Transportation Research Part D 110 (2022) 103428

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Neighborhood, built environment and resilience in transportation during the COVID-19 pandemic

Weiye Xiao [a], Yehua Dennis Wei [b,*], Yangyi Wu [c]

[a] Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing, Jiangsu 214000, China
[b] Department of Geography, University of Utah, Salt Lake City, UT 84112-9155, USA
[c] School of Urban Design, Wuhan University, Wuhan, Hubei 430072, China

ARTICLE INFO

Keywords:
Transit ridership
COVID-19
Bayesian structure time series
Regression tree
Build environment

ABSTRACT

COVID-19 has swept the world, and the unprecedented decline in transit ridership has been noticed. However, little attention has been paid to the resilience of the transportation system, particularly in medium-sized cities. Drawing upon a light rail ridership dataset in Salt Lake County from 2017 to 2021, we develop a novel method to measure the vulnerability and resilience of transit ridership using a Bayesian structure time series model. The results show that government policies have a more significant impact than the number of COVID-19 cases on transit ridership. Regarding the built environment, a highly compact urban design might reduce the building coverage ratio and makes transit stations more vulnerable and less resilient. Furthermore, the high rate of minorities is the primary reason for the drops in transit ridership. The findings are valuable for understanding the vulnerability and resilience of transit ridership to pandemics for better coping strategies in the future.

1. Introduction

The COVID-19 pandemic has challenged the operation of the transportation system worldwide (Hu & Che, 2021; Florida et al., 2021; Tao & Cao, 2021). The travel restrictions limited people's mobility, and the impact on the airline industry is the most significant, with a reduction in the capacity of carriers by about 70 % (Maneenop, Kotcharin, 2020; Sobieralski, 2020). For intra-urban commuting, public transit was less preferred, and car use was more favored to keep social distance and reduce infection risk (De Vos, 2021; He et al., 2022; Kamga & Eickemeyer, 2021; Wang & Noland, 2021). New York, for example, reported a significant decline in public transit ridership in April 2020 when the restrictive policies were implemented in response to COVID-19 (Abreu & Conway, 2021; Bian et al., 2021; Carrión et al., 2021; Wang & Noland, 2021). Although the ridership of the light rail system is recovering, it was only about 50 % in August 2021, and scholars are questioning when public transit can recover and even whether it can recover (Abreu & Conway, 2021). Such a drop in light rail ridership and the lack of alternative transportation are high-risk factors in the decline of labor force participation and the rise of unemployment (Albanesi & Kim, 2021; Kawohl & Nordt, 2020; Ingvardson & Nielsen, 2018). Scholars have also argued about the potential negative impacts of transit ridership decline on urban inequality in economic activities, human mobility, vitality, sustainability, etc. (Hamidi & Hamidi, 2021; Ingvardson & Nielsen, 2018; Richardson & Jensen, 2008).

Regarding the decline in transit ridership and its negative impacts, resilience in transportation has become an emerging issue that identifies transportation systems' ability to maintain functionality and recover from the risk scenarios (Pan et al., 2016). However, the

* Corresponding author.
E-mail addresses: ywxiao@niglas.ac.cn (W. Xiao), wei@geog.utah.edu (Y.D. Wei), yangyi.wu@whu.edu.cn (Y. Wu).

https://doi.org/10.1016/j.trd.2022.103428

Available online 12 August 2022

knowledge about transportation resilience against the prevalence of pandemics is insufficient because such a pandemic influencing transit ridership is not common. The decline in transit ridership results from both the physical built environment and vulnerable population groups' preference to take public transit during pandemics (Hu & Chen, 2021; Kashem et al., 2021). The resilience in transportation should be the nexus of the built environment and people's sociodemographic status because people's preference to take public transit is shaped by the built environment (Gan et al., 2020; Vergel-Tovar & Rodriguez, 2018). Thus, the changing relationship between transit ridership, the built environment, and the neighborhood environment becomes the key to uncovering the mechanism of residence in transportation.

Regarding the physical built environment, planners are not well prepared for running a transportation system during the COVID-19 pandemic because of the complex trade-off between safety and ridership (Luo et al., 2022). For example, the high-density urban design contributes to more ridership but might be a negative determinant of ridership during pandemics because of the social distance policies (Khavarian-Garmsir et al., 2021). The mixed land use for increasing accessibility to various trip destinations (shops, schools, etc.) would not work because some destinations have been shut down during COVID-19 (He et al., 2022). Thus, it is imperative to have an insight into how the built environment influences transit ridership regarding the resilience in transportation.

Another issue about the resilience in transportation is concerning the neighborhood environment, which is usually represented by sociodemographic factors (Hu & Chen, 202; Sy et al., 2021). The uneven drop in public transit ridership is found in less educated, low-income, and minority neighborhoods (De Vos et al., 2020; Sy et al., 2021). These socioeconomically disadvantaged people are the most vulnerable during COVID-19 (Lopez et al., 2021), and the social inequality will intensify if the decline in ridership cannot recover quickly (Carrión et al., 2021). A station-level investigation is expected to reveal what efforts are needed to improve the resilience of transit stations against COVID-19 for different population groups.

This paper focuses on the vulnerability and resilience of public transit ridership, and the decline of transit ridership is used to measure vulnerability, and the recovery of transit ridership is to capture resilience (Pan et al., 2021). This study is implemented based on a station's check-ins data in Salt Lake County, Utah, which has quickly rebounded from the pandemic despite being among the worst in COVID-19 cases. Salt Lake City is a medium-sized metropolitan in the U.S. with a light-rail transit system that is not the dominating commuting mode. This condition, rather than the system in large metropolitans such as New York, is more common in the U.S. and its experience is more likely to be generalized. This study tries to answer the following questions: How does COVID-19 influence the light rail ridership? Which light rail stations are more vulnerable to COVID-19 and recover faster? Drawing upon monthly station check-in data from /01/01/2017 to /08/01/2021, we developed a joint framework incorporating time-series impact inference and statistical analysis, including the neighborhood environment, which could be specified into social disparities in this research and the built environment. We hope the research outcomes provide important implications for developing sustainable cities and communities in the post-COVID-19 era.

2. COVID-19 and the resilience of public transit system

Resilience and vulnerability are usually supported by the adaptive system (Meerow et al., 2016). The vulnerability of transportation systems generally refers to the abnormal sensitivity of transportation systems to internal or external risk scenarios (Pan et al., 2016). Risk scenarios have long-term effects such as natural disasters (Cariolet, Vuillet, & Diab, 2019; Liu et al., 2021) and short-term effects such as daily traffic congestion (Ganin et al., 2017; Zhang et al., 2019). Resilience in transportation is generally defined from two perspectives: 1) The ability to maintain functionality to risk scenarios; 2) Time or resources required for recovery to normal performance (Zhou, Wang, & Yang, 2019). Pan et al. (2021) reviewed the literature and provided more specific definitions. Transportation vulnerability is defined as reducing system capacities, such as reduced accessibility and travel costs, and could be identified as the decline in ridership in this research. Transportation resilience describes the abilities of the transportation system to resist and adapt to external disturbances and then quickly return to a normal service level. In this study, it could be specified as the speed of the ridership growth after the strike of COVID-19.

Although the definitions of the vulnerability and resilience of transit ridership have been clarified, the related literature mainly focuses on the risk scenarios, including noise, environmental pollution, natural hazards, and traffic accidents, rather than pandemics (Gonçalves & Ribeiro, 2020; Liu et al., 2021; Meerow et al., 2016; Zhang et al., 2019; Zhou et al., 2019). The knowledge about the resilience in transportation against pandemics is limited because previous pandemics, such as the SARs virus and bird flu, were not as striking as COVID-19. Existing studies on COVID-19 and public transit stations have paid much attention to the decline in ridership and the impacts of government policies (Chu et al., 2021; De Vos, 2021; He et al., 2022; Kamga & Eickemeyer, 2021; Mishra et al., 2020; Wang & Noland, 2021). However, it is still unknown how to improve transportation resilience by enhancing the built environment and reducing the impacts of social disparities. How to improve the resilience and vulnerability of the public transportation system against COVID-19 need further exploration that would help revive urban vitality (Xin et al., 2021).

The impacts of COVID-19 on transportation are usually examined from two perspectives, the short-term lockdown and the long-term adaptation to the pandemics (Kim, 2021). The short-term decline in public transit ridership is the result of both outbreak of the disease and the lockdown by restrictive policies (Figliozzi & Unnikrishnan, 2021; Hu & Chen, 2021; Kamga & Eickemeyer, 2021). The well-documented public policies or recommendations include "stay at home" order and "social distance", which are the most effective ways to influence transit ridership (Engle, Stromme, & Zhou, 2020). Although the outbreak of COVID-19 was earlier, a sudden decline in public transportation ridership usually happened when the policy was published (Hu & Peng, 2021). The popularity of "working from home" contributes to the decline of transportation ridership because public transportation is critical to daily commuting in large metropolitans (Wang & Noland, 2021). However, it is still doubtful if the policy influences transit ridership when people do not rely on light rail for commuting. On the other hand, people are highly aware that "social distance" can significantly reduce the risk of getting COVID-19, and public transit would not be preferred (De Vos, 2021; Ha, et al., 2022; Kamga & Eickemeyer, 2021). In cities such as Hongkong, Seoul, and Singapore, which are less influenced by these policy restrictions, the ridership is less influenced by COVID-19 and recovers fast (Xin et al., 2021). Thus, political power influenced people's behavior and attitude regarding taking public transit in the era of COVID-19. Also, it raises another question for the urban planners to help passengers keep a "social distance" when they take public transportation.

