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Quantitative resilience assessment of the network-level metro rail service’s responses to the COVID-19 pandemic

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ABSTRACT

The metro rail system has proven to be the most efficient high-capacity carriers. During the unprecedented coronavirus disease 2019 (COVID-19) challenge, non-pharmaceutical interventions become a widely adopted strategy to limit physical movements and interactions. For situational awareness and decision support, data-driven analytics about serviceability are invaluable to metro agencies and decision-makers of cities. This paper presents a data-driven analytical framework that quantitatively evaluates COVID-19-caused resilience performance of metro rails. Several characteristics (e.g., vulnerability, robustness, rapidity, and degree to return) of the metro system’s responses to the disturbance were identified and modeled with multivariate multiple regression. The applicability and rationality of the resilience evaluation model were validated by the metro transit data of the United States. The preliminary results disclosed that metro rail transit encountered more vulnerability (90.6%) in passenger trips than motorbus and light rail (around 70%). A set of statistical models were employed to disentangle the effect of socio-demographic variables and COVID-19-related factors on the metro transit. The disclosed emerging knowledge of resilience provides an in-depth understanding of mobility trends for the public and time-sensitive decision support for the policy effects, to further improve the service and management of the metro system under the spread of the epidemic.

1. Introduction

Metro rail transit system is efficient high-capacity carriers in terms of energy consumption, space occupancy, and passengers transported. To alleviate the traffic congestion on the ground and environmental pollution, especially for the metropolitan cities, the metro construction and operation transporting significantly high volumes of passengers daily is one critical function of urban underground space development in the United States (Loo et al., 2010), China (Chen et al., 2018), India (Mandhani et al., 2020), and other countries around the world. As the metro systems in large cities, in particular of America and Asia, are experiencing to-day heaviest use (Cui & Nelson, 2019), the efficient management of these underground transport systems is an ongoing challenging concern. The high volumes of passengers in confined spaces expose vulnerability to the unexpected disasters. Accurate assessment and management of ridership, in particular during the disruptive events, are essential for the planning and operation of transit services.

The coronavirus disease 2019 (COVID-19) brought unprecedented levels of disruptions to countries throughout the world. Various sudden changes (e.g., remote working, online collaboration, and social distancing) and extensive and strict unprecedented epidemic control measures have a significant impact on the services provided by the metro rail transit transportation. Lockdowns of a majority of sectors in the economy and travel restrictions both resulted in an unprecedented increase in teleworking and online collaboration (Tirachini & Cats, 2020), which further notably reduced the number of commuters in the public transit system. Aside from lockdown and remote working, concerns about riding metro rail transit when exposed to the COVID-19 have also changed the choices of travel behaviors and mobilities. CDC (2021) pointed out that traveling on public transportation increases a person’s risk of getting and spreading COVID-19 by bringing people in close contact with others. The choice of transportation mode may already have varied due to the high risks of pandemic in crowded public transit vehicles and stations. Thus, the pandemic may potentially affect the choices of essential commutes and travels. As for COVID-19 and corresponding policy effects, though limited, a few early studies quantified the policy effect on human mobility change during the pandemic (Engle et al., 2020; Fang et al., 2020).

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Largely due to the limited time into the pandemic and availability of data resources, several major knowledge gaps are worthy of attention. Firstly, most prior studies focused on human mobilities (Hu & Chen, 2021; Asif et al., 2022) or combinations of multiple modes of public transportation (Hu et al., 2021; Beck & Hensher, 2020). Admittedly, these analytical results have disclosed the impact of the pandemic on transportation from a high-level perspective. However, various modes of public transit (e.g., subway, bus, light rail) have significant variations in terms of serving groups of commuters, standard service capacity, and trip duration and distance. Although several previous studies (Basu & Ferreira, 2021; Xiang et al., 2021) screened the metro system with COVID-19 in Boston and Changsha respectively, there is a lack of a specific assessment of metro system services involving the comparison against other public transportation modes. Secondly, there is a lack of quantitative evaluation of public transit transportation with decreasing number of new COVID-19 positive cases and increasing number of fully vaccinated people. This information could play a vital role in the study of public transit resilience during the post-pandemic. The potential reason is that most literature employed considerably limited length of the studied period, even shorter than one year and focused on the direct impact of COVID-19 on the dramatic decrease of public transit ridership.

To fill these important research gaps, a data-driven, mode-specific assessment of the metro rail transit under the outbreak of COVID-19 is an imperative need. This paper aims to analyze the impact of the pandemic on the metro rail transit transportation network and to reveal the resilience-related performances. Several characteristics, such as vulnerability, robustness, degree of return to a reference level, and time taken to reach a new quasi-stable state, of metro system’s response to disturbance that relate to resilience and resistance were characterized with the historical data.

The contribution of this study is twofold. First, this paper articulated the specific features in the impact of pandemic outbreaks on metro rail transit transportation, in particular for the comparison against other transportation modes. The data informatics and disclosed metro resilience trend serves as an in-depth understanding of ridership and mobility trend for the public. Second, this paper demonstrated how data-driven, statistical model-aided methodology can be used to examine the resilience performance of pandemic outbreaks on the metro rail transit using the example of coronavirus COVID-19. The outcomes of this research can be used by decision-makers and metro rail transit to effectively prescreen the operative impacts of epidemic outbreaks on the transportation. They also contribute to the development of efficient recovery policies in case of epidemic outbreaks and effective responses from the perspective of short term and long term in cities. The methodological framework can also be adapted to extreme weather conditions (e.g., hurricane) and other disruptive events.

