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RESEARCH

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Understanding post-pandemic spatiotemporal differences in the recovery of metro travel behavior among different groups by considering the built environment

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Abstract

Numerous studies have substantiated the substantial impact of COVID-19 on metro travel, which is expected to gradually recover once the pandemic is controlled. Given the potentially more severe repercussions of COVID-19 on vulnerable groups like the elderly and people with disabilities, recovery patterns may differ significantly among various demographic segments. However, limited research has addressed this notable disparity. To address this gap, we collected metro travel data in Wuhan from March 2019 to April 2021. We analyzed changes in travel characteristics among different groups, such as the elderly, people with disabilities, commuters, school students, and others, before and after the pandemic. By employing interrupted time series analysis, we explored the short-term impact of the pandemic on different groups and their long-term recovery trajectories. We also investigated the factors influencing the recovery of metro travel among diverse demographic groups. The findings indicate the following: (1) All groups experienced a sharp decline in travel ridership and frequency in the short term due to the pandemic. (2) There are distinct variations in long-term ridership recovery among different groups, with commuters and school students showing the quickest recovery. However, ridership among people with disabilities remained below pre-pandemic levels even a year after the pandemic. (3) Given the inherent spatiotemporal regularity in residents' daily activities, post-pandemic metro travel patterns closely align with the pre-pandemic patterns. (4) Different built environment factors exert varying degrees of influence on the recovery of metro ridership among different groups, and distinctions are evident between weekdays and weekends. These findings enhance our comprehension of the pandemic's impact on diverse demographic groups, which can guide government agencies and urban planners in formulating more resilient strategies for rail transit operations and land use optimization.

Keywords: COVID-19 pandemic, Group disparities, Spatial–temporal travel characteristics, Built environment, Interrupted time series analysis

Introduction

In December 2019, COVID-19, first recorded in Wuhan, became one of the most severe global health crises. In response, countries around the world implemented non-pharmaceutical interventions, including lockdowns, stay-at-home orders, and social distancing measures, to reduce disease transmission [1–3]. However, these measures severely disrupted citizens' mobility and social interactions [4, 5]. Among them, the metro system was particularly affected and showed significant variations across different population groups [6–8].

In this context, scholars are increasingly concerned about the impact of the pandemic on metro travel among different population groups because it is valuable for understanding their reliance on public transportation, explaining the disproportionate effects of the pandemic on vulnerable groups, and testing intervention strategies [4, 9–11]. Previous studies have utilized big data such as mobile phone signals and card swipe data or survey data to explore the effects of the pandemic on metro travel among different population groups in terms of spatial and temporal characteristics, attitudes, preferences, and more, both before and after the outbreak, across multiple temporal and spatial scales [9, 12, 13]. Some studies have confirmed that elderly and disabled individuals, due to their physiological differences, are more susceptible to infection and more likely to develop severe symptoms, leading to a significant reduction in their travel frequency for medical care and leisure purposes, with a shift from public transportation to private cars [10, 11, 14]. In contrast, commuters are influenced by the rigidity of work-related travel, and some low-income groups heavily rely on public transportation because they lack alternative means of travel and must commute to their workplaces, utilizing the metro for transportation between their homes and workplaces [15–17]. However, the extent to which the pandemic has caused a decline in metro ridership among different population groups, the differences in the recovery of metro travel patterns after effective control of the pandemic, and the reasons for the recovery of metro ridership among different population groups remain unclear and require further investigation. To address this research gap, we focus on Wuhan, the first city to experience and effectively control the pandemic globally. Our study systematically analyzes the characteristics of metro travel recovery among different population groups after the effective control of the pandemic and explores the factors that influence the recovery of metro ridership.

The recovery of metro travel behavior among different population groups exhibits significant spatiotemporal variations [18–20]. Previous studies have found that, when comparing residents' spatial movements before and after the pandemic, commuters, driven by the urgency of work-related travel and spatial regularity, experience the fastest recovery of metro ridership, primarily concentrated between residential and employment centers [18, 21]. On the other hand, groups such as the elderly and disabled tend to prefer short-distance, familiar trips [11, 18, 22]. Some studies suggest that the pandemic has led to a decline in the attractiveness of city centers and has given rise to phenomena like remote work and online shopping [23, 24], resulting in a slow recovery of metro travel frequency among residents, possibly remaining below pre-pandemic levels for an extended period [13, 19, 25]. However, some longer-term analyses propose that people will adapt to living with COVID-19, leading to a significant reduction in the impact of subsequent waves of the pandemic on residents' travel behavior [3, 18]. These inconsistent research conclusions call for further validation through studies with longer time-series data.

Furthermore, the recovery of metro travel after the pandemic is also influenced by the built environment and metro station characteristics, but some influential factors may exhibit significant differences compared to the pre-pandemic period [3, 20]. The impact of the built environment on metro travel is often described through the lens of 5D (density, diversity, design, destination, distance) [26–28]. High-density compact development patterns have typically been instrumental in promoting public transportation use [29–31]; however, "social distancing" policies during the pandemic may hinder the use of public transportation [7]. The degree of land use mix is commonly used to enhance regional attractiveness and urban vitality [32–34]; however, population agglomeration during the pandemic could increase virus transmission, potentially reducing the attractiveness of public transportation [35, 36]. Other factors, such as companies, restaurants, shopping centers, and other significant travel destinations before the pandemic, may be more susceptible to COVID-19, introducing uncertainty into their impact on the recovery of metro travel [37]. Metro station characteristics, such as transfer stations, terminal stations, and the number of entrances and exits, have shown a significant positive influence on metro ridership before the pandemic [38, 39], but during the pandemic, they may also present higher infection possibilities, necessitating further confirmation of their role in metro travel recovery [7, 12]. Moreover, the pandemic's impetus towards remote work, online consumption, education, entertainment, and more will lead to a reevaluation of businesses and residents' spatial and distance preferences, thereby redefining the influence of the built environment on residents' rail transit travel in the post-pandemic era [17, 21, 40]. People need to reexamine past research conclusions on the relationship between the built environment and rail transit travel behavior to better guide work related to COVID-19 during and after the pandemic.

As mentioned earlier, we anticipate significant spatiotemporal and group differences in the recovery of metro travel behavior among residents after the resumption of metro operations. The metro travel recovery is expected to be fastest in the city center, especially in the employment centers, while it may be slower in the urban fringe and suburban areas. Additionally, commuters, driven by essential travel needs, are likely to exhibit greater flexibility, leading to a faster recovery of metro travel. Conversely, vulnerable groups such as the elderly and disabled may reduce non-essential travel, and the pandemic's impact on them could be more profound. The built environment is a crucial factor in promoting metro travel recovery; however, its influence may significantly differ from the pre-pandemic period. Therefore, we propose the following hypotheses to investigate the spatiotemporal characteristics of metro travel behavior recovery after COVID-19 and to identify the factors facilitating metro recovery.

Hypothesis 1: There are significant group differences in the recovery of metro ridership among different population groups after the pandemic. Commuters are expected to experience the fastest recovery, while the impact on the elderly and disabled is likely to be the most profound.

