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How Determinants Affect Transfer Ridership between Metro and Bus Systems: A Multivariate Generalized Poisson Regression Analysis Method

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Abstract: Understanding the determinants of transfer ridership is important for providing insights into improving the attractiveness of transit systems and building reliable and resilient metro stations. This study focuses on the transfer ridership between bus and metro systems under different dates and severe weather conditions to quantify the impacts of various attributes on the transfer ridership of different transfer modes (metro-to-bus and bus-to-metro). A multivariate generalized Poisson regression (GPR) model is applied to investigate the effects of critical factors on the transfer ridership of different transfer modes on weekdays, holidays, and typhoon days, respectively. The results indicate that the transfer-related variables, real-time weather, socioeconomic characteristics, and built environment significantly affect the transfer ridership. Concretely, the influence of socioeconomic and demographic factors on transfer ridership is the most significant on different types of dates, which is approximately 1.19 to 9.28 times that of the other variables. Weather variables have little effect on transfer ridership on weekdays, but they have a more significant impact on the transfer ridership on holidays and typhoon days. Specifically, during typhoons, transfer ridership is more affected by the weather factors: the coefficients are about 2.36 to 4.74 times higher than that in the other periods. Moreover, under strong wind speed, heavy rain, and high-temperature conditions, transfer ridership of the metro-to-bus mode significantly increases. In contrast, transfer ridership of the bus-to-metro mode rapidly decreases. Additionally, the peak hours have a strong positive influence on the transfer ridership, and the average hourly transfer ridership during peak hours is 1.16 to 4.02 times higher than that during the other periods. These findings indicate that the effect of each factor on transfer ridership varies with dates and transfer modes. This can also provide support for improving metro stations and increasing the attractiveness of public transport.

Keywords: metro and bus system; transfer ridership; generalized Poisson regression model; intelligent transportation systems; connectivity of different transportation systems; statistical analysis

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1. Introduction

With the rapid development of urbanization and continuous growth in the population, the demand for public transportation is also gradually increasing [1]. Passengers usually cannot reach their destinations directly by a single transport mode, and transfers are often essential, especially for those traveling medium–long distances, who must often make one or more transfers [2,3]. Therefore, the transfer between different transport modes has become an integral part of public transport systems [4]. Although there are many feeder modes connected to metro networks, such as walking, bicycling, and sharing electric bikes, buses are still the main feeder mode for passengers traveling to and from metros [5–8]. Accordingly, this study focuses on the transfer between metro and bus systems. The definitions of the two transfer modes—namely, metro-to-bus and bus-to-metro—can be found in [9]. In this paper, the transfer ridership of the metro-to-bus mode is measured in terms of the number of transfer passengers from metro to bus per hour, and the transfer ridership of the bus-to-metro mode is measured in terms of the number of transfer passengers from bus to metro per hour. A complicated transfer system usually connects a metro network with a feeder bus network and can facilitate travelers, increase the accessibility of metros, and reduce congestion and environmental pollution [10,11]. However, the transfer is unpopular among passengers because it increases travel time and reduces travel efficiency [12,13]. Therefore, it is critical to identify the determinants of transfer ridership to further propose targeted improvement measures to cope with the adverse impacts of various factors on transfer ridership [14]. This can help us better understand the transfer ridership, improve the transfer experience of passengers, and ultimately increase the attractiveness of public transportation [15].

Transfer ridership is affected by multiple factors [9]. Among them, the impact of weather on the transfer ridership cannot be ignored [16]. This is because transfer trips, as an important part of public transportation, are usually exposed to an outdoor activity that can be greatly affected by the weather [17]. Moreover, severe weather conditions may influence the service efficiency of transfer systems, increasing the travel time of transfer passengers [3]. Existing mainstream-related studies have mainly focused on the impact of weather on bus ridership or metro ridership. Many researchers are concerned about the impact of weather on other aspects of public transportation, such as the travel routes, mode shifts, and destination choices [18,19]. These studies have involved different weather conditions and various public transport modes [20,21]. The influence of weather on public transportation has attracted significant attention [22]. However, due to a lack of available datasets, there is less information available on the impact of weather on the transfer ridership. Studies have rarely explored the impact of various factors on the transfer ridership both qualitatively and quantitatively.

Moreover, besides the weather factors, the transfer ridership is also influenced by other factors, such as socioeconomic factors and built environment factors [23]. Some existing studies consider the impact of the travel time, travel cost, environmental factors [24–27], and transfer penalty on the transfer during the morning peak period [12,17]. However, these studies were mainly based on survey data, with a limited sample coverage area and small sample size [28]. Furthermore, they did not investigate the effect of weather conditions and socioeconomic levels on transfer ridership on fine-grained temporal scales.

As a result, little is known about the relationship between the variations in weather factors and the transfer ridership and the mechanism by which various factors impact the transfer ridership, especially how the impact of weather variables on transfer ridership in extreme weather conditions differs from that under normal conditions, and how the impact of each factor on transfer ridership differs between holidays and workdays. Furthermore, it is important to explore the impact of various factors on transfer ridership to understand the relationship between various factors (such as weather conditions) and transfer travel. This also facilitates the development of short-term transit management measures for enhancing resilience to weather changes and responding to sudden increases or decreases in the transfer ridership. It is important to determine the factors that provide more accurate weather information and traffic guidance services to transfer travelers.

Therefore, to fill the research gaps and enrich the transfer-related literature with significant findings on transfer ridership, a generalized Poisson regression (GPR) model is applied to investigate the influence of various factors (especially weather factors) on transfer ridership from both qualitative and quantitative perspectives. We collected a multi-source dataset, which includes the transfer-related characteristics, weather conditions, socioeconomic elements, and metro-station built environment. Combined with the temporal factors (peak hours on weekdays, holidays, and weekends), the scale of analysis (hourly), and transfer modes (metro-to-bus and bus-to-metro), we explore the dynamic impact of these factors on the transfer ridership on a fine-grained temporal scale. This study makes three unique contributions.

- This study analyzes various factors influencing the transfer ridership using a massive smart card dataset and global positioning system (GPS) coordinate data at a fine-grained temporal scale. A comprehensive understanding of different factors that affect the transfer ridership at the station level is obtained.
- We explore the impact of real-time weather on transfer ridership by the GPR model, which is highly important for understanding the relationship between weather and transfer ridership. We identify the incentive/disincentive factors for transfer passengers, which can help decision-makers reduce the adverse effects of factors for the subsequent planning and construction of new metro stations.
- This paper analyzes the difference in the influence of the same factors on the transfer ridership under different weather conditions and different types of dates. We investigated the differences in the impact of each factor on transfer ridership during typhoon weather, holidays, and weekdays.

The organization of this paper is as follows. Section 2 summarizes the relevant literature. Section 3 describes the data and study area. Section 4 puts forward the models and elaborates on analytical approaches. Section 5 discusses the analysis results and summarizes the significant findings of the research. Section 6 concludes the study and points out future work directions.

2. Literature Review

The transfer network is a pivotal component of the public transport system, effectively coupling the metro system with the bus system and providing multi-directional services [23], which can serve passengers who travel medium–long distances [29]. However, the transfer also causes many inconveniences for passengers, such as adding extra travel time [13]. In this context, it is meaningful to determine the influencing factors and weights of the transfer ridership to achieve the targeted improvement of the transfer system and increase the attractiveness of public transportation [30]. Therefore, this study aims to identify the determinants (such as weather factors) of the transfer ridership to achieve more interesting and meaningful findings that will enrich the existing literature. In this section, we summarize the relevant literature and highlight important findings that can lay the foundation for subsequent studies.

Since there are few studies discussing the determinants of transfer ridership, this study refers to the literature on the impact of weather on transport ridership and related studies on transfer analysis. The important literature and main findings are summarized in Table 1 and cover two main aspects: existing studies on the impacts of various factors on the transfer are listed, and the research on the impact of weather on transport ridership is outlined.

2.1. The Transfer-Related Studies

To further identify the determinants of transfer ridership, we reviewed existing studies. There is scarce literature on the impact analysis of transfer ridership, and the subjective analysis of transfer is mainly based on the data samples obtained from surveys [24]. Most studies have discussed the impact of the transfer time, travel cost, and station facilities such as information availability and elevator availability and evaluated the penalized factors [12,13,17]. Among them, the transfer time is a very important factor that affects the transfer disutility of the overall trip [13]. Most studies have focused on the influence of internal factors (such as the transfer time and travel cost) on transfer travel [36]. Few studies have explored the effect of external factors (such as weather conditions) on transfer ridership [37]. More importantly, the existing related studies have mainly focused on the transfer penalties, and the transfer ridership is yet to be explored in depth [17].

Table 1. The summary of related studies.

Authors	Research Subjects	Data and Resource	The Key Findings	The Critical Factors	Methods
(1) The transfer-related studies					
Cheng et al. [31]	The effects of perceived values, free bus transfer, and penalties on the metro–bus transfer users' intention	Questionnaire study survey data, samples include potential and retained users of the metro system	Perceived transfer penalties, perceived values, and free bus transfer all influence metro–bus transfer intentions. Perceived value is the most essential determinant of behavioral intention and can mediate the relationship between free bus transfer and transfer intentions.	perceived value, transfer penalties, FBT, and behavior intention.	Systematic sampling method, the perceived value theory
Navarrete & Ortúzar [17]	Subjective valuation of the transit transfer experience	Stated choice surveys	The most penalized time was the transfer wait time, the next largest time component disutilities were those associated with the initial and final walk times.	Walk time, wait time, travel time, transfer walk time, transfer wait time	The mixed logit (ML) model
Schakenbos et al. [13]	Valuation of a transfer in a multimodal public transport trip	Stated preference experiment	Total disutility during the transfer depends on the total time, the distribution of the time spent, and headway. The most optimal transfer time is found to be 8 min.	Travel time, transfer time, headway, costs, and station facilities	Mixed logit models
Espino & Román [12]	Valuation of transfer for bus users	Stated Preference experiment	The improvement opportunities for transport systems should focus on the reduction in the transfer cost except for individuals of class 2 and improving the level of service.	Travel time, travel cost, headway, transfer waiting time, trip purpose	Mixed logit and latent class (LC) models
Yang et al. [24]	Metro commuters' satisfaction with multi-type access and egress transferring groups	Survey data	With two transfers between bus and metro, transit-metro-transit users indicate that the weak point in the access stage is the crowded spaces on buses. Transit-metro-transit users value bus on-time performance.	Personal attributes, journey details (transfer/commute time ratio), access service, and egress service	Logistic model

Table 1. *Cont.*

Authors	Research Subjects	Data and Resource	The Key Findings	The Critical Factors	Methods
(2) Effects of weather on the transport ridership					
Zhou et al. [32]	Impacts of weather on public transport ridership	Smart card data, meteorological records	The weather has more influence than others on public transportation, metro station in urban are more vulnerable to outdoor weather.	Bus/metro ridership, wind speed, rainfall, humidity	Multivariate regression models
Liu et al. [33]	The influence of weather on an individual's travel mode choice	The travel data is Swedish National Transport Survey Data. The Swedish Meteorological data.	The impacts of weather differ in different seasons and regions. Winter increases the possibility of individuals choosing to walk and public transport and decreases the possibility of individuals choosing cycling, the opposite seems to be true for summer.	Seasons, trip distance/ purpose, precipitation, transformed temperature, car ownership	Multinomial logit models
Miao et al. [34]	Extreme weather influences transport ridership	The Global Historical Climatology Network data, the UTA bus ridership	Bus stop shelters have a modest effect on mitigating ridership losses resulting from these adverse weather conditions. Public transport can attract more ridership on extreme weather days.	Bad weather days, number of transfers, stop density, income, race, age	Panel regression model
Liu et al. [35]	The impacts of weather variability on an individual's daily activity-travel patterns	Datasets from the Swedish National Travel Survey and the Swedish Meteorological	Commuters are much less sensitive to weather changes than non-commuters. Variation of monthly average temperature greatly influences individual travel behavior than the variation of daily temperature relative to its monthly mean.	Endogenous variables, trip purpose, commute distance, weather variables	Structural equation models