2. Literature review

2.1. Impact of COVID-19 on transportation

The emergence of COVID-19 was first identified in December 2019. The World Health Organization (WHO) declared global proportions on 11 March 2020 (WHO, 2020). The economic crisis associated with the road infrastructure recovered much faster as compared to rail and subway networks. In terms of epidemics, Jung (2020) pointed out that the rail network brought extensive damages to the public transit systems of New Jersey in October 2012. Mudigonda et al. (2019) concluded that the rail network was restored to full service in two to 32 days, whereas the recovery of more than 65% of the bus network took two days. The potential reason behind the difference between transit rail network and bus network is that the road infrastructure recovered much faster as compared to rail and subway networks. In terms of epidemics, Jung (2020) pointed out that an epidemic impacts ridership on public transportation, in which a severe disease is able to cause significant impact on public transit ridership with the presence of certain heterogeneity across individuals. Sung (2016) investigated the variations of transit ridership during the outbreak of MERS (Middle East Respiratory Syndrome) in Korea.
Although these are low-frequency-high-impact events, operational and disruption risks are widely existing with considerable demand fluctuations. An important contemporary concern regarding the resilience of metro rail transit systems is quite essential so that countermeasures can be introduced to reduce the level of disruption when it occurs. D’Lima and Medda (2015) pointed out that it is vital to quantifiably measure the resilience of transport systems, and thus figure out how the resilience of the system can be improved. Based on the London Underground system, Cui and Nelson (2019) proposed quantification of the rapidity of the metro system’s recovery from shocks involving severe delays to measure resilience. Besides, the combined changes of future environments, society, and economic were also involved in the resilience analysis. Makana et al. (2016) developed a new sustainable underground use resilience evaluation framework in order to quantify both spatial and temporal impacts of underground urban development. More detailed review of transportation systems’ resilience can be accessible in Zhou et al. (2019).

In addition to these historical events, public transit transportation around the world are encountering substantial changes during the ongoing outbreak of COVID-19, as well as potential challenges in the post-pandemic of COVID-19. There is much evidence that the impact and recovery from the COVID-19 pandemic will be unprecedented. To the authors’ knowledge, quite limited study quantified the resilience of COVID-19 on the metro rail transit. Given their recognized massive and complicated impacts, there are surprisingly few assessments of the resilience-related effects of pandemics on metro rail transportation system.

2.3. Knowledge gap and contribution

Metro rail transit is susceptible to counteract pandemics because of restricted mobility and social distancing. Although a number of publications have investigated the travels, transportation, and supply chains under the pandemic and lockdown policies, previous publications mostly focused on evaluating the transportation performance at the early stage of COVID-19 outbreak. There is a lack of data-driven assessment of metro rail transit performance involving unprecedented pandemic and post-pandemic period. Moreover, few studies developed quantitative assessments of metro transit’s resilience with the consideration of socio-demographic variables and COVID-19-related factors. To narrow these knowledge gaps, this paper quantitatively assesses the impact of the pandemic on the metro transit network, with a focus on the full-time analysis of both passenger counts and vehicle performances. The contribution of this study is to inform changes required in the revision of strategic metropolitan metro transit transport operations, as well as more general perspectives on metro rail transit transportation policy and planning, for practitioners and policymakers.

3. Data source and collection

This study primarily employed the metro rail transit data of the metropolitan cities in the United States as the data samples. These data were collected from the National Transit Database (NTD) of the U.S. Federal Transit Administration (FTA), as the data repository of American transit system’s financial and operating conditions. In this database, transit organization characteristics, transit vehicle fleet characteristics, revenues and subsidies, operating and maintenance costs, inventories of vehicles and maintenance facilities, services consumed and supplied, and safety and security were recorded (Gan et al., 2011). NTD has become the primary source of standardized and comprehensive dataset used by all constituencies of the U.S. transit industry (Lyons & Fleischman, 1992), wherein the NTD contributes to supporting local, state, and regional planning for governments, transit agencies, and other decision-makers. Monthly ridership is one of data categories, in which the monthly-updated transit service information was reported by urban transits. Among a wealth of information measuring transit service provided and consumed, several key metrics reported by transit agencies are employed to describe the mobility of public transit in this study (FTA, 2022):

- Unlinked Passenger Trip (UPT) is the number of passengers who board public transportation vehicles. Passengers are counted each time they board vehicles no matter how many vehicles they use to travel from their origin to their destination.
- Vehicle Revenue Mile (VRM) is defined as the miles that vehicles are scheduled to or actual travel while in revenue service. VRM excludes deadhead, operator training, and vehicle maintenance testing. In this context, for rail modes, a vehicle is a single passenger car, not a train.
- Vehicle Revenue Hour (VRH) is the hours that vehicles are scheduled to or actual travel while in revenue service. VRM includes layover time and recover time, which they exclude deadhead, operator training, and vehicle maintenance testing. In this context, for rail modes, a vehicle is a single passenger car, not a train.