The long-term effects of COVID-19 on transit ridership are primarily influenced by personal preference and adaptation to the post-pandemic urban environment. Several factors potentially influence people's preference to take public transit, including people's awareness, social disparities, and the physical built environment. Unlike fatal diseases such as the Ebola virus from Africa, the death rate from contracting COVID-19 is very low (0.66 % according to Mahase, 2020), which might make people unaware of the danger of COVID-19. A recent worldwide survey reported that about 67 % of people worried that the spread of COVID-19 is fake news (Edelman Trust Barometer, 2020), which is spread by information from various media sources (Bunker, 2020). Even in China, which has strict regulations for COVID-19 prevention, some people know little about the danger of COVID-19 (Sun et al., 2020). Thus, the impacts of COVID-19 on transit ridership have heterogeneity among population groups based on their awareness of the pandemic. Public policies might improve people's awareness of COVID-19. However, they might contribute to the decline of transit ridership because there are many interventions in the social media era (Greer et al., 2020; Mannan & Mannan, 2020). Similarly, people would adapt to living with COVID-19, while evidence suggests that the second wave of COVID-19 did not influence people's behavior as the first outbreak did (Mckenzie et al., 2021). Thus, people's subjective initiative during COVID-19 would influence their behavior, including the preference to take public transit, which also would vary across different population groups.

Social disparity is also a critical concern in the research on COVID-19. The low-income population is more vulnerable to the decline of public transit ridership because it is their primary travel model. Although a recent study reported that public transit was less used and people would like to drive more during the pandemic (Kamga & Eickemeyer, 2021), the low-income and less-educated population are struggling with changing travel modes because they cannot afford the cost of driving (Brough, Freedman, & Phillips, 2021; De Vos, 2020; Park et al., 2021; Sy et al., 2020). For example, in regions such as Santiago, the decline in high-income people's ridership is much higher than that for low-income people who highly rely on public transportation for commuting (Tirachini & Cats, 2020). On the other hand, the minorities are more vulnerable to COVID-19 regarding vaccination, travel mode choice, and unemployment rate (Couch, Fairlie & Xu, 2020; Paul, Steptoe & Fancourt, 2021; Tirachini & Cats, 2020). They are the main population groups who take public transit during pandemics, which increases minorities' vulnerability to pandemics (Hu & Peng, 2021). Furthermore, working from home is a critical reason that transit ridership declines; however, people who take labor-intensive jobs such as transportation and utility cannot work from home and are still taking public transit (Hu & Peng, 2021; Wilbur et al., 2020). Thus, the social disparities regarding income, race/ethnicity, and job types contribute to the heterogeneity of the declines in public transit ridership,

The debates on the impacts of the built environment on transit ridership usually focus on urban density and design, which significantly influence "keeping social distance". High-density urban design is generally suggested to help combat urban sprawl and promote public transit use (Sung & Oh, 2011). However, during the era of COVID-19, the high-density urban design might discourage people from taking public transit because of the "social distance" (Kamga & Eickemeyer, 2021). Thus, the stations with more open space might be preferred over those with high dwelling density or high-density land use design. Other factors such as diverse urban land use to make more trip destinations might be ineffective because small businesses are vulnerable to COVID-19, and many shops and restaurants were closed or relocated (Bartik et al., 2020). These conflicts make the U.S. light rail ridership recover much slower than those in Asian and European cities (Xin et al., 2021). Thus, the distance to destinations would not be considered in this study, given the uncertainty in estimating accessibility to destinations.

Although there is ample literature on the impacts of the COVID-19 pandemic on public transit ridership, the resilience of public transit is still unclear and worthy of further investigation. First, the early research focuses on the impacts of government policies and the COVID-19 outbreak on public transportation ridership. As the pandemic is relieving, how to help the transportation system recover should be an emerging issue, which is also critical to preparing for future challenges of the global epidemic (Gleaser, 2022). Second, there are some attempts to identify the heterogeneity of vulnerability of transportation regarding social disparities and the built environment (Hu & Peng, 2021). This paper is expected to identify which kinds of stations would better adapt to the post-pandemic urban environment regarding neighborhood and the built environment. Third, there is a significant difference between the short-term and long-term impacts of the pandemics on transportation resilience. However, few studies have tried to distinguish the short-term and long-term impacts, which should draw more attention. Regarding these gaps, this paper employs a time-series analysis to provide an insight into the vulnerability and resilience in the transit ridership against the COVID-19 pandemic.

3. Data and methodology

3.1. Research setting

This study is implemented in Salt Lake County, which is one of the most populous regions in the U.S. Mountain States. The population of Salt Lake County is about one million, which makes it a medium-size metropolitan in the U.S. It is also a vital airline hub that makes Salt Lake County (SLCo) more exposed to COVID-19. So far, most of the studies on transit ridership during the COVID-19 period were on large metropolitans (Beck et al., 2021; Hamidi & Hamidi, 2021; Hu & Chen, 2021; Wang & Noland, 2021). Compared with large metropolitans people in small- and medium-sized cities are more vulnerable to COVID-19 for the reasons such as lacking medical resources (Grover et al., 2020; Khavarian-Garmsir et al., 2021). Thus, the research on the TRAX ridership in Salt Lake County could provide implications for other medium-sized metropolitans in terms of transportation resilience against COVID-19. This research

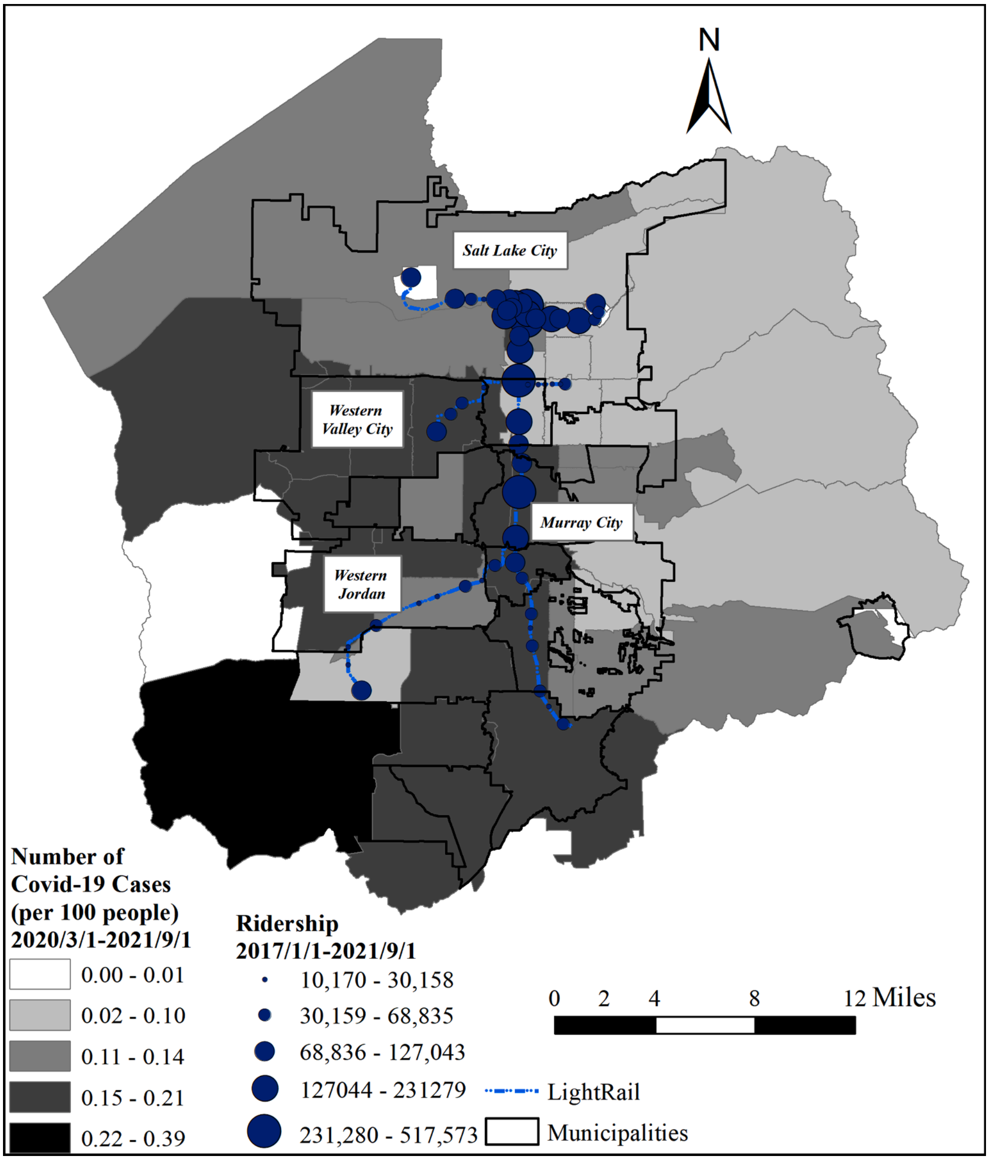

Fig. 1. TRAX ridership and COVID-19 exposure in Salt Lake County, Utah.

primarily focuses on a light rail system in SLCo named TRAX with 56 stations and six lines, making light rail one of the most useful travel modes to connect the airport, Salt Lake City, and others. The ridership of the TRAX stations is presented in Fig. 1.

The Utah Transit Authority (UTA) provides the monthly stations' check-in data from /1/1/2017 to 8/1/2021. The data is light rail station boarding numbers (inbound), and there is no outbound number since UTA does not require checking out when leaving trains. We use the monthly ridership data for analysis because it can avoid periodic ridership changes compared to daily ridership data. The daily COVID-19 cases are provided by the Utah Department of Health which have been aggregated into the zip-code level. The spatial distribution of total COVID-19 cases from /3/1/2020 to /8/1/2021 at the zip-code level is presented in Fig. 1. We also obtained the socioeconomic disparity data from Environmental Protection Agency (EPA) at the block group level, including percentages of minorities, low-income, low educated, and linguistic isolated. The parcel-level land use data were from the Salt Lake County tax assessor's computer-assisted mass appraised (CAMA) data which support the calculation of built environment factors around transit stations.

3.2. Time-series analysis

The Bayesian structural time series (BSTS) model is an emerging state-space technique that combines feature selection and time-series forecasting (Scott & Varian, 2014). As a machine learning tool, the advantage of BSTS compared to the traditional techniques such as difference-in-difference is that it can consider the temporal evolution such as season. Thus, BSTS is one of the best time-series

Table 1
Abbreviations and descriptions of variables and data sources.

