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Association of human mobility with road crashes for pandemic-ready safer mobility: A New York City case study

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1. Introduction

World public health policymakers have provided interventions to address the tragic COVID-19 pandemic; it might also be worth considering another health crisis, i.e., road crashes, which have been silently going on for decades. COVID-19 and road crashes caused suffering, death, and economic hardships. As of February 22, 2021, the World Health Organization claimed that COVID-19 had killed 2,462,911 globally (World Health Organization, 2020). Although the road traffic volumes and mobility, in general, have sharply dropped (Google LLC, 2020) due to the “lockdown” status in the United States, traffic deaths unexpectedly rose 8% in 2020 compared with the same period in 2019. In New York City, 131 people were killed in vehicle crashes, and 5816 people were injured particularly while cycling, which was a 70% and 17.88% increase over 2019, respectively (NHTSA, 2021).

In addition to comparing the extent of suffering and deaths caused by these two horrific reasons, this is an opportune time for local authorities to address road safety in general from this unplanned, natural predication, i.e., the COVID-19 pandemic (Katrakazas et al., 2020; Qureshi et al., 2020; Saladie et al., 2020; Vingilis et al., 2020). Specifically, it is time to strategize by looking at trends that have emerged regarding traffic mobility and road safety and getting better prepared to move forward (i.e., how to revive the transportation system and improve road safety conducive to pandemic-readiness with safer mobility). To the best of our knowledge, most of the recent studies evaluating road safety during COVID-19 are limited to a theoretical context or descriptive analysis, which fails to obtain an in-depth insight by analytical methods. Furthermore, most of them focus on drivers’ behavior, not travel behavior, including walking, biking, public transportation, and private vehicle. Hence, there is still a lack of studies that examine the impact of human mobility changes on road safety.

Timely evaluation of human mobility and safety and how it affects
transportation systems is critical for making sound decisions during and after the pandemic. The human mobility evaluation shows how residents’ behavioral patterns (e.g., travel demands, travel distance, and trip purpose) change in response to contextual factors. Safety evaluation focuses on the associated changes in crash frequency and severity. Fortunately, the wide availability of mobility data (Google, Apple, and Facebook, etc.) has provided an invaluable opportunity to assess the effects on mobility changes (Kraemer et al., 2020; Stavrinos et al., 2020; De Vos, 2020; Oliver et al., 2020; Zhang et al., 2020). For example, C2SMART researchers have developed an interactive data dashboard (Zuo et al., 2020) that explores the changes in transportation systems’ performance and mobility patterns during COVID-19. In New York City, after a sharp drop in traffic volume at the beginning of the pandemic, travel volume increased during the first week of May 2020. Travel patterns changed, with fewer Friday and Saturday trips and an increase in average trip duration in March 2020 compared with the same period in 2019 (Zuo et al., 2020). Zhang et al. (2020) also developed an interactive COVID-19 impact analysis platform to measure the metrics related to human mobility changes that highlight the positive relationship between mobility inflow and infections.

Meanwhile, evaluating traffic safety, according to the crash trends which have emerged in New York City during the pandemic, there are some trend changes in traffic injuries and deaths. The number of pedestrians injured has dropped by 29.20%, whereas the number of cyclists injured has increased by 17.88%. The number of pedestrian and cyclist fatalities during the pandemic is lower than that of 2019 averages. Comparatively, the number of motorist fatalities has increased up to 70.13%, despite a substantial decrease in the number of injuries by 20.8% (New York City Department of Transportation, NYCDOT). Recently, road safety experts have conducted studies speculating that people are prone to decrease outdoor activity and prefer to stay at home, resulting in less traffic and improved safety (De Vos, 2020; Vingilis et al., 2020). In New York City, an 81% reduction in crashes from March 2020 was realized following the implementation of the stay-at-home policies (Zuo et al., 2020). However, other studies indicate that, although crashes decreased, fatalities increased (Bian et al., 2021; Wegman et al., 2017). It may be caused by increased driving speeds associated with fewer road congestion levels after implementing the stay-at-home order (Kamga et al., 2020). Qureshi et al. (2020) speculated that other factors, such as economic pressures on drivers and the increased number of drivers under alcohol or drug influence, may also play a substantial role in severe crash outcomes. Lockdown reduced total number of road traffic crashes, but not those resulting in injuries and fatalities (Qureshi et al., 2020).

