cases, with 1.4 million confirmed cases

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and 25,413 deaths (Worldometer, 2021).

COVID-19 spreads from person to person through sneezing, coughing, or touching contaminated surfaces. According to the Harvard Medical School, the virus can be airborne for up to several hours and can live on various surfaces for multiple days (Harvard Medical School, 2020). Thus, individuals can be at risk of exposure to it when visiting different locations to fulfill their daily activities (e.g., workplaces, schools, shopping centers, bars and restaurants, and hospitals) or when using different modes of transportation, especially the ones which are shared with other passengers.

The pandemic provokes public fear, which may result in changes in travel behavior, and more specifically, alterations in the activities people engage in and transportation modes they use to reach their activity locations. One of the major factors which can substantially explain people's behavior during a health crisis (e.g., COVID-19 pandemic) is the perceived risk of performing various activities (Hotle, Murray-Tuite, & Singh, 2020). It is imperative for transportation authorities to properly identify the different types and degrees of behavioral changes among various groups of society. In this sense, investigating the inter-personal variations in the perceived risk of exposure to COVID-19 is the first step in understanding the adjustments people may make in their travel behavior to protect themselves, including canceling their trips, avoiding public transit, and avoiding public places, among others (Hotle et al., 2020). These adjustments can certainly impact the behavioral process of activity planning and scheduling, destination choice, mode choice, and eventually traffic congestion patterns and emissions.

Reviewing the literature, concrete evidence could be found on the impacts of the viral pandemics and other public threats alike in the past. However, the impacts of the recent COVID-19 pandemic on travel behavior are relatively understudied. Among the limited number of studies on the impacts of COVID-19, we can refer to the literature (e.g., Bucsky, 2020; De Vos, 2020; Hotle et al., 2020; Ito, Hanaoka, & Kawasaki, 2020; Sobieralski, 2020; Teixeira & Lopes, 2020). Although these studies are informative and provide invaluable insights into the changes in performing various activities and use of different modes, characterizing individuals' risk perception due to the COVID-19 pandemic has yet to be investigated. The present study is thus designed to investigate the risk that individuals perceive while using public transit and ridesharing services (as the widespread types of shared mobility solutions) during the COVID-19 pandemic. Early evidence highlights the vital role of shared mobility, and more importantly, public transit, in economic recovery after the pandemic (Sifuentes, 2020).

Pursuing the goals of this study, we used the data collected through a multidimensional travel behavior survey instrument. This online survey was conducted in the Chicago region from April 25 to June 2, 2020 and collected a rich set of data regarding the residents' socio-demographic details, their health-related background, as well as an extensive set of information about their daily activity-travel behavior. Specifically, two questions of the survey were designed to inquire about individuals' risk perception toward using public transit and ridesharing services during the COVID-19 pandemic. To characterize individuals' perceived risk of exposure to COVID-19, we utilized the bivariate ordered probit model, which characterizes the influential factors affecting the risk perception of using those modes while accounting for the potential correlation between their unobserved factors. Our findings can help policymakers better understand changes in people's travel behavior during a health crisis such as the COVID-19 pandemic.

The rest of this study is organized as follows. In the next section, we review the underlying literature and the insights provided to our research. Then, we briefly present the survey designed for this study along with a summary statistic of key variables to provide preliminary insight based on the observations. Following that, we review the methodological background implemented in this study in the Method section. Next, we present an in-depth discussion on estimation results and interpretation of the model parameters in the Result section. In the end, the paper concludes with a summary of discussions and directions for future studies.

2. Background

The association between travel behavior and perceived risk of exposure to a public health crisis similar to the COVID-19 pandemic has received little attention in literature, even though the risk perception significantly characterizes individual travel behavior (Hotle et al., 2020). In a recent study, Elias, Albert, and Shifan (2013) investigated the changes in travel behavior caused by a terror threat in Israel and showed that fear and risk perception are vital in understanding travel behavior with respect to public transportation. In this study, women were found to perceive more risk than men, and thus, such impacts on women's travel behavior are found to be more extensive. As a result, an undesired modal shift from public transportation to personal cars might occur.

Focusing on the effect of the perceived risk of viral outbreaks on travel behavior, Rittichainuwat and Chakraborty (2009) conducted a study in Thailand and found that people did not completely discontinue traveling during the outbreak caused by SARS (Severe Acute Respiratory Syndrome); instead, they selected different options from less dangerous destinations. Moreover, the authors showed that although all travelers perceived risk of diseases, the level of risk might differ from person to person, depending on whether one is either a first-time or frequent traveler. In another study, Wen, Huimin, and Kavanaugh (2005) analyzed the impact of SARS on the travel behavior of Chinese domestic tourists focusing on their leisure travel. Running a survey among those who were affected, the authors found that SARS has dramatically changed people's life, work, and traveling during the SARS period; however, the level of the impacts on people's preference to travel and the preference of leisure trips might be different. Besides, the decrease in travel was caused by a combination of internal motivation (e.g., perceived risks) and external enforced measures (e.g., travel bans, stay-at-home orders).

