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# Stratified Assessment of Urban Low-Carbon Travel Potential

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**ABSTRACT**

Non-motorised travel and public transportation travel are recognised as low-carbon travel modes, in contrast to car travel, which is considered a non-low-carbon option. Based on this, the paper proposes a stratified assessment method for the urban low-carbon travel potential. The proportion of the motorised travel population that could potentially shift to non-motorised travel within the entire travel population is defined as the urban Tier 1 low-carbon travel potential. Meanwhile, the proportion of the car travel population that could potentially shift to public transportation travel within the entire travel population is defined as the urban Tier 2 low-carbon travel potential. This method holistically presents the potential for improvement in urban traffic carbon emission control. This method considers distance as a primary negative factor affecting the residents' willingness to engage in non-motorised travel compared to motorised travel. Additionally, it recognises connection, delay and transfer as the main negative factors influencing the residents' willingness for public transportation travel over car travel. By comparing the actual travel distances of residents and the actual intensity of connection, delay and transfer in public transportation travel modes with the assumed maximum acceptable distances and intensity for residents, the method identifies the number of people who could potentially shift to corresponding levels of low-carbon travel in hypothetical scenarios. Based on this, the corresponding low-carbon travel potential values are calculated. The method then further analyses the trend of these values as the residents' acceptable thresholds for non-motorised travel distances and acceptable intensity for public transportation travel connection, delay and transfer change. A relationship curve is fitted, which intriguingly exhibits a reverse "S" shape, allowing for the identification of the "rapid release zone" and "key points" on the curve. These insights are essential for effectively targeting interventions to increase the adoption of low-carbon travel modes. This paper takes the cities of Shanghai and Wuhan in China as examples, conducting a stratified assessment of the low-carbon travel potential for both cities based on 19,732 daily travel origin–destination (OD) survey samples from residents. Additionally, the low-carbon travel potential of the two cities is visualised by district, enabling an analysis of the characteristics of low-carbon travel potential in each city and a comparison of the differences in low-carbon travel potential between them.

**KEYWORDS**

urban low-carbon travel potential; non-motorised travel; public transport travel; connection; delay; transfer.

## 1. INTRODUCTION

The rapid advancement of modern industrial society has been paralleled by a surge in carbon emissions, which, after propelling human industrial civilisation into the 21st century, has introduced significant environmental challenges, garnering global attention. The Paris Agreement, ratified by 178 nations in December 2015, aims to confine the global average temperature rise to well below 2°C above pre-industrial levels, with an aspirational target of limiting it to 1.5°C [1]. By October 2021, the "carbon neutrality" goal has encompassed over 80% of the global GDP (calculated using purchasing power parity) and over 77% of greenhouse gas emissions [2]. Urban transportation contributes a substantial share to total carbon emissions, offering considerable scope for energy conservation and emission reduction. The International Energy Agency (IEA) forecasts that by 2030, the transportation sector's carbon emissions will constitute 41% of the total CO2 emissions from fuel combustion, a rise from 24.6% in 2018 [3]. Moreover, a resurgence of global transportation activities to pre-COVID-19 levels could lead to an additional 600 million tons of carbon emissions in 2021 [4]. In China, based on 2020 statistical data, transportation carbon emissions account for 15% of terminal carbon emissions, with road traffic carbon emissions representing 90% of the total transportation carbon emissions and passenger road transport contributing 42%, of which 90% is attributed to passenger cars.

Non-motorised and public transportation modes significantly contribute to reducing the overall carbon emissions of cities [5–8]. Non-motorised travel, which includes walking and cycling, is characterised by a zero-carbon footprint when focusing solely on the act of travel. Public transport, with its higher passenger capacity compared to private vehicles [9–12], results in significantly lower per capita carbon emissions for these modes of travel. According to statistics from the UK Department for Business, Energy and Industrial Strategy, the carbon emissions per person per kilometre for a mid-sized gasoline car is approximately 192 g, while for buses, it is only about 105 g per person per kilometre; it is even lower for rail transit, at about 41 g per person per kilometre [13]. Considering that both non-motorised travel and public transportation are considered low-carbon travel modes, but they differ in degree and focus, this study defines non-motorized travel as "Tier 1 low-carbon travel", public transportation as "Tier 2 low-carbon travel" and car travel as "non-low-carbon travel".