2.2. Effects of Weather on the Transport Ridership

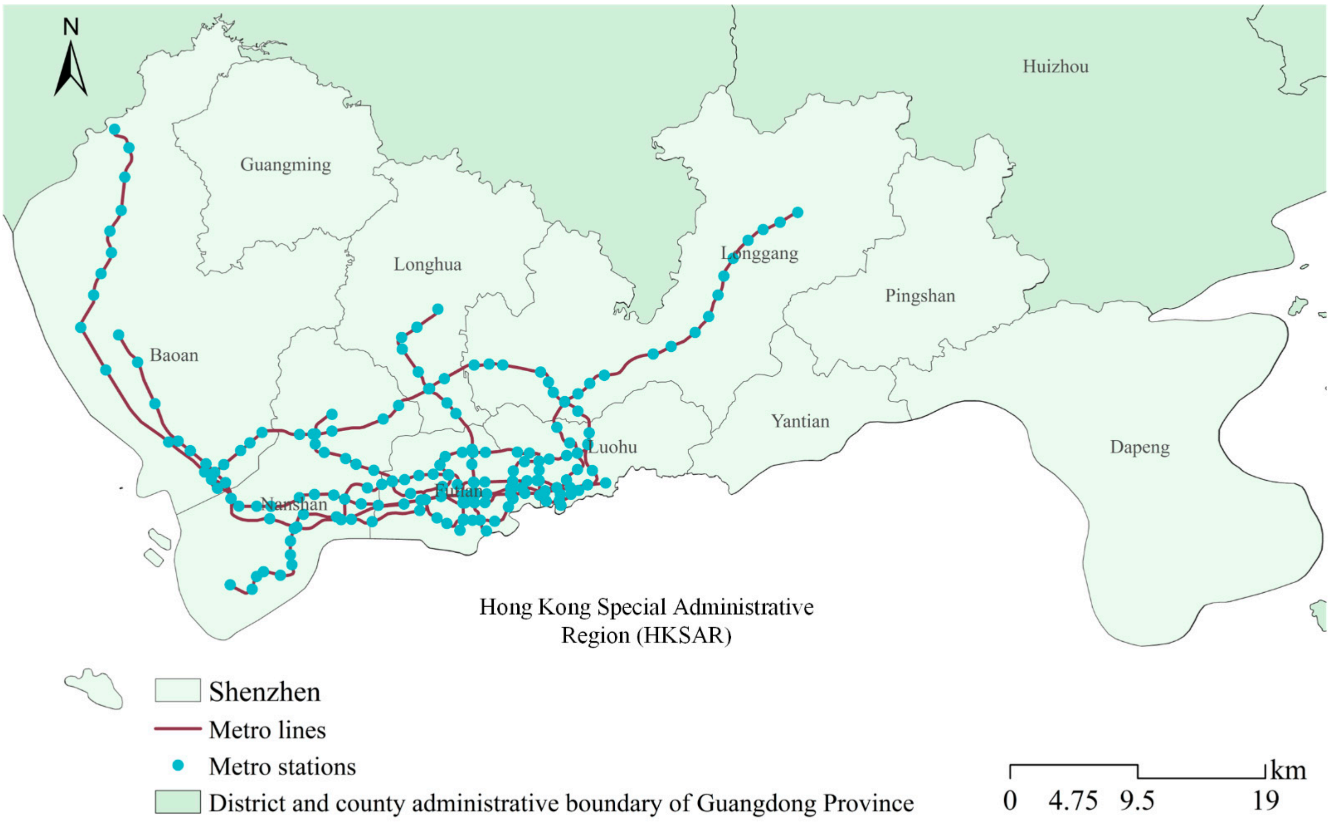
To the best of our knowledge, there is no consensus on the impact of weather factors on the transfer ridership. Because of the limitation of available data, the impact of weather on the transfer ridership has not been further explored. For example, Taylor et al. [38] only reported that weather has an impact on the transfer penalties. Many passengers only transfer in extreme weather because of the addition of walking and waiting times [39]. Moreover, these related studies did not analyze the impact of weather on the transfer ridership from both qualitative and quantitative perspectives [40]. In contrast, the impact of weather factors (such as rain, wind, temperature, and snow) on transport ridership has been well studied [3]. Related studies have reported that weather factors significantly influence ridership and travel demand [41,42]. The main studies and important findings are summarized in Table 1 below. The impact of weather on public transport travel is complex [16]. Each weather factor has a significant impact on bus and metro travel [43]. In particular, strong winds, rainfall, and high temperatures have a prominent effect on public transportation [41–45]. Furthermore, the influence on weekends is higher than that on working days [16]. The impact of weather on public transportation trips also varies on different days of the week [24]. Rainfall and low temperature are negatively correlated with ridership during weekends or leisure trips [42]. These studies accounted for the variation in the travel demand caused by real-time fluctuations and average weather changes [46]. They also demonstrated that travel ridership usually changes with the public transport modes, regions, weather conditions, and dates (weekends or workdays) [47]. In addition, the research results proved that adverse weather conditions can have both positive and negative effects on public transport ridership [48].

Therefore, inspired by existing studies on the effect of weather on transport ridership, this study also analyzes the effect of weather variables on transfer ridership. However, there are still some limitations, mainly in two respects. First, these studies mainly focused on the internal factors of the transfer system and did not discuss the impact of external factors, especially the weather, on the transfer ridership in detail. Second, the datasets obtained through surveys had certain limitations, with relatively small sample sizes. Moreover, the survey data can only ascertain the average influence of various factors on the transfer ridership, and it is difficult to obtain the real-time effects. An effective alternative to survey data would involve using a large dataset recorded by an automatic fare collection system. This method has been widely used to discuss the impact of weather on public transport ridership, and high-quality samples usually contribute to satisfactory results.

Consequently, to clarify the relationship between transfer ridership and various factors (such as the weather) and enrich the existing literature, in this study, we discuss the impact of external weather conditions and internal system attributes on transfer ridership. A transfer-related dataset is obtained by mining large-scale smart card data, metro and bus station coordinates, and public transport GPS data. Combined with the modeling methods reported in the literature, based on the hourly transfer time data and hourly weather, and other related data, we explore the impact of various factors on the transfer ridership of the metro-to-bus and bus-to-metro modes on a fine-grained time scale.

3. Study Area and Data

To investigate the effects of multiple variables, such as weather, on transfer ridership, the multisource dataset is utilized in this study. The multisource dataset includes smart card data from the automatic fare collection system of public transport, meteorological data recorded by the China Meteorological Administration from Shenzhen, China, in October 2017, and socioeconomic and demographic data from the National Statistics Bureau. The raw data was collected in October 2017. The multisource data were pre-processed and integrated for the follow-up study. This section provides an overview of the study area and public transportation network in Figure 1. The details of data sources and data processing, as well as the distribution characteristics of significant variables are also described.



Population and climate condition of Shenzhen in 2017	
Total population situation	
Population	over 12 million
The population density	over 6000 people per square
Annual average weather	
Temperature	23.6 °C
Cumulative rainfall	1967.1 mm
Average climate	subtropical monsoon climate, warm and humid.
Weather in October	
The average temperature	25.8 °C
The total rainfall	102.2 mm
The maximum temperature	34.2 °C
The lowest temperature	17.6 °C

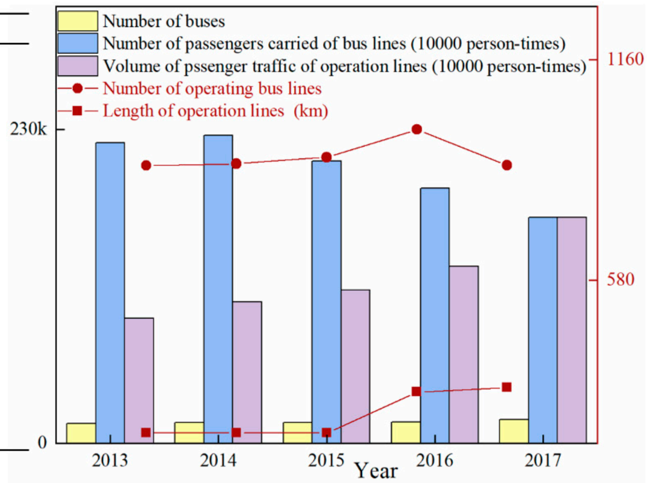


Figure 1. Geographical location, climate characteristics, and travel demand in Shenzhen, China.

3.1. Study Area

Shenzhen is selected as the study area in this paper due to the prevalence of public transport, a relatively high travel proportion of passengers using smart cards, and a dense public transport network. The main reasons are as follows: first, Shenzhen, located in the Pearl River Delta, is adjacent to the Hong Kong special administrative region and is one of the fastest growing and most economically developed cities in China. Second, as shown in Figure 1, the climatic conditions change greatly, and the weather in October is hot. If the temperature is higher than 25 °C, it is considered a hot day [16]. Third, as one of the first-tier cities in China, Shenzhen has experienced rapid growth in private cars and taxis. However, public transport remains the major travel mode for most people in this city. According to the Shenzhen Statistical Yearbook 2018, at the end of 2017, the public system comprised nine metro lines with 123 stations and 992 bus routes with 17,430 buses. In this year, the total number of bus trips was 1654.25 million, which was a decrease of 11.44% compared with the previous year. In addition, the passenger volume of buses has decreased continuously over the past four years. The total number of metro trips was 1655.45 million, up 27.62% from the previous year, indicating that the ridership of the metro has increased year by year. This may be because some travelers shifted from bus to metro travel. Moreover, many existing studies have chosen Shenzhen as the study area [11,49–52]. Therefore, Shenzhen is an apt study area.

The entire month of October 2017 was chosen as the study period in this study. There are two reasons for this: first, October 2017, with 16 workdays, eight holidays (including the National Day and Mid-Autumn Festival), and six ordinary weekends, meets the scope and requirements of this study. We can also capture the transfer ridership affected by various occasions besides the general travel characteristics. Second, the weather in October changes dramatically; there are strong typhoons, and stormy weather is suitable for our research on the impact of extreme weather on the transfer ridership. In addition, the selected period was from 6:00 to 22:59 on these days, which is consistent with the running time of public transport.

Although we studied only one month of sample data from October 2017, the sample still covered the metro and bus systems in Shenzhen. The sample size of this paper is sufficient to support the research content of this study. We are confident in the validity and generalizability of the findings. Moreover, some existing related studies also only used one month of sample data and the conclusions obtained are feasible [32,53]. Shenzhen is a rapidly developing city; five years ago, a new metro network and bus network were built. The new metro stations and bus stops are mainly distributed in the suburbs. The essential factors affecting the transfer ridership are still the weather variables and the economic level of the city, the built environment, and other factors. Therefore, the use of data from one month five years ago can provide accurate and useful information. Furthermore, there are also relevant studies that use data from five years ago to analyze the impact of various factors on transfer [54].

3.2. Data sources and Data Description

The main datasets employed in this study include the one-month smart card transaction data of public transport for all cardholders, one-month meteorological data from all weather stations in Shenzhen, population data, and socioeconomic data from the Shenzhen Statistical Yearbook. Additional data include the location coordinates of all metro stations and bus stops, built environment, and vector maps of the Shenzhen districts. This section describes the raw data sources, data processing, and distribution characteristics of the variables. The transfer process between the metro and the bus systems is shown in Figure 2. The hierarchy of variables in models is shown in Figure 3. The specific descriptions and definitions of these variables are as follows.

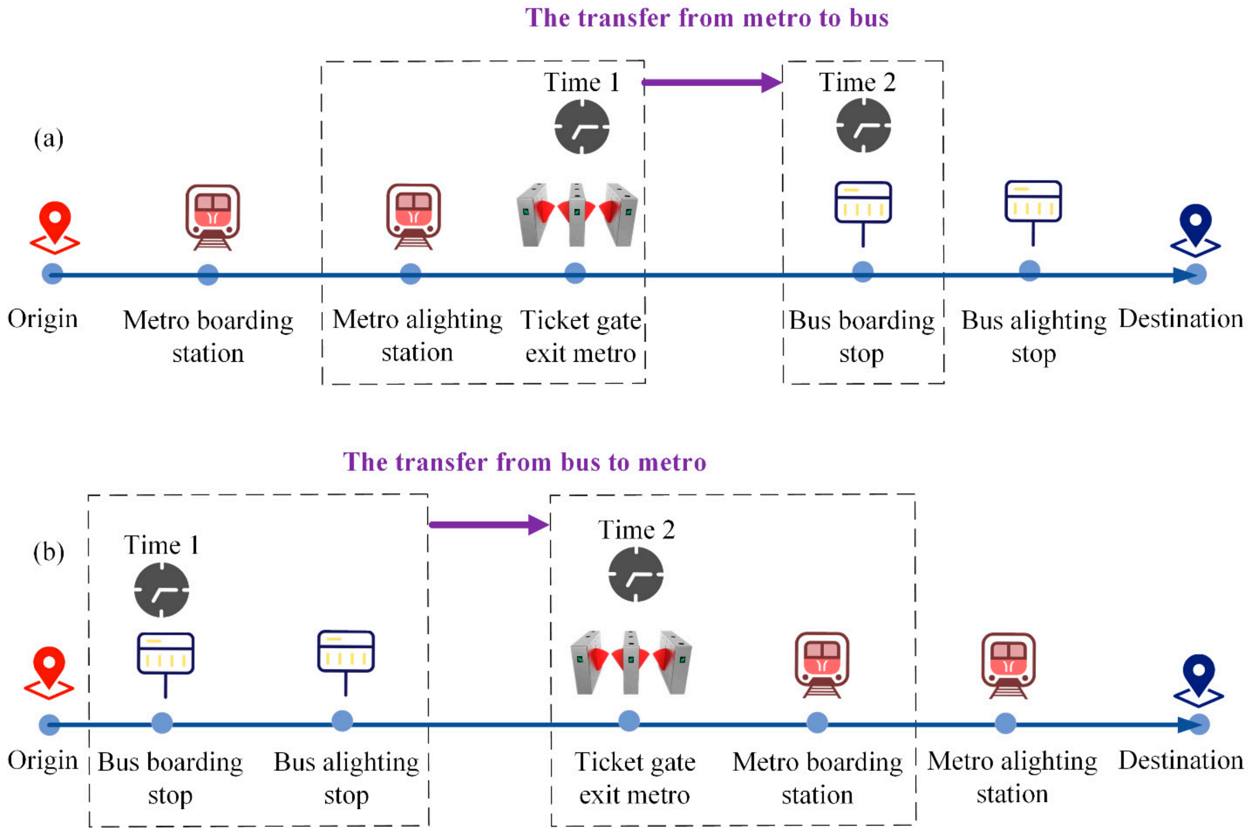


Figure 2. The transfer process between the metro and the bus systems: (**a**) the transfer from metro to bus and (**b**) the transfer from bus to metro.