Moreover, Liu, Moss, and Zhang (2010) studied the effects of the SARS outbreak on travel between the U.S. and three destinations: China, Hong Kong, and Taiwan. The authors found that although the frequency of trips was decreased in all countries, the level of risk was perceived differently among those countries, highlighting the influence of lifestyles on travel behavior during an outbreak. Hotle et al. (2020) investigated risk perception and risk mitigation of travel-related decisions concerning influenza to characterize the risk perceptions. The authors highlighted that being female and having experienced influenza-like symptoms significantly increased risk perception at the locations that people perform mandatory and health-related activities (e.g., doctor's offices and hospitals).

Furthermore, their results showed that high perceived risks of exposure to an influenza virus do not lead people to travel to their workplaces less frequently.

There are a limited but growing number of studies focusing on the impacts of the COVID-19 pandemic on individuals' travel behavior (Mirtich, 2021; Salon, 2021; Capasso da Silva et al., 2021; Chauhan et al., 2021). Bucsky (2020) analyzed the demands for various modes of transport such as public transport, personal vehicle, and bike during the COVID-19 pandemic in Budapest, Hungary. The author observed that the usage of public transit decreased dramatically by 80%, while the overall mobility was reduced, at least by 51% and maximally by 64%. On the other hand, modal shares of personal vehicles and bikes increased to 65% and 4% from 43% and 2%, respectively.

In another study conducted in the Netherland, de Haas, Faber, and Hamersma (2020) found that approximately 80% of people engaged in out-of-home activities less frequently. Moreover, seniors turned out to be less active than before the pandemic. The authors also observed that the number of trips and vehicle-mile traveled (VMT) are reduced by 55% and 68%, respectively, as compared with the fall of 2019. The demand for public transit is impacted severely with a decrease of over 90% of ridership; Most people preferred individual modes compared to public or shared modes of transport. Teixeira and Lopes (2020) focused on the usage of bike-sharing and the subway system during the COVID-19 pandemic in New York and observed that Citi Bike (i.e., the bike-sharing system operating in New York) was revealed to be more resilient than the subway system, with a less significant ridership reduction and an increase on its trips' average duration. Moreover, the author found a potential modal transfer from some subway users to the bike-sharing system.

3. Survey design and data analysis

We designed and performed a stated preference-revealed preference (SP-RP) survey in the Chicago metropolitan area (including the counties of Cook, DuPage, Kane, Kendall, Lake, McHenry, and Will) to understand the dynamics of daily travel behavior, as well as multiple aspects of people's long-term travel habits, attitudes, and preferences during the COVID-19 pandemic. For the RP part of the survey, the respondents were asked to provide their travel behaviors before and during the pandemic. For the SP part, they were asked to indicate their expected behavior for the future when the pandemic is over.

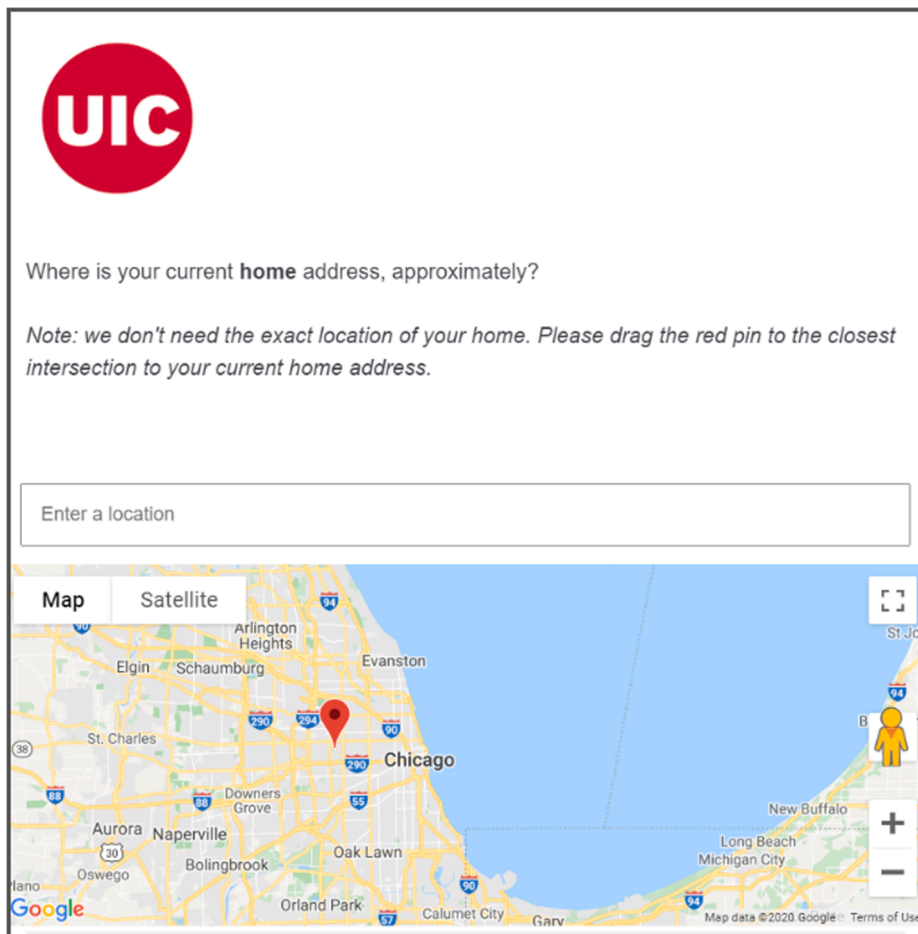


Fig. 1. A screenshot of the online survey (using Google Map API to specify residential location).