To investigate the influence mechanism of urban transportation system factors on the residents' travel mode choice preferences, we propose a stratified urban low-carbon travel potential assessment method. This method aims to provide urban managers and builders with insights for city development, offering theoretical support for guiding the residents' travel behaviour toward more low-carbon travel options. The stratified assessment method defines the proportion of the population that could potentially shift to Tier 1 and Tier 2 low-carbon travel within the total travel population as the urban Tier 1 and Tier 2 low-carbon travel potential, respectively. This represents the potential space for residents to transition from non-low-carbon to low-carbon travel modes through traffic guidance measures. The higher the potential value, the greater the proportion of residents who could potentially shift to low-carbon travel modes under effective measures, thus enhancing the value of implementing traffic guidance strategies. This method is based on origin-destination (OD) surveys of urban residents and assesses the number of people who might shift to low-carbon travel by considering their acceptable thresholds for non-motorized travel distances and the connection, delay and transfer intensity for public transportation modes. The urban low-carbon travel potential values established by this method fluctuate as the residents' acceptable intensity thresholds change and analysing these trends is a key objective of the research. The thresholds associated with the rapid release zone help urban managers to discern urban travel patterns, identify differences between cities and develop targeted transportation policies. As a result, this can lead to a reduction in the overall carbon emissions from urban transportation at a lower marginal cost.

This study uses two major cities in China, Shanghai and Wuhan, as examples to apply the method for a stratified assessment of urban low-carbon travel potential. There are differences in the development status of various regions within large cities and urban development and improvement strategies should be carried out with a focus on specific areas. Infrastructure construction conditions vary across different urban districts, with city centres typically offering better environments for non-motorised travel and more extensive public transportation coverage. To provide a more nuanced analysis of the differences between various urban areas, the study conducts district-level assessments based on the rapid release zone and key scenarios of the urban low-carbon travel potential. Key scenarios form the foundation for further sub-district analysis within a city. By comparing the proportion of the residents' travel modes under various key scenarios, the study examines the changing characteristics and inter-district differences in different areas of multiple cities. This analysis provides a basis and reference for developing tailored development strategies for each district.

In summary, this study makes innovative contributions in the following three aspects:

Firstly, the study introduces a stratified assessment method for urban low-carbon travel potential that comprehensively considers both non-motorised travel and public transportation travel of residents. The research focus is on the potential for low-carbon travel in cities, rather than an evaluation of the current state, which is the most significant contribution of this paper.

Secondly, the study simultaneously considers non-motorised and public transportation travel as low-carbon modes of travel for residents and classifies them based on their carbon reduction levels. It offers a comprehensive examination of the potential changes in urban transportation carbon emissions as the city transitions towards low-carbon travel modes. The study defines evaluation metrics for each tier of low-carbon travel, choosing the total distance for non-motorised travel and the aspects of connection, delay and transfer for public transportation travel as the negative factors affecting travel choices. It investigates how these travel factors influence the residents' mode selection and their underlying impact mechanisms.

Thirdly, the study focuses on the delineation of the rapid release zone of urban transportation low-carbon travel potential as a key research element and establishes the corresponding non-motorised travel distance thresholds and public transportation connection, delay and transfer thresholds for the study areas. It also considers the developmental differences among various urban regions, assesses the low-carbon travel potential of urban transportation in different areas and conducts comparative analyses between regions.

The three contributions outlined above are pivotal in guiding the creation and optimisation of urban low-carbon travel strategies, offering novel methods and perspectives for cities in the pursuit of identifying areas in need of improvement. This method's low dependency on data volume makes it accessible for use in urban and regional contexts with varying levels of development.

## 2. LITERATURE REVIEW

This section of the literature focuses on three primary areas: the assessment and control of carbon emissions in urban transportation, the distances urban residents travel and aspects of transportation connection, delay, and transfer and the migration of the urban residents' travel patterns.

### 2.1 Urban transportation low-carbon travel intentions and travel choices

In the overall carbon emissions of a city, transportation carbon emissions constitute a significant portion. Assessing this component and promoting its gradual reduction have a positive impact on the improvement of total carbon emissions. The residents' adoption of low-carbon travel methods can effectively reduce urban traffic carbon emissions and their willingness to engage in low-carbon travel indirectly affects the city's total carbon emissions. Relevant research has found that the residents' personal characteristics [14, 15] and their subjective perceptions of the neighbourhood environment [16], travel time [17] and low-carbon knowledge [18] all influence their choice of travel mode. The number of parking lots within a city, the level of traffic congestion and the overall standard of public transportation are urban characteristics that also influence the residents' choices of travel modes [14].