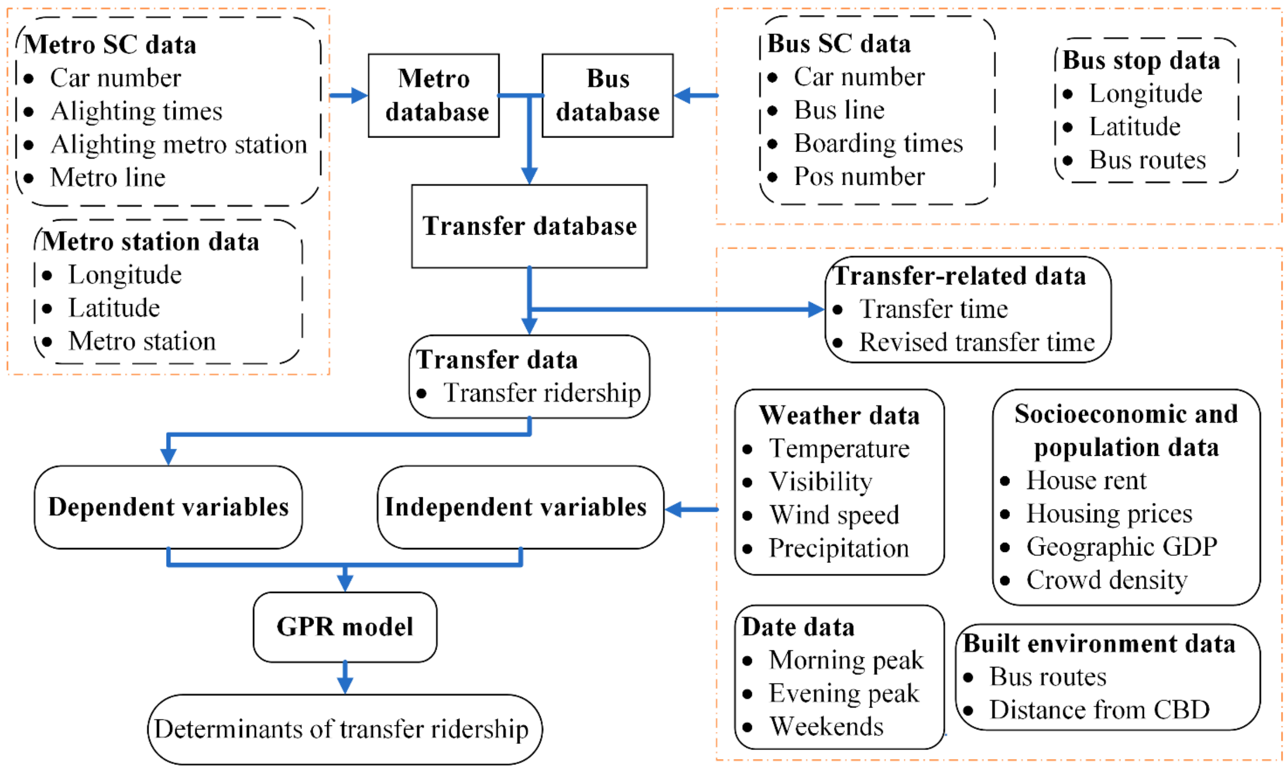


Figure 3. The hierarchy of variables and models.

3.2.1. Weather Variable

Temperature, wind, visibility, and rainfall have been widely considered in related studies on weather–ridership relationships [20]. Therefore, in this study, the four real-time weather variables are extracted from the raw weather data to investigate the impacts of weather on the transfer ridership. Referring to the existing related research, many studies have adopted continuous weather variables to observe the continuous impact of weather variables on transport ridership [32,43]. In this study, the original continuous data between 6:00–22:59 are selected for the weather variables. Among them, the maximum temperature per hour is used to represent the hourly temperature. The wind speed is represented by the maximum value observed during a given hour. Similarly, visibility is represented by the minimum value in each corresponding hour. The rainfall corresponds to the total precipitation over a given hour. The distributions of the four weather variables are shown in Figure 4. Each weather variable fluctuates significantly over time. These weather variables are then matched with the transfer data to obtain the influence of each weather variable on the transfer ridership.

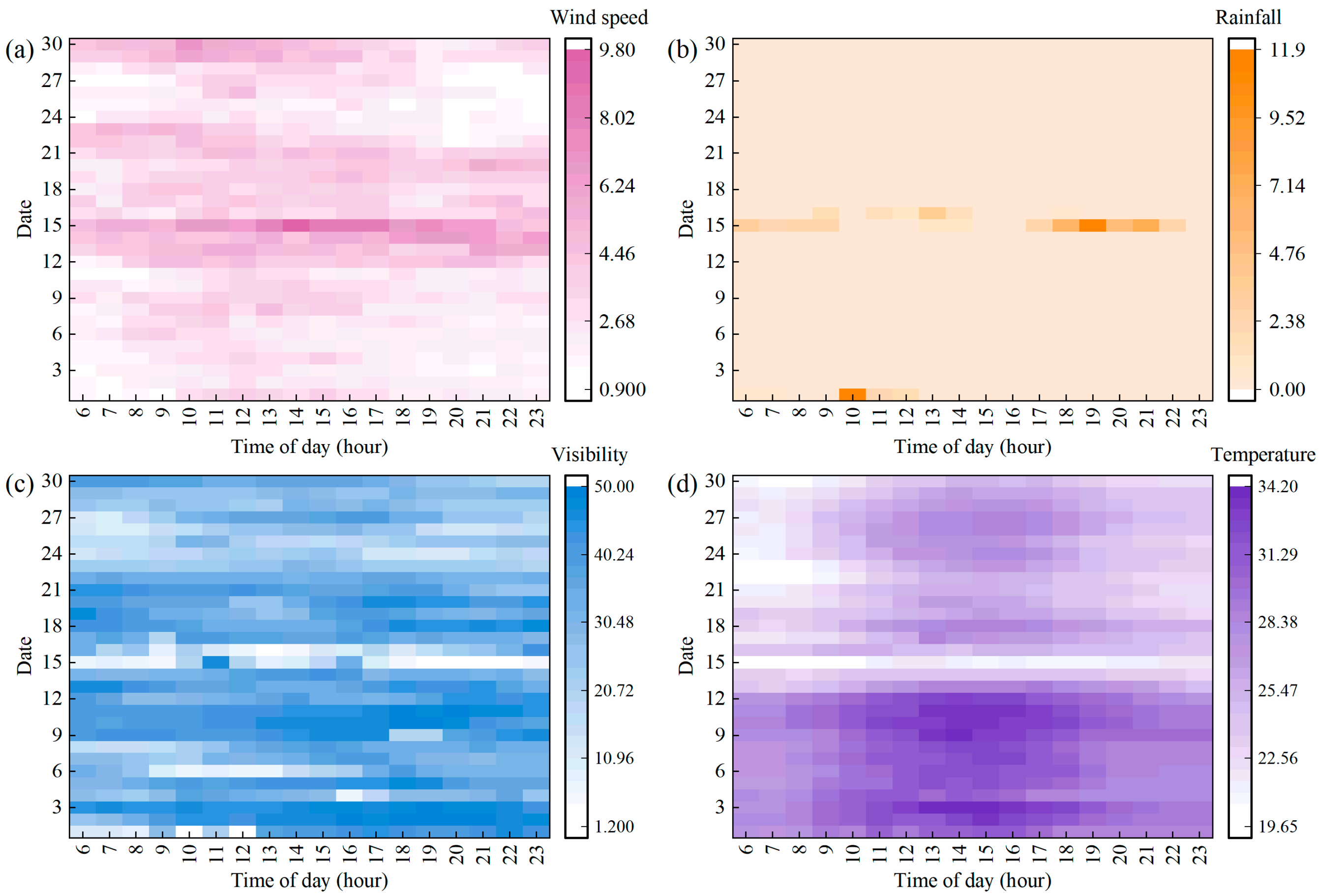


Figure 4. The distribution of weather variables: (**a**) wind speed, (**b**) rainfall, (**c**) minimum visibility, and (**d**) maximum temperature.

From Figure 4, it can be seen that the four weather variables—wind speed, rainfall, temperature, and visibility—have great fluctuations on 14, 15, and 16 October. This is an extreme weather condition, which is also typhoon weather. Therefore, it is necessary and meaningful to analyze the transfer ridership in typhoon weather separately.

3.2.2. Transfer-Related Variables

The transfer-related variables mainly include the transfer ridership, transfer time of the metro-to-bus mode, and the revised transfer time of the bus-to-metro mode, obtained by mining the smart card data. To obtain the transfer-related variables between the metro and bus systems, the one-month smart card transaction data of the metro and bus systems in October 2017 are extracted with average daily data of more than 3 million. The raw smart card transaction dataset includes the identification card number, card type, metro station, bus line, and transaction timestamp.

The method for identifying transfer time and transfer ridership is derived from the literature [10,55,56] and has been improved based on the following aspects. First, we record the travel time of all passengers every hour from the metro station to a candidate bus station, which is less than the upper bound of 40 min. We also record the travel time of all passengers every hour from the bus stop to a candidate metro station that is less than the upper bound of 50 min. Specifically, the upper bounds of 40 min and 50 min are mainly set in accordance with the literature related to recognizing transfer methods [10,57]. Existing survey studies show that 95% of the transfer ridership of the metro-to-bus mode has transfer times within 40 min, while 95% of the transfer ridership of the bus-to-metro mode has transfer times within 50 min [58]. Therefore, for the initial identification of the transfer ridership, we set the upper bound of 40 min and 50 min as the elapsed time thresholds for the metro-to-bus mode and bus-to-metro mode, respectively. Then, the 95th percentile of the travel time of the filtered passengers is regarded as the metro-to-bus (or bus-to-metro) transfer time threshold of every hour, namely, transfer time. Finally, based on the transfer time threshold, we identified the hourly transfer ridership at each metro station. The transfer processes of the metro and bus systems are shown in Figure 2. Moreover, to analyze the distribution characteristics of metro and bus ridership, we explored the hourly travel-related variables. The travel-related variables include the inbound ridership, outbound ridership, and bus ridership at each station, which is derived from the metro smart card transaction data.

To show more clearly the distribution of different transfer-related variables on different dates, we added heat maps of transfer ridership and transfer time, as shown in Figure 5 below:

Figure 5 shows that the transfer ridership has great fluctuations on 14, 15, and 16 October, with significant morning and evening peaks. Therefore, it is necessary and meaningful to analyze the transfer ridership in typhoon weather separately.

Moreover, to further demonstrate the distribution characteristics of transfer-related variables, the travel-related variables are visualized, as shown in Figures 6–8. From these three figures, it can be seen that the distributions of the bus ridership, metro ridership, metro inbound ridership, metro outbound ridership, and transfer ridership have clear morning peaks and evening peaks. Moreover, the distributions of the metro station ridership and transfer ridership are similar. The distribution of the bus ridership is highly similar to that of the transfer ridership at the stations. However, the distribution characteristics of transfer time on different dates are similar, and there is no morning or evening peak phenomenon. The specific analysis is as follows:

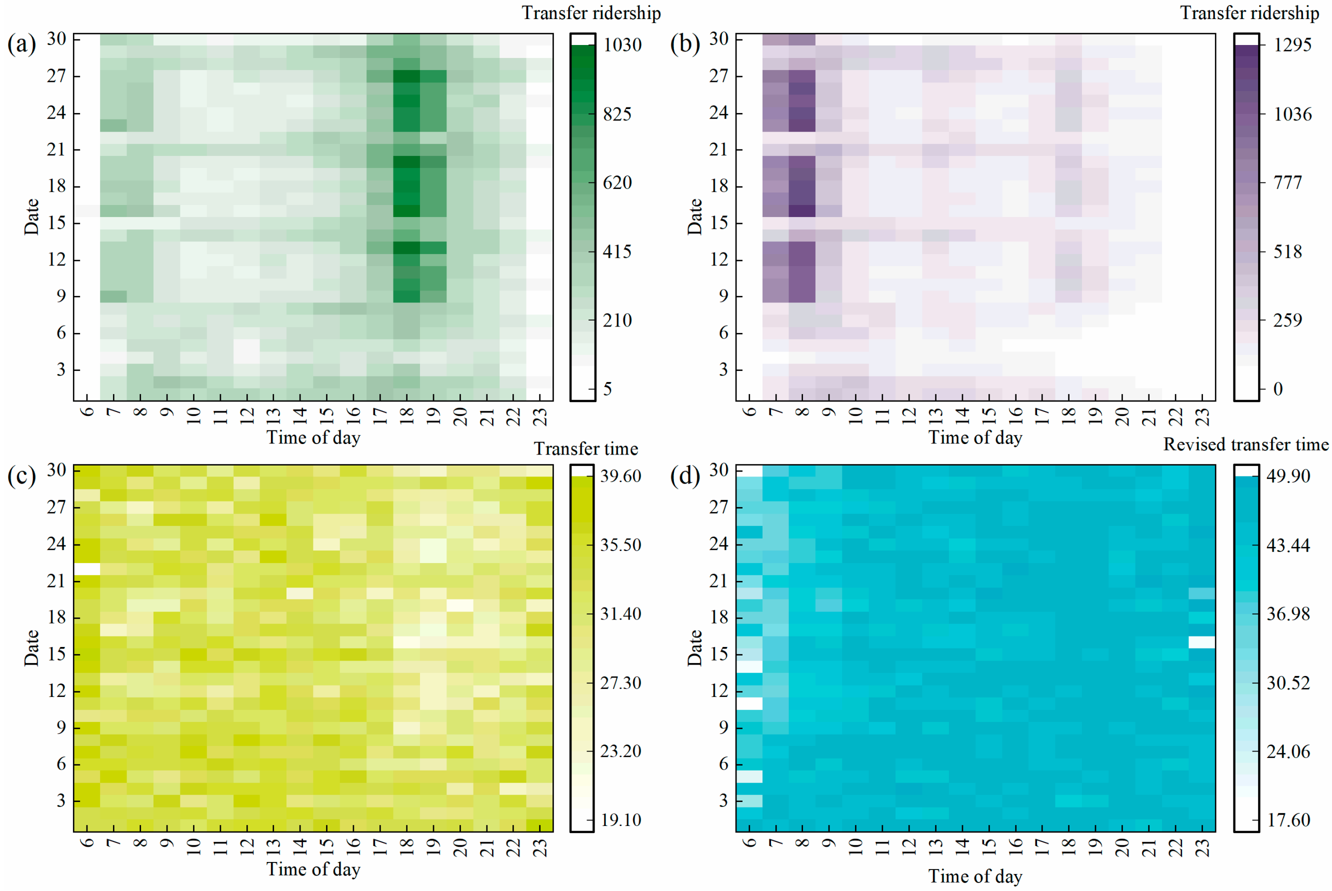


Figure 5. The distribution of transfer ridership and transfer time: (**a**) the transfer ridership of the metro-to-bus mode, (**b**) the transfer ridership of the bus-to-metro mode, (**c**) the transfer time of the metro-to-bus mode, and (**d**) the revised transfer time of the bus-to-metro mode.

Figure 6a1–c1 show that there is a strong consistency in the distribution of metro ridership, inbound ridership, and outbound ridership from 6:00 to 22:59 on weekdays. Moreover, the distribution of metro ridership, inbound ridership, and outbound ridership shows the same significant morning peak and evening peak. The morning peak hours are from 7:00–9:00, and the evening peak hours are from 17:00–20:00. These findings are consistent with that of the related research [56]. Comparing Figure 6a2–c2, it can be found that the distribution of metro ridership, inbound ridership, and outbound ridership is significantly different between Saturday and Sunday. The distribution of metro ridership, inbound ridership, and outbound ridership has a strong consistency on Saturday, with significant morning and evening peak hours. Peak hours on Saturdays are similar to that on weekdays. In contrast, the distribution of metro ridership, inbound ridership, and outbound ridership on Sundays greatly varies without significant peak hours. The distribution trends of metro ridership, inbound ridership, and outbound ridership on holidays in Figure 6a3–c3 are a large variability across days. This is similar to the distribution of metro ridership, inbound ridership, and outbound ridership on Sundays, both without significant peak hours.