The survey was structured to collect a rich set of information in the following major areas: 1) socio-demographic information such as residential location, age, gender, ethnicity, as well as the economic factors such as job status and household income; 2) health-related factors including disability status, pre-existing conditions, and physical exercise habits, as well as COVID-19 exposure risk factors such as smoking and obesity; and 3) an extensive set of questions regarding the perceived risk of exposure to the SARS-CoV-2 virus while using shared mobility, including public transit and ridesharing services.

We used the Qualtrics online platform to distribute the survey from late April to early June of 2020 in the Chicago metropolitan area. In order to consider the variation of the spread of COVID-19 within the study area, we incorporated the Google Maps API to collect respondents' approximate residential locations (i.e., the nearest intersection to their home address) in the questionnaire. Fig. 1 shows a screenshot from our survey. Furthermore, multiple quality checks were utilized in the questionnaire to identify the respondents who have not devoted sufficient attention to the survey. In this way, we excluded those who failed to correctly pass the quality checks, overly fast responses (i.e., less than 15 min), and responses with missing information. Full information about the design of various parts of the survey, implementation, and summary statistics of the data can be found in the authors' previous work (Shamshiripour, Rahimi, Shabanpour, Mohammadian, 2020b).

The final and cleaned data contains 915 responses. To make sure that our sample represents the Chicago Metropolitan Area, we weighted the sample based on the travel survey conducted by the Chicago Metropolitan Agency for Planning (CMAP). Table 1 reports a summary of respondents' key characteristics alongside both weighted and unweighted shares.

Moreover, we incorporated the survey data with built environment information from the Smart Location Database (SLD) prepared by the Environmental Protection Agency (EPA) (EPA, 2014). This information is provided at the census block group level and could provide insights into understanding the effect of built environment settings on the perceived risk of exposure to the SARS-CoV-2 virus. To better account for the effect of spreading the virus on the perceived risk of exposure to it, we also used the frequency of confirmed COVID-19 cases at a zip code-level resolution throughout the study area provided by the Illinois Department of Public Health (IDPH) (IDPH, 2020). Fig. 2 presents the respondents' approximate residential locations mapped on the zip code boundaries of the Chicago metro area, which are color-coded based on the number of confirmed COVID-19 cases. As can be seen in Fig. 2, the respondents were decently scattered across the study area.

Since the scope of this study is to investigate the perceived risk of using public transit and ridesharing services among those who are actual users of these modes, we utilized 398 observations in which respondents indicated they had an experience of using public transit and ridesharing services.

Our dependent variables are derived from questions focusing on people's perceived risk of exposure to the SARS-CoV-2 virus when using shared mobility options. More specifically, we asked respondents to indicate how they perceive the risk of being exposed to the SARS-CoV-2 virus while using public transit (i.e., bus system) and ridesharing services (e.g., Uber, Lyft) during the COVID-19 pandemic. For this question, we provided each respondent with a five-point Likert scale ranging from "extremely high risk" to "extremely low risk" to choose based on their experience of using these options. Fig. 3 shows the distribution of responses in our sample. For the sake of comparison, we also presented the perceived risk of exposure to the virus while driving a personal vehicle in this figure. As can be seen, more than 90% of the respondents indicated that they associate transit and ridesharing services with medium to extremely high risk of exposure to the SARS-CoV-2 virus, while this value is around 15% for a personal vehicle. Table 2 also defines explanatory variables that turned out to be significant in the final model.

4. Method

Since the dependent variables in this study are ordinal in nature, we utilized an ordered probit structure to characterize the factors affecting the risk perceptions. Ordered probit models assume a normal distribution for error terms and prevent the estimation difficulties related to the logit structure; thus, ordered probit models are preferred compared with ordered logit models in literature (Rahimi, Shamshiripour, Samimi, & Mohammadian, 2020; Washington, Karlaftis, & Mannering, 2010).

Table 1
Summary statistics of the respondents' key characteristics.

Variable	Category	Share (percentage)		
		Unweighted	Weighted	CMAP
Gender	Male	55.19	47.80	47.8
	Female	44.81	52.20	52.2
Age	Younger than 20	9.07	29.88	29.88
	20–24	5.90	6.69	6.69
	25–54	45.03	44.90	44.9
	55–64	18.58	7.93	7.93
	65 and above	21.42	10.60	10.6
Ethnicity	White/Caucasian	71.37	65.41	65.42
	African American	10.71	18.93	18.93
	Other	17.92	15.66	15.66
Education	Less than high school or high school	37.60	34.45	34.45
	College or associate degree	31.91	16.85	16.85
	Bachelor's degree	18.69	27.24	27.24
	Graduate degree	11.80	21.46	21.46