The carbon emission reduction benefits of low-carbon travel behaviours are also a focus of research. Some researchers have assessed the reduction in urban traffic carbon emissions resulting from low-carbon travel replacing car travel for short-distance trips [19] and following the improvement of low-carbon transportation systems [20]. The assessments primarily consider objective factors such as travel distance [21], travel purpose [21], population size [22], environmental characteristics [22] and land use [23], as well as the residents' subjective satisfaction with low-carbon travel.

### 2.2 Urban residents' travel distance and transportation connection, delay and transfer

In the study of the transition between motorised and non-motorised travel modes in the residents' daily commutes, static threshold values of various indicators are often used as a basis for assessment. This leads to the determination of the proportion of motorised travel that could be converted within the city and, consequently, an estimation of the potential reduction in urban carbon emissions that could be achieved through the shift in travel modes. Among these, travel distance serves as a key indicator for the transition from non-motorised to motorised travel, with the threshold commonly set at three miles [24] and some studies set it at eight miles [25]. In the process of transitioning from car travel to public transport, factors such as connection, delay and transfer within the public transportation system have a significant negative impact [26].

Current research generally posits that the residents' travel distance is simultaneously related to both individual resident attributes and societal public characteristics. Individual resident attributes include factors such as income level, interest in car ownership and travel purposes [27]. Social public attributes encompass factors like urban form and regional characteristics [27, 28]. Travel distance further influences the choice of the residents' travel modes [29] and it is significantly higher than other factors across different populations [30]. At the same time, the shorter the average travel distance of residents, the higher the urban traffic efficiency, the lower the probability of traffic congestion, and reducing the motorised travel distance of residents can also decrease the carbon emissions of urban transportation [31]. Numerous scholars have explored control measures for the residents' motorised travel distances, including urban planning [32], travel policies [33] and the dissemination of traffic information [34], as well as the effectiveness of these measures.

Research on urban public transportation focuses on the last mile of public transportation travel, and how to quickly transfer residents to main transportation arteries is key to improving its transportation efficiency. The connection of rail transit is a hot topic in research and the convenience of connections is one of the core indicators for assessing the suitability of rail transit [35]. In addition to residents walking directly to rail transit stations, feeder buses are the primary mode of connection, with ride-hailing services, taxis and shared bicycles also complementarily handling a portion of the connection flow [36]. The operating hours and route accessibility of feeder buses play a crucial role in the overall accessibility of urban public transportation [37], and their route demand [38] and dispatching [39] are key to optimising public transportation efficiency.

Research on urban traffic delays primarily focuses on the reliability of travel time, as it directly affects whether city residents can reach their destinations within predefined time thresholds, making it one of the most crucial traffic indicators of concern to urban residents. The reliability of travel time depends on the probability of unforeseen delays occurring during travel. To improve the reliability of travel time, scientific prediction of travel time is essential. Some researchers have constructed vehicle travel time prediction models based on urban traffic big data [21, 40] and introduced various external influencing factors to assess their impact on vehicle travel time [41]. Some studies have also analysed the subjective inclination characteristics of the population towards high-delay probability travel [42] and the impact of travel delays on population traffic behaviour [23], considering optimising urban vehicle operation systems to reduce overall travel time [43]. Additionally, compared to driving, public transportation travel is characterised by higher delays and lower emissions. Comparing the travel times of these two modes [44], researchers have evaluated the inherent relationship between this difference and emission reduction [22], as well as estimated the reduction in emissions from substituting public transportation for driving [45]. These aspects have received considerable attention from researchers.

The issue of transfers within urban public transportation systems centres on identifying factors that affect transfer barriers in an intermodal transportation framework and their potential solutions. Macro-level influencing factors mainly include station location [46], socio-economic factors [47], built environment [47] and transportation modes [48]. Micro-level factors are primarily the waiting time and walking distance associated with transfers [49], and the psychological state of passengers during the transfer process is also included in the research scope [50]. In terms of strategy, some researchers have constructed optimisation models for urban public transportation networks that can reduce the number of transfers E and minimise waiting times [51], aiming to enhance the connectivity of the urban transportation system [52]. Additionally, some studies have assessed the transfer costs of urban public transportation systems and proposed related improvement measures [53].