Hypothesis 2: The post-pandemic recovery of metro travel behavior among different population groups exhibits significant spatiotemporal variations. The city center, especially the employment centers, is anticipated to have the fastest recovery, but the recovery in suburban areas may be slower.

Hypothesis 3: After the pandemic, residents' willingness for non-essential metro travel may decline, resulting in a potential inability to fully restore metro travel frequency to the pre-pandemic average level.

Hypothesis 4: The built environment significantly influences the recovery of metro travel behavior among different population groups, but its impact may differ significantly from the pre-pandemic period.

Our research findings furnish comprehensive evidence for the post-pandemic recovery of subway ridership, offering valuable guidance for subway operations. Our contributions are manifold: firstly, we illuminate the behavioral characteristics of residents' subway travel under pandemic influence, examining both the short-term impacts on subway station footfall and the long-term variations. Secondly, through the nuanced analysis of subway card data, we segment populations, revealing the pandemic's disparate effects on subway travel among different groups, particularly emphasizing the impact on vulnerable populations. Lastly, we uncover the influence of built environment factors on the post-pandemic recovery of residential subway ridership, exploring the variations in this impact between weekdays and weekends. These findings augment our understanding of the pandemic's differential impacts on diverse demographic groups, providing actionable insights for governmental agencies and urban planners to formulate more resilient strategies for optimizing rail transit operations and land use.

Methods

Study area

To meet these objectives, we selected Wuhan as our research subject, the first city globally to report cases of COVID-19 and rapidly become an epicenter. To effectively contain the spread of the virus, Wuhan implemented a city-wide lockdown on January 23, 2020, which led to the closure of all urban metro services. Following 2 months of effective control of the COVID-19 outbreak, Wuhan resumed operations on six metro lines on March 28, 2020, gradually restoring other metro routes, with all services back in operation by April 22, 2020. Divided by the Yangtze and Han Rivers, Wuhan can be generally categorized into three towns: Hankou, Wuchang, and Hanyang. The urban spatial pattern can be further divided into suburbs, urban areas, and core areas, delineated by the Third Ring Road and metropolitan development areas. The core area within the Third Ring Road is the employment and population center of Wuhan, while the metropolitan development areas represent the main expansion zones for urban functions, accommodating all existing rail transit systems (Fig. 1).

Data and variables

This study utilizes metro card swipe data before the COVID-19 pandemic (from March 2019 to January 2020) and after the pandemic (from April 2020 to April 2021, during which time Wuhan reported no new local cases and achieved comprehensive resumption of work and production). The automatic fare collection (AFC) system of urban rail transit records information such as cardholder ID, transaction number, transaction

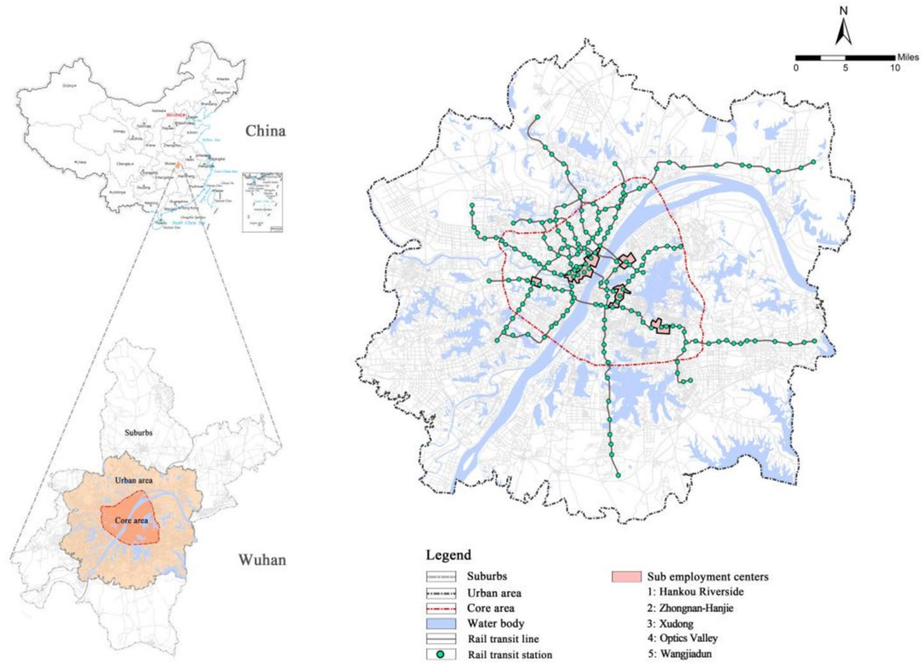

Fig. 1 Research area

time, transaction route, transaction station, transaction type (entry or exit), card type (e.g., senior citizen, disabled person, student), and other details. By categorizing the card types, data for senior citizens, disabled individuals, and students can be extracted. The data is used to construct a dynamic and granular mobility network for different population groups, allowing for the effective analysis of spatiotemporal characteristics of metro ridership recovery after pandemic control, as well as the restoration of metro travel frequency and spatiotemporal characteristics among different groups. First, we extracted data for senior citizens, people with disabilities, and primary/secondary school students based on their card types and grouped them accordingly. Subsequently, we identified commuters from the remaining dataset. In accordance with established research, the rules for extracting commuter data were as follows [3, 41]: To be classified as subway commuters traveling from station A to station B, an individual must have used the subway to travel from station A to station B on at least three workdays within 1 week, both in the morning and in the evening, with a time gap of more than 6 h between the two journeys. After extracting the commuter data, the remaining individuals are categorized into other groups. As of March 2019, there were a total of 189 operational metro stations in Wuhan. To ensure effective comparison of metro travel behavior among different population groups before and after the pandemic, this study focused on the 189 metro stations that were operational in March 2019 and excluded the subsequent 93 stations that were opened in the following two years. The data structure is presented in Table 1.

The Wuhan population data from 2019 to 2021 is acquired from the Global Population Data Assessment website (www.worldpop.com). In addition, the data used in this study includes built environment data (building density, plot ratio, and mixed land use), station characteristic attribute data (whether it is an interchange station, whether it is a terminal station, the number of station entrances and exits, etc.), and poi data (places

Table 1 Metro swipe card data structure

Card number	**Transaction serial number**	**Transaction time**	**Lines where transactions take place**	**Stations where transactions take place**
8027110110066333	3424	20190311071359	06	0643
Type of transaction	**Card type**	**Corresponding entry transaction times**	**Corresponding site builder line**	**Corresponding entry stations**
29	1101	20190311070004	03	0346

visited by food and beverage facilities, companies and enterprises, and life service facilities, etc. with the residents' daily metro trips), which are then matched to the metro stations by coordinates. Among the built environment data mainly used in the 2016 land use status quo data, which has year differences with other data, but because its main use is to calculate the land use mixing degree around the metro station, etc., considering the lag effect of the impact of rail transit on urban land use, the impact of using this data on the research results can be ignored. In addition, compared with the land use classification data obtained by other methods such as satellite remote sensing data interpretation, the use of official vector data can ensure the accuracy of the research results. The calculation method of land use mixing degree is calculated by the entropy value method. The POI data of Wuhan was crawled through the API interface of AMap. AMap point of interest (POI) covers various spatial geographic information (latitude, longitude, detailed address) as well as attribute information such as the name of specific facilities and main categories, which are presented in the form of spatial points.