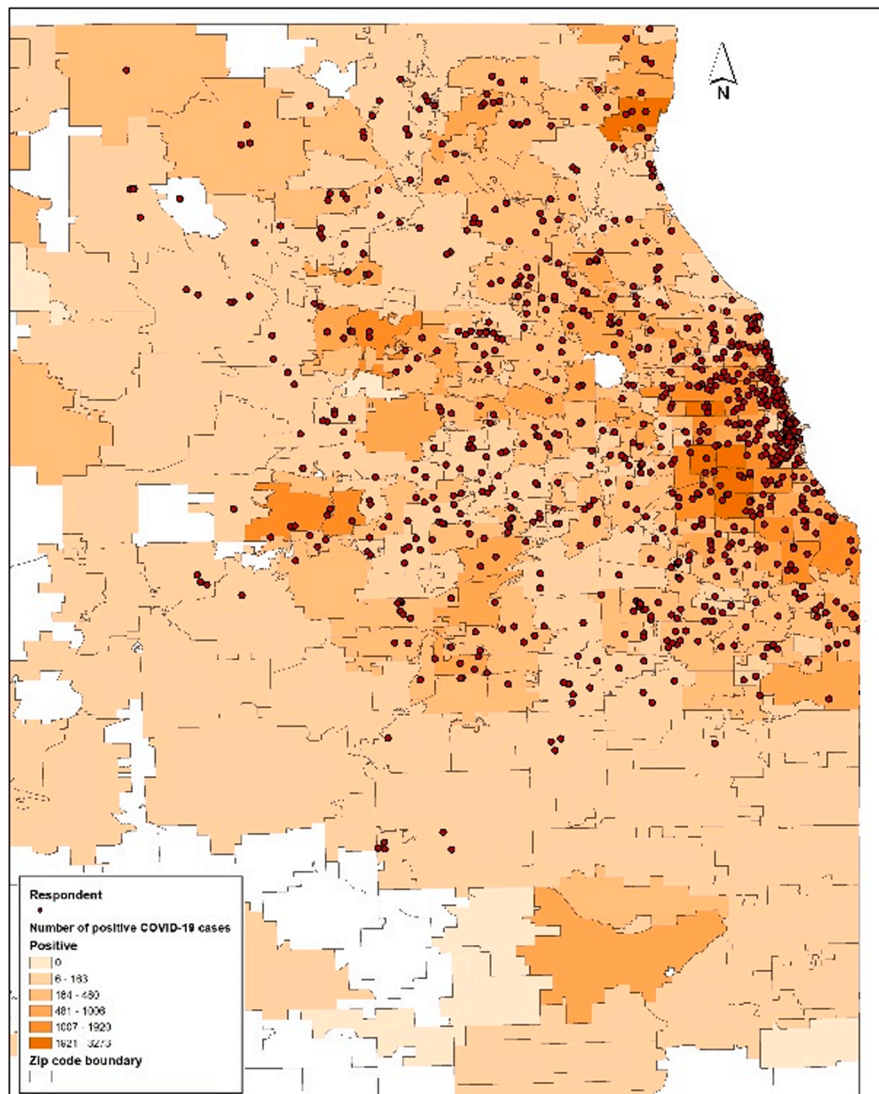


Fig. 2. Respondents’ residential locations mapped on the number of positive COVID-19 cases (as of June 6, 2020) in each zip code within the study area.

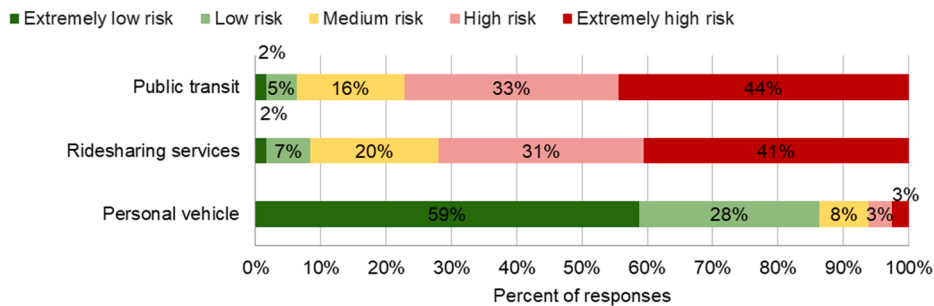


Fig. 3. Perceived risk of traveling with public transit and ridesharing services as compared with a personal vehicle during the COVID-19 pandemic.

The model structure has an underlying random utility or latent regression component, in which the probabilities of ordinal outcomes in the ordered probit model is driven by considering a continuous latent utility (i.e., measure), y^* (Greene & Hensher, 2010; Samimi & Rahimi, 2020; Washington, Karlaftis, & Mannering, 2010; Greene, 2003). This measurement variable is typically specified as

Table 2
Definition of explanatory variables turned out to be significant in the model.