4. Methodology

4.1. Framework of resilience analysis for metro transit operation

As a study aiming to evaluate the network-level metro system’s resilience, this paper quantitatively measures the systems’ ability to absorb perturbations, but also its ability to recover from perturbations. A variety of measures describing the metro transit services were employed in this study in order to examine the resilience of the metro transit system to the unprecedented pandemic. Specifically, four resilience-related characteristics of the response of a metro rail transit system function to the COVID-19 disturbance were identified, which are vulnerability, robustness, degree to return, and return time during which the variable reaches a new stable or quasi-stable state. Todman et al. (2016) pointed out that although any one of these characteristics can define resilience, each may lead to different insights and conclusions. In this paper, all these four metrics are employed to quantify the resilience of metro rail transit systems is quite essential so that countermeasures can be introduced to reduce the level of disruption when it occurs. D’Lima and Medda (2015) pointed out that it is vital to quantifiably measure the resilience of transport systems, and thus figure out how the resilience of the system can be improved. Based on the London Underground system, Cui and Nelson (2019) proposed quantification of the rapidity of the metro system’s recovery from shocks involving severe delays to measure resilience. Besides, the combined changes of future environments, society, and economic were also involved in the resilience analysis. Makana et al. (2016) developed a new sustainable underground use resilience evaluation framework in order to quantify both spatial and temporal impacts of underground urban development. More detailed review of transportation systems’ resilience can be accessible in Zhou et al. (2019).

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| Name of Data Source | Refs. | Basics of Data |
|---------------------|-------|----------------|
| National Transit Database of U.S. FTA | (FTA, 2022) | UPT, VRM, and VRH of transit agencies, in which modes include metro rails, light rails, motorbuses, and commuter rails |
| U.S. Census Bureau QuickFacts | (Census, 2021) | Population of local area |
| U.S. CDC | (CDC, 2022) | Statistics of positive COVID-19 cases, number of deaths caused by COVID-19 |
time series of the transportation service performance. Detailed illustrations of the framework of resilience analysis are presented in Fig. 1. It is developed based on the service performance of the public transportation system with partial reference to Wang et al. (2018).

4.1.1. Vulnerability ($P_v$) and degree of return ($P_d$)

Vulnerability in resilience has been defined as the extent that it is reacted adversely during the occurrence of a disruptive event in one system. As the susceptibility to the perturbation, vulnerability is one measure of the degree to which the targeted variable comes from an original state. In other words, vulnerability measures the amount of remaining transportation service performance during the ongoing pandemic. This metric has been widely used in the studies of resilience, such as Marasco et al. (2021) and Wan et al. (2018). Degree of return is a similar metric in resilience, in which the degree between an observed equilibrium reference level and expected equilibrium is measured. In particular, this prescribed, equilibrium reference level could be the level of variable before the disturbance, then the degree of return is expected to equal to the vulnerability. Meanwhile, the underlying trending (e.g., increase or decrease) of the reference level modulated by potential factors normally exists and results in the difference between these two metrics. For example, the newly built metro rail transit lines and growing population of local area may lead to an accumulating trend of the equilibrium level. In order to take these potential circumstances and distinctions into consideration, vulnerability and degree of return, as two similar but different metrics, are covered in this paper. One normalization index, transit traffic variation index (TTVI), is employed in the evaluation of metro transit system’s service performance.

A transit traffic variation index (TTVI) presents the average reduction or increase of traffic volume compared to a reference period. It is worth mentioning that both vulnerability and degree of return are defined to measure the degree of fluctuation in transportation service performance. These fluctuations are dynamic and there are no consistent trends during the original performance and new equilibrium state periods. Therefore, using the concept of average value can better reflect the systematic performance over a period of time. TTVI, as a quantitative indicator, can demonstrate the average concept and further measure the degree of fluctuation. Similar index was also proposed and employed in the previous study. In the evaluation of the impact of different COVID-19 containment measures on electricity consumption in Europe (Bahmanyar et al., 2020), the demand variation index was employed to present fluctuation characteristics before and after the pandemic that are in line with the modeling of the vulnerability and degree of return of transit transportation system in general.

TTVI is defined with formula as below:

$$TTVI_{n,m} = \frac{V^n - V^m \times 100\%}{V^n} = \frac{\left(\sum_{i=1}^{k} V^n_i \right)/k - \left(\sum_{i=1}^{k} V^m_i \right)/m}{V^n} \times 100\%$$

(1)

Where $V^n$ and $V^m$ are the average traffic volume during the previous reference period (named as the old period) and during the latter reference period (named as the new period), respectively, $V^n_i$ is the traffic volume for time $i$ of the old period and $V^m_i$ is the traffic volume for time $i$ of the new period, $k$ and $m$ are the numbers of months in the two state periods.

Based on the normalized characteristics of TTVI, the vulnerability ($P_v$) and degree of return ($P_d$) are respectively defined as below:

$$P_v = \frac{V^n - V^m}{V^n} \times 100\% = \frac{V^n(t_n) - V^m(t_m)}{V^n(t_n)} \times 100\%$$

(2)

$$P_d = \frac{V^n - V^m}{V^n} \times 100\% = \frac{V^n(t_n) - V^m(t_m)}{V^n(t_n)} \times 100\%$$

(3)

Where $V^n$, $V^m$, and $V^n_i$ are the transit transportation traffic feature for time period before the pandemic, the peak period during the pandemic, and the ending period, respectively, while $V^m$ is the expected feature value during post-pandemic. $t_n$, $t_m$, and $t_e$ are three moments within the studied 10-year period that will be introduced in Fig. 1.