After necessary data cleaning, drawing from existing research [26, 27], we extract the "5D" elements (including density, diversity, design, destination accessibility, and distance to metro stations) of the built environment around metro stations and the characteristics of the metro stations themselves, using housing prices as a representation of socioeconomic attributes. The final variables are determined as the number of resident population, road length, plot ratio, land use mixing degree, number of road intersections, whether the station is a transfer station, whether the station is a terminal station, number of station entrances, distance from the city center, distance from the city subcenter, number of food and beverage facilities, number of companies, number of life service facilities, and the number of bus stops, then the coordinates are matched with the metro stations. The rail transit card data and the characteristics of the built environment are shown in Table 2.

Modeling approach

Interrupted time series (ITS) analysis is a commonly used quasi-experimental method in the fields of social policy, pharmaceutical policy, and environmental policy to explore the effects of policy interventions or medical drugs. The advantage of ITS lies in its comparison before and after the intervention, without the need for a parallel control group. Therefore, in the absence of an effective control group, the ITS design can yield robust estimation results [3, 43, 44]. Since the outbreak of the COVID-19 pandemic significantly affected all residents, the use of ITS to analyze changes in residents' rail transit

Table 2 Descriptive statistics of variables

Variables	Descriptions	Mean, before	Std., before	Mean, after	Std., after
Number of dining facilities	Natural logarithm of the number of dining facilities POIs	123.13	120.25	124.61	121.38
Number of enterprises	Natural logarithm of the number of enterprises' POIs	98.88	98.27	99.19	98.34
Number of service facilities	Natural logarithm of the number of service facilities POIs	57.75	59.84	58.18	60.12
Number of bus routes	Natural logarithm of the total number of routes for each bus station	7.54	5.55	7.59	5.57
Number of residents	Natural logarithm of the number of permanent residents	1.90	1.71	1.93	1.72
Road length	Calculate the length of the road	8.29	2.55	8.34	2.55
Floor area ratio	$= \frac{\text{Grossfloorarea}}{\text{MSAArea}}$	0.81	0.67	0.81	0.67
Land use mix	An entropy index measuring a mixture of residential, public, commercial, industry, green, and other land uses $\text{Landuse} = \frac{-\sum_{i=1}^{k} P_{ki}\ln(P_i)}{\ln k}$, where k is the type of land use and P_{ki} is the proportion of type i land use to the total land area [42]	0.65	0.21	0.65	0.20
Number of road intersections	Calculate the number of road intersections	18.92	10.42	19.05	10.41
Transfer station	The number of rail transit lines passing through the station	0.14	0.35	0.14	0.35
Terminal	Determine whether each metro station is a terminus	0.10	0.30	0.10	0.30
Number of entrances and exits	Calculate the number of entrances and exits in each metro station	5.25	3.36	5.26	3.35
Distance to the city center	Distance to the city center of Wuhan (km)	11.82	6.75	11.79	6.76
Distance to the subcenter	Minimum distance to the subcenters of Wuhan (km)	7.12	5.82	1.09	5.79
Average housing price	Average housing price for each MSA (K RMB)	7.82	0.43	1.82	0.43

behavior before and after the pandemic can effectively assess the impact of the pandemic on residents' rail transit behavior [45]. The basic formula for ITS is as follows:

$$\mathrm{Y_t} = \beta_0 + \beta_1\mathrm{X_1} + \beta_2\mathrm{X_2} + \beta_3\mathrm{X_3} + \varepsilon_\mathrm{t} \tag{1}$$

In the equation, Y_t represents the travel behavior of the rail transit station (ridership, travel duration, travel distance, etc.), X_1 is the equal time interval (monthly), X_2 is a categorical variable (0 before the pandemic, 1 after the pandemic), X_3 is change in slope before and after the outbreak which replaced by the interaction term with X_1 and X_2, and ε_t is the residual term. β_1 refers to the changed slope of Y before the intervention,β_2 is Y's average amount of change before and after the intervention, β_3 is Y's amount of change in the slope of the trend before and after the intervention, and then the slope of Y after the intervention $= \beta_1 + \beta_3$. Further, the idea of ITS is reflected in Fig. 2.

Due to the significance of the built environment and residents' socio-economic attributes as key variables influencing rail transit travel behavior [26, 46, 47], this study extends the basic ITS framework by incorporating built environment variables and socio-economic attributes at the station level to investigate the impact of the built environment on rail transit travel behavior before and after the pandemic. The extended ITS formula with the addition of built environment variables and socio-economic attributes is as follows:

$$\mathrm{Y_t} = \beta_0 + \beta_1 \mathrm{X_1} + \beta_2 \mathrm{X_2} + \beta_3 \mathrm{X_3} + \beta_4 \mathrm{BE_t} + \beta_5 \mathrm{SE_t} + \varepsilon_\mathrm{t} \quad (2)$$

In the equation, BE_t represents the built environment variables at the station level, mainly consisting of the "5D" elements SE_t represents residents' socio-economic attributes, represented by the average housing price. The entire analysis was conducted using RStudio 4.1.3.

Results

Spatial and temporal characteristics of metro ridership recovery after the pandemic

Figure 3 displays the recovery patterns of metro ridership for different population groups after the pandemic. Commuters and school students showed the fastest recovery on weekdays, while the ridership of disabled individuals did not return to pre-pandemic levels even after 1 year. Specifically, metro ridership was relatively stable in different months before the pandemic, especially for commuters and students, with little seasonal variation. However, the outbreak of the pandemic significantly impacted metro ridership for all groups. In April 2020, compared to the pre-pandemic average, student ridership decreased by over 99%, while senior citizens and disabled