Type	Abbreviation	Description	Data source
Built Environment	DD	Dwelling density: The density of households in the buffer area (per square kilometer).	Tax Assessor CAMA (Parcel level)
	Intersection	The number of road intersections that are intersected with over three streets in the buffer area	Utah Automatic Geographical Reference Center (AGRC)
	LUM	Land use mix: An entropy to describe the mixed land use. LUM= (-1) * [(b1/a)*ln (b1/a) + (b2/a)*ln(b2/a) + (b3/a)*ln(b3/a)] / ln(3) b1, b2, b3 represent the residential, industry and commercial land.	Tax Assessor CAMA (Parcel level)
	BCR	Building coverage ratio: base floor area divided by total area for present the open space in the building area	Same as the above
Socioeconomic Disparity	P_Minority	Percentage of minorities	Environmental Protection Agency (EPA) block group level
	P_Linguistic	Percentage of individuals in linguistic isolation	Same as the above
	L_education	Percentage of people educated less than high school	Same as the above
	L_income	Percentage of low-income population	Same as the above
Others	Cases	Accumulative COVID-19 cases from 2017/1/1 to 2021/8/1	Utah Department of Health, Zipcode level
	Ridership	Accumulative transit ridership from 2017/1/1 to 2021/8/1	Utah AGRC, station level

analysis tools for predicting public transportation ridership long-term. Hu & Chen's study (2021) has proven that the BSTS model predicts light rail ridership during the COVID-19 pandemic. The basic expression of the BSTS model would be written as two equations:

$$Ride_t = Z_t^T\alpha_t + \varepsilon_t, \varepsilon_t \in N\left(0, \sigma_t^2\right) \quad (1)$$

$$\alpha_{t+1} = T_t\alpha_t + R_t\eta_t, \eta_t \in N(0, \omega_t^2) \quad (2)$$

$Ride_t$ is the observed monthly ridership at each station, α_t is the state vector of latent variables, Z_t is a vector that links the latent variable, T_t is the transition matrix describing the evolution of the state vector of latent variables, R_t is the control matrix allowing the incorporation of the state components, η_t and ε_t are error terms following the Gaussian distribution with ω_t and σ_t as the noise variables. More details about Kalman filters and spike-and-slab regression for variable selection are available in Scott and Varian's articles (2013 & 2014).

Based on the BSTS model results, we can infer the relative impact of COVID-19 on TRAX ridership with the three following steps. First, define the pre-intervention and post-intervention periods based on the time-series COVID-19 data. In this case, the impacts of COVID-19 break out on TRAX ridership happen on/3/1/2020, which is defined as the breaking time point. Second, predict the ridership after 3/1/2020 using the results of the BSTS model, which is the expected ridership without the impacts of COVID-19. The third step is calculating the relative pointwise effects by comparing the observed ridership and predicted ridership as Eq. 3–4.

$$\beta_t^{(\tau)} = (y_t - y_t^{(\tau)})/y_t^{(\tau)} \quad (3)$$

$$RI_{n+1:m}^{(\tau)} = \frac{1}{m-n} / \sum_{t=n+1}^{m} \beta_t^{(\tau)} \ (m > n)$$

β is the relative impact attributed to the intervention at time t while y_t and $y_t^{(\tau)}$ are the observed and predicted ridership at time t. *R.I.* is the final estimation of relative impact for stations which is the average value of relative impact between time point m and time point n. Since we use monthly ridership for analysis, the time step for estimating relative impact is one month.

To identify the short-term and long-term impacts of COVID-19, we break the post-intervention period into two terms since there was a new outbreak of COVID-19 around 12/1/2020. The first term was from 3/1/2020 to 12/1/2020, which describes the relative effects of the first strike of COVID-19 as the short-term effect. The long-term relative effect is estimated from 12/1/2020 to 8/1/2021 for the impact of the second wave of COVID-19. The resilience index of the TRAX stations to the COVID-19 pandemic is calculated as the long-term relative impact minus by short-term impact. We calculated each station's short-term and long-term relative impacts and resilience index. The relative impact is negative, and a lower value means more relative impacts, while a higher resilience index means faster recovery from the COVID-19 pandemic. The time-series analysis is implemented using R with the package "bsts" and "CausalImpact".

3.3. Regression tree analysis

The regression tree model is a machine learning modeling tool as well. Different from the traditional regression models, the ultimate goal of a regression tree is to generate a binary tree based on some rules. Thus, it is suitable to explore the non-linear relationship between the variables while the traditional regression models focus on the linear relationship. Furthermore, the regression tree model can reveal the relative importance of the independent variables to the dependent variable. An overall measure of variable importance is the sum of the goodness of split measures to determine the primary variable (Omczyk & Ewertowski, 2013).

Table 2
Descriptive analysis.

Types	Abbreviation	Mean	SD	Min	Max
Independent variables					
Short-term Vulnerability		−0.65	0.16	−0.93	−0.30
Long-term Vulnerability		−0.598	0.16	−0.87	0.02
Resilience		0.05	0.08	−0.20	0.59
Dependent variables					
Built environment	DD	120	72	13	710
	Intersection	74	31	2	159
	LUM	0.57	0.26	0	0.95
	BCR	0.44	0.35	0.117	0.87
Socioeconomic disparities	P_Minority	53.9 %	18.7 %	2.0 %	81.1 %
	P_Linguistic	51.7 %	31.2 %	3.7 %	95.5 %
	L_education	74.1 %	17.8 %	45.2 %	94.8 %
	L_income	68.9 %	28.2 %	1.36 %	95.5 %
Others	Cases	3563	2489	0	8700
	Ridership	97,512	100,565	10,170	517,537

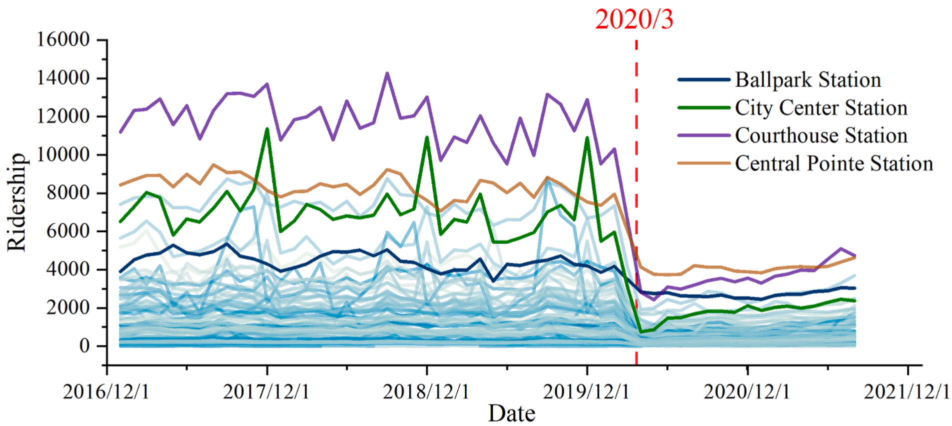

Fig. 2. The ridership of the public transit stations, 1/1/2017–8/1/2021.

Given these advantages, the regression tree is used to explore the determinants of the short-term and long-term effects of COVID-19 on TRAX ridership and resilience. There are three regression tree models separately for the short-term relative impact, the long-term relative impact, and the resilience index. The dependent variables include the built environment and socioeconomic disparity as discussed in the literature, the COVID-19 cases, and the observed ridership. The minimum node is set by four to avoid the condition that the regression tree model generates too few nodes. The regression tree models are implemented using the R package "rpart" and python library "sklearn".

The built environment variables are selected based on the "3D" variables framework (density, diversity, and design), including dwelling density, street connectivity, land use mix, and building coverage ratio. These four variables are calculated based on the land use parcels within the 800-meter network buffer of each station, while 800 m is the most popular threshold in walking research (Cardozo et al., 2012; Xiao & Wei, 2021). Dwelling density generally refers to population density, and street connectivity is the number of intersections that are the ones that intersect with three streets. Land use mix is the entropy describing the mixed land use (the calculation of land use mix is available in Table 1), and building coverage ratio is the ratio between building area and parcel area, representing the open space. Socioeconomic disparity variables such as low-income population, low-educated population, minority rate, and linguistically isolated people are also calculated based on the average value of the block groups within an 800-meter network buffer. The COVID-19 cases are the total number in the zip code where the stations are located, and the ridership is the monthly check-in data. The details and the data sources are available in Table 1. The statistics of the variables are presented in Table 2, and we find many TRAX stations located in minority neighborhoods.

4. Results

4.1. Vulnerability and resilience of TRAX ridership

Fig. 2 presents the ridership of each station in Salt Lake County from 1/1/2017 to 8/1/2021. The periodical change would be detected before the outbreak of COVID-19, while the ridership of stations would increase rapidly at the end of the year. There has been a trend of decline since the first COVID-19 case was detected in January 2020. A shape decline happened after the "stay at home"

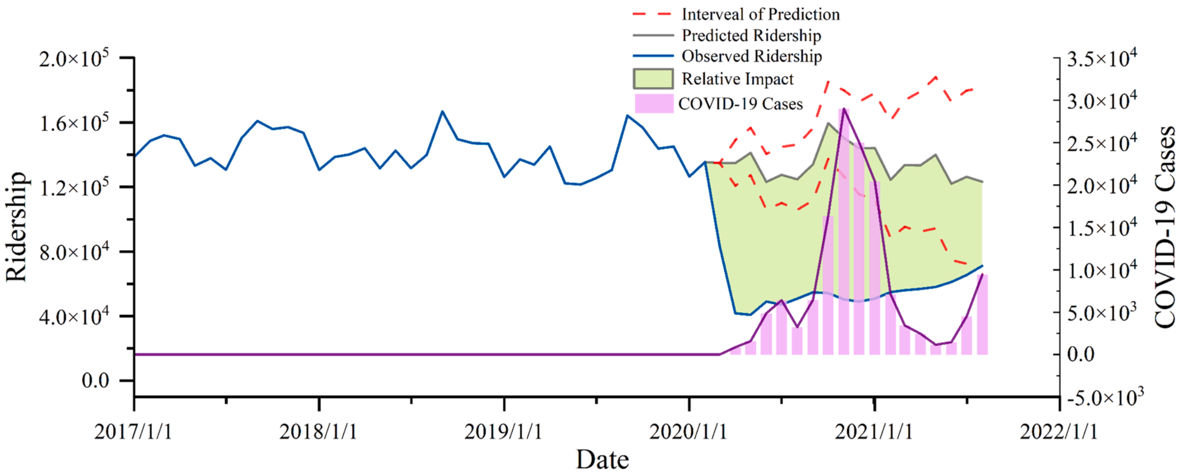

Fig. 3. The relative impact of COVID-19 on ridership based on BSTS model and COVID-19 cases, 1/1/2017–8/1/2021.