### 2.3 Urban residents' travel mode transition

Research on the transition of the urban residents' travel modes focuses on how travel patterns change under various conditions, including changes in the travel environment [54–56], the process of transportation facility deployment and shifts in traffic safety hazards. Environmental changes encompass extreme conditions such as disastrous weather [57], floods [58], road damage [59] or energy constraints [60]. The analysis also considers the influencing factors that lead to these changes, such as the built environment [61], residential location [62], demographic characteristics [63], social psychology [64], transportation layout [65] and work systems [65], along with their impact characteristics [66].

In the construction of urban traffic resilience assessment systems, some researchers have also considered the migration of the residents' travel patterns. For example, Martins et al. [67] introduced the concept of "maximum possible distance" as the critical distance for the transition between walking, cycling and motorised travel. Using this concept, they assessed the proportion of non-motorised travel under certain conditions as a primary basis for evaluating the intrinsic traffic resilience of a city. Based on the premise of the migration of the residents' travel patterns due to the changes in the acceptable intensity thresholds for public transportation connection, delay and transfer, this study constructs an assessment system for the low-carbon travel potential of urban transportation.

## 3. DATA SOURCES AND CALCULATION METHODS

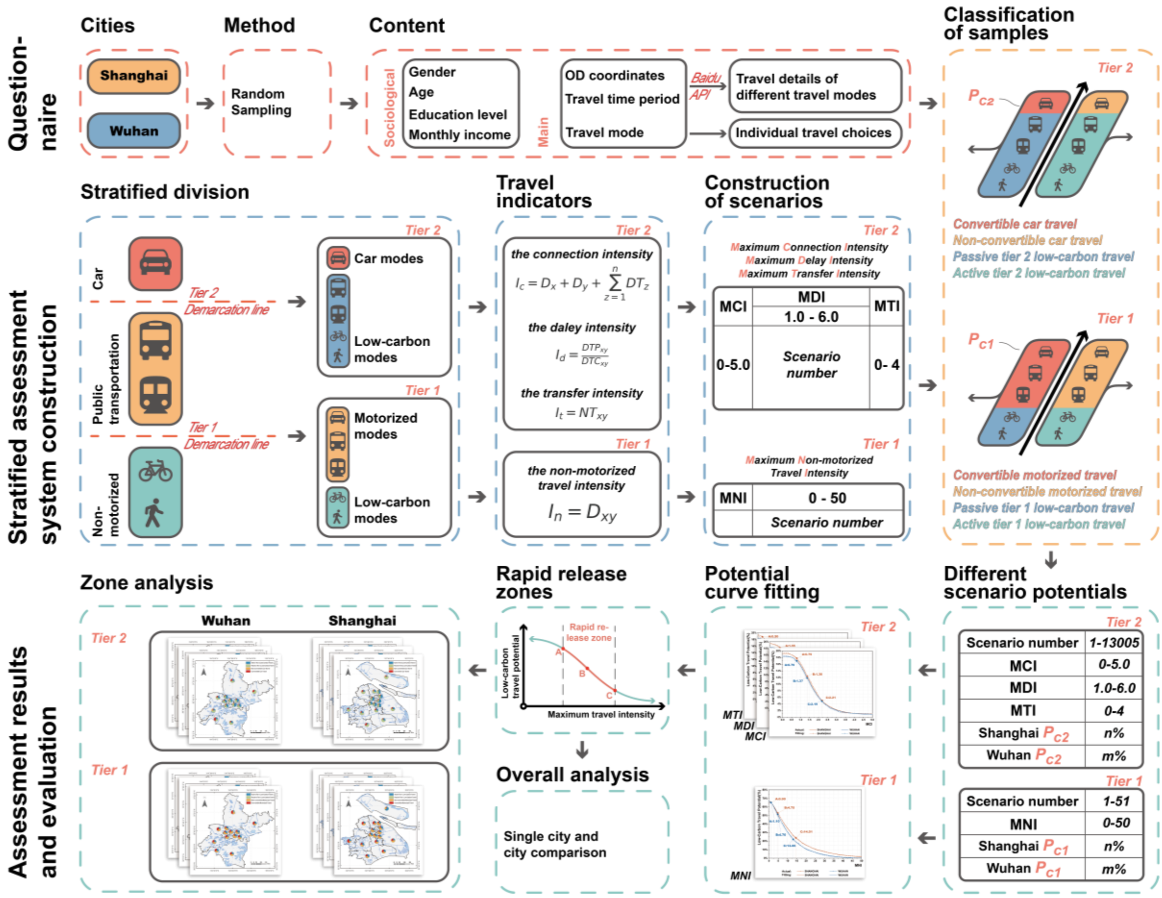



*Figure 1 – Framework of the Stratified Assessment System*

The stratified research method primarily includes several stages: stratified division, determination of travel intensity indicators, construction of assumption scenarios, classification of samples within a single scenario, fitting of low-carbon travel potential trends with changes in travel intensity and determination of key points and rapid release zones, among others. *Figure 1* illustrates the overall framework and analytical process. The stratification is carried out based on different travel mode classification standards. Sample classification within a single scenario considers both the travel details and actual travel modes of respondents within the selected travel time for the given OD coordinates. Finally, through the determination of key points and rapid release zones, it is possible to conduct analyses between cities as well as analyses of different zones within a city. In section 3 of the article, "Data sources and calculation methods," we primarily explain the Questionnaire and the stratified assessment system construction. The part on Assessment Results and Evaluation is detailed in section 4, "Assessment results and discussion."

### 3.1 Urban resident daily travel OD survey

*Analysis area and data sources*

This study selects Shanghai and Wuhan as the research objects to investigate the OD data of the urban residents' daily travel. Shanghai, located in the eastern region of China, is a direct-administered municipality of the People's Republic of China and serves as the country's economic and financial hub, with a permanent population of over 24 million [68]. Shanghai has a high level of urban development and its slow-moving traffic and public transportation systems are at the forefront [69]. As one of the cities with the densest permanent population in China, Shanghai has a strong demand for rail transit. By 30 December 2021, Shanghai's rail transit