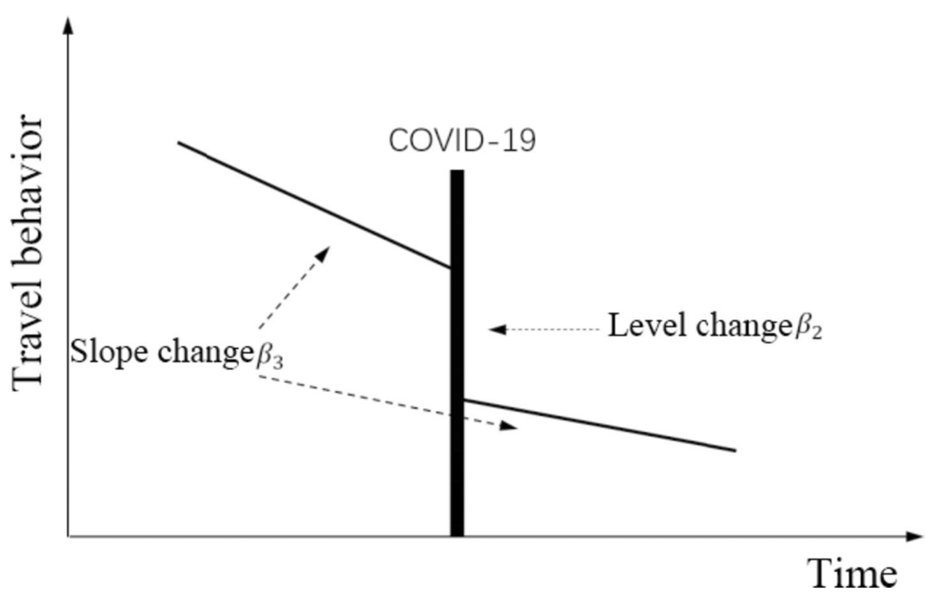

Fig. 2 Change in the level of intervention effect and change in slope

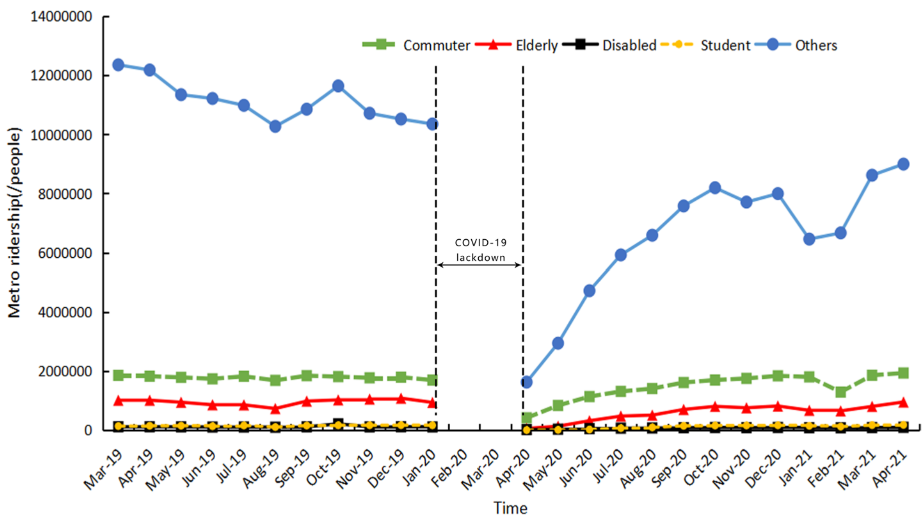

Fig. 3 Ridership resumed among different groups network-wide after the pandemic

individuals experienced reductions of 85% and 76%, respectively. Commuters had the smallest decline but still a substantial 76%. For all groups, the pandemic's impact was greater on weekends than on weekdays. As the pandemic was brought under control, the recovery of metro ridership for different groups also exhibited significant variations. Weekday commuters saw the earliest recovery, and school students quickly rebounded after the resumption of offline classes, with both groups returning to pre-pandemic levels after approximately 6 months of metro operation. However, weekend ridership only reached pre-pandemic levels after 1 year of operation. Like the recovery rate of weekday and weekend commuters, senior citizens' metro ridership on weekdays and weekends returned to pre-pandemic levels approximately 1 year after the resumption of metro services. However, ridership for disabled individuals and other groups remained at around 80% of the pre-pandemic average even after 1 year of metro operation.

Figure 4 illustrates the recovery of metro station ridership after the pandemic. Overall, ridership for all population groups showed a declining trend. However, there was a significant increase in commuter ridership in the eastern industrial development zone of Wuhan and a notable upward trend in metro ridership for school students in the southern part of the city on weekdays. Generally, the decline in ridership at metro stations within the third ring road (core area) was less severe than those outside the third ring road. The stations with the largest decline in metro ridership for all groups were also located outside the third ring road. The population groups that showed higher metro ridership after the pandemic compared to the pre-pandemic average were mainly commuters and school students. Among them, the regions with a significant increase in commuter ridership were concentrated in the eastern part of Wuhan, an area designated as a key strategic emerging industry development zone in recent years, with a substantial increase in the working population and a corresponding rise in commuting demands. The areas with a significant increase in school student ridership were concentrated in the southern part of Wuhan, where there is a lack