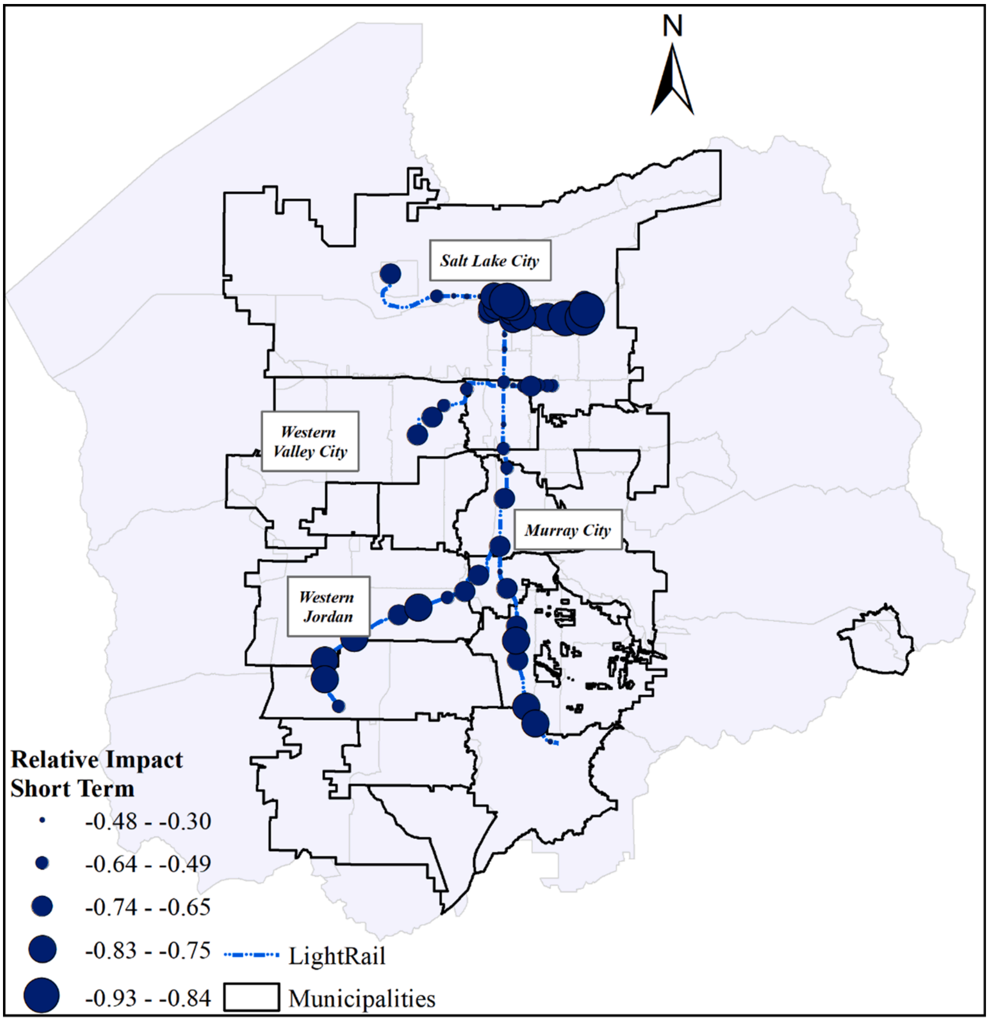

Fig. 4. Short-term relative impact based on BSTS model of all the stations in Salt Lake County.

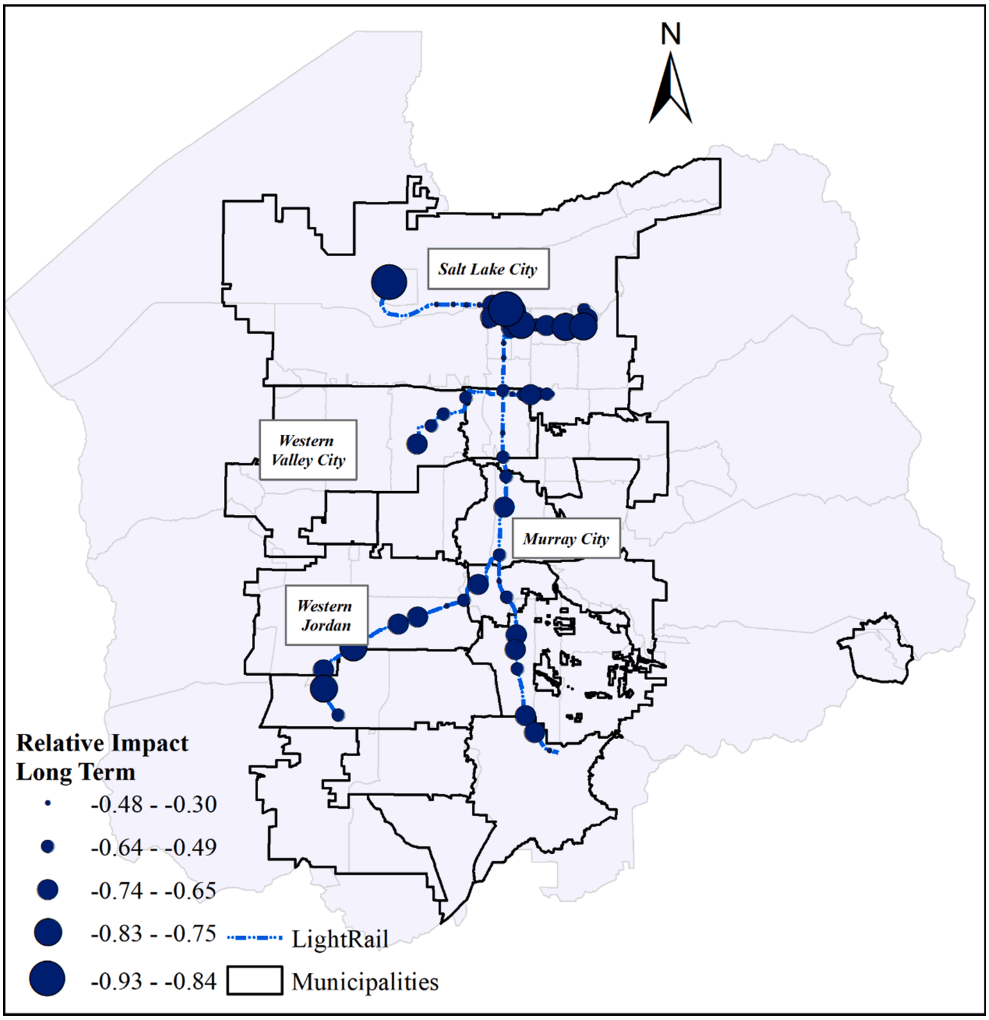

Fig. 5. Long-term relative impact based on BSTS model of all the stations in Salt Lake County.

recommendation was published in March 2020. Particularly the stations located in the downtown area of Salt Lake City, such as "Courthouse Station" and "City Center Station" with the highest ridership at the end of the year 2019, experienced a dramatic drop in ridership. The "Central Pointe Stations" and the "Ballpark Station" are primarily used to connect Salt Lake City and others for daily commuting, which also had high volumes of ridership in 2019. However, they are less influenced by the "stay at home" recommendations or the outbreak of COVID-19. Thus, the daily commuting between Salt Lake City and others did not decline much, particularly for the low-income people without vehicles for commuting. The commercial activities in the downtown area of Salt Lake County have been significantly reduced, and the high-density urban center is less likely to be selected as a trip destination.

The BSTS model is employed to predict the TRAX ridership without the outbreak of COVID-19 (Fig. 3). The region between observed ridership and predicted ridership is taken as the relative impact of COVID-19. We find that the relative effect was highest with the publication of the "stay at home" recommendation, which kept decreasing as the ridership recovered. The ridership is expected to return to normal conditions at the end of 2022 if there are no additional prevalence or policy interventions. It is also interesting that TRAX ridership in Salt Lake County only has a few associations with the COVID-19 cases after the early outbreak. There was a slight fluctuation while observed COVID-19 peaked, but the TRAX ridership continued to increase before the COVID-19 cases went down. Thus, the primary determinants of TRAX ridership are government recommendations such as "stay at home" or the fear of the virus at the early stage. It is also possible that people have adapted to living with COVID-19 in the long run (Mckenzie, 2021), and the rising number of COVID-19 cases might have little impact on transit ridership.