had opened 20 lines with an operational mileage of 831 kilometres [70], leading the country in rail transit mileage. Wuhan, the capital of Hubei Province, holds the top position in urban scale and development level in the central region of China, with a permanent population of over 13 million [71]. The Yangtze River and the Han River converge here and the city is dotted with numerous lakes, earning it the reputation of "City of a Hundred Lakes" [72]. The natural geographical environment poses many restrictions on the construction of Wuhan's traffic network. Both cities hold significant economic, social and transportation statuses.

Considering these factors, selecting Shanghai and Wuhan for a comparative study on low-carbon travel potential is justified. Despite both cities being intersected by rivers, their scales differ significantly. This disparity influences urban layouts; Wuhan's city centre is more dispersed due to the division by the Yangtze and Han rivers, leading to diverse and complex transportation demands among residents. In contrast, Shanghai's city centre is more concentrated, facilitating easier coverage by public transportation systems into core urban areas. Additionally, Wuhan's stage of urban development differs from Shanghai; although it ranks fifth in China for metro operational mileage [73], its network coverage lags behind Shanghai's. Shanghai boasts more advanced transportation infrastructure and higher public transportation usage, while Wuhan requires further improvements in public transportation and pedestrian facilities.

By conducting a comparative analysis of Shanghai and Wuhan, we gain a comprehensive understanding of their similarities and differences in terms of low-carbon travel. This not only helps identify their respective strengths and weaknesses but also provides valuable insights for other cities to develop scientifically sound strategies for low-carbon travel, thereby promoting sustainable urban development.

In the study of the urban residents' daily travel issues, it is a common method to divide the city into several traffic analysis zones (TAZs) and convert OD points to the centre of their respective TAZs for analysis and processing, thereby simplifying the data calculation [74–76]. However, in the urban residents' daily travel, the specific location within the TAZ cannot be ignored due to the issues involved in the residents' walking and the "last mile" connection of public transportation. If the TAZ is too large, it cannot accurately reflect the problems in travel; if the TAZ is too small, it cannot serve the purpose of simplifying calculations. Therefore, it is more rational to calculate directly using precise OD point data. To obtain precise OD point information for the sample, a map selection function is embedded in the electronic survey questionnaire. However, regional analysis in urban traffic optimisation is a necessary step. By analysing TAZs one by one, the differences in low-carbon travel potential between different urban areas can be intuitively demonstrated, which helps identify the main reasons for the differences and facilitates urban builders in carrying out targeted urban traffic optimisation. Therefore, in the regional analysis of cities, the delineation of TAZs is necessary. Considering the large area of the two cities and to ensure that each analysis zone has enough samples and considering that in Chinese urban construction, districts are generally used as basic management and approval units, the administrative divisions of the cities are used as the basis for TAZs in this study.