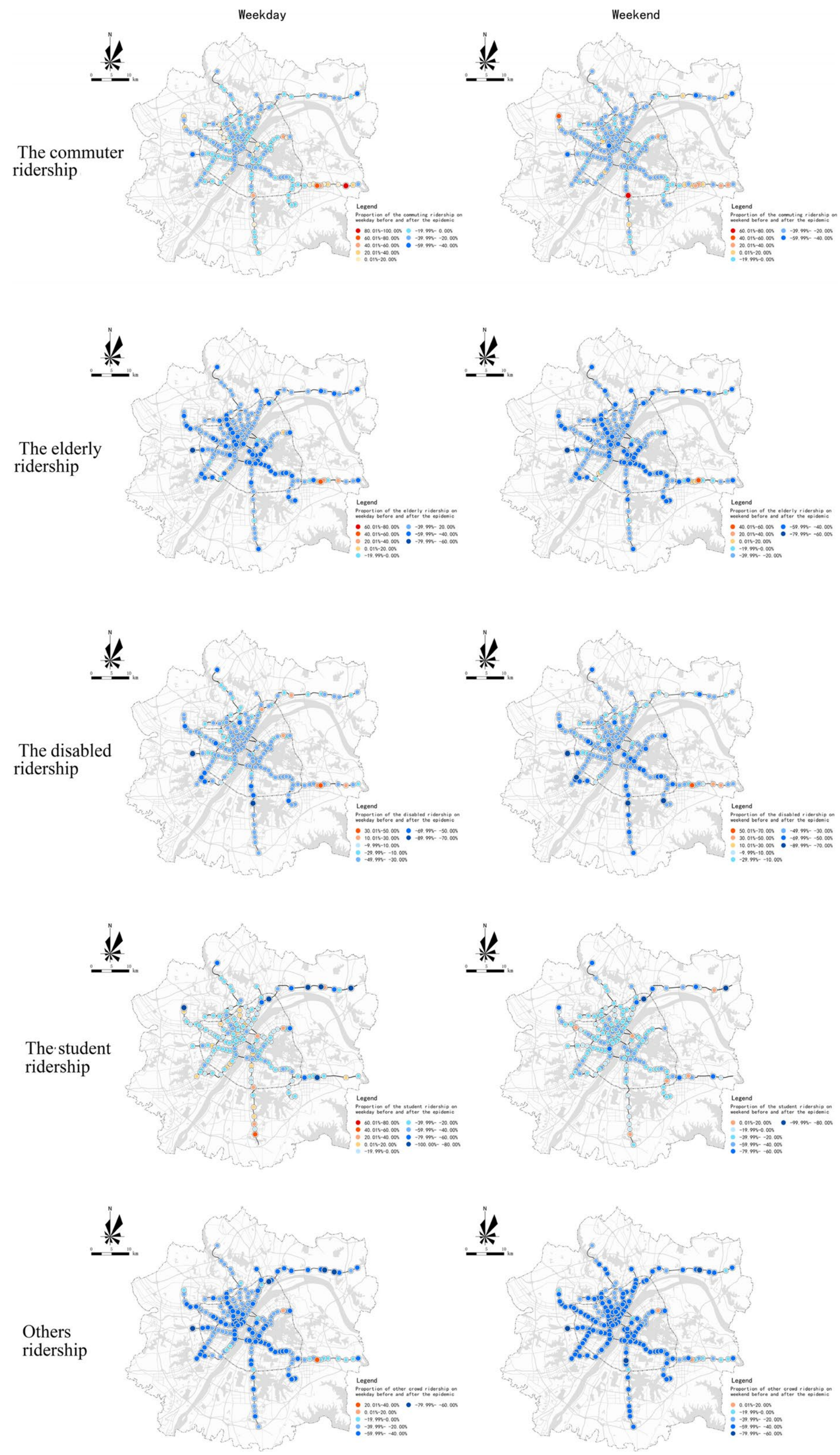

Fig. 4 Post-epidemic different groups of metro network-wide ridership resumed

of high-quality educational facilities and limited ground-based bus density due to the presence of lakes and waterways, making metro transportation more advantageous for school commuting.

Recovery characteristics of spatio-temporal travel patterns in different population groups after the pandemic

Figure 5 displays the recovery of spatiotemporal characteristics in different population groups after the pandemic. Due to the highly predictable nature of daily activities, the spatiotemporal characteristics of metro travel for residents after the resumption of metro operations were highly consistent with the pre-pandemic patterns. From the perspective of departure time, commuters and school students on weekdays exhibited significant bimodal patterns, with morning and evening peaks both before and after the pandemic. In contrast, travel patterns for other groups, such as disabled individuals and elderly citizens, were relatively dispersed, with more pronounced staggered travel patterns observed for the latter during the morning peak. Regarding travel duration, over 60% of residents had travel times within 30 min both before and after the pandemic, with school students showing the highest concentration of short-duration trips. Consistent with the travel time budget theory [48], over 90% of metro travelers spent less than 60 min on their journeys. On weekends, the travel duration for different groups

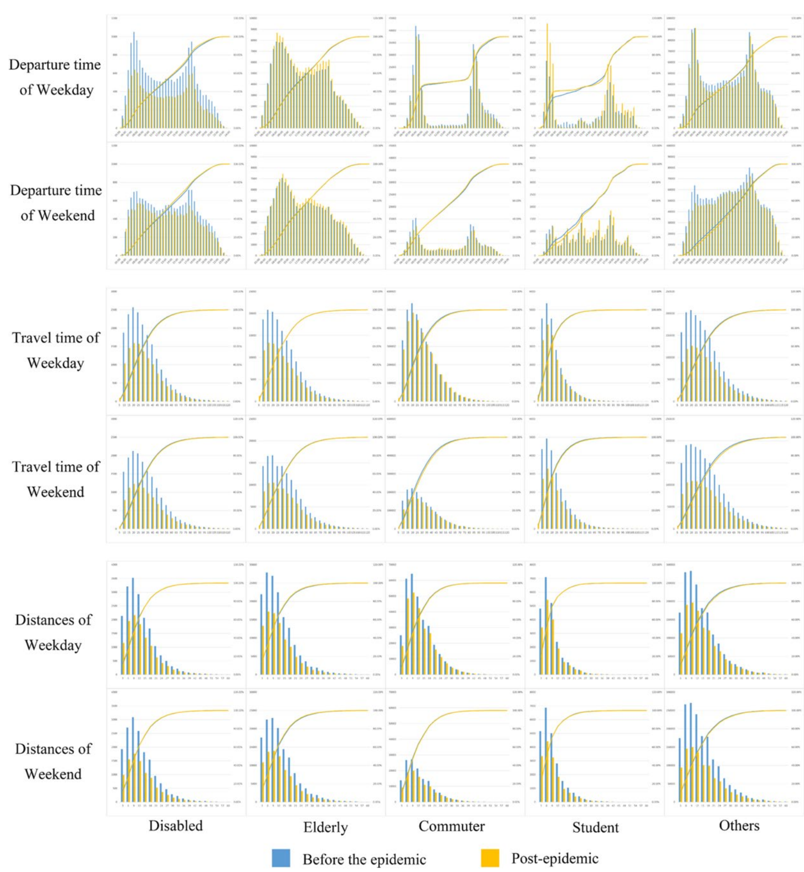

Fig. 5 Recovery of spatio-temporal characteristics of metro travel for different groups after the epidemic

showed a significant increase compared to weekdays, with the most notable increase observed for commuters. As for travel distance, school students had the shortest average travel distance, with over half of them traveling less than 6 km. Disabled individuals and commuters, on the other hand, had relatively longer average travel distances, with around 70% of their trips being within 15 km. Furthermore, there were also differences in travel distances between weekends and weekdays. Generally, weekend travel distances were higher than those on weekdays, with elderly individuals showing more significant changes compared to other groups.

Recovery characteristics of travel frequency in different population groups after the pandemic

Figure 6 illustrates the recovery characteristics of travel frequency in different population groups after the pandemic. Commuting travel frequency rebounded rapidly, while the impact on disabled individuals was more profound. Prior to the pandemic, except for the higher weekend travel frequency (2.89) compared to weekdays (2.80) among primary and secondary school students, other groups showed a trend of higher travel frequency on weekdays. Specifically, disabled individuals had the highest average travel frequency on weekdays, reaching 2.97 times, followed by primary and secondary school students and the elderly, while commuters had the lowest travel frequency, at 2.26 times. However, after the pandemic, commuting travelers' weekend travel frequency recovered the fastest, reaching pre-pandemic levels within the first month of lifting restrictions, and weekday travel frequency reached 2.02 times, recovering to pre-pandemic levels within six months. Primary and secondary school students' travel frequency was closely related to the resumption of offline classes. After resuming full offline teaching in August, their travel frequency gradually returned to pre-pandemic levels by September. On the other