Other than the temporal variance, this paper also tries to identify the spatial heterogeneity among the TRAX stations. Figs. 4 and 5 present the short-term and long-term relative effects on different stations that are expected to distinguish the impacts of two waves of the COVID-19 pandemic. Regarding the short-term relative impact, the high values are mainly concentrated in the central urban area of Salt Lake City, which has a high-density urban design. Also, the stations at the end of the TRAX lines are more likely to be influenced than those that work as connections because people would avoid unnecessary travel (Zhang, 2020). The long-term impacts show a

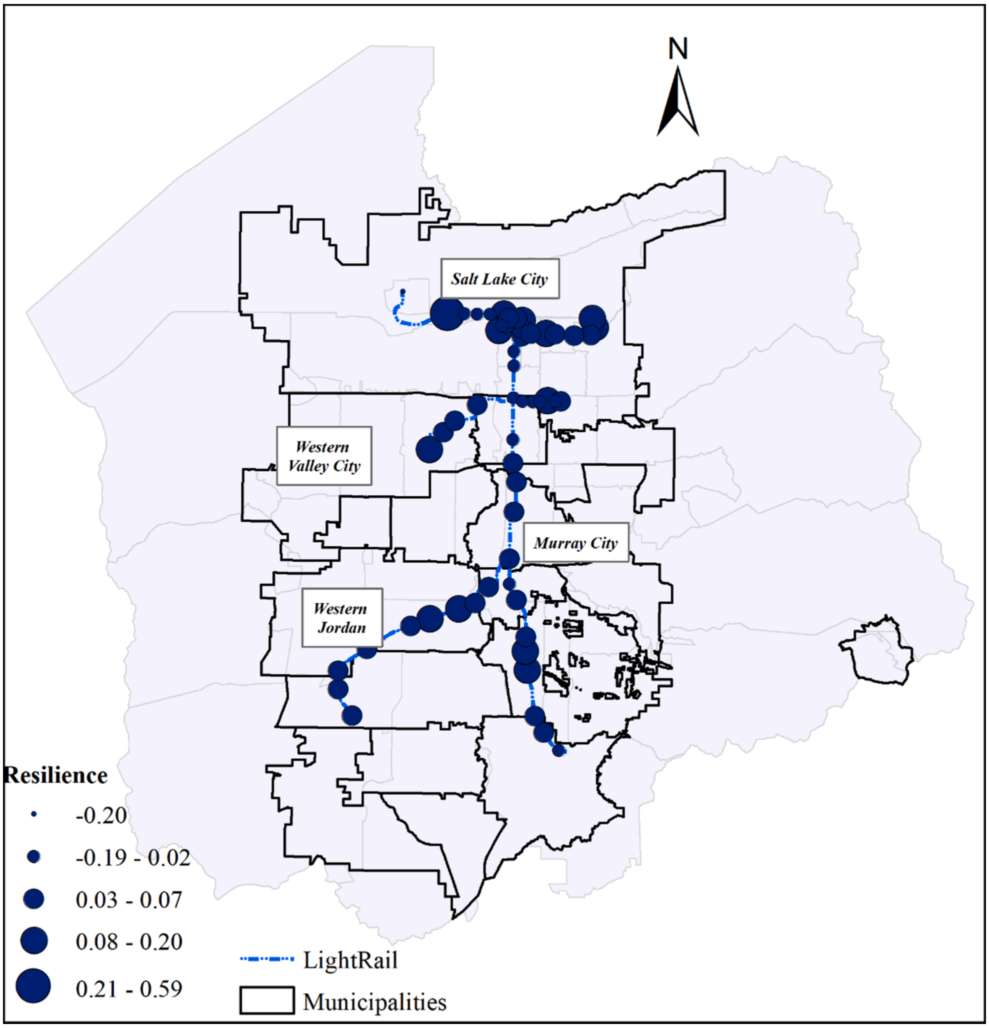

Fig. 6. Resilience index based on BSTS model of all the stations in Salt Lake County.

similar spatial pattern, while the overall relative impacts have been smaller than short-term impacts. Notably, the relative impact on transit ridership in the airport stations becomes significant. Thus the first wave of COVID-19 increases people's awareness, and they would intentionally avoid the long trip to the airport, which is highly sensitive to the number of COVID-19 cases (Choi, 2021; Sjsda, 2021).

The difference between the short-term and long-term relative impacts is taken as the indicator of TRAX stations' resilience to COVID-19 (Fig. 6). The stations in the downtown area of Salt Lake City have a high vulnerability to COVID-19 but are slow in recovering. Comparing the resilience index with the relative impacts, we find that COVID-19 is less likely to influence the stations for connections. However, they show high resilience to COVID-19. Although the ridership of almost all the stations is recovering with considerable speed, the heterogeneity still exists, and the roles of built-in environment and socioeconomic disparity need further exploration.

4.2. *The determinants of resilience of light rail transit system*

The results of the regression tree models have been portrayed in Figs. 7–9, and the relative importance is presented in Table 3. The existing number of splits can provide high values of R^2 (over 0.8), suggesting that current modeling results are powerful in explaining the determinants of vulnerability and resilience of light rail ridership regarding the built-in environment and socioeconomic disparities.

The built environment factors do not contribute a lot to resisting the impact of COVID-19 at the early stage since these four variables account for only about 25 % of the variance. The race is the dominating determinant because many whites work from home after the first outbreak of COVID-19, while the minorities have to take public transit to commute. The regions with well-connected streets have a slower drop in transit ridership because these regions cannot be avoided in daily travel, making the ridership less influenced by

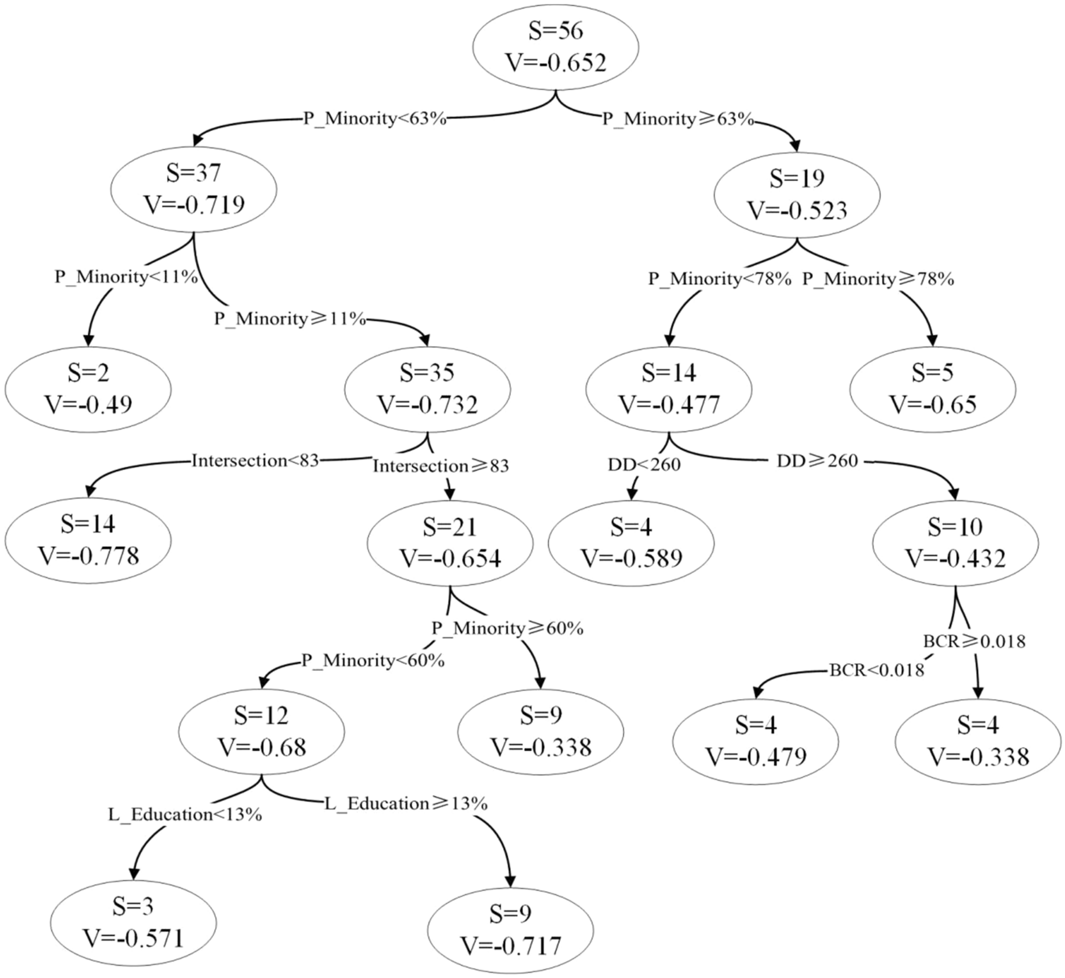

Fig. 7. The regression tree model for short-term relative impacts.

COVID-19. During the second outbreak of COVID-19, the impacts of race decreased, and the built environment variables played more critical roles. For example, mixed land use benefits transit ridership by creating trip destinations for riders. Still, it does not work during the pandemic because most destinations are destroyed by the pandemic (Bartik, et al., 2020). Also, regions with mixed land use usually have a compact urban design (Abdullahi et al., 2015), making these kinds of stations vulnerable to pandemics. Instead, the stations with a lower building coverage ratio could provide more open space and are more preferred for keeping social distance. Thus, density design is critical to determine the vulnerability of transit ridership against COVID-19. More open space might make a low regular ridership; however, it would make the transit ridership less likely to be influenced by pandemics.

Furthermore, the open space plays a more important role in improving resilience, while the model results suggest that the building coverage ratio is much more important than any other variable. Mixed land use contributes to transit ridership recovery because some destinations re-open when the pandemic is relieved (Bartik et al., 2021). So far, the transit ridership has not gone back to normal, and land use is expected to contribute more to improving resilience in the future. During the prevalence of COVID-19, the number of COVID-19 cases has little impact on transportation resilience which might be because people have adapted to living with COVID-19 and are less sensitive to a new outbreak.

Another notable influencing factor of the vulnerability and resilience of transit ridership is the percentage of minorities in the surrounding neighborhood. This finding is consistent with the one in Chicago (Hu & Peng, 2021) that the stations in the minority neighborhood did not experience a huge drop in transit ridership with the outbreak of COVID-19. It is suggested that the minorities have to keep taking light rail because they do not have other available commuting modes, and they usually cannot work from home. The regression tree models manifest that located in the minority neighborhoods is the primary reason some stations still can keep ridership rather than other socioeconomic disparities or built environments. It does not mean that these stations are resilient during the pandemic but show the heterogeneity in social disparities.