4.1.2. Robustness ($R_b$)

Robustness is a valuable strategy in transportation to assess the redundancy and availability of targeted features. It is generally defined as the ability to absorb or withstand disturbances and remaining capability after the outbreak of perturbations. Differing from reliability that measures the probability of meeting a required level of service, robustness quantifies the remaining level of functionality in the context of disruption. In this study, robustness is measured via the absolute values of the public transportation service, although it has overlaps with other relevant concepts (e.g., degree of return, vulnerability). In this study, the performance of metro rail transit system and other alternative public transportation calibrate the number of passengers, the miles

![Fig. 1. Schematic of resilience performance in public transportation system.](image-url)
traveled, the vehicle hours scheduled, and the number of revenue vehicles in the manner of UPT, VRM, VRH, and VOMS, respectively. The robustness can be represented via \( R_b \) with below formulas:

\[
R_b = (1 - P_v) \times \left( \frac{\sum_{i=1}^{k} V^i_p}{\sum_{i=1}^{r} V^i_r} \right) / r
\]  

Where \( V^i_p \) and \( V^i_r \) are the transportation traffic volume for time \( i \) of the original period before the pandemic and during the pandemic. \( k \) and \( r \) are two periods’ durations that will be determined based on collected real-world data.

4.2. Multivariate multiple regression analysis

The ability to assess and accurately predict fluctuations in ridership of metro rail transit systems from the perspective of resilience can help managers plan service adjustments effectively and in a timely manner (Xin et al., 2021). In addition to the empirical analysis of public transit statistics’ trends and variations, it is also essential to evaluate the potential associations between metro rail transit’s resilience characteristics and the development of the pandemic (new cases, death) can also potentially affect the performance of network-level resilience. Therefore, in order to achieve comprehensive evaluation and comparison, statistical analysis of the collected characteristics in the metro rail transit system based on COVID-19 informatics is developed in this paper.

5. Descriptive analysis and statistical modeling of public transits’ resilience

The service performance characteristics, including UPT, VRM, VRH, and VOMS, are analyzed in this study. The time period is from January 2012 to December 2021. As mentioned in Section 3, in addition to the metro rail transit systems, three alternative public transit modes (e.g., motorbus, light rail, commuter rail) were also collected and explored. Based on the ten-year transit data, these four public transit modes contribute to a majority of services. Specifically, the combination of four studied transit modes takes account for over 94.5% of passenger ridership (84.7 billion UPTs of 39.4 billion UPTs) and 72.5% of vehicle miles (28.6 million VRM of 39.4 million VRM). The resilience attributions of metro rail transit, including the comparison against other three modes, are investigated in the following sections.

5.1. Service performance by public transit transportation modes

To avoid the noises from the public transit transportation systems with interrupted services, the agencies that start to provide services between studied periods or terminates transit services are excluded from the below analysis. After preliminary data cleaning, 495 motorbus agencies, 23 light rail agencies, 24 commuter rail agencies, and 15 metro rail transit agencies of the United States are collected for the quantitative analysis. The probability mass function of negative binomial regression is presented below:

\[
f(y; \mu, \beta) = \frac{\Gamma(r + y)}{\Gamma(r) \cdot \left(1 + \frac{1}{\beta}\right)^r} \left(\frac{1}{1 + \frac{1}{\beta}}\right)^y
\]  

Where \( r \) is shape parameter and \( \beta \) is the rate parameter. The expected value and variance are:

\[
E(Y) = \frac{(1 + \beta) \times r}{\beta} = \mu
\]

\[
Var(Y) = \frac{(1 + \beta) \times r}{\beta^2} = \mu + \frac{1}{r}\mu^2
\]

Then the basic framework of the negative binomial regression is as follow:

\[
\mu_i = \exp\left(\alpha_0 + \sum_{m=1}^{n} \alpha_m X_{mi}\right)
\]

Where \( \mu_i \) is the estimated rapidity for public transportation (including metro rail transit group), \( \alpha_0 \) is the intercept and \( \alpha_m \) is \( m \)th parameter coefficient for public transportation group; \( X_{mi} \) is \( m \)th explanatory variable for public transportation group.

If the variance is roughly equal to the mean value, Poisson regression model, as a special case of the negative binomial distribution, is more practical. Overall, the negative binomial regression is more flexible than Poisson regression. The difference in terms of formula is that the negative binomial distribution has one parameter more than the Poisson regression \((r \rightarrow \infty \text{ or } r^{-1} \rightarrow 0)\) that adjusts the variance independently from the mean. Considering these two facts, this paper will firstly focus on the negative binomial regression model. If the mean and variance of studied metro rail transit resilience metrics are consistent, Poisson regression model will be built up to avoid biased standard errors.
Fig. 2. Distribution of transit service performances by transit modes, from 2012 to 2021.