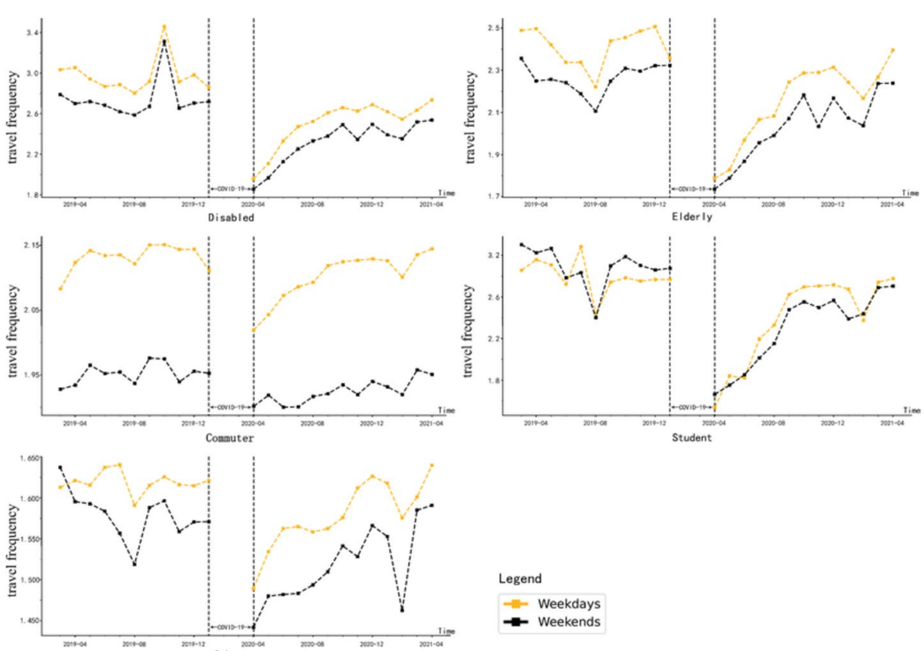

Fig. 6 Recovery of spatio-temporal characteristics of metro travel for different groups after the pandemic

hand, recovery was slower for vulnerable groups such as the elderly and disabled individuals. It took about a year after the resumption of metro operations for the travel frequency of the elderly to return to pre-pandemic levels. However, the travel frequency of disabled individuals remained at around 90% of pre-pandemic levels.

Impact mechanism of built environment on metro ridership recovery after the pandemic

We conducted a variance inflation factor (VIF) test, and all variables showed VIF values < 10, indicating the absence of multicollinearity among the variables. Tables 3 and 4 present the results of the ITS analysis for metro ridership. The pandemic led to a sharp decline in metro ridership, and after effective control of the pandemic, the metro ridership gradually recovered, but the recovery rate varied significantly among different population groups. Specifically, the pandemic caused an instantaneous and substantial drop in metro ridership in April 2020. The decline was drastic, with primary and secondary school students' ridership dropping by over 99%, the elderly by over 90%, and commuters experiencing the smallest decline, but still exceeding 75%. After effective control of the pandemic, on weekdays, the ridership for other population groups and commuters quickly recovered at rates of 2288 and 454 passengers per month, respectively. The recovery rates were followed by the elderly and primary and secondary school students,

Table 3 Results of ITS on weekday metro riderships for different population groups

Variable	The disabled	The elder	Commuter	The primary and secondary school students	Others
	Estimate	Estimate	Estimate	Estimate	Estimate
(Intercept)	486.700***	3710.071***	1676.958**	261.300***	27,592.900***
Time	5.846***	17.802	− 31.796	10.270***	− 574.941***
Exposure	− 495.202***	− 5617.950***	− 9170.290***	− 1070.000***	− 51,018.800***
Number of catering facilities	0.173*	− 0.881	− 3.688**	0.360*	3.053**
Number of corporate enterprises	0.046**	1.579***	3.098***	0.010	42.232***
Number of amenity facilities	− 0.760***	1.710	3.534	− 0.060	− 55.036***
Number of bus stop	0.570	− 3.070	− 115.295***	− 9.370***	− 283.555***
Number of permanent residents	− 13.512***	− 146.282***	373.286***	− 28.390***	154.054
Length of road	8.830**	− 12.019	313.617***	12.590**	− 553.517*
Plot ratio	64.693***	450.553***	2519.660***	28.270	11,718.510***
The degree of land use mixture	− 116.804***	− 1151.660***	− 3203.190***	− 26.740	− 3904.840
Number of road intersections	− 1.110	− 13.137**	− 139.327***	− 8.170***	− 247.278***
Transfer station	− 40.453**	− 111.722	398.854	56.300*	− 492.059**
Terminal	− 117.356***	− 1027.520***	− 871.504***	− 201.800***	− 8507.390***
Exit quantity	2.857*	4.739**	41.112	− 0.450	149.404
Distance from the city center	− 9.225***	− 46.047***	211.223***	3.350	− 143.720
Distance from the subcity center	8.084***	47.899***	− 154.243***	− 2.320	882.771***
House prices	1.932	600.784***	2772.407***	193.600***	8822.700***
Time: exposure	13.822***	221.444***	454.436***	45.440***	2287.844***

Table 4 Results of ITS on weekend metro ridership for different population groups

Variable	The disabled	The elder	Commuter	The primary and secondary school students	Others
	Estimate	Estimate	Estimate	Estimate	Estimate
(Intercept)	175.781***	1286.731***	541.441***	90.024***	14,370.000***
Time	3.556***	14.666***	− 1.573	5.858***	− 266.100***
Exposure	− 180.703***	− 2043.040***	− 1823.120***	− 426.048***	− 22,820.000***
Number of catering facilities	0.026	− 0.641**	− 1.016***	− 0.039	0.311
Number of corporate enterprises	0.029	0.584***	0.711***	0.145***	20.220***
Number of amenity facilities	− 0.182**	1.117**	− 0.235	0.081	− 25.630***
Number of bus stop	0.196	− 0.854	− 17.627***	− 3.321***	− 96.110**
Number of permanent residents	− 7.441***	− 55.315***	27.435*	− 18.733***	− 187.700
Length of road	1.544	− 15.096*	28.246**	6.487**	− 488.700***
Plot ratio	26.406***	168.332***	573.424***	51.394***	5163.000***
The degree of land use mixture	− 37.904***	− 337.527***	− 222.122**	− 7.774	547.800
Number of road intersections	− 0.078	− 0.529	− 17.590***	− 3.004***	− 66.140*
Transfer station	− 13.135*	− 40.237	29.244	22.718*	253.800
Terminal	− 41.449***	− 358.721***	− 294.810***	− 75.806***	− 3508.000***
Exit quantity	0.713	3.074	− 5.083	− 2.488**	− 10.520
Distance from the city center	− 3.460***	− 18.170***	13.684**	− 2.896**	− 146.700**
Distance from the subcity center	3.123***	21.483***	11.609**	3.121**	483.900***
House prices	− 2.799	172.346***	381.751***	82.922***	2301.000***
TIME: exposure	3.867***	75.339***	81.177***	15.259***	1010.000***

Exposure: instantaneous effects; Time: exposure: long-term effects

Note: ***, **, and * mean significant at the 1%, 5%, and 10% levels, respectively

while the slowest recovery rate was observed among disabled individuals, with only 13.8 passengers per month on weekdays. Furthermore, there were significant differences in the recovery rates between weekdays and weekends. Weekdays showed a notably higher recovery rate than weekends. Among the groups, the difference in recovery rates was most significant for commuters, with weekend ridership reaching only 17.86% of the weekday level. The next significant differences were observed for disabled individuals (27.98%), primary and secondary school students (33.58%), and the elderly (34.02%). The smallest difference was seen in other population groups, with weekend ridership recovering at 44.15% of the weekday level.