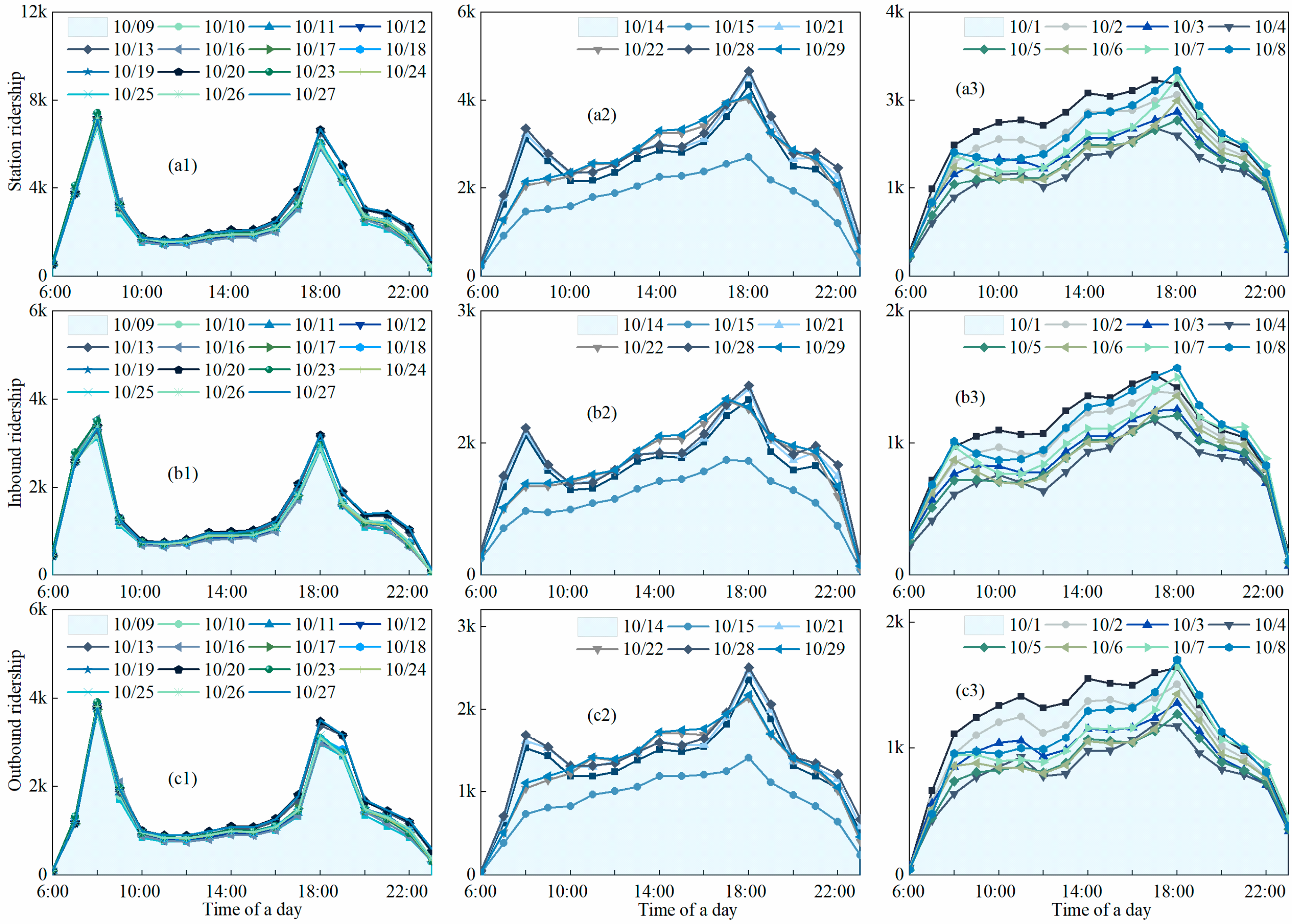


Figure 6. The distribution characteristics of metro ridership: (**a1**–**a3**) denote metro ridership on weekdays, weekends, and holidays, respectively; (**b1**–**b3**) denote inbound ridership on weekdays, weekends, and holidays, respectively; (**c1**–**c3**) denote outbound ridership on weekdays, weekends, and holidays, respectively.

Figure 7 shows that the distribution of transfer ridership is similar to the distribution of metro ridership. The distribution of transfer ridership on weekdays has a strong consistency with a significant morning and evening peak. The morning peak hours are from 7:00–9:00, and the evening peak hours are from 17:00–19:00. For metro-to-bus transfer mode, the transfer ridership in the evening peak is higher than in the morning peak, while the opposite is true for the transfer ridership of the bus-to-metro mode. This may be ascribed to the fact that commuters go to work in the morning and go home in the evening in the opposite direction. The distribution of transfer passenger flows on Saturdays is similar to that of weekdays, which also have significant morning and evening peaks. This may be because some commuters also work on weekends. Similarly, the distribution of transfer ridership on Sundays is consistent with that of transfer ridership on holidays, with large differences in the distribution of transfer ridership on different days. This is probably because people travel freely on holidays and have flexible schedules. Moreover, for the metro-to-bus mode, the distribution of transfer ridership on holidays shows a significant evening peak, and the transfer ridership is significantly higher than during other periods, while for the bus-to-metro mode, the distribution of ridership on holidays is the opposite, showing a significant morning peak. This is because many transfer passengers go out from home in the morning and return home in the evening by transportation modes that are in opposite directions.

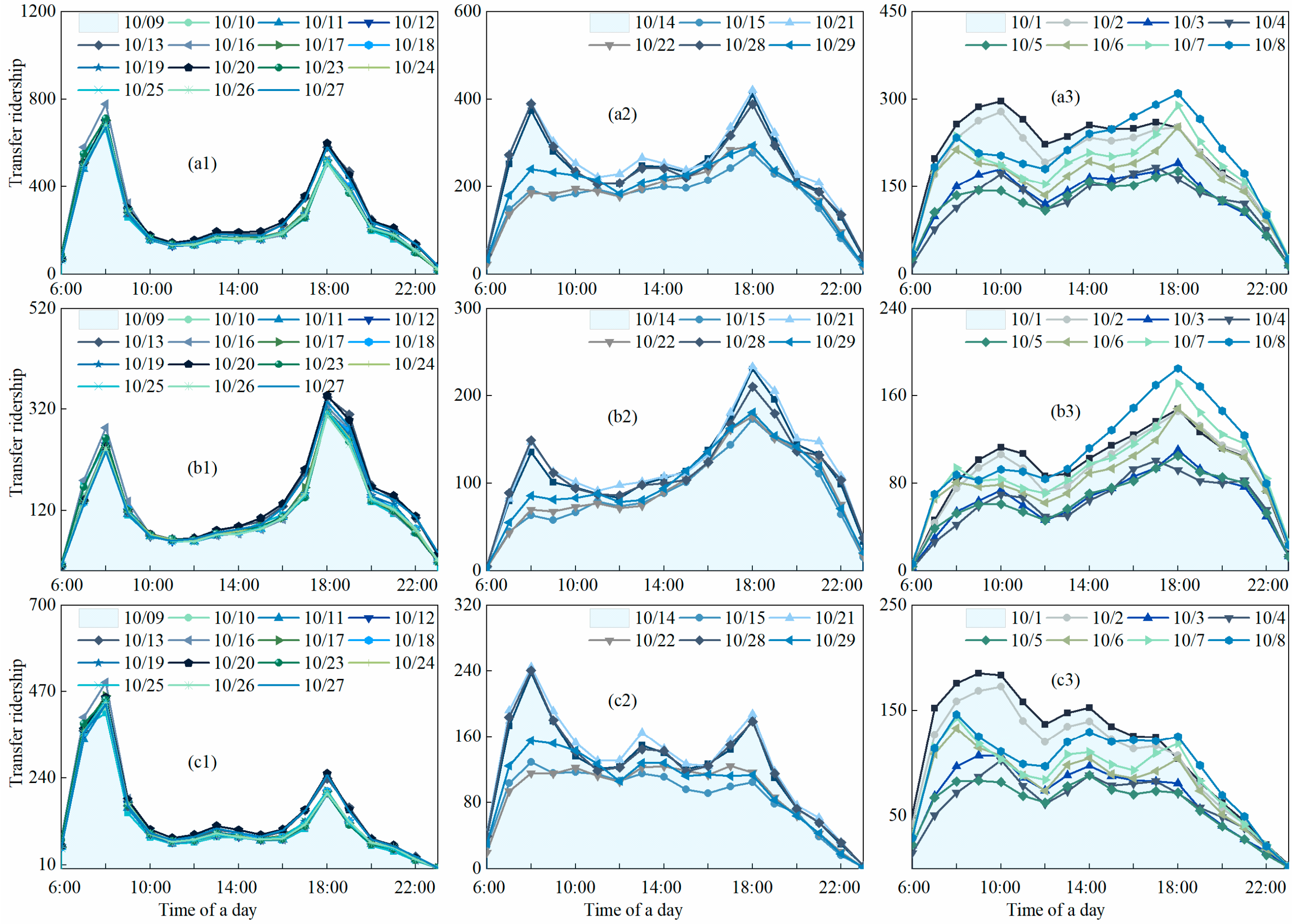


Figure 7. The distribution characteristics of the transfer ridership: (**a1**–**a3**) denote transfer ridership of metro stations on weekdays, weekends, and holidays, respectively; (**b1**–**b3**) denote transfer ridership of the metro-to-bus mode on weekdays, weekends, and holidays, respectively; (**c1**–**c3**) denote transfer ridership of the bus-to-metro mode on weekdays, weekends, and holidays, respectively.

Figure 8 shows that the distribution of bus ridership on weekdays has a strong consistency, and the bus ridership at the same moment on different days is almost the same with a significant morning and evening peak. Similarly, the distribution of bus ridership each Saturday is also very consistent and has significant morning and evening peaks. The morning peak hours are from 7:00–9:00, and the evening peak hours are from 17:00–19:00. The distribution of bus ridership is relatively similar on Sundays and holidays, with large differences on different days, and has no significant morning or evening peak hours. Unlike the distribution of transfer ridership, the distribution of transfer time shows a strong consistency on weekdays, weekends, and holidays without significant morning or evening peaks. Moreover, the transfer time on weekdays is significantly less than the transfer time on weekends and holidays. Because the frequency of metro and bus is higher on weekdays considering the larger commuter traffic, the headway time is smaller than that of weekends and holidays, so the transfer time is shorter on weekdays. This difference in transfer time between weekdays and holidays is even more pronounced for passengers of the metro-to-bus mode. This is because the transfer passengers of the metro-to-bus mode are more affected by the bus headway than passengers of the bus-to-metro mode.

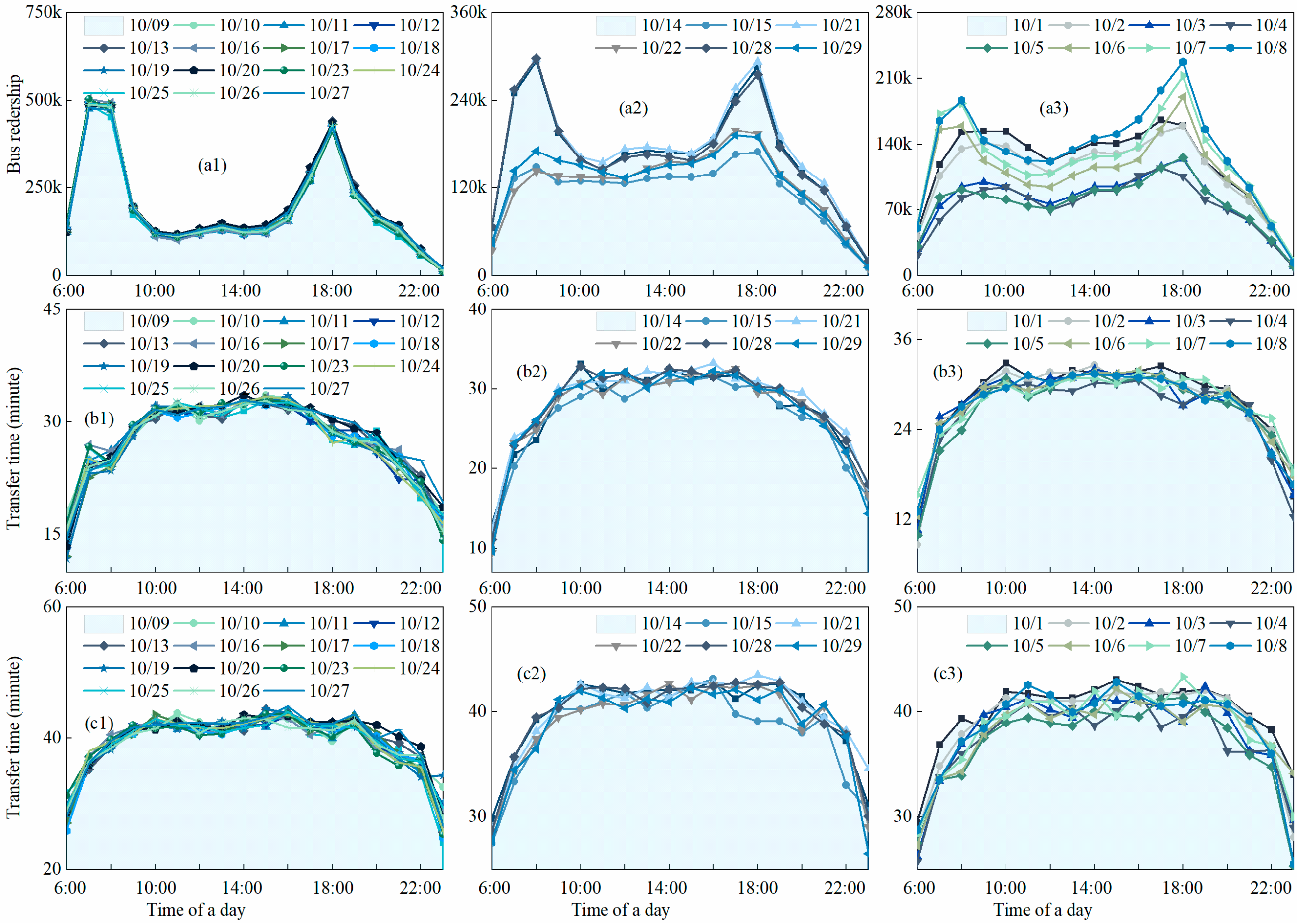


Figure 8. The distribution characteristics of bus ridership and transfer time: (**a1**–**a3**) denote bus ridership on weekdays, weekends, and holidays, respectively; (**b1**–**b3**) denote transfer time of the metro-to-bus mode on weekdays, weekends, and holidays, respectively; (**c1**–**c3**) denote revised transfer time of the bus-to-metro mode on weekdays, weekends, and holidays, respectively.