(a) Unlinked Passenger Trips (UPT)

(b) Vehicle Revenue Miles (VRM)

(c) Vehicle Revenue Hours (VRH)
characteristics of transit transportation, it is essential to first assess the variations of their services before the outbreak of the COVID-19 via Statistical tests. Considering the fluctuations in the transit service performances before the outbreak of COVID-19, the existence of significant trends is validated via the Mann-Kendall test. This test is a nonparametric test of monotonic trends and can provide an indication of whether the trend exists. If a statistically significant trend is verified, bivariate regression is used to test whether the trend is positive or negative and what the slope is using ordinary least square regression to fit the best trend. Based on this parametric method and historical data, not only the monotonic trend can be quantified, the state of transit system performance at a future time is also able to be predicted under the assumption that the same monotonic relationship will be observed. In the Mann-Kendall test, p-values greater than 0.05 indicate there is not enough evidence to reject the null hypothesis of no significant trend, while the smaller p-values support the acceptance of the alternative hypothesis of a monotonic trend.

As shown in Table 2, a majority of the combinations of transit modes and transit features has a slightly growing trend before the outbreak of COVID-19, except for the UPT of motorbus and UPT of metro rail. Within the roughly 8-year period, U.S. motorbus experienced a relatively obvious decreasing trend (-8.8%) in the passenger ridership. Based on a study of bike-sharing and bus in New York, Campbell and Brakewood (2017) concluded that the sharing services of bikes, electric scooters, and similar new modes were expected to have an association with decreases in bus ridership. In terms of metro rail transit, the vehicle operating hours and operating distance both had a more or less expanding trend that may be related to more optimal transit schedules and the extension of metro rail services. However, the number of passenger ridership has a statistically insignificant trend in general. This is potentially related to the extremely high construction costs and quite a few newly built metro transit lines in the past decades. Besides, the uses of bike-sharing and Transportation Network Companies (e.g., Uber and Lyft) in the U.S. appears to limit the expending of metro transit quite a few newly built metro transit lines in the past decades. Besides, whether the trend exists. If a statistically significant trend is verified, the degree to return is based on the observed new equilibrium and estimated transit service performance with a bivariate regression model, involving the consideration of uncertainty in the expected transit service estimation during post-pandemic. The percentages within the brackets indicate the 95% confidence intervals of each category. From the view of transit operators (e.g., VRH or VRM), there was only smaller than 10% reduction existing in motorbus and metro rail. The reduction rates for light rail and commuter rail are two-fold of the other two modes in both VRH and VRM. The remaining extent coming back to an expected equilibrium level for UPT are still extensive. However, UPT takes longer time durations to achieve stable or quasi-stable service performance for metro rail transit, as well as other types of transit mode. In summary, the nationwide metro rail transit has greater reductions of passenger ridership in the network-level serviceability than light rail and commuter rail. Metro rail transit has a similar performance with other transit modes in terms of rapidity.

5.2. Agency-specific metro rail transit resilience distribution analysis

This section mainly discloses the metro rail transit agency-specific resilience assessment. In total, 15 metro rail agencies that cover almost all metropolitan cities of the United States are assessed based on historical data (Table 3). New York City subway system accounts for over half of nationwide UPT, VRM, or VRH in total. Following section focuses on the agency-specific resilience performance analysis based on 15 metro rails’ historical data and time series prediction.

Agency-specific metro rail system services’ resilience features are extracted from the publicly accessible transit data release by the FTA with aforementioned calculation methods and definition in Section 4. Basic characteristics are presented in Fig. 3 via violin plots. This type of plots not only presents median values and data skewness via the quantiles, minimum value, and maximum value, the distribution density can also be disclosed. Thus, in this combination of the box plot and kernel

Table 2

| Feature/Type of Modes | P-Value in Mann-Kendall test | Bivariate Regression Coefficient | Std. Error | Characteristics of Resilience | Degree to Return | Robustness | Rapidity |
|-----------------------|-----------------------------|---------------------------------|------------|-----------------------------|-----------------|------------|----------|
| **UPT (in million)**  |                             |                                 |            |                             |                 |            |          |
| Motorbus              | <0.001                      | -0.884                          | 0.0783     | 69.2%                       | 29.2%           | 25.1%      | 32.9%    | 106.4     | 18         |
| Light Rail            | 0.005                       | 0.026                           | 0.0084     | 77.5%                       | 44.4%           | 41.7%      | 46.9%    | 9.3       | 18         |
| Commuter Rail         | <0.001                      | 0.023                           | 0.0067     | 94.0%                       | 57.2%           | 55.5%      | 58.7%    | 2.5       | 18         |
| Metro Rail            | 0.832                       |                                 |            |                             | 90.6%           | 42.2%      | 30.0     | 18         |
| **VRM (in million)**  |                             |                                 |            |                             |                 |            |          |
| Motorbus              | <0.001                      | 0.100                           | 0.018      | 27.0%                       | 8.5%            | 6.2%       | 10.6%    | 112.2     | 6          |
| Light Rail            | <0.001                      | 0.028                           | 0.0013     | 30.9%                       | 20.5%           | 18.4%      | 22.5%    | 7.3       | 6          |
| Commuter Rail         | <0.001                      | 0.030                           | 0.0041     | 42.3%                       | 37.3            |            |          |
| Metro Rail            | <0.001                      | 0.055                           | 0.072      | 38.2%                       | 9.5%            | 7.1%       | 11.7%    | 36.5      | 6          |
| **VRH (in million)**  |                             |                                 |            |                             |                 |            |          |
| Motorbus              | <0.001                      | 0.013                           | 0.0015     | 28.2%                       | 9.5%            | 7.3%       | 11.5%    | 9.5       | 6          |
| Light Rail            | <0.001                      | 0.002                           | 0.0001     | 35.9%                       | 19.7%           | 17.0%      | 22.1%    | 6.4       | 6          |
| Commuter Rail         | <0.001                      | 0.002                           | 0.0001     | 45.3%                       | 22.6%           | 21.0%      | 24.1%    | 0.6       | 3          |
| Metro Rail            | <0.001                      | 0.003                           | 0.0004     | 37.9%                       | 9.3%            | 6.7%       | 11.7%    | 1.8       | 3          |