Additionally, studies suggest providing temporary or permanent facilities to promote walking and cycling to comply with social distancing orders during the pandemic (World Bank Blogs). It means that there might be benefits to adopting new modes of transportation, such as using motorcycles and e-bikes post-pandemic (albeit individuals may initially feel less safe but have more flexibility). Walking and cycling as promoted modes have also become more attractive (Bouaoun et al., 2015; WHO, 2004, 2011). In particular, the disruption created by COVID-19 has significantly changed people’s travel modes choices (see Fig. 1). In New York City, a sharp reduction in relative change volume of different travel modes, i.e., walking, driving and transit was observed during the lockdown. But after implementing reopening strategies, the relative volume changes grew faster in driving than in walking (see Fig. 1). Therefore, an in-depth understanding of factors contributing to crash occurrences by different travel modes (i.e., motorists, pedestrians, and cyclists) during the pandemic is imperative. And then contributing to enhancing the safety performance of transport systems and helping to advance agendas for urban sustainability, both now and through the post-pandemic phase.

Human mobility is one crucial factor that contributes to crash risk during the pandemic. One major challenge associated with safety assessment is the availability of reliable, high-resolution, and large-scale data to characterize human mobility changes (Elia et al., 2010). Due to the short period of time to do research, data analysis of extreme events occurring was unavailable. Most previous studies applied the travel characteristics obtained from long-term census surveys, including trip productions/attractions (Abdel-Aty et al., 2011a,b; Bao et al., 2018; Dong et al., 2015, 2016; Huang et al., 2013; Siddiqui et al., 2012; Xu et al., 2021), work trips (Xu et al., 2017), non-home-based work trips (Naderan & Shahi, 2010, Wang et al., 2017; Weng et al., 2015) as the exposure measures for crash analysis. Researchers have also found the number of pedestrian crashes increased significantly with increases in traffic volume (Cai et al., 2016, 2017; Cottrill & Thakuriah, 2010; DiMaggio, 2015; Dong et al., 2020; Guo et al., 2017; Lam et al., 2014; LaScala et al., 2000; Lee et al., 2015; Loukaitou-Sideris et al., 2007; Naderan & Shahi, 2010; Wang & Kockelman, 2013; Wier et al., 2009) and pedestrian activity (Cai et al., 2016; Wang & Kockelman, 2013; Guo et al., 2017; Osama & Sayed, 2017; Sze et al., 2019). Exposure-based studies of cyclist safety used travel behavior (e.g., cycling distance or

![Fig. 1. Percentage of relative volume changes of different travel modes in New York City during COVID-19. Source: Apple mobility trends, 2020.](image-url)
duration) data for model analysis (Götschi et al., 2016; Vanparijs et al., 2015). It found a higher crash risk for cyclists when fewer people are cycling (Branion-Calles et al., 2020).

Although the household mentioned travel-diary survey data had been widely used for most safety studies, smartphone data is a more feasible option with a high penetration rate, overcoming many time and sample size limitations. Take COVID-19 as an example: a global community called for action to share mobile phone data for disease monitoring and controlling in the first weeks of the pandemic (Kraemer et al., 2020). Recent studies proposed some metrics, including travel trips, miles traveled per person, work trips, and the percentage of residents staying at home, to measure these mobility changes. Compared with mobility data via a travel-diary survey, smartphone data represents the dynamics of human mobility behavior. Additionally, since the COVID-19 outbreak, anonymous phone mobility data has increasingly become publicly available to identify and detect infectious diseases. It provides us invaluable information to evaluate how mobility changes contribute to road crashes during COVID-19.