In short, transfer ridership, transfer time, bus ridership, and metro ridership are distributed in different patterns at different times. It is necessary and important to classify these factors by different types of dates for exploring the determinants of transfer ridership. Therefore, this paper developed separate ridership models for the time during workdays + weekends, and during holidays.

3.2.3. Built Environment Variables

The built environmental factors in this study mainly include the distance to CBD and feeder bus routes to the metro station. The feeder bus routes indicate the number of bus routes connected within 1000 m of the metro station. This is inferred from the static GPS coordinates of the metro stations and bus stops. The distance to CBD denotes the distance of metro stations from CBD in Shenzhen. The specific calculation method can be found in the literature [10,59].

3.2.4. Socioeconomic and Population Variable

The socioeconomic variables include house rent, housing prices, and geographic GDP. The population variable includes crowd density. Crowd density indicates the hourly density of pedestrian traffic near a metro station. House rent indicates the average house rent near a metro station, and the house rent is obtained from the house rent data published on major rental websites in October 2017. The housing prices indicate average housing prices near metro stations, and the housing prices are obtained from the house prices data published on major house sale websites in October 2017. Geographic GDP indicates geographically weighted GDP near metro stations. First, the GDP of each administrative area is derived from the Shenzhen Statistical Yearbook 2018. Then, based on the GDP of each administrative area, the geographic GDP data of each metro station is obtained by calculating the geographic distance from each metro station to the center of each administrative region through geographic weighting.

3.2.5. Date Variables

As shown in Figures 6–8, as the public transportation travel and transfer-related characteristics exhibit significant differences on different dates, it is important to consider the date as an independent variable. Each travel variable and transfer variable has different distribution characteristics at different times of a working day. Therefore, the date is used as a categorical variable and represented by a dummy variable coded as '1′ and '0′. According to the distribution characteristics of the variables, we consider the date as an independent variable divided into four categories, including the off-peak hours of working days, morning peak hours and evening peak hours of working days, and ordinary weekends. Because the distribution of travel variables and transfer variables on holidays is significantly different from other dates, we examine holiday data as a separate case study.

3.3. Description and Statistical Distribution of the Variables

The definitions of these variables are summarized in Table 2. The attributes considered in our analysis include the weather variables (maximum temperature, rainfall, maximum wind speed, and minimum visibility), public transport transfer-related variables (transfer time and revised transfer time), socioeconomic and population variables (house rent, housing prices, geographic GDP, and crowd density), built environment variables (feeder bus routes and CBD-distance), and date variables (morning peak and evening peak of weekdays and weekends). Transfer ridership is the dependent variable in this study. Other variables are independent variables.

Table 2. Definitions and descriptive statistics of variables.

Variables	Definitions	Unit	Mean	Sd.
Dependent variables				
Transfer ridership	The number of transfer passengers from metro to bus per hour.		111	165
	The number of transfer passengers from bus to metro per hour.		120	198
Independent variables				
Weather variables				
Temperature	Highest temperature per hour.	°C	26.8	3.47
Wind	Average wind speed per hour.	m/s	3.16	1.34
Visibility	Minimum visibility per hour.	m	31.94	10.92
Rainfall	Hourly accumulated precipitation.	mm	0.15	0.94
Transfer-related variables				
Transfer time	Hourly difference time threshold from metro alighting to bus boarding.		28.6	7.56
Revised transfer time	Hourly difference time threshold from bus boarding to metro boarding.		39.92	8.66
Socioeconomic and population variables				
House rent	Average house rent near metro stations.	$/m^2$	12.57	3.26
Housing prices	Average housing prices near metro stations.	$/m^2$	8953.10	2547.12
Geographic GDP	Geographically weighted GDP near metro stations.	$	3468.77	875
Crowd density	The hourly density of pedestrian traffic near a metro station.		5.62	1.19
Built environment variables				
Feeder bus routes	Number of bus lines connected within 1000 m of the metro station		30	12
CBD-distance	Distance of a metro station from the CBD.	m	9600.29	6604.44
Date variables (dummy variable)				
Morning peak	7–9 a.m. on weekdays in October 2017.		0.14	0.34
Evening peak	5–8 p.m. on weekdays in October 2017.		0.18	0.39
Weekends	Ordinary weekends, 14, 15, 21, 22, 28, and 29 in October 2017.		0.20	0.40

Note: the date variables are dummy variables, others are continuous variables.

Most of the continuous variables presented in Table 2 have different dimensions. These variables are easy to understand and do not need to be elaborated on. It can also be observed that the distribution characteristics of different variables are quite different. Therefore, to eliminate the influence of different dimensions on the results, all continuous independent variables are normalized. To eliminate the influence of different dimensions on the results, all continuous independent variables are normalized. The calculation formula is as follows:

$$x' = (x - X_{min})/(X_{max} - X_{min}) \tag{1}$$

where x' denotes the normalized value, x denotes the raw value, X_{max} is the maximum value of the variable sample, and X_{min} is the minimum value of the variable sample. It is scaling all variables to the same scale. The range of the variable after scaling is from 0 to 1. Moreover, after normalization, all the variables are normally distributed, and the impact of each factor in the regression models on transfer ridership can then be compared. Therefore, when comparing the coefficients, the variables have been normalized to the same scale.

4. Methodology

The principal objective of this paper is to present a critical analysis of the various elements that affect transfer ridership. We aim to determine the most relevant variables in the transfer experience and relative weights, with emphasis on the impact of the weather variables on the transfer ridership. The study framework for exploring the determinants of transfer ridership is shown in Figure 9.

From the qualitative and quantitative perspectives, this study analyzes the factors that affect the transfer ridership between metro and bus systems. The hourly transfer ridership is counting data, obeying the Poisson distribution. The generalized Poisson regression is the most popular method used to model count data [60,61]. This study focuses on exploring the effects of multiple variables on transfer ridership. Therefore, the generalized Poisson regression (GPR) model models the relationship between multiple variables and transfer ridership. The basic theory of the GPR model is briefly described as follows [62]:

$$P(Y = y_i|x_i, z_i) = \begin{cases} \varphi_i + (1-\varphi_i)f(k;\mu_i,\alpha),\ y_i = k \\ (1-\varphi_i)f(y_i;\mu_i,\alpha),\ y_i \neq k \end{cases} \tag{2}$$

where $0 < \varphi_i < 1$, and $f(y_i;\mu_i,\alpha)$ is the GPR model used to model with various data sets. x_i is the explanatory variable. y_i is the count data following the Poisson distribution, y_i = 0, 1, 2, . . . The expression of the GPR model is as follows [63]:

$$f(y_i;\mu_i,\alpha) = \left(\frac{\mu_i}{1+\alpha\mu_i}\right)^{y_i} \frac{(1+\alpha y_i)^{y_i-1}}{y_i!} \exp\left[\frac{-\mu_i(1+\alpha y_i)}{1+\alpha\mu_i}\right] \tag{3}$$

$$\mu_i = \mu_i(x_i) = \exp\left(\sum_{j=1}^{p} x_{ij}\beta_j\right) \tag{4}$$

where y_i = 0,1, . . . , $\mu_i > 0$ and $x_i = (x_{i1} = 1, x_{i2}, x_{i3}, \ldots, x_{ip})$ denotes the ith row of covariate matrix **X**. $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_p)$ denotes the p-dimensional vector of the regression parameters to be estimated. The mean and variance of Y_i are $\mu_i(x_i)$ and $\mu_i(1+\alpha\mu_i)^2$. α is the parameter that can measure the dispersion of the count data. When α = 0, the GPR model is reduced to the Poisson regression (PR) model [64]. The expression is as follows:

$$f(y_i;\mu_i) = \frac{{\mu_i}^{y_i} e^{-\mu_i}}{y_i!},\ y_i = 0,\ 1,\ 2,\ \ldots,\ \mu_i > 0 \tag{5}$$

$$\mu_i = \exp\left\{{x_i}^T \boldsymbol{\beta}\right\} \tag{6}$$

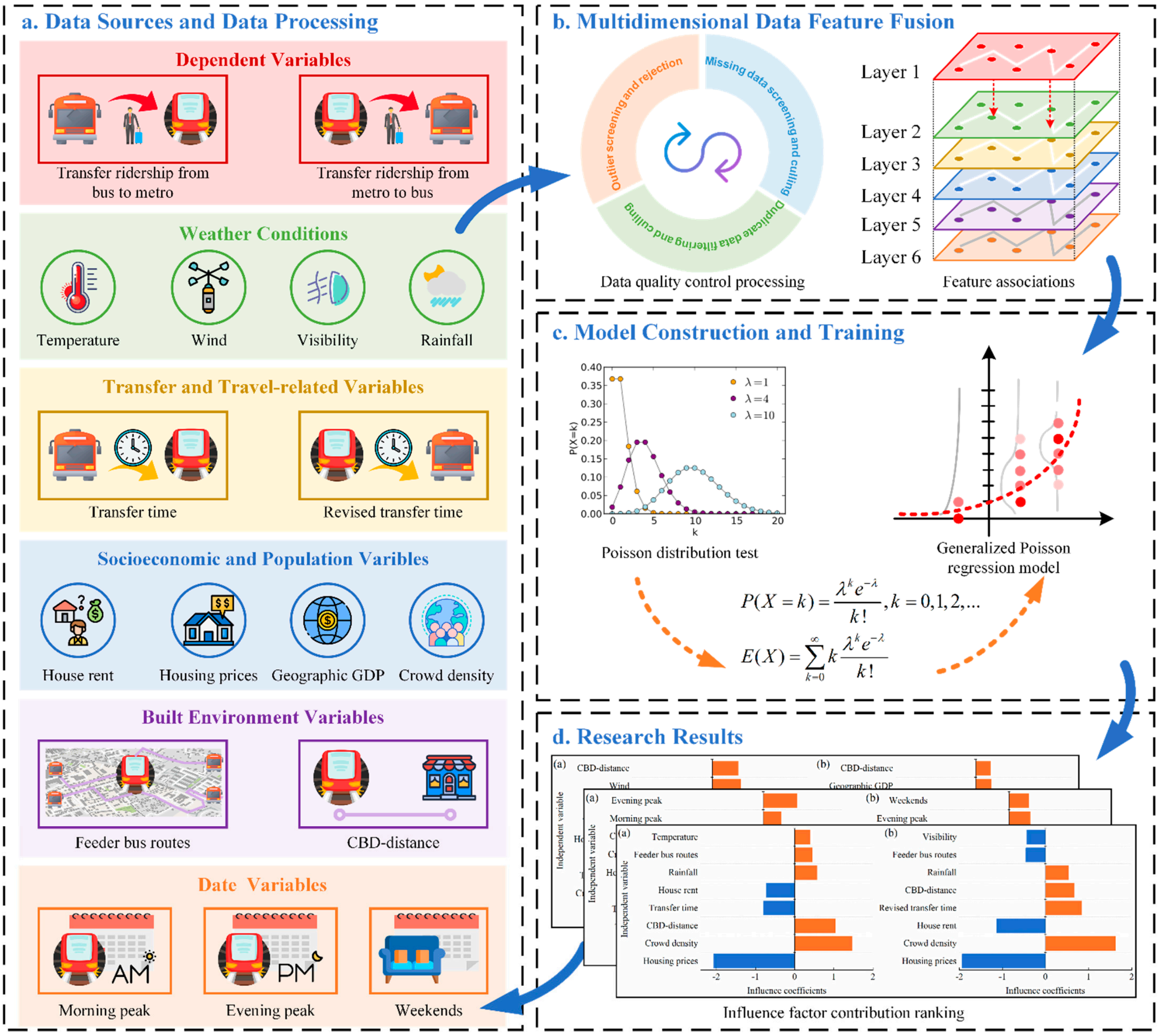


Figure 9. The study framework of the GPR model for exploring the determinants of transfer ridership.

When $\alpha>0$, the variance is greater than the mean, and the GPR model indicates the count data with over-dispersion. When $\alpha<0$, the GPR model indicates the count data with under-dispersion [65]. If $-f(k;\mu_i,\alpha)[1-f(k;\mu_i,\alpha)]^{-1}\varphi_i<1$, the generalization in Equation (2) allows for a gradual decrease in the proportion of k-values. $\mu_i=\mu_i(x_i)$ and $\varphi_i=\varphi_i(\mathbf{z}_i)$ meet $\log(\mu_i)=\sum_{j=1}^{k}x_{ij}\beta_j$ and $\text{logit}(\varphi_i)=\log\left(\frac{\varphi_i}{1-\varphi_i}\right)=\sum_{j=1}^{m}z_{ij}\delta_j$, where $\mathbf{z}_i=(z_{i1}=1,z_{i2},z_{i3},\ldots,z_{im})$ denotes the ith row of covariate matrix $\mathbf{Z}$, $\boldsymbol{\delta}=(\delta_1,\delta_2,\ldots,\delta_m)$ denotes the m-dimensional vector of the regression parameters to be estimated [66]. The φ_i and μ_i denote modeling by logit link function and log link function, respectively.