Notes:
- *: The temporal trend of this group is statistically insignificant based on both Mann-Kendell test and regression model, thus no coefficient and standard error for this.
- †: This group has not achieved a new equilibrium by the end of the studied period (December 2021).
density plot, the median and interquartile range are shown via the white dot and black bars in the violin plot, respectively. Overall, in the metro rail transit, the passenger trips have greater values of median and interquartile than VRM and VRH, no matter for vulnerability, degree to return, or rapidity. It means that the metro rail operating agencies tend to provided relatively limited impact on the operating hours and operating distances during the outbreak of COVID-19 than the passenger mobility. The values of rapidity also verify that the metro rail operating agencies resumed the serviceability in a shorter period. The potential cause is that metro rail transits require the ability to maintain six feet of distance between every passenger and minimize overcrowding-caused risks. Kamga and Eickemeyer (2021) pointed out that cities that are

Table 3

| Agency                                      | Main City      | UPT Before | UPT After | VRM Before | VRM After | VRH Before | VRH After |
|---------------------------------------------|----------------|------------|-----------|------------|-----------|------------|-----------|
| Massachusetts Bay Transportation Authority Subway | Boston         | 4.4%       | 3.7%      | 3.4%       | 3.3%      | 4.4%       | 4.5%      |
| MTA New York City Subway                    | New York       | 70.1%      | 77.8%     | 51.4%      | 53.2%     | 56.6%      | 56.6%     |
| Port Authority Transit Corporation - PATCO Speed Line | Philadelphia  | 0.3%       | 0.2%      | 0.7%       | 0.7%      | 0.4%       | 0.4%      |
| Port Authority Trans-Hudson Corporation     | New York-Newark | 2.3%       | 1.9%      | 1.9%       | 2.1%      | 2.3%       | 2.8%      |
| Staten Island Rapid Transit Operating Authority | New York      | 0.2%       | 0.2%      | 0.4%       | 0.4%      | 0.5%       | 0.5%      |
| Southeastern Pennsylvania Transportation Authority | Philadelphia | 2.5%       | 2.3%      | 2.5%       | 2.6%      | 2.7%       | 2.9%      |
| Washington Metropolitan Area Transit Authority - Metro Rail | Washington | 6.6%       | 3.4%      | 12.0%      | 10.7%     | 9.9%       | 8.9%      |
| Baltimore Metro SubwayLink                   | Baltimore      | 0.3%       | 0.1%      | 0.7%       | 0.7%      | 0.6%       | 0.6%      |
| Metropolitan Atlanta Rapid Transit Authority | Atlanta        | 1.8%       | 1.5%      | 3.1%       | 2.9%      | 2.4%       | 2.1%      |
| County of Miami - Metrorail                  | Miami          | 0.5%       | 0.6%      | 1.2%       | 0.9%      | 1.0%       | 0.9%      |
| Alternativa de Transporte Integrado - Tren Urbano | San Juan     | 0.2%       | 0.1%      | 0.3%       | 0.2%      | 0.3%       | 0.2%      |
| The Greater Cleveland Regional Transit Authority - Red Line | Cleveland | 0.2%       | 0.2%      | 0.4%       | 0.4%      | 0.4%       | 0.4%      |
| Chicago Transit Authority - L Line          | Chicago        | 6.1%       | 4.8%      | 10.5%      | 11.6%     | 11.6%      | 12.4%     |
| San Francisco Bay Area Rapid Transit        | San Francisco  | 3.4%       | 1.6%      | 10.6%      | 9.4%      | 6.0%       | 5.8%      |
| Los Angeles County MTA - Metro Rail         | Los Angeles    | 1.2%       | 1.5%      | 1.0%       | 1.0%      | 0.9%       | 0.9%      |

Fig. 3. Distribution of agency-specific metro rail transits’ resilience features.
heavily reliant on public transit and/or commuter rail for their workers’ daily commutes (e.g., New York City, Philadelphia, Boston, Vancouver) returning to the actual peak were expected to re-enter into services before a majority of business and people return to work. Instead, the users of metro rail transit spend longer time in resuming quite limited ridership. The density plots in Fig. 3 summary the probability of each value, such as thicker ploy with higher probability and thinner plot with lower probability. Fig. 3 shows that in terms of vulnerability, UPT has fewer dispersions than VRM and VRH. In other words, the reduction ranges caused by the pandemic are more consistent for metro transits in different cities, while the transit services (e.g., operating hours and operating distances) have greater scatterings among 15 studied agencies. The potential reason may be the variations of policies and responses released by city-based administrations. This trend is not quite conspicuous for degree to return or rapidity, in which the dispersions among UPT, VRM, and VRH has insignificant difference.