In this study, we propose survival analysis methods to relate three types of crashes (motorists, pedestrians, and cyclists) to various factors: human mobility, social economy, and weather conditions during the COVID-19 pandemic. The survival analysis involves modeling the time-to-event data and applying the hazard function to capture the conditional probabilities (i.e., the likelihood of crash occurrence based on frequency patterns; Chang & Jovanis, 1990; Manering, 1993; Xie et al., 2019). We took the time interval between two crashes as a dependent variable in the survival analysis model, which can model the temporal heterogeneity for individual crash risk differences (Aalen, 1992). Using New York City as a case study, we first analyzed how the NPIs (i.e., social distancing, mass gathering limit, and bars and restaurants) affect human mobility patterns and road safety during COVID-19. We also quantified the hazards of human behaviors on this time. The hazard function is defined as follows:

$$ h(t) = \frac{F'(t)}{F(t)} $$  \hspace{1cm} (4)

where $F'(t)$ is the derivative of $F(t)$.

Then we need to select an appropriate probability distribution (e.g., Exponential and Weibull) for the duration of time until a crash happened to fit with the data. Since the purpose of a parametric survival analysis model is to find if there is a good way at predicting distribution, we will use the Akaike Information Criterion (AIC) approach. This AIC can be calculated as Eq. (6) to construct the hazard function,

$$ \text{AIC} = 2k - 2\ln(L) $$  \hspace{1cm} (6)

where $k$ is number of estimated parameters, $L$ is the maximum value of the likelihood function for this model. Minimum AIC value gives the best fit model. We did AIC test and found the Exponential and Weibull distribution assumption best fit our data.

Two distributions are assumed to our model, i.e., Exponential and Weibull. The two parameters Exponential has

$$ F(t) = \exp[-\gamma t] $$  \hspace{1cm} (7)

with hazard,

$$ h(t) = \gamma $$  \hspace{1cm} (8)

The two parameters Weibull has

$$ F(t) = \exp[-\gamma t^\gamma] $$  \hspace{1cm} (9)

with hazard,

$$ h(t) = \gamma \alpha t^{\gamma-1} $$  \hspace{1cm} (10)

To consider the effects that covariates, i.e., human mobility factors, have on time until crash occurrence. Given the selection of the Exponential and Weibull distribution for crash hazard parameter $h_0(t)$, the following proportional hazards model $h(t|X)$ with exponential and Weibull can be specified respectively as follows,

$$ h(t|X) = h_0(t)\exp(-\beta X) $$  \hspace{1cm} (11)

$$ h(t|X) = \gamma \exp(-\beta X + \beta_p X_p) $$  \hspace{1cm} (12)

$$ h(t|X) = \gamma \alpha t^{\gamma-1}\exp(-\beta X + \beta_p X_p) $$  \hspace{1cm} (13)

where $h(t|X)$ is the hazard function conditioned on covariate vector $X$, $h_0(t)$ is the baseline hazard (the hazard for an individual for whom the vector $X$ is zero). $\beta$ and $\beta_p$ are model coefficients to be estimated and $\beta_p$ represents the safety effect of NIPs implemented, $X$ is the covariate factors and $X_p$ is defined as a dummy variable with 0 for reopen strategy and 1 for control policy implemented.

3. Data description

Several factors were identified, and a dataset was formulated. The six variables dataset was observed from March 1, 2020, to December 4, 2020, in New York City. The variable characteristics are displayed in Table 1, with more detailed comments provided below.

Crash data: the dependent variable is the time between two consecutive crashes. The dependent variable’s units are hours. Our crash data were obtained from the Traffic Accident Management System (TAMS) maintained by the New York Police Department. The crash records contained motor vehicle collisions where someone was injured or killed and detailed descriptions of each accident, e.g., crash data, crash
time, location, number of persons (pedestrians, cyclists, and motorists) injured and killed. Only one crash was recorded, even if there were multiple victims or vehicles involved. The police reported 25,165 crashes between March 1, 2020, and December 4, 2020, in New York City. For this study, we divided motor vehicle collisions into three crash types: a) pedestrians, b) cyclists, and c) motorists.