To accurately capture the entire travel process of residents, this study employs the Baidu Maps API to obtain the best transportation options for residents. In this study, we selected the shortest travel time route as the optimal route. Baidu Maps (https://map.baidu.com/), being one of the most popular internet mapping service providers in China, integrates real-time road conditions such as road classifications and speed limits into its recommended routes for car travel. For public transportation, it considers multiple modes including rail transit and buses. We obtained the shortest travel time routes for non-motorised travel, public transport travel and car travel based on the respondents' preferences and travel times, which serve as the baseline for subsequent analysis. Detailed route information for public transport includes key data such as total walking distance, total travel time and number of transfers.

*Survey process and socio-demographic characteristics of respondents*

To obtain sample data on the travel characteristics of urban residents in Shanghai and Wuhan, this study conducted a survey using questionnaires. The survey was carried out in 2020 and lasted over three years. The research team distributed electronic survey questionnaires via the internet, totalling 19,732, of which 9,581 were valid for Shanghai and 10,151 were valid for Wuhan. The content of the survey questionnaires mainly covered the respondents' daily travel patterns and OD coordinates.

Given that both cities are mega-cities, with the survey targeting the entire resident population, it is impractical to conduct a reasonable survey through quota sampling. Therefore, we adopted a random sampling method. We used the Cochran formula to calculate the sample size, considering the population size, confidence level (95%) and margin of error (1%), resulting in an approximate sample size of 9,603 for each city. Ultimately, we distributed 10,000 questionnaires in Shanghai and received 9,581 valid responses; in Wuhan, we distributed 11,000 questionnaires and received 9,432 valid responses, totalling 19,732 valid samples with an effective response rate of 93.96%. During the questionnaire screening process, we verified the OD points and travel mode information in each questionnaire individually, excluding significantly invalid questionnaires to ensure data accuracy and representativeness.

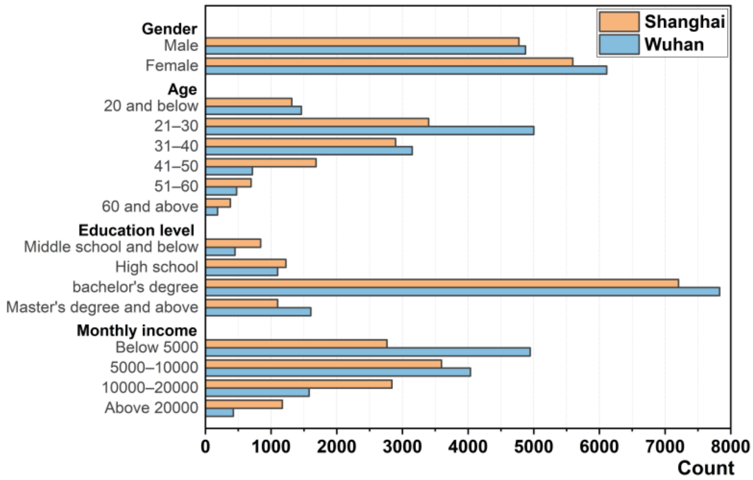



*Figure 2 – Sociodemographic statistics of survey respondents*

In the survey questionnaire, we also collected sociodemographic information such as gender, age, education level and monthly income (in Chinese Yuan) of the respondents, as shown in *Figure 2*. The figure reveals that there are slightly more female respondents than male respondents overall, with this difference being more pronounced in Wuhan compared to Shanghai. In Wuhan, there is a higher proportion of younger respondents, whereas in Shanghai, the distribution of respondents is more even across age groups. Overall, the ratio of male to female respondents is close to 1:1 and respondents are broadly distributed across different age groups, education levels and monthly income levels. While not fully reflective of the entire urban population, these findings are representative to a certain extent.

## 3.2 Urban low-carbon travel potential intensity indicators

*Calculation of non-motorised travel intensity*

In this study, non-motorised travel intensity is defined as the total distance travelled between the origin and destination using non-motorised modes, such as walking or cycling, denoted as $I_n$.