The upper boundary and lower boundary are limited within the range of the observed, instead of smooth shape of violin plots. It should be noted that the lowest value of degree to return in the feature of VRH is smaller than 0. It indicates that this metro rail transit (i.e., San Francisco Bay Area Rapid Transit) has been providing vehicle operating hours that are greater than the corresponding level before the outbreak of COVID-19. To achieve a far-reaching analysis of this transit mode, alternative transportation modes, such as motorbus, light rail, and commuter rail, are also added in Fig. 3 to support a comparative evaluation. It validates that although New York City Transit accounting for a large percentage of conventional public transport is unable to meet the impose regulation, the upper boundary and lower boundary are limited within the range of the observed, instead of smooth shape of violin plots.

The potential reason is that when taking metro rail transit system with higher density distribution of stations and lines, it is more feasible for passenger to choose alternative transportation modes (e.g., bikes, electric scooters) (Wang & Noland, 2021; Manzira et al., 2022). For example, Wang and Noland (2021) concluded that there should be some shifts from subway to bike based on the examination of the New York City under the COVID-19. Benita (2021) also reviewed the analysis of non-motorized mobility and concluded that bike sharing systems have shown to be less significant ridership drops and more resilient than the metro rail systems. However, the conventional public transport is unable to meet the impose regulations sometimes. The number of bike trips has gradually recovered to the pre-pandemic level, while the New York City subway ridership has been only 30% of the corresponding level in 2019 by the end of 2020.

### Table 4

| Independent Variable | Descriptions | Model 1 In Vulnerability Coefficient (t-stat) | Model 2 In Degree to Return Coefficient (t-stat) | Model 3 In Robustness Coefficient (t-stat) | Model 4 In Rapidity Coefficient (z-stat) |
|----------------------|--------------|---------------------------------------------|-----------------------------------------------|------------------------------------------|----------------------------------------|
| Station              | Number of Metro Station | 0.0061* (-2.340)* | 0.0027 (-1.214) | 6.53E-03 (-0.010) | 0.0167 (-1.091) |
| System Length        | Length of Metro Rail Track | -0.010* (-2.470)* | -0.0055 (-1.575) | -4.23E-03 (-0.004) | 0.0098 (-1.607) |
| Population           | Total Population in 2020 | 3.30E-07 (1.881) | 0.548 (-0.005) | 7.81E-03 (-0.027) | 0.0069 (0.459) |
| Ridership Rate       | Trips per Population | -0.0009 (-0.778) | -0.0221* (-2.170)* | 7.01E-03 (-0.027) | 0.0069 (0.459) |
| VRM Rate             | Operating Miles per Population | 0.0181* (2.483)* | 0.0062 (-0.992) | -2.01E-03 (-0.001) | 0.0142 (0.459) |
| VRH Rate             | Operating Hours per Population | -0.0992 (-0.568) | 0.1420 (-1.023) | 6.66E-05 (-0.016) | -0.9117 (1.264) |
| Case Rate-1          | Cumulative Cases in April 2020 | -0.0785 (-1.755) | -0.0315 (-0.824) | -1.51E+05 (-0.013) | 0.3394 (1.815) |
| Case Rate-2          | Cumulative Cases in December 2021 | -0.0002 (-1.723) | -0.0002 (-0.118) | 4.88E-03 (-0.012) | 0.0163* (2.287)* |
| Death Rate-1         | Cumulative Cases in April 2020 | 0.9346 (1.942) | 0.248 (-0.604) | 1.46E+06 (0.012) | -1.651 (0.842) |
| Death Rate-2         | Cumulative Deaths in December 2021 | -0.0669 (-0.397) | -0.0615 (-0.427) | -3.45E+05 (-0.008) | -1.014 (1.365) |
| Case Increase Rate   | Increasing Rate in Cumulative Cases | -0.0019 (-0.830) | -0.0013 (-0.667) | -6.02E+03 (-0.011) | 0.0224* (2.264)* |
| Death Increase Rate  | Increasing Rate in Cumulative Death | 0.0049* (2.546)* | 0.0001 (-0.544) | 4.25E+03 (-0.009) | 0.0014 (0.188) |
| Type of Features     | UPT (Reference) | 1 | 1 | 1 | 1 |
|                      | VRM          | -0.537*** (-2.456)* | -0.496*** (-0.544) | 4.638*** (-0.009) | -4.178*** |
|                      | VRH          | -0.539*** (-2.456)* | -0.472*** (-0.544) | 4.638*** (-0.009) | -4.178*** |

Notes: Values within brackets are t statistics for Models 1, 2, and 3 or z statistics for Model 4; *** indicates that p-value is smaller than 0.001, ** is for p-value ∈ (0.001, 0.01), and * is for p-value ∈ (0.01, 0.05).

5.3. Evaluation of contributing factors in metro rail transit resilience

The potential impact of additional independent variables including but limited to the COVID-19 cases and related deaths, COVID-19 caused death, and population are assessed via developing the regression models. Specifically, the resilience characteristics of vulnerability, degree to return, and robustness are modeled with multivariate multiple regression model, while the rapidity is along with the negative binomial regression model. As shown in Table 4, the coefficient, t-value, and the p-value guiding the acceptance or rejection of null hypothesis are included for each targeted variable.