From the perspective of the built environment's impact on metro ridership recovery, there are significant differences in the recovery among different population groups, both on weekdays and weekends. Regarding density, the plot ratio shows a significant positive effect on metro ridership for all groups on weekdays and weekends. However, the resident population, apart from commuters, exhibits a significant negative impact on disabled individuals, the elderly, and primary and secondary school students. Similar to the resident population, land use mix also demonstrates a significant negative impact on metro ridership for disabled individuals, the elderly, and commuters on both weekdays and weekends. In terms of design, the number of road intersections shows a significant negative effect on metro ridership for most groups. However, the road length exhibits a significant positive impact on primary and secondary school students and commuters and a significant positive impact on metro ridership for disabled individuals on weekdays. Regarding destination accessibility, the number of companies and enterprises shows a significant positive impact on metro ridership for commuters, the elderly, and other groups on weekdays and weekends. On the other hand, the number of life service facilities exhibits a significant negative impact on metro ridership for disabled individuals and other groups on both weekdays and weekends. The distance to the city center has a positive impact on metro ridership for commuters on weekdays but a negative impact on most other groups. Conversely, the distance to the city subcenter shows a significant positive impact on metro ridership for most groups, except for commuters on weekdays. Additionally, the number of bus stations, used to measure the convenience of multimodal transportation, shows a significant negative impact on metro ridership for commuters, primary and secondary school students, and other groups on both weekdays and weekends.

Regarding metro station characteristics, transfer stations show a significant positive impact on metro ridership for primary and secondary school students on both weekdays and weekends, but they have a significant negative effect on disabled individuals. Additionally, terminal stations exhibit a significant negative impact on metro ridership for all population groups on both weekdays and weekends. The number of entrances and exits at metro stations shows a significant positive impact on metro ridership for disabled individuals on weekdays and has a significant negative impact on metro ridership for primary and secondary school students on weekends. Regarding socio-economic characteristics, housing prices have a significant positive impact on metro ridership for most population groups, except for disabled individuals, where they show no impact.

Economic evaluation of subway operation after the pandemic

Table 5 provides an overview of Wuhan Metro's operating costs and revenues from 2019 to 2021, as reported by the Wuhan Metro Group. Operating costs primarily include expenses related to labor, energy, maintenance, and depreciation, while revenues comprise income from primary resource development, operational business activities, and other sources. In 2019, Wuhan Metro Group's main income sources were primary resource development and operational business revenue, totaling 5.548 billion RMB and 2.572 billion RMB, respectively, resulting in a total income of 9.028 billion RMB. However, in 2020, the pandemic's impact was evident, leading to a decrease of 228 million RMB in primary resource development income and 362 million RMB in operational business revenue. This translated to a total income of 8.474 billion RMB, a reduction of 554 million RMB, which imposed significant financial strain. Fortunately, by 2021, effective pandemic control measures had been implemented, resulting in a rapid recovery of subway ridership to 80% of pre-pandemic levels within 6 months. As a result, Wuhan Metro Group's overall income increased by 1.696 billion RMB. Primary resource development income and operational business revenue also saw gains of 245 million RMB and 1.258 billion RMB, respectively. The pandemic caused notable decreases in other

Table 5 The operating income of Wuhan Metro's rail transit operations over the past 3 years

Item	2019		2020		2021	
	Amount (RMB ten thousand)	%	Amount (RMB ten thousand)	%	Amount (RMB ten thousand)	%
Main operating income						
Primary resource development	554,856.60	61.46	532,047.41	62.79	556,544.84	54.73
Operating business	257,269.27	28.50	221,042.47	26.09	346,783.46	34.10
Other operating income						
Leasing business	54,583.95	6.05	33,412.41	3.94	42,849.02	4.21
Advertising agency	1415.18	0.16	1060.11	0.13	257.72	0.03
Interface fee income	3303.32	0.37	1323.62	0.16	836.69	0.08
Capital use fee income	21,653.56	2.40	20,216.75	2.39	19,107.17	1.88
Service fees	5484.40	0.61	–	–	–	–
Others	4270.02	0.47	38,273.42	4.52	50,588.80	4.97
Total	902,836.30	100.00	847,376.19	100.00	1,016,967.70	100.00

subway income sources in 2020, including a 94 million RMB reduction in leasing business income. Therefore, in the post-pandemic era, it becomes essential to provide safe, convenient, and comfortable subway services to maintain ridership at a consistently high level, ensuring financial stability and promoting the subway system's sustainable development.

Discussion

To formulate sustainable metro operation strategies and mitigate the adverse impacts of the pandemic on different population groups, especially vulnerable ones, government decision-makers, and planners need reliable and comprehensive data, along with a comprehensive estimation of the recovery of different population groups' spatiotemporal characteristics after the pandemic.

Our research findings provide comprehensive evidence of metro ridership recovery after the pandemic, which offers guidance for metro operations. We observed three characteristics in the spatiotemporal recovery of metro travel. Firstly, regarding the time effect of metro ridership recovery, during the initial stage of metro resumption, the ridership was only about 11.93% of the pre-pandemic average, which then gradually increased at a monthly rate of around 11%. After 6 months, the metro ridership reached approximately 80% of the pre-pandemic level and stabilized thereafter. This pattern aligns with the recovery trend observed in Seoul after the impact of Middle East respiratory syndrome (MERS). When there were a significant number of MERS cases and fatalities, people tended to avoid using public transportation for their commutes. However, as MERS became effectively controlled, passenger patterns gradually returned to normal [49]. Secondly, due to the highly regular spatiotemporal patterns of residents' travel, the proportions of metro ridership before and after the pandemic showed high consistency throughout the day, with distinct dual peaks during morning and evening rush hours and relative dispersion during other periods. Additionally, the recovery of metro ridership differed between weekdays and weekends, with the recovery rate on weekends significantly lower due to decreased travel demands for commuting and going to school.

Lastly, due to the pandemic's impact, Wuhan's metro operating income in 2020 decreased by 5.546 billion yuan, representing a 6.14% decline. This is consistent with the findings of most existing studies, highlighting that the decrease in metro ridership caused by the pandemic intensified the financial pressure on metro operating departments [3, 37, 49]. Balancing the reduction of metro operational costs while meeting the commuting needs of residents is a significant challenge in the post-pandemic era. In this context, we suggest that in the post-pandemic era, metro frequencies can be maintained at higher levels during weekday morning and evening rush hours, while during other time periods and weekends, frequencies can be appropriately reduced in response to ridership. As the reopening progresses, metro frequencies can gradually increase. After 6 months of reopening, frequencies during periods other than morning and evening rush hours can stabilize at around 80% of pre-pandemic levels, and we can gradually adjust the train frequency in line with the dynamics of metro ridership recovery. Furthermore, in order to ensure the safety of metro passengers, Wuhan city implemented stringent security measures during the height of the pandemic, which included enforcing social distancing, conducting temperature checks, and requiring mask-wearing [50]. These safety measures effectively contained the spread of the virus and facilitated a rapid recovery in metro ridership. Therefore, in the event of similar pandemics in the future, implementing similar safety measures can enhance the resilience of metro travel and ensure the safety of metro ridership.