5. Results and Discussions

In this section, the modeling results concerning the impacts of various factors, such as the weather, on the system-wide and station-level transfer ridership between different travel modes are presented and discussed. The empirical analysis presented in this study involves estimating the effect of the weather elements, public transport transfer and travel-related variables, socioeconomic and population variables, built environment variables, and date factors on the transfer behavior using multivariate regression models. It is noteworthy that in the model specification, correlation and multicollinearity between the independent variables considered in the two models are verified. The estimation results of the models are presented in Tables 3–5. The variables in the two models have similar specifications. The detailed results analysis and discussions of the models are presented subsequently.

Table 3. Results of models on workdays and weekends.

Variables	The Metro-to-Bus Mode				The Bus-to-Metro Mode			
	Coefficient	t	p	VIF	Coefficient	t	p	VIF
Intercept	4.618	80.334	0 ***		2.952	40.057	0 ***	
Weather variables								
Temperature	0.536	11.183	0 ***	1.77	−0.063	−1.245	0.213	1.73
Wind	0.060	1.155	0.248 *	1.28	−0.033	−0.602	0.547	1.29
Visibility	−0.083	−2.151	0.032 *	1.43	0.074	1.808	0.0706	1.36
Rainfall	0.012	0.152	0.879	1.03	0.241	3.186	0.001 **	1.03
Transfer-related variables								
Transfer time	−2.127	−44.037	0 ***	1.24	N/A	N/A	N/A	N/A
Revised transfer time	N/A	N/A	N/A	N/A	0.793	14.318	0 ***	1.18
Socioeconomic and population variables								
House rent	−1.078	−19.083	0 ***	2.40	−1.54	−23.792	0 ***	2.61
Housing prices	−1.266	−17.693	0 ***	1.75	−1.394	−16.002	0 ***	1.98
Geographic GDP	0.176	5.035	0 ***	1.69	0.182	4.885	0 ***	1.69
Crowd density	1.738	34.56	0 ***	1.26	1.937	31.447	0 ***	1.24
Built environment variables								
Feeder bus routes	0.420	9.992	0.003 **	1.36	−0.316	−6.691	0 ***	1.35
CBD-distance	0.501	10.92	0 ***	1.73	0.291	6.088	0 ***	1.80
Date variables								
Morning peak	0.451	15.885	0 ***	1.81	1.289	47.648	0 ***	2.16
Evening peak	0.855	38.686	0 ***	1.59	0.437	16.036	0 ***	1.49
Weekends	0.395	14.877	0 ***	1.60	0.400	14.067	0 ***	1.63
Diagnostic statistics								
Observations	16,684				17784			
Null deviance	2,935,091				3,927,336			
Residual deviance	1,706,702				2,187,363			
AIC	1,803,456				2,280,442			
R^2	0.5887				0.6304			

Note: "*", "**" and "***" denotes significance in the confidence level of 95%, 99%, and 99.9%, respectively. "N/A" denotes the variables not considered in the model. The date variables in the above table are dummy variables, the other variables are continuous, and the continuous variables have been normalized before the regression simulation.

Table 4. Results of models on holidays.

Variables	The Metro-to-Bus Mode				The Bus-to-Metro Mode			
	Coefficient	t	p	VIF	Coefficient	t	p	VIF
Intercept	3.624	33.478	0 ***		3.140	26.497	0 ***	
Weather variables								
Temperature	0.397	5.586	0 ***	1.41	0.337	4.783	0 ***	1.31
Wind	0.087	1.046	0.296	1.07	0.336	4.138	0 ***	1.06
Visibility	0.223	3.133	0.002 **	1.40	−0.434	−6.49	0 ***	1.41
Rainfall	0.568	3.729	0 ***	1.15	0.530	4.281	0 ***	1.19
Transfer-related variables								
Transfer time	−0.798	−9.044	0 ***	1.26	N/A	N/A	N/A	N/A
Revised transfer time	N/A	N/A	N/A	N/A	0.844	8.686	0 ***	1.19
Socioeconomic and population variables								
House rent	−0.726	−7.024	0 ***	2.73	−1.133	−10.549	0 ***	2.86
Housing prices	−2.070	−14.3	0 ***	1.98	−1.933	−12.669	0 ***	2.11
Geographic GDP	0.299	4.875	0 ***	1.65	0.362	5.868	0 ***	1.66
Crowd density	1.469	18.021	0 ***	1.12	1.619	17.674	0 ***	1.10
Built environment variables								
Feeder bus routes	0.445	6.225	0 ***	1.39	−0.456	−5.708	0 ***	1.41
CBD-distance	1.037	13.498	0 ***	1.9	0.663	8.582	0 ***	1.95
Diagnostic statistics								
Observations	6813				6654			
Null deviance	803,506				903,526			
Residual deviance	585,865				606,788			
AIC	623,445				641,036			
R^2	0.5000				0.5301			

Note: "*", "**" and "***" denotes significance in the confidence level of 95%, 99%, and 99.9%, respectively. "N/A" denotes the variables not considered in the model. The date variables in the above table are dummy variables, the other variables are continuous, and the continuous variables have been normalized before the regression simulation.

Table 5. Results of models during the typhoon.

Variables	The Metro-to-Bus Mode				The Bus-to-Metro Mode			
	Coefficient	t	p	VIF	Coefficient	t	p	VIF
Intercept	3.438	16.943	0 ***		4.291	18.698	0 ***	
Weather variables								
Temperature	1.265	8.476	0 ***	3.07	−0.593	−4.02	0 ***	2.75
Wind	0.714	4.767	0 ***	2.42	−1.143	−7.005	0 ***	2.36
Visibility	0.123	1.193	0.233	1.73	0.294	2.654	0.008 **	1.74
Rainfall	0.745	4.487	0 ***	2.11	−0.904	−4.178	0 ***	1.92
Transfer-related variables								
Transfer time	−1.756	−13.626	0 ***	1.21	N/A	N/A	N/A	N/A
Revised transfer time	N/A	N/A	N/A	N/A	0.233	1.407	0.16	1.20
Socioeconomic and population variables								
House rent	−1.348	−8.286	0 ***	2.46	−1.796	−9.92	0 ***	2.60
Housing prices	−1.319	−6.483	0 ***	1.79	−1.391	−5.9	0 ***	1.95
Geographic GDP	0.262	2.704	0.007 **	1.64	0.386	3.785	0 ***	1.64
Crowd density	2.092	15.794	0 ***	1.12	2.277	14.278	0 ***	1.11
Built environment variables								
Feeder bus routes	0.434	3.69	0 ***	1.38	−0.286	−2.179	0.029 *	1.39
CBD-distance	0.654	5.244	0 ***	1.75	0.38	2.948	0.003 **	1.78
Diagnostic statistics								
Observations	2601				2523			
Null deviance	422,791				496,331			
Residual deviance	274,574				320,820			
AIC	289,524				335,059			
R^2	0.5307				0.5422			

Note: "*", "**" and "***" denotes significance in the confidence level of 95%, 99%, and 99.9%, respectively. "N/A" denotes the variables not considered in the model. The date variables in the above table are dummy variables, the other variables are continuous, and the continuous variables have been normalized before the regression simulation.

5.1. Results

To explore the effects of various factors on the transfer ridership on different types of dates (such as workdays and weekends, holidays, and typhoon days), six separate models are developed for the metro-to-bus and bus-to-metro transfer modes. In theory, different variables may have some degree of association [57]. For example, high wind speeds may be associated with heavy rainfall [32]. Therefore, possible collinearity between the independent variables is examined. The variance inflation factor (VIF) is used to examine multicollinearity among independent variables. If VIF values are less than 5, it indicates that there is no multicollinearity between the independent variables of models [23,45]. The corresponding results are presented in Tables 3–5. The level of the variance inflation factors (VIF) is calculated, and all are less than 4, suggesting that no multicollinearity exists among the independent variables.

Transfer ridership (the dependent variable) is the discrete distribution of count data and meets the Poisson distribution. Therefore, to identify the factors that significantly influence the transfer ridership of the metro-to-bus and bus-to-metro modes on different dates, we employ GPR models to explore the relationship between the transfer ridership and various factors on workdays and weekends, holidays, and during the typhoon, respectively. The estimation results are listed in Tables 4 and 5. Most of the independent variables are significant at the 0.001 confidence level. The GPR models provide a basic understanding of the variation in the transfer ridership. Different variables have different effects on the transfer ridership. To show how well the GPR model fit the data, we used R^2 to evaluate the goodness of fit of the model [67]. The formula is as follows:

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - \overline{y}_l)^2 - \sum_{i=1}^{n}(y_i - \widetilde{y}_l)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_l)^2} \tag{7}$$

where n is the sample size of the dependent variable, y_i is the real values of the dependent variable, $\overline{y}_l$ is the mean value of the real dependent variable, and $\widetilde{y}_l$ is the fitted values of the dependent variable by the GPR model.

Moreover, this study used a multivariate approach. To further illustrate the correlation between the variables in each model, we calculated Pearson correlation coefficients between the variables and visualized the coefficients as shown in Figures 10–12 below.

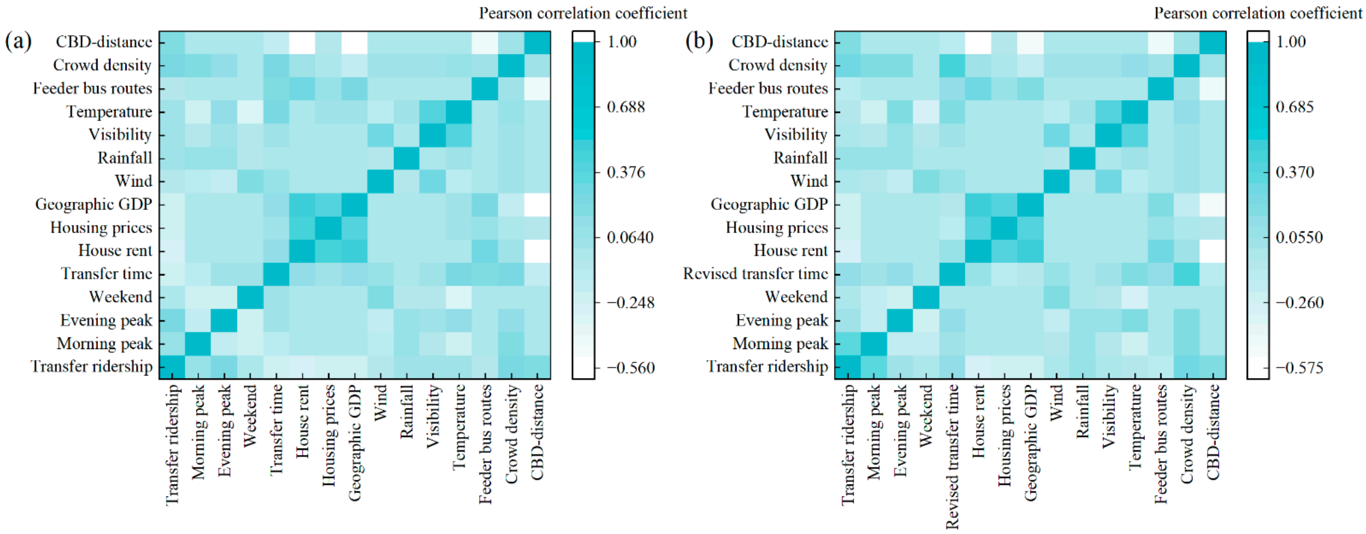


Figure 10. The Pearson correlation coefficient of various variables on workdays and weekends: (**a**) the metro-to-bus mode and (**b**) the bus-to-metro mode.

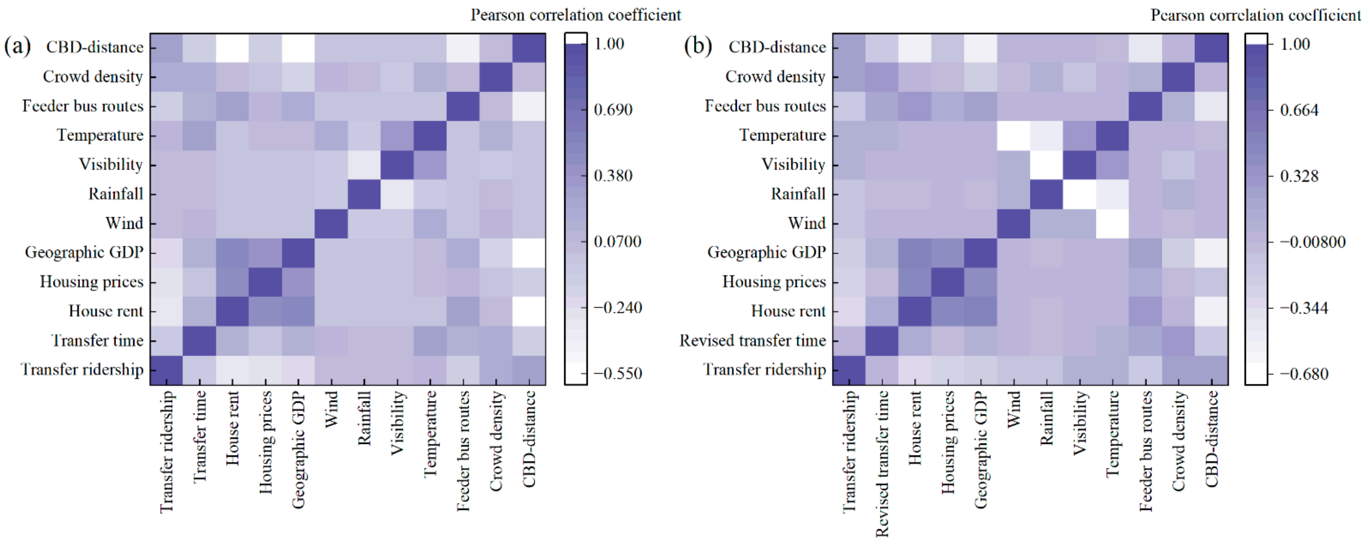


Figure 11. The Pearson correlation coefficient of various variables on holidays: (**a**) the metro-to-bus mode and (**b**) the bus-to-metro mode.

Figures 10–12 show that the correlation coefficients of the variables in each model are less than 1, and most of the correlation coefficients are less than 0.5. Therefore, the variables are independent of each other, which satisfies the requirements of each model for the independent variables.