In this far-reaching analysis of metro rail transit, several characteristics of local area or the development of COVID-19 are statistically correlated with the vulnerability, degree to return, or rapidity. However, there is no significantly correlation between robustness and studied variables. Firstly, in terms of vulnerability, modeling results indicate that number of station, length of metro system lines, the operating miles normalized by population, and COVID-19 caused death increasing rate have statistically significant impacts on this resilience feature. More metro stations and shorter metro system lines are expected to result in greater values of passenger trip reductions. The potential reason is that when taking metro rail transit system with higher density distribution of stations and lines, it is more feasible for passenger to choose alternative transportation modes (e.g., bikes, electric scooters) (Wang & Noland, 2021; Manzira et al., 2022). For example, Wang and Noland (2021) concluded that there should be some shifts from subway to bike based on the examination of the New York City under the COVID-19. Benita (2021) also reviewed the analysis of non-motorized mobility and concluded that bike sharing systems have shown to be less significant ridership drops and more resilient than the metro rail systems. However, the conventional public transport is unable to meet the impose regulations sometimes. The number of bike trips has gradually recovered to the pre-pandemic level, while the New York City subway ridership has been only 30% of the corresponding level in 2019 by the end of 2020.
In the measure of degree to return, the ridership normalized by the local population has statistically significant impact. The negative coefficient of this independent variable discloses that a smaller reduction of metro rail transit serviceability as recovering to a quasi-stable service level exists if a larger proportion of population choose to take local metro rail transit. The causes may be related to the mobility uses from metro transits to non-motorized transport and motivations of the remote working arrangement. Working from home is expected to have motivations from the perspectives of individuals, companies, and even government. Specifically, telecommuting brings high potential for moving towards a more sustainable future. It can also benefit in the significant improvements in travel networks and become the policy lever available to government with flexible working arrangements (Benita, 2021). Moreover, the cumulative COVID-19 cases normalized by the population and its increasing rate are statistically correlated with rapidity. In other words, for one metro rail transit locating in a city with higher number and greater growing trend of the positive COVID-19 cases, it is expected to take longer time for the agency and passengers to recovery back to the new equilibrium level. The statistical testing results in Table 4 also present the quantitative relationships between UPT, VRM, and VRH. Using UPT as the reference in this independent variable, the coefficients of VRM and VRH are quite similar in all four models. For example, the estimated coefficients of VRM and VRH of vulnerability and degree to return are roughly -0.5 with less than 2% of error. These values also validate the finding disclosed in Section 5.1, in which the passenger trips encountered more peak reductions during the outbreak of COVID-19 and remained greater gaps between expected serviceability and observed quasi-stable level than metro operating qualities.

6. Conclusions

This paper investigates the impact of the COVID-19 pandemic on the serviceability of the metro rail transit systems in the United States based on the historical data and statistical analysis. Network-level metro rail transits’ performance before and after the pandemic was assessed via four metrics of system resilience, which are vulnerability, degree to return, robustness, and rapidity. To dig an in-depth analysis of metro rail transit under the pandemic, the motorbus, light rail, and commuter rail are also included to provide comparative evaluation. These transit transportation modes were profoundly affected by the pandemic and encountered major reductions in passenger trips and agency services. Metro rail transit witnessed more significant reductions of passenger ridership (90%), as well as operating miles and operating hours (around 40%) than motorbus and light rail. The time duration recovering from the worst scenario to a stable or quasi-stable state also takes longer period for metro rail transit than other transportation modes. Moreover, the distribution of metro rail transit-specific UPT has fewer dispersion than that of VRM or VRH. It indicates that metro rail transit agencies in various cities may apply distinct policies during the COVID-19, while the responses of metro rail passengers involve fewer dissimilarities. Statistical models were also constructed to extract the effect of this pandemic on transit service and transit ridership with the consideration of socio-demographic effect and pandemic development.

The quantitative resilience assessment of the network-level metro service’s responses to the covid-19 pandemic is able to support the effective management for the decision-makers and metro rail transit to preserve the operation impacts and epidemic outbreaks of to enhance the efficient responses to the severability recovery during post-pandemic. More general perspectives on future metro rail transit transportation policy and planning, for practitioners and policymakers can also be generated from the comparisons against motorbus, light rail, and commuter rail. The methodological framework can also be adapted to extreme weather conditions (e.g., hurricane) and other special events that are able to disrupt the normal services of metro rail systems.

Future work

Although this study provides an assessment of metro rail transit-specific resilience analysis based on the state-of-the-art data, future study is needed to extend the research scope and limitations of this study. Firstly, due to data limitation, this study employs monthly ridership and operating characteristics of each transit agency. Future analysis can achieve daily or weekly metro rail transit operation conditions once these data are available. Then more precise conclusions can be extracted based on these data. Secondly, these are still positive cases in almost all areas during the study of this paper. A more comprehensive evaluation of metro rail transit under post-pandemic should be developed in the near future. Involving comparison with other disruptive events (e.g., hurricane or previous pandemic), it can also be measured from a longer perspective and extract universal characteristics.

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.

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