Our above analysis presents the determinants of vulnerability and resilience of the TRAX stations in Salt Lake County separately. The built environment and the minority rates are suggested to be the primary contributors, and the determinants of vulnerability and resilience differ. However, the ideology of the planning for transit stations expects to make less vulnerable TRAX stations which also

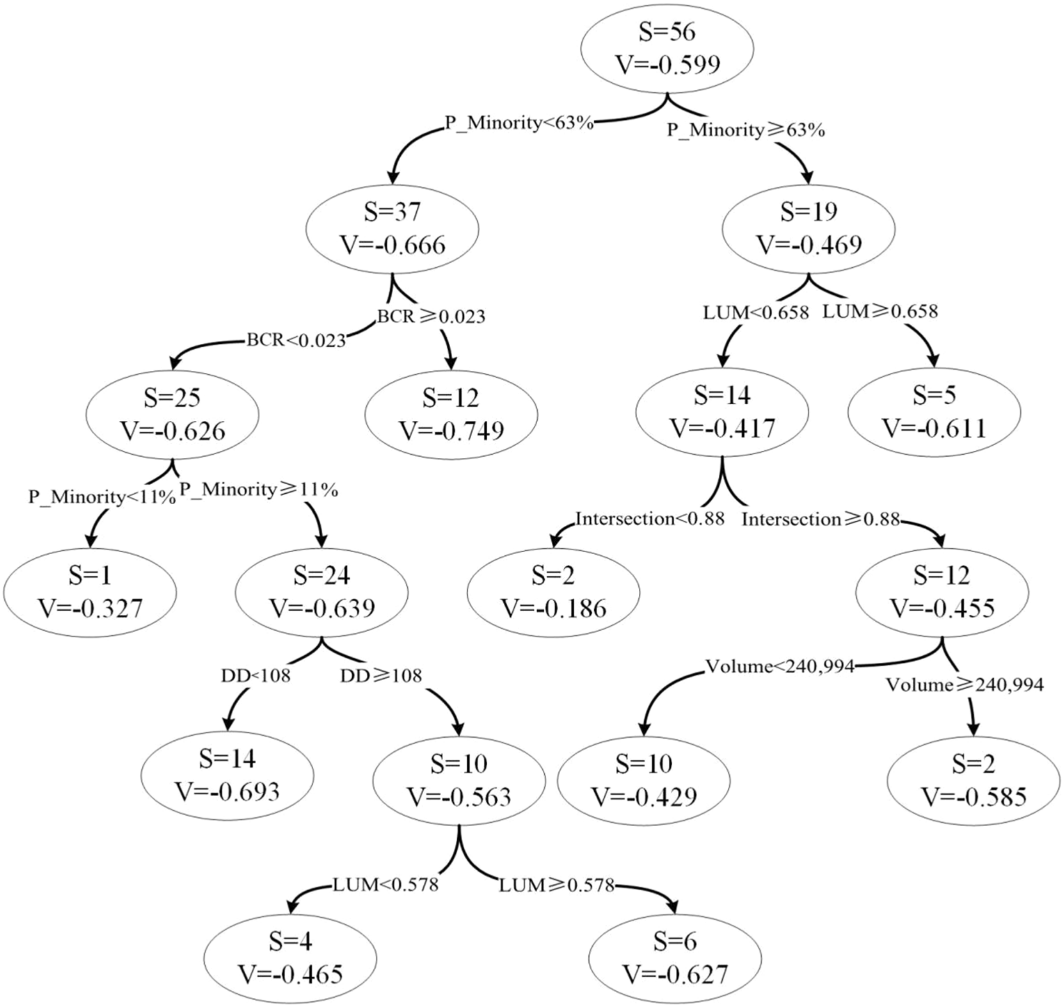

Fig. 8. The regression tree model for long-term relative impacts.

can recover fast from pandemics. Thus, we zoom into the vulnerability and resilience of each station and implement a quartile analysis concerning all the important variables mentioned above, including building coverage ratio, land use mix, dwelling density, and rate of minority (Fig. 10).

In the minority neighborhood, the TRAX station with a lower building coverage ratio and mixed land use was the best practice, with low vulnerability and high resilience. The resilience of the TRAX stations in the minority neighborhood decreased rapidly as the urban density increased, while the vulnerability was less influenced. The failure of the TRAX station was found in the white neighborhood with a high-density urban design with high vulnerability and low resilience. A lower building coverage ratio can help the TRAX stations in the white neighborhood recover fast from pandemics. However, they are still highly vulnerable to COVID-19.

5. Discussion and conclusions

his study tries to identify the vulnerability and resilience of the TRAX stations in Salt Lake County using a BSTS model. Then the regression tree model is employed to explore the determinants of transit ridership vulnerability and resilience to COVID-19 from the perspectives of the built environment and socioeconomic disparities. There are some interesting findings worthy of further discussion.

First, the temporal pattern suggests that the transit ridership was not highly sensitive to the number of COVID-19 cases after the early outbreak in Salt Lake County. People may have adapted to life with COVID-19 after the first strike of COVID-19, and their travel behavior would not have been influenced by the rising number of COVID-19 cases then. Thus when COVID-19 peaked at the end of the year 2020, the transit ridership was not significantly influenced. This finding in Salt Lake County is not the same as in other regions, such as New York City and Chicago, where transit ridership is periodical and corresponds to the COVID-19 cases (Osorio et al., 2022; Wang & Noland, 2021). It could be assumpted that people in medium-size cities are more likely to be adapted to living with COVID-19 than large metropolitans where the risk of infection is high.

It is also possible that people have poor awareness of the local COVID-19 cases and do not know they are more exposed to COVID-19

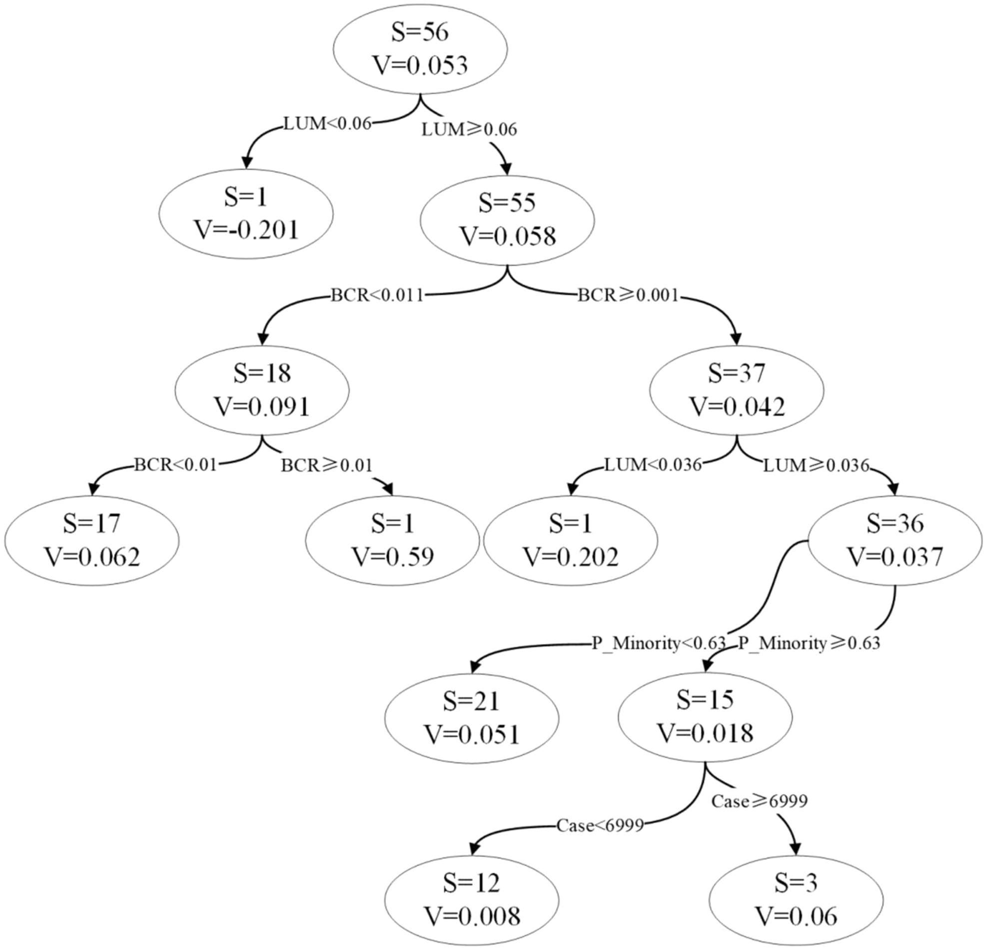

Fig. 9. The regression tree model for resilience.

Table 3
Relative importance of the variables in regression tree models.

Short-term relative impacts		Long-term relative impacts		Resilience	
Variables	Importance	Variables	Importance	Variables	Importance
P_Minority	70 %	P_Minority	57 %	BCR	73 %
Intersection	11 %	LUM	15 %	P_minority	19 %
DD	6 %	BCR	10 %	LUM	6 %
LUM	5 %	DD	8 %	Case	2 %
L_education	4 %	Intersection	7 %	Others	<1%
BCR	3 %	Volume	3 %		
Other	1 %	Others	<1%		

during that period. The rapid decline in March 2020 might not be the result of the COVID-19 pandemic, and it is caused by the "stay at home" recommendation from the federal government, which significantly improves people's awareness of the outbreak of COVID-19 (Greer et al., 2020; Mannan & Mannan, 2020). Similar findings are available in China, where the decline in ridership happened in January 2020 when some restrictive policies were published (Xin et al., 2021). Since there is a time lag between government policies and people's awareness, the minority people with poor access to information might be highly exposed to COVID-19 (Bian et al., 2021). This paper cannot provide an insight into the underlying mechanism to explain the causal relationship between ridership and COVID-19, which is worthy of further investigation because public transit is suggested as the primary source of COVID-19 infecting (Florida et al., 2021).