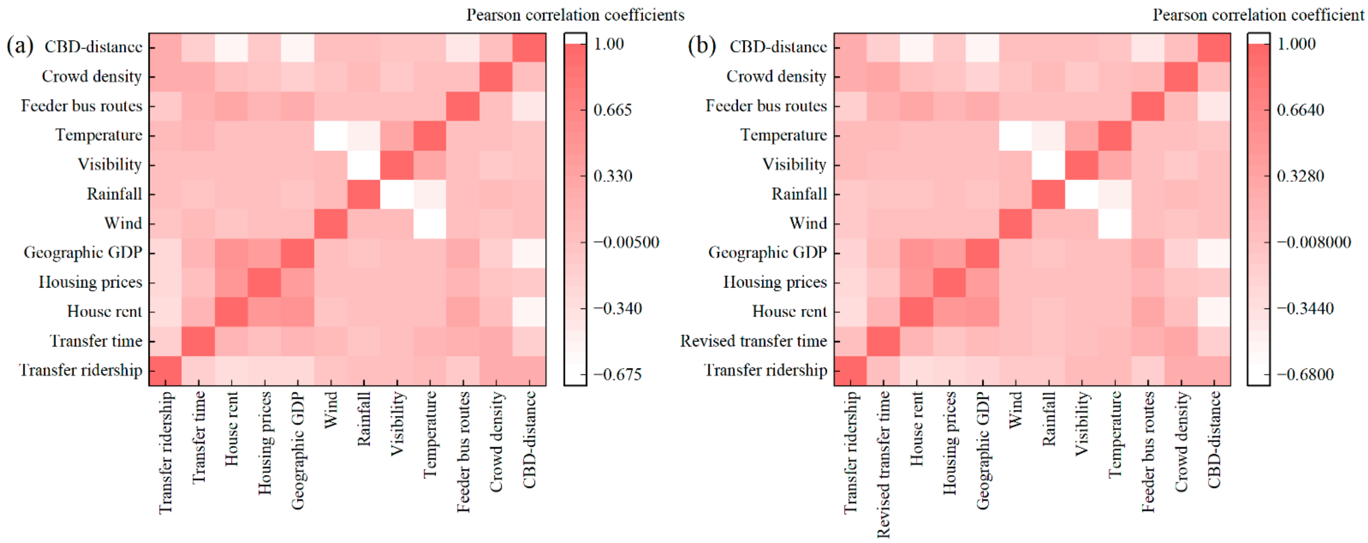


Figure 12. The Pearson correlation coefficient of various variables during typhoon weather: (**a**) the metro-to-bus mode and (**b**) the bus-to-metro mode.

5.1.1. The Determinants of Transfer Ridership on Weekdays and Weekends

We have explored the impact of various factors on transfer ridership of the metro-to-bus mode and the bus-to-metro mode on weekdays and weekends. The results are shown in Table 3. The detailed analysis is as follows:

For the metro-to-bus mode, it can be seen that the effect of transfer time on transfer ridership is the most significant among all independent variables at about 1.22 to 35.45 times that of other variables. Those numbers are derived based on the estimated coefficients: 2.127/0.06 = 35.45. In this study, we compare the impact of each factor on the transfer ridership by the estimated influencing coefficients. The transfer time is negatively associated with the transfer ridership because the transfer passengers from metro to bus wish to take the bus earlier with the shorter transfer time, which can attract more transfer passengers. Among the weather variables, high temperature has a positive and significant impact on ridership at about 64.58 to 89.33 times that of other weather variables. High temperatures, high winds, and low visibility conditions will increase the transfer ridership. This is because, in bad weather conditions, passengers prefer to transfer by public transport rather than by walking, driving a private car, or cycling.

For the bus-to-metro mode, crowd density has the most significant impact on transfer ridership at about 1.26 to 10.64 times that of other variables. Among the weather variables, only rainfall affects transfer ridership, and heavy rainfall increases the transfer ridership. The revised transfer time has a positive impact on transfer ridership. This is because the revised transfer time includes the in-vehicle time of taking the first bus, so the longer the revised transfer time is, the more transfer ridership is. Feeder bus routes are negatively correlated with transfer ridership because the next trip for transfer passengers is the metro. Therefore, the metro and bus routes compete, and the fewer bus routes there are, the more transfer passengers will choose the metro.

For the metro-to-bus mode and the bus-to-metro mode, socioeconomic and population variables have a significant influence on the ridership. Among them, the rent and housing prices are negatively associated with the transfer ridership, while the geographic GDP and crowd density are positively associated with the transfer ridership. This may be because people in stations with higher rent and housing prices usually have higher incomes and travel mostly by taxi or private car, rarely relying on public transportation. Metro stations with higher geographic GDP are usually economically developed and have better public transportation networks, making it more convenient for people to travel and transfer, with higher transfer ridership. The CBD distance has a positive impact on the ridership. This is ascribed to metro stations being far from the CBD, less developed economic levels, and people who travel medium–long distances usually transfer by public transportation, so there is more transfer ridership. In addition, the date variable has a significantly positive impact on transfer ridership. Among the date variables, the evening peak has the greatest impact on the transfer ridership of the metro-to-bus mode, while the morning peak has the greatest impact on the transfer ridership of the bus-to-metro mode. This is consistent with the distribution of transfer ridership on weekdays shown in Figure 7. The travel of commuters on weekdays is mainly concentrated in the morning and evening peak, and the morning and evening peak travel path direction is just the opposite. Therefore, more people transfer from bus to metro in the morning peak, while they transfer from metro to bus in the evening peak.

5.1.2. The Determinants of Transfer Ridership on Holidays

We have investigated the effects of various factors on transfer ridership of the metro-to-bus mode and the bus-to-metro mode on holidays. The results are shown in Table 4. The following is a detailed analysis.

For the metro-to-bus mode, the estimated coefficient of the housing prices is the largest among the independent variables and is approximately 1.41 to 9.28 times that of the other independent variables. The housing prices are negatively correlated with transfer ridership. Weather variables have a significant impact on the transfer ridership. High temperatures, heavy rain, or low visibility conditions can increase transfer ridership. Among the weather variables, the influencing coefficient of rainfall is the greatest at about 1.43 to 2.55 times that of other weather variables. Similar to the transfer ridership on weekdays, transfer time is significantly negatively correlated with transfer ridership. Feeder bus routes are positively correlated with transfer ridership. Because the next trip of transfer passengers is to take the bus, the more feeder bus routes there are, the more convenient it is for people to transfer, and the more transfer ridership there is.

For the bus-to-metro mode, among all variables, housing prices have the most significant effect on transfer ridership at approximately 1.19 to 5.75 times that of other variables. Housing prices are negatively associated with transfer ridership. Weather variables have a significant impact on transfer ridership. Among them, the maximum temperature, rainfall, and maximum wind speed have a positive impact on the transfer ridership, whereas minimum visibility has the opposite effect. This shows that under the conditions of high temperature, heavy rainfall, strong wind, or low visibility, more travelers choose to transfer from the bus to the metro, leading to an increase in the transfer ridership. Moreover, among the weather variables, rainfall has the greatest impact on transfer ridership at approximately 22.12% to 57.74% higher than other weather variables. The revised transfer time has a significant positive impact on transfer ridership. Feeder bus routes are negatively associated with transfer ridership. These findings are similar to the factors influencing transfer ridership on weekdays.

Furthermore, bad weather will increase the transfer ridership. This is because transfer passengers usually cannot take a single vehicle directly to their destination and therefore need to transfer. On holidays, people's travel time is more flexible. Moreover, in bad weather, such as high temperatures, heavy rain, strong wind, or low visibility conditions, people prefer to take public transportation over other transfer modes, such as shared bikes, electric bikes, or walking. Therefore, bad weather will increase the transfer ridership. In other words, in bad weather, for those transfer passengers who took the metro or bus for the first leg of their journey and had to make a transfer to reach their destination, most of them chose to take the bus or metro to reach their destination on the second leg of their journey. As a result, high temperatures, heavy rain, or low visibility conditions can increase transfer ridership of the metro-to-bus mode, and under the conditions of high temperature, heavy rainfall, strong wind, or low visibility, more travelers choose to transfer from the bus to the metro.

For the metro-to-bus mode and the bus-to-metro mode, similar to the case with weekdays, socioeconomic and population variables have a significant impact on transfer ridership. Among them, rent and housing prices have a positive impact on the transfer ridership, whereas the geographic GDP and crowd density have the opposite effect. CBD distance is positively associated with the transfer ridership. The farther the metro station is from the CBD, the more transfer passengers there are.

5.1.3. The Determinants of Transfer Ridership during the Typhoon

We have revealed the effects of various factors on transfer ridership of the metro-to-bus mode and the bus-to-metro mode during the typhoon. The results are shown in Table 5, and the following is a detailed analysis.

For the metro-to-bus mode, among all variables, the impact of crowd density on transfer ridership is the most significant at about 1.19 to 7.98 times greater than other variables. The crowd density is positively correlated with transfer ridership. This is because the metro station has high crowd density, and there is significant transfer ridership. Weather variables have a significant positive effect on transfer ridership. High temperatures, strong wind speed, and heavy rainfall increase the transfer ridership. Of the weather variables, the temperature has the greatest impact on transfer ridership at about 70 % to 77% higher than the other weather variables. The transfer time has a significant negative impact on the transfer ridership. The metro station with a short transfer time can attract large transfer ridership. Feeder bus routes are positively associated with transfer ridership. This indicates that the more bus routes there are connected to the metro stations, the higher the transfer ridership is.

For the bus-to-transfer mode, among all variables, the crowd density has the greatest influence on transfer ridership at about 1.27 to 7.74 times that of other variables, which is positively associated with the transfer time. This indicates that crowd density can facilitate transfer ridership at metro stations. Unlike the case of the metro-to-bus mode, temperature, wind, and rainfall have a remarkably negative effect on the transfer ridership, whereas visibility has the opposite impact. Moreover, among the weather variables, wind speed has the greatest impact on transfer ridership at about 1.26 to 3.89 times that of other weather variables. This indicates that the transfer ridership is sensitive to changes in weather conditions. This may be ascribed to the fact that the first trip of the bus-to-metro mode is taking a bus. During typhoon days, in extremely bad weather (strong wind speed and rainstorm conditions), few passengers choose to take the bus for the first part of the journey, so there is less transfer ridership. Similar to the cases of weekdays and holidays, the revised transfer time has a considerably positive impact on the transfer ridership. Feeder bus routes are negatively associated with the transfer ridership.

For the metro-to-bus mode and the bus-to-metro mode, similar to the cases of weekdays and holidays, socioeconomic variables have a significant impact on transfer ridership. Among them, rent and housing prices have a negative impact on the transfer ridership, whereas the geographic GDP has the opposite effect. CBD distance is positively associated with the transfer ridership.

5.2. Discussions

In this study, a GPR model is used to explore the influence of various variables on the transfer ridership of the two transfer modes on weekdays and weekends, holidays, and typhoon days, and the results are shown in Tables 3–5. These variables include weather variables, public transport transfer-related variables, socioeconomic and population variables, built environment variables, and date variables. We ranked the top eight factors influencing transfer ridership in each model based on the impact coefficients, and the results are visualized, as shown in Figures 13–15 below. Based on the previous analysis, this section mainly discusses the influence of these eight factors on the transfer ridership of two transfer modes on weekdays and weekends, holidays, and typhoon days. The details are discussed below.

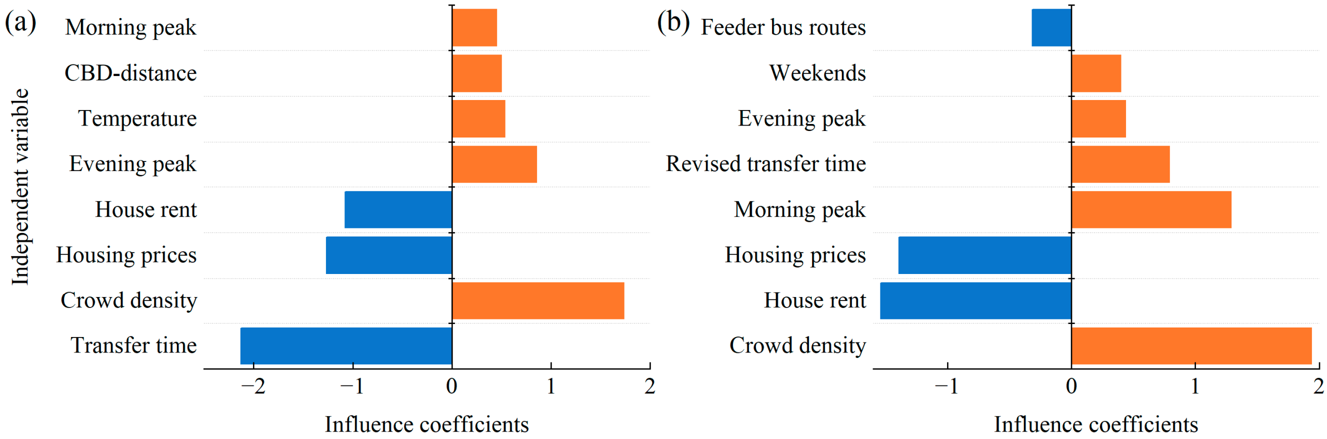


Figure 13. Influence coefficients are associated with the transfer ridership on weekdays and weekends: (**a**) the metro-to-bus mode and (**b**) the bus-to-metro mode.