Human mobility data: daily data for the percentage of individuals staying at home and non-work trips per person was collected from the COVID-19 impact analysis platform (Zhang et al., 2020). All individual mobility location data was clustered into activity location (home, work and other point-of-interest visited) to impute trip information for each trip including travel origin, destination, and departure and arrive time, trip purpose (work or non-work), travel mode (driving, walking, bicycle) at the census block group using HDBSCAN clustering and multi-layer DNN methods (Ester et al., 1996; Xiong et al., 2020; Zhang et al., 2020). The individual mobility data is privacy protection, and we used the travel behavior data aggregated at the census block group level for macro-level crash analysis. A “non-work trip” was defined as not going to or coming home from work. It may include, for example, a trip to the grocery, to the restaurant, or to park, etc. The distinguishing between work and non-work trips depends on the dwell time of staying at the location. When someone works from home, there will be no trip generation. Given the home and work census block groups (CBGs), other travel purposes could be identified by trip end locations and point of interest (POI) dataset that refers to the location’s purpose. CBG-level travel behavior data have been aggregated to city-level, and then it could be considered because macro-level risk factors can affect road safety. It represents the person and vehicle movements of anonymized mobile services, including walking, biking, mass transit, ride-share services, scooters, and personal vehicles, etc. One of the crucial human mobility matrices is the social distancing index for county-level, representing the extent to which residents and visitors practice social distancing. This daily index can be calculated as Eq. (14) (Zhang et al., 2020):

$$\text{Social distancing index} = 0.8*\left[\%\text{H}_{\text{stayin}} + 0.01*\left(100 - \%\text{H}_{\text{stayin}}\right)\right] \times (0.1*\%\text{RT} + 0.2*\%\text{W} + 0.4*\%\text{NONW} + 0.3*\%\text{TD}) + 0.2*\%\text{RO}$$  \hspace{1cm} (14)

where $\%\text{H}_{\text{stayin}}$ is the percentage of staying home in New York City, $\%\text{RT}$ is the reduction percentage of all trips compared to pre-COVID-19 benchmark, $\%\text{W}$ is the reduction percentage of work trips, $\%\text{NONW}$ is the reduction percentage of non-work trips, $\%\text{TD}$ is the reduction of daily travel distance, RO is the reduction of out-of-country trips.

Socio-economic data: weekly unemployment rate data in New York City was collected from the Department of Labor. We selected unemployment rate data as a variable in this study for exploring the impacts of the economic downturn caused by the pandemic on road fatalities and injuries.

Weather data comprised of daily mean temperature, mean precipitation, and mean accessed visibility from the National Oceanic and Atmospheric Administration (NOAA) and Global Surface of the Day (GSOD) weather data about New York City (NOAA, 2020). Visibility measures the distance at which one can discern an object or light, which depends on the surrounding air’s transparency.

NPIs status data was collected by New York City Centers for Disease Control and Prevention (CDC). Fig. 2 showed “new cases daily” and eight kinds of NPIs were implemented in New York City - between February 29, 2020, and March 1, 2021. In Table 2, we listed the date and name of these NPIs (implemented during the pandemic), including emergency declaration, limits on mass gathering, stay at home, and reopening strategies (phase 1 to phase 4). Police impound status variables were set up, i.e., control NPIs (policy 1 to policy 3 and 8) for 1, no control NPIs (policy 4 to 7) for 0.

4. Model selection

The present study indicated that significantly reduced travel for both work-based and non-work-based trips during the COVID-19 pandemic (Pawar et al., 2021). Therefore, the non-work trip, social distance index, and the percentage of people staying at home have been treated as travel behavior variables to change the crash risk during the pandemic.

Parametric survival models (exponential, Weibull, log-normal, and logistic distributions) were illustrated on this data along with their AIC values. There were six models stratified by road user types (i.e., motorists, pedestrians, and cyclists) and injury outcomes (fatal injuries and all injuries). According to Table 3, Weibull and Exponential distributions were found to be better fitted to our data with a low AIC value (Table 3). Hence, the survival models were estimated in the freeware R package.
used to indicate the significant predictors. The sample size is too small because the fatal crashes are too infrequent to pick up. To avoid the sample size effects in the fatal model (Xu, 2017), we added a z-score to perform the significance of predictors. In Table 4(a), the results show no significant predictor in the fatal model based on the z-score value, which is less than 1.96 or more than –1.96.