The research outcomes highlight the significance of building coverage ratio around the transit stations to help improve resilience. The "social distance" recommendation suggests that people should keep a 6-feet distance from others to prevent infecting and contracting COVID-19. A lower building coverage ratio around stations creates more open space and makes "social distance" possible,

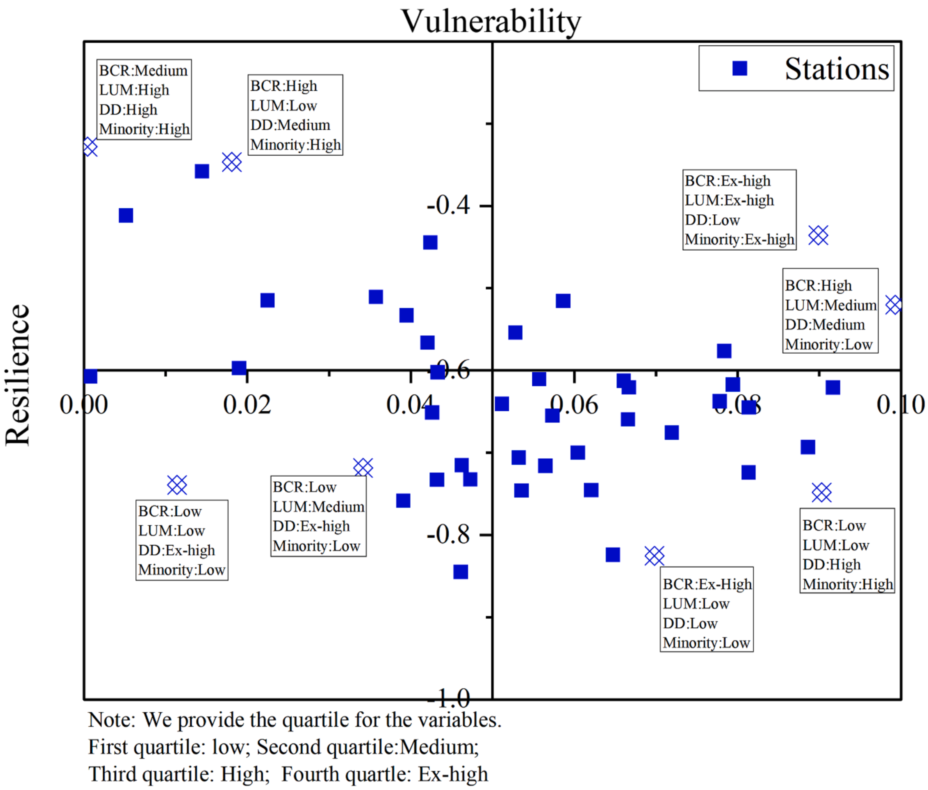

Fig. 10. Resilience and vulnerability of the TRAX stations. Note: we provide the quartile for the variables. First quartile: Low; Second quartile: Medium; Third quartile: High; Fourth quartile: Ex-High.

improving people's sense of safety when they take the TRAX during COVID-19 (Blake et al., 2021). While the traditional high-density urban design improves ridership, our findings suggest that the open space around the TRAX stations should be reserved to improve the resilience against the pandemic. The current TOD planning strategies (density, diversity, design, etc.) pay more attention to enhancing walking/biking accessibility and increasing ridership but pay little attention to combating pandemics. Pandemics similar to the COVID-19 are not uncommon in the U.S. because flu has killed many people and contributed to many economic losses every year. Since the virus mobility by public transportation is facilitated (Prager et al., 2017), resilience against pandemics should be incorporated while considering transportation safety. Even in Salt Lake County, where public transit is not the dominating commuting mode, many people still rely on public transportation, particularly the minorities.

Minorities' commuting behavior is less likely to be influenced by the COVID-19 pandemic, implying that minorities are more exposed to the disease. Although there are few details about why minorities are more sensitive to COVID-19, there is much evidence that race and ethnicity determine the vulnerability to COVID-19 (Greenaway et al., 2020; Jahromi & Hamidianjahromi, 2020). Our study provides a potential explanation that the minorities cannot "work from home", and taking public transit makes them more likely to be exposed to COVID-19. Also, the percentage of the minority is emphasized in this paper as the dominating determinant of the vulnerability of transit ridership compared to neighborhood environment factors in Salt Lake County, where the percentage of minorities keeps rising. Given the fact that minorities are socioeconomically less advantaged, the emergency is to help their daily commuting. Otherwise, the COVID-19 pandemic would intensify social inequality while the transit ridership in the minority neighborhoods does not recover faster than in others.

Although the data analysis provides some implications about the resilience in transportation, limitations still exist regarding variable selections and geographical scales of the data sets. First, the distance to trip destinations is not considered in this research because many trip destinations are damaged during the pandemic. More efforts could be devoted to how the closure of trip destinations such as small businesses for entertainment influences transit ridership. Also, the zip code-level COVID-19 case data might contribute to a biased estimation of COVID-19, which is expected to be addressed in future studies when more elaborated data is available.

Despite these limitations, the research helps gain more knowledge and experience to combat global pandemics. First, the literature suggests that more COVID-19 cases usually contribute to more decline in transit ridership (Hu & Peng, 2021). However, both the trend of temporal variance of COVID-19 cases and the model results indicate that people's preference to take public transit is not highly sensitive to COVID-19 cases. It might be the disadvantages of small-medium cities where people do not have a high awareness of COVID-19 as residents in large cities such as Chicago and New York (Hu & Peng, 2021; Osorio, Liu, and Yang, 2022; Wang & Noland, 2021). Second, the building coverage ratio is critical in improving resilience against pandemics because people would feel safe by keeping a social distance. This finding calls for more attention to the trade-off between urban density and reserved open space for urban planners (McFarlane, 2021; Hamidi & Hamidi, 2021; Ingvardson & Nielsen, 2018). So far, the COVID-19 pandemic has not ended, and further analysis is expected to provide more insight into the long-term impact of the built environment. Also, particular attention should be paid to the minorities who are vulnerable to COVID-19. Our analysis highlights the minorities' reliance on public transit in the post-pandemic urban environment, which makes the minorities more vulnerable to the pandemic (Couch, Fairlie & Xu, 2020; Paul, Steptoe & Fancourt, 2021; Tirachini & Cats, 2020). Last, the transportation system operators should pay attention to the fact that there is a difference between the short-term and long-term effects of COVID-19 on public transit. These research outcomes are expected to help decision-making and better face the challenges of the pandemic in the future.

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.

Data availability

Data will be made available on request.

Acknowledgements

We would like to acknowledge the funding of Jiangsu Funding Program for Excellent Postdoctoral Talent and International Postdoctoral Exchange Fellowship Program, Grant No.YJ20220202.

References

Abdullahi, S., Pradhan, B., Mansor, S., Shariff, A.R.M., 2015. GIS-based modeling for the spatial measurement and evaluation of mixed land use development for a compact city. GIScience Remote Sens. 52 (1), 18–39.

Abreu, L., Conway, A., 2021. A qualitative assessment of the multimodal passenger transportation system response to COVID-19 in New York City. Transport. Res. Rec. 03611981211027149.

Albanesi, S., Kim, J., 2021. Effects of the COVID-19 recession on the U.S. labor market: occupation, family, and gender. J. Econ. Perspect. 35 (3), 3–24.

Bartik, A.W., Bertrand, M., Cullen, Z., Glaeser, E.L., Luca, M., Stanton, C., 2020. The impact of COVID-19 on small business outcomes and expectations. Proc. Natl. Acad. Sci. 117 (30), 17656–17666.

Beck, M.J., Hensher, D.A., Nelson, J.D., 2021. Public transport trends in Australia during the COVID-19 pandemic: An investigation of the influence of bio-security concerns on trip behaviour. J. Transp. Geogr. 96, 103167.

Bian, Z., Zuo, F., Gao, J., Chen, Y., Pavuluri Venkata, S.S.C., Duran Bernardes, S., Ozbay, K., Ban, X.(., Wang, J., 2021. Time lag effects of COVID-19 policies on transportation systems: A comparative study of New York City and Seattle. Transport. Res. A: Pol. Pract. 145, 269–283.

Blake, H., Knight, H., Jia, R.u., Corner, J., Morling, J.R., Denning, C., Ball, J.K., Bolton, K., Figueredo, G., Morris, D.E., Tighe, P., Villalon, A.M., Ayling, K., Vedhara, K., 2021. Students' views towards Sars-Cov-2 mass asymptomatic testing, social distancing and self-isolation in a university setting during the COVID-19 pandemic: a qualitative study. Int. J. Environ. Res. Public Health 18 (8), 4182.

Brough, R., Freedman, M., Phillips, D.C., 2021. Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic. J. Reg. Sci. 61 (4), 753–774.

Bunker, D., 2020. Who do you trust? The digital destruction of shared situational awareness and the COVID-19 infodemic. Int. J. Inf. Manage. 55, 102201.

Cardozo, O.D., García-Palomares, J.C., Gutiérrez, J., 2012. Application of geographically weighted regression to the direct forecasting of transit ridership at station-level. Appl. Geogr. 34, 548–558.

Cariolet, J.-M., Vuillet, M., Diab, Y., 2019. Mapping urban resilience to disasters – a review. Sustain. Cit. Soc. 51, 101746.

Carrión, D., Colicino, E., Pedretti, N.F., Arfer, K.B., Rush, J., DeFelice, N., Just, A.C., 2021. Neighborhood-level disparities and subway utilization during the COVID-19 pandemic in New York City. Nat. Commun. 12 (1), 1–10.

Choi, J.H., 2021. Changes in airport operating procedures and implications for airport strategies post-covid-19. J. Air Transp. Manage. 94 (11), 102065.

Chu, Z., Cheng, M., Song, M., 2021. What determines urban resilience against COVID-19: City size or governance capacity? Sustain. Cities Soc. 75, 103304.

Couch, K.A., Fairlie, R.W., Xu, H., 2020. Early evidence of the impacts of COVID-19 on minority unemployment. J. Public Econ. 192, 104287.