This finding also indicates significant disparities in metro ridership recovery among different population groups, prompting us to pay special attention to vulnerable groups such as disabled individuals and the elderly, who may suffer disproportionately from the pandemic [10, 11, 14]. The pandemic had a devastating impact on metro ridership for all population groups in the short term. After effectively controlling the pandemic, metro ridership for commuters and school students can recover to pre-pandemic levels in a relatively short time. However, compared to other population groups, the pandemic's impact on disabled individuals and the elderly is more profound.

This corresponds to the majority of existing literature [51, 52]. In China, the outbreak of the pandemic led to the development of a smartphone-based health system by the government for monitoring residents' health, requiring people to present their health information using smartphones when traveling. However, some elderly individuals, due to limited technological proficiency, still struggle to regain their mobility after travel restrictions are lifted, which also hinders the recovery of elderly people's metro travel [51]. Furthermore, the impact on disabled individuals has been more severe than on the elderly, as 1 year after the metro resumed operations, the metro ridership of disabled individuals has yet to return to pre-pandemic average levels. This further substantiates existing research findings that, compared to other population groups, disabled individuals are more severely affected by more severe outbreaks of the pandemic, and they face a higher risk of mortality due to COVID-19 [10, 52]. Furthermore, policies such as social distancing have exacerbated the travel challenges for disabled individuals. Their inability to travel has also increased their difficulty in accessing food and medication, further intensifying the impact of the pandemic on disabled individuals. This highlights the need to prioritize assistance and support for vulnerable groups, such as disabled individuals and the elderly, to reduce the sustained effects of the pandemic on them. Firstly, it is crucial to develop more effective travel control policies to ensure convenient travel for elderly and disabled individuals who may not be well-versed in using technology. Secondly, there should be a concerted effort to enhance the construction of accessible transportation infrastructure, thereby facilitating the mobility of the elderly and disabled. This involves reinforcing the implementation of accessibility standards within metro stations and improving accessible infrastructure in the vicinity of these stations. Additionally, there must be a specific focus on ensuring access to healthcare, food, and other essential necessities for disabled and elderly individuals during a pandemic. This is instrumental in strengthening their ability to cope with health-related risks.

These results also confirm that the built environment significantly influences metro ridership recovery after the pandemic, providing detailed evidence for post-pandemic metro operation strategies and epidemic prevention measures. Unlike the pre-epidemic study [31, 50–52], our findings show that residential population density has a significant negative impact on metro ridership for most population groups under the influence of the pandemic. This is likely due to the increased risk of infection caused by excessive population aggregation. It reminds us to carefully consider existing compact urban development strategies and equip areas with high population density with adequate medical and other public service facilities to enhance urban resilience in dealing with infectious diseases and other health threats. The impact of land use mix on metro ridership also differs significantly from most previous studies [40], showing a significant negative influence for all population groups. This is because a higher land use mix implies more well-equipped public service facilities and higher attractiveness, often leading to higher human flow and thus a higher probability of infection. However, land use mix is an essential means to enhance urban vitality and plays a crucial role in maintaining urban attractiveness and promoting economic development. This study is analogous to the case in Shenzhen, where high land use mixing promotes individual travel [48]. However, residential areas with dense and mixed-use built environments are often located in city centers, making it challenging to provide sufficient space for various types of travel. Therefore, high land use may not necessarily promote health when it is difficult to accommodate a variety of travel modes. Therefore, we suggest installing infrared temperature screening and other facilities in areas with high land use mix to ensure regional safety. The negative impact of catering facilities on metro ridership further confirms the challenges faced by the catering industry during the pandemic, as observed in previous studies [37]. Thus, the government should implement measures to support the catering sector in coping with the pandemic's impact, and catering businesses can enhance their attractiveness by adopting contactless meal services and other measures. Furthermore, the number of companies, distance to urban subcenters, and other factors show significant positive effects on metro ridership for most population groups. Strengthening epidemic prevention and control measures in densely populated company areas and urban subcenters can be more effective in managing the spread of infections during the post-pandemic period [3].

Certainly, this study has certain limitations. Firstly, although we used a quasi-natural experiment to explore the recovery of subway ridership for different population groups and the role of the built environment, the model still cannot establish causal relationships between the pandemic, the built environment, and subway travel behavior among different groups. In the future, more rigorous experimental designs will be needed to obtain more robust conclusions. Secondly, this study did not consider residents' socioeconomic attributes, which have been proven to be significant factors influencing subway travel behavior. Future research should incorporate questionnaire surveys to combine small-sample survey data with large-scale data, such as subway card swiping data, to obtain more comprehensive research results. Additionally, this study was conducted in Wuhan, a densely developed city that implemented the strictest lockdown measures during the pandemic. In the future, it is necessary to include cities with different levels of density and varied pandemic response measures as research subjects to obtain more generalizable results. Nevertheless, our data and methods are designed to provide effective analytical tools for exploring the impact of the COVID-19 pandemic on subway travel behavior among different population groups and the role of the built environment. These tools can support government decision-makers and planners in formulating effective subway operation and epidemic prevention measures in the post-pandemic.

Conclusions

By utilizing long-term subway travel data for different population groups before and after the outbreak of the pandemic, we have observed that all groups experienced significant impacts on their travel patterns during a certain period following the outbreak. With effective control measures in place, commuter and primary/secondary school subway ridership rebounded swiftly. However, 1 year after the pandemic was brought under control, the travel levels for individuals with disabilities and the elderly have yet to recover to pre-pandemic levels. Furthermore, employing an Intelligent Transportation System (ITS) analysis, we have discerned that the built environment surrounding subway stations significantly influences the recovery of ridership among diverse groups. Among these factors, building density, land use mix, and the presence of dining establishments exhibit pronounced negative impacts on the recovery of subway ridership for most demographic groups. Conversely, the number of corporate entities and entrances/exits at subway stations display notable positive effects on ridership recovery for several groups. Based on our research findings, we propose that post-pandemic adjustments to train frequencies should be made in accordance with the recovery of travel patterns. Additionally, we advocate for a focus on vulnerable groups, such as the elderly and disabled individuals. Diverse measures should be taken to enhance their ability to withstand the risks posed by the pandemic. Finally, we recommend a cautious reconsideration of existing compact urban development strategies. Population-aggregated areas should be equipped with comprehensive medical and other public service facilities to enhance urban resilience in the face of infectious disease threats.

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JP and XL were major contributors in writing the manuscript. SG also conducted the experimental analysis and comparison. All of them were the main authors of the manuscript. HY guided and revised the paper. All authors read and approved the final manuscript.

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Availability of data and materials
The data that support the findings of this study are available from the Wuhan Transportation Development Strategy Institute, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission from the Wuhan Transportation Development Strategy Institute.

Declarations

Competing interests
The authors declare that they have no competing interests.

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