### Table 2
The date and name of NPIs in New York City during the pandemic.

| Date       | Declaration of emergence | Limits on mass gathering | Stay at home | Reopen phase* |
|------------|--------------------------|--------------------------|--------------|---------------|
| 12-Mar-20  | Policy 5                 | Policy 6                 | Policy 7     | Policy 8      |
| 16-Mar-20  |                          |                          |              |               |
| 20-Mar-20  |                          |                          |              |               |
| 8-Jun-20   | 22-Jun-20                | 6-Jul-20                 | 20-Jul-20    | 11-Nov-20     |
|            | reopen phase2*           | reopen phase3*           | reopen COVID-19 phase4* | restriction |

*Reopen phase 1: Nonessential businesses (manufacturers, nonessential retail stores, wholesalers) that are allowed to resume in this stage. Reopen phase 2: several indoor businesses were allowed to reopen, but with capacity limits, strict cleaning requirements and mandatory social distancing. Reopen phase 3: Gatherings of up to 25 people (up from 10) are permitted in parts of the state that have entered this phase and indoor dining at restaurants is allowed to start. Reopen phase 4: More indoor activities for complete reopen include low-risk indoor arts and entertainment activities.

### Table 3
Performance of different parametric models (AIC values).

| Distribution | Killed _pedestrian | Killed _cyclist | Killed _motorist | Injured _pedestrian | Injured _cyclist | Injured _motorist |
|--------------|--------------------|----------------|------------------|--------------------|-----------------|------------------|
| Weibull      | 822.16*            | 323.54*        | 1046.26          | 11009.00*          | 11160.54*       | –6082.46*        |
| Logistic     | 822.40             | 325.72         | 1056.74          | 11998.76           | 11971.60        | 1308.93          |
| Exponential  | 825.00             | 324.29         | 1044.34*         | 12404.05           | 12742.59        | 4176.62          |
| Lognormal    | 822.55             | 328.07         | 1056.41          | 14879.14           | 15146.55        | 9816.24          |

*We selected as distribution assumption in our models due to lower AIC value.

### 5. Findings

Three separate models were developed by different crash types: (1) pedestrians, (2) cyclists, (3) motorists. Each of the models has been further classified into two crash categories of killed and injured. Overall, six different crash models have been applied: two different modeling techniques (Exponential and Weibull); were applied to three crash types (pedestrian, cyclist, motorist); at two different crash levels (killed and injured). All explanatory variables shown in Table 1 were initially included in the models. The estimation results for the Exponential and Weibull proportional hazard models are presented in Table 4. P-value is used to indicate the significant predictors. The sample size is too small because the fatal crashes are too infrequent to pick up. To avoid the sample size effects in the fatal model (Xu, 2017), we added a z-score to perform the significance of predictors. In Table 4(a), the results show no significant predictor in the fatal model based on the z-score value, which is less than 1.96 or more than –1.96.

#### 5.1. Estimated injured crash hazards and human mobility

Many human mobility factors (covariates) were common to injured pedestrians and cyclists’ crash hazard models. The first was the percentage of staying at home; the coefficient was significantly positive (0.019 and 0.020), as expected, indicating that an increase in the rate of staying at home decreases the hazard (i.e., reduces the likelihood of crash occurrence). However, more people have stayed at home, resulting in the motorist crash risk increased because: (a) pedestrians and cyclists are exposed to a lower crash injuries risk due to travel decreases; (b) increased traffic speed may increase the injuries and fatalities for motor vehicles drivers (Finch, 2020; Kamga et al., 2020; Qureshi et al., 2020); (c) increased stress and consumption of alcohol and drugs triggered by the stay-at-home order implemented during the pandemic, might well have adverse effects on motorist driving behavior (Qureshi et al., 2020).

This negative relationship was reflected in our results for both injured pedestrian and cyclist model analysis. Non-work trip per person is linked to the duration of time until crash occurrence by the value of “–0.395” and “–0.568” respectively, i.e., residents may have more non-work trips during the pandemic, the pedestrian and cyclist crash hazard increased. These results were consistent with the previous studies that analyzed the walking trips and crash rate/injured rate suggesting that walking/cyclist trips do affect road safety (Dong et al., 2020; Elvik, 2016; Guo et al., 2017; Miranda-Moreno et al., 2011; Osama & Sayed, 2017; Sze et al., 2019; Xie et al., 2018). Non-work trips production, including shopping, recreation, and going to a restaurant, positively contributed to crash occurrences. This was expected because: (a) people were prone to walking and biking instead of taking a bus or mass transportation, resulting in an uptick in walking/cycling frequency and walking time, thereby increasing the pedestrians and cyclists crash risk, which was consistent with the previous studies (Sze et al., 2019); (b) the study shows that most of the non-work trips are for essential grocery shopping no other recreational trips during the pandemic (Pawar et al., 2021). Long distance grocery trips are mostly made by private vehicles during the pandemic and so more vehicle are involved in crashes; and (c) accessed reports (Apple, 2020; Google, 2020) showed