Explanatory variable	Definition	Mean	Std. Dev.	Frequency (%)
Socio-demographic: AfricanAmerican	1: If the respondent's ethnicity is African American/ 0: Otherwise			21.52
Socio-demographic: LowIncome	1: If the respondent is less than \$20 K/ 0: Otherwise			6.24
Socio-demographic: Female	1: If the respondent's gender is female/ 0: Otherwise			46.69
Socio-demographic: Senior	1: If the respondent's age is 65 years old or more/ 0: Otherwise			4.54
Socio-demographic: Job_Transportation	1: If the occupation of the respondent is transportation services/ 0: Otherwise			3.88
Socio-demographic: LivingWithGrandparent	1: If the respondent is living with their grandparent(s)/ 0: Otherwise			1.91
Health: Covid_Positive	1: If the respondent has been a confirmed case of COVID-19 in the past 14 days/ 0: Otherwise			2.17
SARS-CoV-2 virus spread: ConfirmedCaseDensity	The number of confirmed COVID-19 cases within a zip code divided by the population of the zip code, where the respondent is living	0.012	0.007	
Built environment: SLD_D3aao	Network density in terms of facility miles of auto-oriented links per square mile in a census block group, where the respondent is living	1.15	3.19	
Built environment: SLD_D4b050	Proportion of census block group employment within ½ mile of fixed-guideway transit stops in a block group, where the respondent is living	0.38	0.44	
Built environment: SLD_D4d	Aggregate frequency of transit service per square mile in a block group, where the respondent is living	2622.47	5476.02	
Built environment: SLD_D3apo	Network density in terms of facility miles of pedestrian-oriented links per square mile in a block group, where the respondent is living	15.63	7.21	
Travel behavior: Regular Transit User	1: If the respondent uses transit for any of his/her daily activities on a regular basis/ 0: Otherwise			19.00
Law: OverActingBasedOnLaw	1: if the respondent is following restrictive measures (i.e., self-quarantine) on the top of the official restrictions enacted/ 0: Otherwise			48.18

Table 3
Estimation results of the bivariate ordered probit model.

Parameters	Public transit		Ridesharing services	
	Coefficient	t-stat	Coefficient	t-stat
Constant	0.827***	12.40	0.827***	12.50
Explanatory variables				
Socio-demographic: AfricanAmerican	-0.158*	-1.35	-	-
Socio-demographic: LowIncome	0.503**	1.77	-	-
Socio-demographic: Female	0.364***	3.08	0.265**	2.35
Socio-demographic: Senior	-	-	0.376***	2.66
Socio-demographic: Job_Transportation	-0.592**	-2.37	-	-
Socio-demographic: LivingWithGrandparent	-	-	0.465*	1.36
Health: Covid_Positive	-0.518*	-1.36	-0.707*	-1.62
SARS-CoV-2 virus spread: ConfirmedCaseDensity	-	-	13.136**	2.18
Built environment: SLD_D3aao	0.041**	2.33	-	-
Built environment: SLD_D4b050	-0.158*	-1.41	-	-
Built environment: SLD_D4d	-	-	-0.00001*	-1.57
Built environment: SLD_D3apo	-	-	0.017**	2.41
Travel behavior: Regular Transit User	-0.198*	-1.58	-	-
Law: OverActingBasedOnLaw	0.125*	1.35	-	-
Thresholds				
μ_1	-1.930***	-12.36	-	-
μ_2	-1.521*	-11.73	-	-
μ_3	-0.788***	-7.28	-	-
μ_4	0.204**	1.99	-	-
γ_1	-	-	-1.645***	-8.21
γ_2	-	-	-0.758***	-4.89
γ_3	-	-	0.210*	1.44
γ_4	-	-	0.972***	6.42
Model Statistics				
Number of observations	398			
Log-likelihood at zero	-922.038			
Log-likelihood at convergence	-910.44			
Joint parameter				
Correlation of error terms (ρ)	0.679***			

Note: *, **, and *** mean 90%, 95%, and 99% level of confidence, respectively.

a linear function for each observation (Greene, 2003; Washington et al., 2010), as in Eq. (1), where, \mathbf{X} is a vector of explanatory variables, β' is a vector of parameters to be estimated, and $\varepsilon \sim N(0, 1)$ is the error term which is normally distributed across observations.

$$y^* = \mathbf{X}\beta' + \varepsilon \tag{1}$$

The dependent variable (y) that is observed in discrete form through a censoring structure as in Eq. (2) (Greene, 2003; Greene & Hensher, 2010; Washington et al., 2010), where μ_1, \dots, μ_{J-1} are threshold parameters which are estimated jointly along with β' .

$$y = 0 \text{ if } y^* \leq 0, y = 1 \text{ if } 0 < y^* \leq \mu_1, y = 2 \text{ if } \mu_1 < y^* \leq \mu_2, \dots, y = J \text{ if } \mu_{J-1} < y^* \tag{2}$$

In this study, we aim to model people’s perceived risk of exposure to the SARS-CoV-2 virus during travel with two types of shared mobility options: 1) public transit and 2) ridesharing. Accordingly, there might be a correlation between unobserved factors of the models. To account for the potential correlation, we implemented a bivariate mechanism of ordered probit approach instead of a univariate one. The bivariate ordered probit model is an extension of the traditional ordered probit model, in which two measurement variables, y_1^* and y_2^* , are estimated simultaneously while error terms are assumed to be correlated (Greene & Hensher, 2010):

$$y_1^* = \mathbf{X}_1\beta_1' + \varepsilon_1, \varepsilon_1 \sim N[0, 1], y_1^* = J \text{ if } \mu_{J-1} \leq y_1^* < \mu_J, y_2^* = \mathbf{X}_2\beta_2' + \varepsilon_2, \varepsilon_2 \sim N[0, 1], y_2^* = K \text{ if } \gamma_{K-1} \leq y_2^* < \gamma_K \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \rho & 0 \\ 0 & \rho \end{pmatrix}\right) \text{Cor}(\varepsilon_1, \varepsilon_2) = \rho. \tag{3}$$

5. Results and discussion

Table 3 presents the estimation results for the bivariate ordered probit model. The results include the estimated parameters, t-statistics, and the log-likelihood values at both convergence and zero. We assured that the coefficients in the model are statistically significant, at least within a 90 percent confidence level. More importantly, the correlation of error terms turned out to be significant with a positive sign. This indicates that the unobserved factors increasing the perceived risk of exposure to the SARS-CoV-2 virus while riding public transit might also increase the perceived risk of exposure to the virus during the use of ridesharing services. Indeed, both risk perceptions are, in fact, reflections of latent constructs.