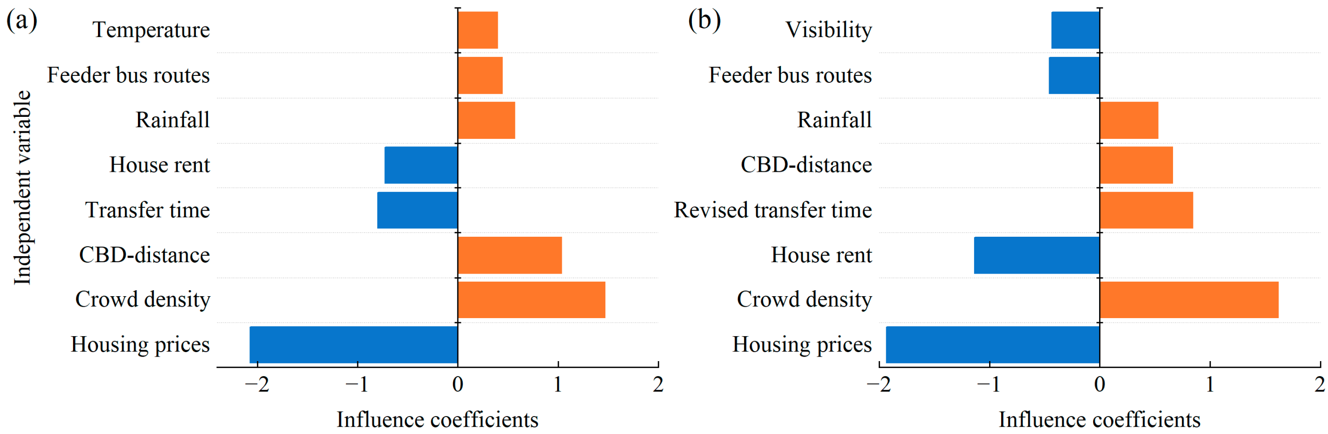


Figure 14. Influence coefficients are associated with the transfer ridership on holidays: (**a**) the metro-to-bus mode and (**b**) the bus-to-metro mode.

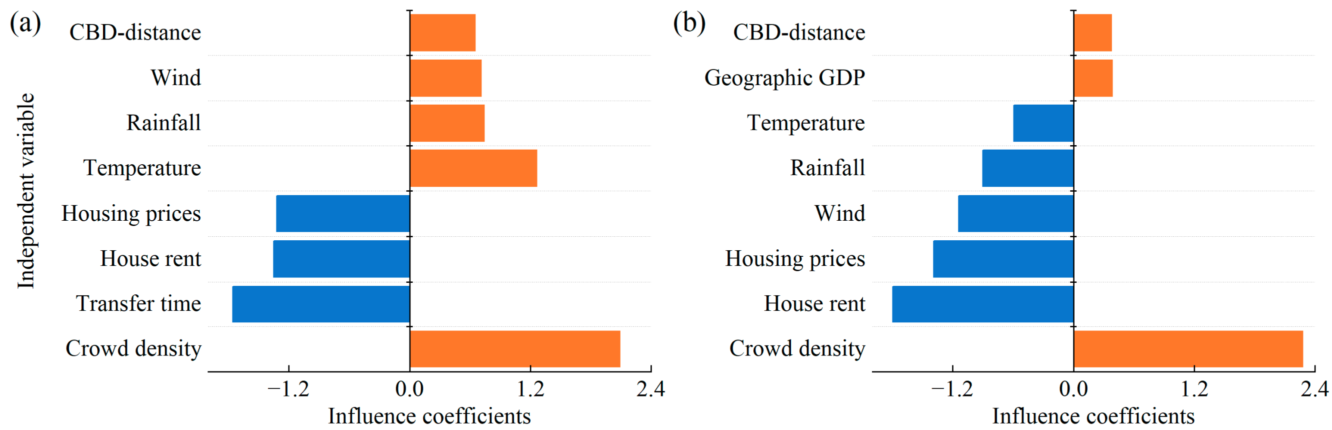


Figure 15. Influence coefficients are associated with the transfer ridership during typhoon weather: (**a**) the metro-to-bus mode and (**b**) the bus-to-metro mode.

Figure 13 shows that among the influencing factors, transfer time, socioeconomics, and population have a significant impact on transfer ridership on weekdays and weekends. Peak hours positively influence the transfer ridership. Morning peak, evening peak, low housing prices, low rent, and high crowd density can attract more transfer ridership at metro stations, while the opposite can attract less transfer ridership at metro stations. This may be explained by the large number of commuters gathering during peak hours. The majority of commuters require transfers to reach their destination. Rent and housing prices are negatively associated with the transfer ridership. This may be because people in stations with higher rent and housing prices usually have higher incomes and travel mostly by taxi or private car, rarely relying on public transportation. Crowd density is positively associated with transfer ridership because metro stations with high pedestrian density usually have more transfer passengers.

Additionally, the impact of some factors on transfer ridership varies under different transfer modes. For example, temperature and CBD distance have a significantly positive effect on the transfer ridership of the metro-to-bus mode. This is ascribed to the fact that metro stations are far from the CBD, less developed economic levels, and people who travel medium–long distances usually transfer by public transportation, so there is more transfer ridership. In high temperatures, people prefer to transfer by public transportation than other transfer modes such as biking or walking, while the feeder bus routes negatively influence the transfer ridership of the bus-to-metro mode because the next trip for transfer passengers is the metro. Therefore, the metro and the bus routes compete, and the fewer bus routes there are, the more transfer passengers will choose the metro. Transfer time has a significant negative impact on the transfer ridership of the metro-to-bus mode, while the revised transfer time has a significant positive impact on the transfer ridership of the bus-to-metro mode. Moreover, the former has a greater impact on transfer ridership than the latter at about 2.68 times as much as the latter. This is because the revised transfer time includes the in-vehicle time of taking the first bus, so the longer the revised transfer time is, the more transfer ridership there is. The transfer passengers from metro to bus wish to take the bus earlier with the shorter transfer time, which can attract more transfer passengers.

Figure 14 shows that weather, built environment, and socioeconomic and demographic variables have significant effects on transfer ridership on holidays. Among them, housing prices and crowd density have the most significant impact on transfer ridership. Compared to the transfer ridership on weekdays, transfer ridership on weekends is more susceptible to weather factors. This is because passengers on holiday are more flexible in terms of travel time and purpose, and many will change their travel plans because of weather changes, such as canceling trips, changing their travel destinations, or changing their travel mode. Low housing prices, low rent, high crowd density, heavy rain, and being a long distance from CBD can attract more transfer ridership at metro stations. Moreover, the impact of some factors on transfer ridership differs in different transfer modes. For instance, temperature positively affects the transfer ridership of the metro-to-bus mode. This may be because people in stations with higher rent and housing prices usually have higher incomes and travel mostly by taxi or private car, rarely relying on public transportation. Crowd density is positively associated with transfer ridership because metro stations with high pedestrian density usually have more transfer passengers. This is ascribed to the fact that metro stations are far from the CBD, the less developed economic levels, and people who travel medium-long distances usually transfer mainly by public transportation, so there is more transfer ridership, while visibility negatively influences transfer ridership of the metro-to-bus mode. This may be because the lower the visibility is, the fewer passengers choose to walk or bike and the more passengers choose public transportation to transfer. Transfer time has a significant negative impact on the transfer ridership of the metro-to-bus mode, while the revised transfer time has a significant positive impact on the transfer ridership of the bus-to-metro mode. This is because the revised transfer time includes the in-vehicle time of taking the first bus, so the longer the revised transfer time is, the more transfer ridership there is. The transfer passengers from metro to bus wish to take the bus earlier with the shorter transfer time, which can attract more transfer passengers. Feeder bus routes have a positive impact on the transfer of the metro-to-bus mode, while feeder bus routes have a negative impact on the transfer ridership of the bus-to-metro mode. Because the next trip for transfer passengers of the bus-to-metro mode is the bus, there are more bus routes, which means there is more transfer ridership. For the bus-to-metro mode, the next trip for transfer passengers is the metro. Therefore, the metro and the bus routes compete, and the fewer bus routes there are, the more transfer passengers will choose the metro.

Figure 15 shows that socioeconomic and demographic variables, weather variables, and the built environment have significant effects on transfer ridership during typhoon weather. Among them, housing prices have the most significant impact on transfer ridership. Low housing prices, low rent, high crowd density, and being a long distance from CBD can attract more transfer ridership at metro stations. This may be because people in stations with higher rent and housing prices usually have higher incomes and travel mostly by taxi or private car, rarely relying on public transportation. Crowd density is positively associated with transfer ridership because metro stations with high pedestrian density usually have more transfer passengers. This is ascribed to the fact that metro stations are far from the CBD, the less developed economic levels, and people who travel medium–long distances usually transfer by public transportation, so there is more transfer ridership. Moreover, the impact of some factors on transfer ridership varies with transfer modes. Notably, the three weather variables have completely different effects on the transfer ridership for the two transfer modes. Strong winds, heavy rain, and high temperatures will increase the transfer ridership of the metro-to-bus but reduce the transfer ridership of the bus-to-metro mode. This result is counterintuitive because it is more dangerous to take the bus (outdoors) while the indoor metro station is safer. This may be ascribed to the fact that travel in typhoon weather differs from that under normal weather conditions. To explain this phenomenon, we will further investigate the impact of other factors such as the travel purpose of transfer passengers on transfer ridership. Moreover, among the weather variables, the temperature has the greatest impact on the transfer ridership of the metro-to-bus mode, while wind speed has the greatest impact on the transfer ridership of the bus-to-metro mode. This may be ascribed to the fact that transfer activities are usually exposed to the outdoors and are more affected by the weather conditions. The metro-to-bus mode has the opposite path to the bus-to-metro mode. Furthermore, in bad weather, such as hot weather, people prefer to take public transportation over other transfer modes, such as shared bikes, electric bikes, or walking. Therefore, high temperatures will increase transfer ridership. In other words, in bad weather, for those transfer passengers who took the metro for the first leg of their journey and had to make a transfer to reach their destination, most will choose to take the bus to reach their destination on the second leg of their journey. As a result, high temperatures will increase the transfer ridership of the metro-to-bus mode.

Comparing Figures 13–15, we find that weather variables have little effect on transfer ridership on weekdays but have a greater effect on the transfer ridership on holidays and typhoon days. Moreover, compared to the ridership on weekdays and holidays, the weather has the most significant impact on transfer ridership during typhoon weather. This indicates that the transfer trips on weekdays are more fixed and less disturbed by external factors. On the other hand, during holidays and typhoons, the travel modes of passengers have more flexibility and are more susceptible to external factors. Socioeconomic variables have the greatest impact on transfer ridership. The impact of socioeconomic and demographic factors on transfer ridership is significant on different types of dates. Improvements in the metro stations and planning of new metro stations should focus on the impact of these factors on transfer ridership.

Besides revealing the relationship between transfer ridership and various critical factors, there are also other benefits to the GPR model that can be applied in real life. The GPR model can also be used to analyze the impact of various factors on metro ridership or bus ridership. Moreover, the results of this paper can help decision-makers in terms of improving transit planning. For example, bad weather can promote an increase in transfer ridership on holidays; thus, public transport practitioners should ensure the safe travel of transfer passengers and establish effective measures to defend against bad weather. Typhoon weather affects transfer ridership, so public transportation management should focus on safe transfers of transfer passengers in extreme weather. The economic level near the metro stations has a negative impact on transfer ridership. Therefore, in regions with poor economic levels, transportation decision makers should improve the accessibility of bus and subway networks and improve the transfer services. In areas with high pedestrian density, which usually have a great transfer ridership, transportation decision makers should take steps to improve transfer efficiency, such as reducing bus headways and adjusting metro schedules. In brief, these important findings can be used in real life and can help transportation decision makers and managers to improve public transportation network planning and improve metro and bus stations to enhance the service capacity and attractiveness of public transportation.

6. Conclusions

This study focused on the transfer ridership of different transfer modes to quantify the influence of weather, transfer and travel-related variables, socioeconomic characteristics, and built environment on transfer ridership on different dates. Considering that the interchange is count data and conforms to the Poisson distribution, the GPR model is utilized to investigate the determinants of the transfer ridership of the metro-to-bus mode and the bus-to-metro mode on weekdays, holidays, and typhoon weather, respectively. First, the transfer ridership, transfer time, and revised transfer time were extracted from large-scale smart card data and bus GPS data. Meanwhile, various influencing factors, including weather factors, socioeconomic and demographic factors, and built environment factors, were obtained from multivariate sources. Second, the GPR model was built to reveal the effects of various factors on transfer ridership. The results demonstrate that transfer-related variables, real-time weather, socioeconomic and demographic characteristics, and built environment comprehensively impact transfer ridership. The important findings of this study are detailed below.

- It is feasible to adopt the GPR model to investigate the influence of each factor on the transfer ridership of different transfer modes on weekdays, holidays, and typhoon days, respectively.
- The distribution of transfer ridership on weekdays consistently has a significant morning and evening peak. The distribution of transfer passenger flows on Saturdays is similar to that of weekdays and also has significant morning and evening peaks. Similarly, the distribution of transfer ridership on Sundays is consistent with that of transfer ridership on holidays, with large differences in the distribution of transfer ridership on different days. Moreover, the distribution of transfer time shows a strong consistency on weekdays, weekends, and holidays without significant morning or evening peaks.
- The impact of each factor on transfer ridership varies with dates and transfer modes. The impact of socioeconomic and demographic factors on transfer ridership is the most significant on different types of dates.
- Weather variables have little effect on transfer ridership on weekdays, but they have a greater effect on transfer ridership on holidays and typhoon days. Moreover, compared to the ridership on weekdays and holidays, the weather has the most significant impact on transfer ridership during typhoon weather.
- Strong winds, heavy rain, and high temperatures increase the transfer ridership of the metro-to-bus mode but reduce the transfer ridership of the bus-to-metro mode. Moreover, among the weather variables, the temperature has the greatest impact on the transfer ridership of the metro-to-bus mode, while wind speed has the greatest impact on the transfer ridership of the bus-to-metro mode.

In summary, the findings indicate substantial differences in how different transfer modes and individual weather factors affect transfer ridership. This can provide support for improving metro stations and increasing the attractiveness of public transport. However, this study has some limitations. The dataset is limited to one month, which limits the potential for longitudinal analyses that consider seasonality and hinders a better exploration of the impact of weather variables at different levels. The study should be extended to include seasonal variations to determine the relationship between transfer ridership and weather conditions. It would be worthwhile to present studies confirming the results achieved or possibly to carry out studies periodically—e.g., in four seasons. Therefore, we will subsequently conduct a periodical study to explore the influence of various factors on transfer ridership during all seasons of the year to derive the variability of transfer ridership affected by various factors in different seasons. Moreover, in this study, other nonlinear models should be used to discuss the relationship between any existing nonlinearities. In the subsequent study, we will explore the possible non-linear relationship between dependent and independent variables by adding polynomial terms for the independent variables. Subsequent studies should also consider the spatial impact of each factor on transfer ridership, and a spatial model should be used to explore the spatial heterogeneity and spatial associations of each factor and transfer ridership.

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