![Fig. 2. New COVID-19 cases daily and NPIs implemented in New York City from February 29, 2020 to March 1, 2021.](image-url)
that reduced traffic volumes (due to) lockdown, led to an increase in speeds by 6–11%, and more frequent harsh driving behavior during the pandemic (Katrankazas et al., 2020).

### 5.2. Injury crash hazards and unemployment rates and weather factors

The unemployment rate was a statistically significant predictor affecting injury crashes, but it was insignificant regarding fatality crash rates. Although the previous study found higher risks of pedestrian crashes were related to high unemployment rate levels (Zegeer & Bushell, 2012), some pedestrian behavioral changes were attributed to psychological precautions taken during the pandemic, such as keeping social distance and taking less hurried non-work trips. These factors may contribute to improved pedestrian safety. But we found that the unemployment rate has a positive effect on motorist injured crash hazards. It may be caused by the “risky” driver groups prone to speeding more and becoming intoxicated with alcohol due to economic downturns.

Our study’s primary forms of mean precipitation variables included rain, sleet, snow, ice and hail. It was used as the most influential weather control variable and was found by a statistically significant positive predictor affecting injured motorists. These parameters’ signs were generally consistent with empirical judgments and the results of previous studies (Theofilatos & Yannis, 2014).

The findings indicated that the likelihood of an injured pedestrian and motorist crash increases during periods of high visibility. This nonlinear relationship between visibility and crash hazard risk has been widely reported (Das et al., 2017). It may result from drivers’ tendencies to change their behavior to adapt to new conditions presented by low visibility. High visibility gives a non-safety concern for driving and pedestrian traffic. Good weather with high temperatures increased cyclist trips, resulting in more injured cyclists. But the relationship between temperature and motorist injury crashes was significantly negative. One plausible explanation was that trip plans for recreational purposes were usually made for good weather during off-peak hours and less hurriedness (Naderan & Shahi, 2010).

### 5.3. Policy status

This kind of negative relationship was clearly reflected in our injured motorist crash hazard model’s results. Control NPIs (i.e., lockdown status implemented) were linked to the injured motorist crash risk. A previous study indicated the relation between mandated societal lockdown NPIs and severe or fatal injuries was unclear (Qureshi et al., 2020), but speculated that increased traffic speed caused by lower congestion results in crash injuries. Knowledge of these NPIs statuses implemented was essential to developing long-term safety plans and establishing specific countermeasures (Naderan & Shahi, 2010; Qureshi et al., 2020). The extension of social distancing measures implemented in New York City resulted in a negative relationship with injured motorists crash occurrence, indicating that the motorists’ awareness was raised by enforcing social distancing orders.

### 6. Conclusion

A reduction in human mobility worldwide has previously been linked to pandemic and economic downturn (United Nations Department of Economic and Social Affairs Economic Analysis, 2020). This paper explored the relationship between road traffic crash injuries and

### Table 4a

| Duration until crash occurrence for fatel model (Exponential and Weibull). | pedestrian killed | cyclist killed | motorist killed |
|---|---|---|---|
| Dependent variable | coefficient | p-value | z-score | coefficient | p-value | z-score | coefficient | p-value | z-score |
| human mobility | | | | | | | | | |
| social distancing index | −0.0067 | 0.805 | −0.28 | 0.0411 | 0.58 | 0.59 | 0.00302 | 0.915 | 0.11 |
| Non-work trip/person | −1.08583 | 0.089 | −1.75 | 1.1499 | 0.6 | 0.57 | −0.43592 | 0.433 | −0.78 |
| %/staying at home | −0.01388 | 0.815 | −0.23 | −0.0341 | 0.85 | −0.18 | −0.00961 | 0.845 | −0.2 |
| Socio-economic unemployment rate | 0.07123 | 0.234 | 0.21 | 0.2699 | 0.17 | 1.42 | −0.07047 | 0.14 | −1.48 |
| Weather | | | | | | | | | |
| temperature | 0.00205 | 0.908 | 0.13 | −0.0741 | 0.27 | −1.12 | 0.00948 | 0.551 | 0.6 |
| precipitation | −0.12096 | 0.761 | −0.34 | −2.2604 | 0.61 | −0.53 | 0.35891 | 0.35 | 0.93 |
| visibility | 0.04038 | 0.885 | 0.17 | −0.2137 | 0.6 | −0.53 | −0.12895 | 0.427 | −0.79 |
| Policy status | 0.17312 | 0.644 | 0.53 | −0.1224 | 0.9 | −0.13 | 0.46556 | 0.162 | 1.4 |