De Vos, J., 2020. The effect of COVID-19 and subsequent social distancing on travel behavior. Transport. Res. Interdiscipl. Perspect. 5, 100121.

Edelman Trust Barometer, 2020. Spring update: Trust and the Covid-19 pandemic. https://www.edelman.com/research/trust-2020-spring-update.

Engle, S., Stromme, J., Zhou, A., 2020. Staying at home: mobility effects of covid-19. Available at SSRN 3565703.

Figliozzi, M., Unnikrishnan, A., 2021. Home-deliveries before-during COVID-19 lockdown: accessibility, environmental justice, equity, and policy implications. Transporta. Res. D: Transp. Environ. 93, 102760.

Florida, R., Rodríguez-Pose, A., Storper, M., 2021. Cities in a post-COVID world. Urb. Stud. 00420980211018072.

Gan, Z., Yang, M., Feng, T., Timmermans, H.J., 2020. Examining the relationship between built environment and metro ridership at station-to-station level. Transport. Res. D: Transp. Environ. 82, 102332.

Ganin, A.A., Kitsak, M., Marchese, D., Keisler, J.M., Seager, T., Linkov, I., 2017. Resilience and efficiency in transportation networks. Sci. Adv. 3 (12), e1701079.

Gonçalves, L.A.P.J., Ribeiro, P.J.G., 2020. Resilience of urban transportation systems. Concept, characteristics, and methods. J. Transp. Geogr. 85, 102727.

Greenaway, C., Hargreaves, S., Barkati, S., Coyle, C. M., Gobbi, F., Veizis, A., Douglas, P., 2020. COVID-19: Exposing and addressing health disparities among ethnic minorities and migrants. J. Travel Med. 27(7), taaa113.

Greer, S.L., King, E.J., da Fonseca, E.M., Peralta-Santos, A., 2020. The comparative politics of COVID-19: The need to understand government responses. Global Public Health 15 (9), 1413–1416.

Grover, S., McClelland, A., Furnham, A., 2020. Preferences for scarce medical resource allocation: Differences between experts and the general public and implications for the COVID-19 pandemic. Brit. J. Health Psychol. 25 (4), 889–901.

Ha, J., Jo, S., Nam, H.-K., Cho, S.-i., 2022. The unequal effects of social distancing policy on subway ridership during the COVID-19 pandemic in Seoul, South Korea. J. Urban Health 99 (1), 77–81.

Hamidi, S., Hamidi, I., 2021. Subway ridership, crowding, or population density: determinants of COVID-19 infection rates in New York City. Am. J. Prev. Med. 60 (5), 614–620.

He, Q., Rowangould, D., Karner, A., Palm, M., LaRue, S., 2022. Covid-19 pandemic impacts on essential transit riders: Findings from a U.S Survey. Transport. Res. D: Transp. Environ. 105, 103217.

Hu, S., Chen, P., 2021. Who left riding transit? Examining socioeconomic disparities in the impact of COVID-19 on ridership. Transport. Res. D: Transp. Environ. 90, 102654.
Ingvardson, J.B., Nielsen, O.A., 2018. How urban density, network topology and socio-economy influence public transport ridership: Empirical evidence from 48 European metropolitan areas. J. Transp. Geogr. 72, 50–63.
Jahromi, A.H., Hamidianjahromi, A., 2020. Why African Americans are a potential target for COVID-19 infection in the United States. J. Med. Int. Res. 22 (6), e19934.
Kamga, C., Eickemeyer, P., 2021. Slowing the spread of COVID-19: Review of "Social distancing" interventions deployed by public transit in the United States and Canada. Transp. Pol. 106, 25–36.
Kashem, S.B., Baker, D.M., González, S.R., Lee, C.A., 2021. Exploring the nexus between social vulnerability, built environment, and the prevalence of COVID-19: A case study of Chicago. Sustain. Cities Soc. 75, 103261.
Kawohl, W., Nordt, C., 2020. COVID-19, unemployment, and suicide. The Lancet Psychiatry 7 (5), 389–390.
Khavarian-Garmsir, A.R., Sharifi, A., Moradpour, N., 2021. Are high-density districts more vulnerable to the COVID-19 pandemic? Sustain. Cities Soc. 70, 102911.
Kim, K., 2021. Impacts of COVID-19 on transportation: Summary and synthesis of interdisciplinary research. Transport. Res. Interdiscipl. Perspect. 9, 100305.
Liu, X., Li, S., Xu, X., Luo, J., 2021. Integrated natural disasters urban resilience evaluation: the case of China. Nat. Hazards 107 (3), 2105–2122.
Lopez, L., Hart, L.H., Katz, M.H., 2021. Racial and ethnic health disparities related to COVID-19. JAMA 325 (8), 719.
Luo, Q., Gee, M., Piccoli, B., Work, D., Samaranayake, S., 2022. Managing public transit during a pandemic: the trade-off between safety and mobility. Transport. Res. C: Emerg. Technol. 138, 103592.
Mahase, E., 2020. Covid-19: death rate is 0.66% and increases with age, study estimates. BMJ: Brit. Med. J. (Online) 369.
Mannan, D.K.A., Mannan, K.A., 2020. Knowledge and perception towards Novel Coronavirus (COVID 19) in Bangladesh. Int. Res. J. Bus. Soc. Sci. 6 (2).
McFarlane, C., 2021. Repopulating density: COVID-19 and the politics of urban value. Urban Studies, 00420980211014810.
McKenzie, K., Murray, G.C., Martin, R., 2021. 'it's been adapted rather than impacted': a qualitative evaluation of the impact of covid-19 restrictions on the positive behavioural support of people with an intellectual disability and/or autism. J. Appl. Res. Intellect. Disabil. 34 (4), 1089–1097.
Meerow, S., Newell, J.P., Stults, M., 2016. Defining urban resilience: a review. Landscape Urban Plann. 147, 38–49.
Mishra, S.V., Gayen, A., Haque, S.M., 2020. COVID-19 and urban vulnerability in India. Habitat Int. 103, 102230.
Osorio, J., Liu, Y., Ouyang, Y., 2022. Executive orders or public fear: What caused transit ridership to drop in chicago during COVID-19? Transport. Res. D: Transp. Environ. 103226.
Pan, S., Yan, H., He, J., He, Z., 2021. Vulnerability and resilience of transportation systems: a recent literature review. Phys. A 581, 126235.
Park, K., Chamberlain, B., Song, Z., Nasr-Isfahani, H., Sheen, J., Larsen, T., Christensen, K., 2021. A Double Jeopardy: COVID-19 impacts on the travel behavior and community living of people with disabilities. Transport. Res. A: Pol. Pract.
Paul, E., Steptoe, A., Fancourt, D., 2021. Attitudes towards vaccines and intention to vaccinate against COVID-19: Implications for public health communications. Lancet Regl. Health-Europe 1, 100012.
Prager, F., Wei, D., Rose, A., 2017. Total economic consequences of an influenza outbreak in the United States. Risk Anal. 37 (1), 4–19.
Richardson, T., Jensen, O.B., 2008. How mobility systems produce inequality: Making mobile subject types on the Bangkok sky train. Built Environ. 34 (2), 218–231.
Scott, S.L., Varian, H.R., 2014. Predicting the present with bayesian structural time series. Int. J. Math. Model. Num. Optim. 5 (1/2), 4.
Sobieralski, J.B., 2020. COVID-19 and airline employment: Insights from historical uncertainty shocks to the industry. Transport. Res. Interdiscipl. Perspect. 5, 100123.
Sun, C.X., Bin, H.E., Di, M.U., Li, P.L., Zhao, H.T., Li, Z.L., Li, Z.J., 2020. Public awareness and mask usage during the COVID-19 epidemic: a survey by China CDC new media. Biomed. Environ. Sci. 33 (8), 639–645.
Sung, H., Oh, J.T., 2011. Transit-oriented development in a high-density city: Identifying its association with transit ridership in Seoul, Korea. Cities 28 (1), 70–82.
Sy, K.T.L., Martinez, M.E., Rader, B., White, L.F., 2021. Socioeconomic disparities in subway use and COVID-19 outcomes in New York City. Am. J. Epidemiol. 190 (7), 1234–1242.
Tao, T., Cao, J., 2021. Exploring the interaction effect of poverty concentration and transit service on highway traffic during the COVID-19 lockdown. J. Transport Land Use 14 (1), 1149–1164.
Tirachini, A., Cats, O., 2020. COVID-19 and public transportation: current assessment, prospects, and research needs. J. Public Transport. 22 (1), 1.
Vergel-Tovar, C.E., Rodriguez, D.A., 2018. The ridership performance of the built environment for BRT systems: evidence from Latin America. J. Transp. Geogr. 73, 172–184.
Wang, H., Noland, R.B., 2021. Bikeshare and subway ridership changes during the COVID-19 pandemic in New York City. Transp. Pol. 106, 262–270.
Wilbur, M., Ayman, A., Ouyang, A., Poon, V., Kabir, R., Vadali, A., et al., 2020. Impact of COVID-19 on public transit accessibility and ridership. arXiv preprint arXiv: 2008.02413.
Xiao, W., Wei, Y.D., 2021. Multiscale analysis of urban walkability and Pedestrian's destination choice. J. Urban Plan. Dev. 147(1), 05020034.
Xin, M., Shalaby, A., Feng, S., Zhao, H., 2021. Impacts of COVID-19 on urban rail transit ridership using the synthetic control method. Transp. Policy 111, 1–16.
Zhang, J., 2020. Transport policymaking that accounts for COVID-19 and future public health threats: a PASS approach. Transp. Pol. 99, 405–418.
Zhang, L., Zeng, G., Li, D., Huang, H.J., Stanley, H.E., Havlin, S., 2019. Scale-free resilience of real traffic jams. Proc. Natl. Acad. Sci. 116 (18), 8673–8678.
Zhou, Y., Wang, J., Yang, H., 2019. Resilience of transportation systems: concepts and comprehensive review. IEEE Trans. Intell. Transp. Syst. 20 (12), 4262–4276.