5.1. Socio-demographics

As shown in Table 3, the model indicates that ethnicity might be an important factor influencing the perceived risk of exposure to the SARS-CoV-2 virus while using shared mobility options. Per the results, African Americans perceive the risk of using transit services lower than others.

Also, the annual household income is found to be significant in the risk perception associated with the usage of public transit. Based on the model, individuals living in extremely low-income households (i.e., who earn less than \$20 K per year) perceive a higher risk of using public transit as compared to others. This finding supports the idea that as people’s income levels increase, their overall perceptions of the world as a risky place decrease (Dosman, Adamowicz, & Hrudehy, 2001). One possible explanation is that high-income individuals can spend more on minimizing their exposure to (or mediate the level of) the risks. This is in good agreement with Dosman et al. (2001) and Hotle et al. (2020).

Concerning gender, the results indicate that females perceive a higher risk than males regarding using shared mobility options during the COVID-19 pandemic. Overall, the literature evidenced that males usually tend to perceive lower levels of risk as compared to females in similar circumstances (Davidson & Freudenburg, 1996; Dosman et al., 2001; Flynn, Slovic, & Mertz, 1994; Gustafson, 1998; Hotle et al., 2020; Lin, 1995). For instance, Davidson and Freudenburg (1996) highlighted that the traditional gender role of females, who are care providers within a household, might lead them to perceive higher health risks. Furthermore, Hotle et al. (2020) showed that females are more likely than males to avoid public transit due to the threat of outbreaks.

According to Table 3, the age of respondents is found to affect the risk-perception behavior associated with choosing ridesharing services as a transport mode. Specifically, seniors are more likely to perceive the exposure to the SARS-CoV-2 virus higher risk than younger respondents. Several possible reasons might explain this finding. First, seniors are more likely to have underlying health conditions, increasing the risk of dying from coronavirus. According to the CDC, the highest risk for severe illness from COVID-19 is among older adults, including seniors (CDC, 2020). As another reason, seniors have experienced previously the possible effects of health issues associated with viral diseases similar to the COVID-19; thus, they perceive similar crises as high-risk incidents (Dosman

et al., 2001).

We found that being the main driver of a household's vehicle affects the perceived risk of exposure to the COVID-19 during the use of the public transit system. This variable can be a proxy for having auto-oriented lifestyles. Moreover, we also found that an individual's occupation might impact the perceived risk of exposure to the virus. Specifically, individuals who work in transportation service industries (e.g., bus drivers) perceive lower risk of exposure to the virus while using the shared mobility. Supported by intuition, such individuals might have more experience dealing with such health-related issues; thus, they perceive less threat than others.

5.2. Virus spread

The perceived risk of exposure to the SARS-CoV-2 virus also varies by being a confirmed case of COVID-19. More specifically, respondents who have experienced the novel coronavirus disease in the past 14-days perceive lower risk than others to use shared mobility options. One possible reason is that such individuals trust the early evidence, showing that levels of neutralizing antibodies against the SARS-CoV-2 virus remain relatively high for a few weeks after infection but then usually begin to decline (Callaway, Ledford, & Mallapaty, 2020). In line with our finding, moreover Hotle et al. (2020) studied the risk perception associated with visiting public places during an influenza outbreak for individuals who had experienced the flu symptoms in the past six months. They found that having such experiences might, to some extent, lead individuals to be more risk-taking than others in terms of visiting public places during an outbreak.

Another variable that turned out to be significant in the model is the density of confirmed COVID-19 cases within a zip code (i.e., the number of confirmed COVID-19 cases within a zip code divided by the population of the zip code) where the respondent resides. As can be seen in Fig. 2, the novel coronavirus has not been spread evenly throughout the study area. Per the model, the more the novel coronavirus spreads among the population of a specific zip code where an individual is living, the more he or she might perceive the risk of exposure to the virus during the use of ridesharing services. This finding is in good agreement with the literature (Davidson & Freudenburg, 1996; Dosman et al., 2001), emphasizing the effect of surroundings on shaping risk perceptions. However, this variable was not found to be significant in the perceived risk of using public transit.