*Distinct variables with bold font are the ones who were found statistically significant (*p-value* < 0.05).
fatalities, and human mobility relationship. To the best of our knowledge, there have not been any studies on this topic in city cases. Therefore, we proposed the model-based approach to answer the overall question for road safety professionals: the effects of human mobility changes from the starting of the COVID-19 could have on road safety. More importantly, what can we learn about this natural experiment to make road safety policy support for considering potential personal and environmental factors associated with the pandemic? The main findings of this study presented in this paper can be summarized as follows:

First, the assessment of abrupt human mobility changes is critical for predicting the effect of COVID-19 on crash risk. Although the household travel-diary survey data is valuable and widely used for most safety studies, utilizing smartphone data is a more salient choice due to the high penetration rate, overcoming many limitations of time span and sample size, thus providing that the usage of mobile phone data is a good estimator of the relationship between human mobility changes (i.e., social distancing index, non-work trips per person, and the percentage of staying at home) in three kinds of crash types involving fatalities and injured, affecting pedestrians, cyclists, and motorists.

Second, the results indicated that non-work trips during the pandemic had significant adverse effects on the increased crash injuries risk (of pedestrians, cyclists, and motorists). More research on the frequency and accessibility of non-work trips could help forecast non-work human mobility for urban development and land-use planning. Additionally, activity-based human mobility models could also focus on estimating non-work trip time and distances estimation so that specific transportation policies can be evaluated, for example, exploring the potential safety benefits associated with shifting away from motor vehicle usage to alternative modes of transportation, such as walking and cycling for non-work trips in metropolitan areas.

Third, the effects of the COVID-19 on the three crash types significantly changed people’s perception of travel mode choice, suggesting that decision-makers could rethink the role of active transport and seize that momentum to advance possible their urban sustainability agendas. Therefore, the relationship between the percentage of those staying at home and pedestrian and cyclist crash injuries could help evaluate the safety effects of working remotely. Post pandemic, the government could make active modes (i.e., walking and biking) inherently more appealing to the user and encourage the development of street design for more walking and biking friendly.

Our study was not without limitations. Generally, less traffic would be expected to reduce collisions, injuries, and fatalities. Although the relationship between human behavior and crash injured hazard occurrence was investigated, other factors such as increased stress and consumption of alcohol and drug usage during the pandemic could not be explored. Additionally, increased driving speeds brought from the reduction of travel kilometers traveled (VKT) could not be analyzed due to data unavailability. Future investigations may focus on understanding the relationship between driving behavior and crash fatalities. Despite human mobility factors in this study that unrelated to crash fatalities hazard, the complex interactions between macroeconomic conditions, human/driving behavior, and risk factors need to be examined. In addition, when getting the mobility data during pre-pandemic, further study could compare and judge the differences between the influencing factors of the crashes analyzed under COVID-19 and those without COVID-19.

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CRediT authorship contribution statement

Ni Dong: Conceptualization, Methodology, Writing – review & editing. Jie Zhang: Methodology, Data curation, Writing – review & editing. Xiaobo Liu: Writing – review & editing. Pengpeng Xu: Writing – review & editing. Yina Wu: Writing – review & editing. Hao Wu: Data curation. This paper is dedicated to the memory of our dear friend and colleague: Dr. Jie Zhang. We would like to thank Dr. Xi Zhu for providing the insightful, thoughtful and comments that helped us to substantially improve the quality and readability of our manuscript.

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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