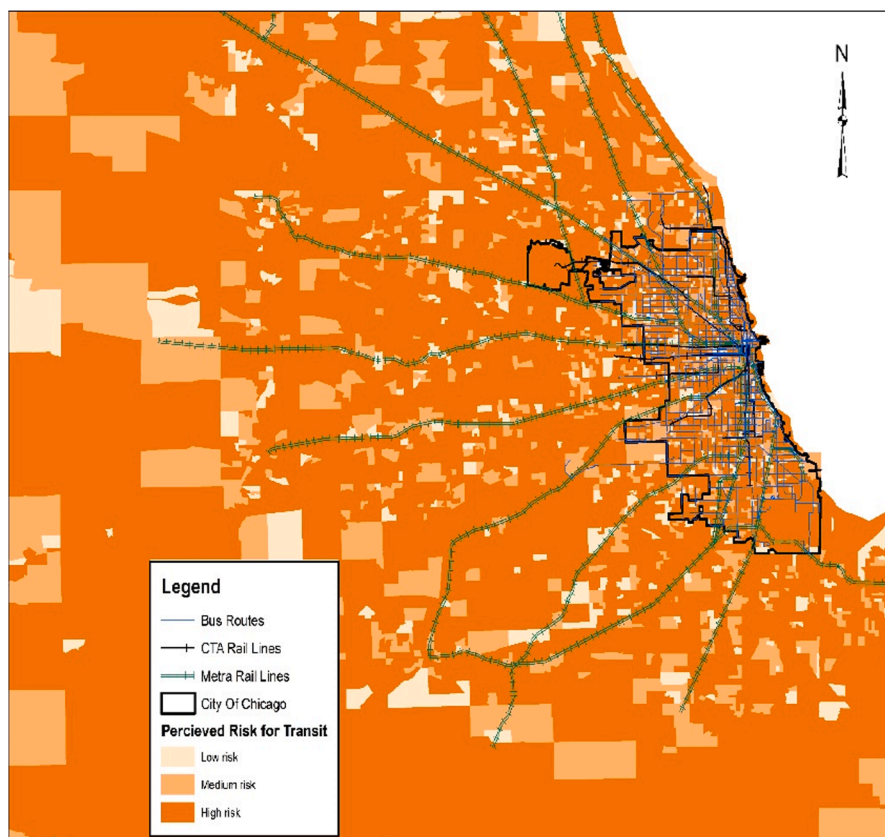


Fig. 4. Perceived risk of exposure to the novel coronavirus for using public transit.

5.3. Built environment settings

The impacts of built environment and urban development on public health has been suggested previously in the literature (e.g., Samimi & Mohammadian, 2010). Our results add that the transportation network density in terms of facility miles of auto-oriented links per square mile in the census block group where respondents reside might lead them to perceive higher risk regarding the use of public transit system during the COVID-19 pandemic. In line with the literature, highlighting the effect of the built environment on shaping individuals' modality styles (i.e., the lifestyle associated with long-term mode choice decisions) (Shamshiripour, Rahimi, Shabanpour, Mohammadian, 2020a) and risk perception (Davidson & Freudenburg, 1996), this finding provides another implication of built environment settings in influencing people's travel behavior. Arguably, those who live in such areas are more prone to personal vehicles than shared mobility. Thus, they might perceive higher levels of risk while using public transit during a health crisis like the COVID-19 pandemic, since they are less acquainted with this mode. This result also further supports our aforementioned finding on the effect of being the main driver of a household vehicle (as the proxy of being auto-oriented). With a similar argument, our results reveal that individuals who live in transit-oriented areas perceive lower risk than others in terms of using public transit during the COVID-19 pandemic.

Another transit-related built environment variable that turned out to be significant in the model is the aggregate frequency of transit service per square mile in a block group where the respondent resides. Living in such transit-oriented areas leads people to perceive less risk and are probably more prone to use shared mobility options. Furthermore, the results show that individuals who live in areas with a higher level of access to active transportation infrastructure might perceive a higher risk of using ridesharing services than active modes. This finding is in good agreement with Bucsky (2020) who observed that people are more inclined to substitute shared mobility options such as public transit with active transport modes such as walking and biking as safer options.

5.4. Travel behavior

We also tried to investigate the relationship between risk perception and actual travel behavior. Being a regular transit user was found to be influential on the perceived risk of using public transit. Our finding suggests that those who used public transit regularly before the COVID-19 pandemic perceive a lower risk of using public transit during the pandemic.

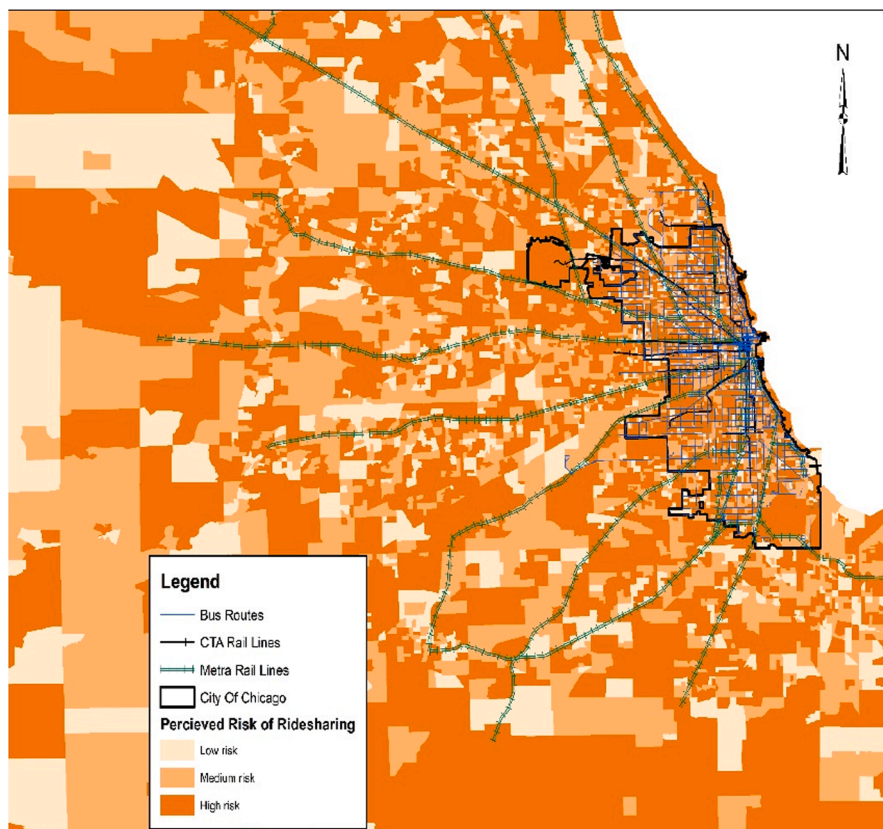


Fig. 5. Perceived risk of exposure to the novel coronavirus for using ridesharing services.

5.5. Laws and restrictions

In the survey, we asked the respondents to indicate which types of official restrictions associated with the COVID-19 pandemic currently exist in their residential area. Then, we compared individuals' responses with the official guidelines available during the time of the survey according to the specific guidelines put forth by the governor of the state of Illinois (State of Illinois, 2020). An indicator variable (i.e., *Law: OverActingBasedOnLaw*) was created for individuals who selected more restrictions than the ones that were already put in place. Therefore, if an individual selected more restrictions than those already in place (i.e., the indicator variable takes 1), it could be concluded by the rationale that the individual is voluntarily imposing more limitations to his/her way of life, which could be due to perceiving higher levels of risk. Accordingly, our results reveal that such individuals are likely to be more concerned than others about using shared mobility options, including public transit and ridesharing services.

5.6. Simulation of the perceived risks

To demonstrate the spatial distributions of the perceived risk of using public transit and ridesharing services, we simulated the proposed model for individuals who live in the Chicago metropolitan area at a census block-group level resolution. Figs. 4 and 5 present the perceived risk of exposure to the novel coronavirus while riding public transit and ridesharing services, respectively. We also aggregated the risk levels into three categories of (1) low risk, (2) medium risk, and (3) high risk. Overall, the perceived risk of exposure to the novel coronavirus while using the public transit system is significantly higher, as compared with using ridesharing services in the region. More interestingly, the simulation results reveal a distinction between individuals who live in the suburbs and those who live in the city for the perceived risk of exposure to the virus while using ridesharing services. According to Fig. 5, individuals who live in the suburbs perceive less risk when using ridesharing services, as compared with those who live in the city. Accounting for the perceived risk of using public transit, however, we found no distinction between the two groups of the population. In other words, the use of the public transit system is perceived to be associated with high levels of risk in most census block groups in the Chicago metro area.

6. Conclusion

In this study, we aimed to investigate risk perceptions toward using shared mobility solutions during the pandemic. It is vital for policymakers to accurately characterize the different types and degrees of behavioral changes among various groups of society. Risk perception of using various modes is one of the major factors which can substantially explain individuals' travel behavior changes during a health crisis. The focus of this study is on public transit and ridesharing services since these options are the most widespread forms of shared mobility in the current transportation system. We utilized a bivariate ordered probit modeling approach in order to consider the correlation among unobserved factors while accounting for the ordinal nature of risk perception outcomes. The data used in this study is provided by a recent multidimensional travel-behavior survey instrument in the Chicago Metropolitan Area focusing on the impacts of the COVID-19 pandemic on individuals' travel behavior. We started the online survey in the Chicago region on April 25 and concluded on June 2, 2020 and collected a rich set of data regarding the residents' socio-demographic details, their health-related background, as well as an extensive set of information about their daily activity-travel behavior.

According to the results, a wide range of explanatory variables is found to be significant in the risk perception model, including socio-demographic variables, built environment, health condition, virus spread, travel behavior, and the restriction factor. Our findings provide insights into the influential factors on perceiving the risk of using shared mobility services during the pandemic. The findings revealed that risk perception behaviors might vary based on the special characteristics of places where individuals reside. Besides, the spread of the novel coronavirus might also affect the risk perception behavior in each neighborhood. These findings highlighted the idea that mitigating strategies should be adaptive based on the specific characteristics of each neighborhood. In other words, a common strategy will not be able to mitigate the risks associated with the use of shared mobility options throughout the area. Furthermore, since risk perceptions are also driven by the actual risk (at least for ridesharing), it would be beneficial that the risks (for different neighborhoods) are communicated.

For future studies, one might incorporate the proposed model into a mode choice framework (or a simulation tool) to explore the impacts of risk perceptions on various characteristics of the transportation network, including congestion, VMT, and emissions. Also, it would be informative if future studies investigate the relationship between the risk perceptions and the current use of public transit and ridesharing services. Furthermore, we asked for the risk perception information from actual users of transit and ridesharing services since we did not have information about risk perception for non-users. Future studies can investigate the risk perception for both actual users and non-users and compare the findings.

CRedit authorship contribution statement

Ehsan Rahimi: Conceptualization, Data curation, Methodology, Formal analysis, Writing - original draft. **Ramin Shabanpour:** Conceptualization, Writing - review & editing. **Ali Shamshiripour:** Conceptualization, Data curation, Formal analysis, Writing - review & editing. **Abolfazl (Kouros) Mohammadian:** Funding acquisition, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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