The acceptable non-motorised travel distance for urban residents is influenced by various factors, including the built environment, travel philosophy and road safety [77–79]. However, in the analysis of urban residents as a group, travel distance is the most important and universally applicable factor. By assessing travel distance, the differences brought about by the built environment in different urban areas can be reflected [80]. Non-motorised travel includes various modes such as walking and cycling and there are differences in the routes taken for different travel modes. However, the overall differences are relatively small. Statistical data from the entire sample shows that cycling routes, on average, increase by 3.299% compared to walking routes. Considering that both cities in this study are flat terrain, in actual travel, the walking distance often represents the shortest path for non-motorised travel. Therefore, we use walking distance to represent non-motorised travel distance. Therefore, the calculation of non-motorised travel intensity for urban residents should be as follows:

$$I_n = D_{xy} \tag{1}$$

where $I_n$ represents the non-motorised travel intensity between points $x$ and $y$ for residents, measured in kilometers (km); $D_{xy}$ represents the actual distance travelled by non-motorised means between points $x$ and $y$.

*Calculation of public transportation travel intensity*

In this study, the intensity of public transportation travel is composed of three aspects: connection intensity, delay intensity and transfer intensity.

Connection intensity ($I_c$) is defined as the total walking distance during the entire process of travelling between the origin and destination using public transportation. Delay intensity ($I_d$) is defined as the ratio of the travel time of the shortest path between the origin and destination using public transportation to the travel time of the shortest path for car travel. Transfer intensity ($I_t$) is defined as the number of transfers required when travelling between the origin and destination using public transportation.

In urban commuting, the maximum acceptable connection distance for residents does not have a linear relationship with the total travel distance. Casey P. and Wen also highlighted the non-vehicular connection distance in public transportation as a critical indicator of the probability of low-carbon travel [81, 82]. Therefore, the absolute value of the connection distance is more important. Therefore, the connection intensity is calculated based on the total walking distance extracted from the shortest travel time optimal public transport route. Therefore, the calculation formula for connection intensity is as follows:

$$I_c = D_x + D_y + \sum_{z=1}^{n} DT_z \tag{2}$$

where $I_c$ represents the connection intensity of public transportation travel between points $x$ and $y$, measured in kilometres (km). $D_x$ represents the non-motorised travel distance from the origin point $x$ to the departure station, $D_y$ represents the non-motorised travel distance from the arrival station to the destination point $y$, $DT_z$ represents the non-motorised travel distance during the z$^{th}$ transfer and $n$ represents the number of transfers.

The maximum acceptable delay distance for residents differs from the connection distance and changes with the increase in travel distance. In both long-distance and short-distance travel, residents are willing to accept different time differences between public transportation and cars. Using the absolute size of time differences between different modes of travel to reflect delay levels is not appropriate. It is more reasonable to use the ratio of travel times between public transportation and other car travel modes, such as driving, taxis or ride-hailing services [44, 83]. Singapore's plan to reduce door-to-door travel time for public transportation to 1.5 times that of car travel by 2020 supports this perspective [84, 85] and this 1.5 times ratio of public transportation to car travel time has also been used to evaluate the public transportation accessibility of Shenzhen's urban network. Therefore, delay intensity is defined as the ratio of the minimum travel time for public transportation to the minimum travel time for car travel, and the formula is as follows:

$$I_d = \frac{DP_{xy}}{DC_{xy}} \tag{3}$$

where $I_d$ represents the delay intensity of public transportation travel between points $x$ and $y$, $DP_{xy}$ represents the minimum travel time for public transportation travel between points $x$ and $y$ and $DC_{xy}$ represents the minimum travel time for car travel between points $x$ and $y$.

Transfers between different public transportation modes or lines can also reduce the residents' willingness to choose public transportation. The issue of transfers in public transportation is influenced by various factors, including the distance to the connection point and the design of the connection station, which is already reflected in the connection intensity. Other factors are affected by the design of individual transfer stations. To assess the impact of transfers on the residents' travel at the urban scale, the transfer intensity is defined as the number of transfers on the route with the shortest travel time. The calculation formula is as follows:

$$I_t = NT_{xy} \tag{4}$$

where $I_t$ represents the transfer intensity of public transportation travel between points $x$ and $y$, $NT_{xy}$ represents the number of transfers during public transportation travel between points $x$ and $y$. In cases where public transportation provides a direct route without transfers, $NT_{xy}$ is taken as 0, so $NT_{xy}$ is an integer greater than or equal to 0.

### 3.3 Urban low-carbon travel mode classification

*Construction of the classification reference system*

The necessity of travel [81] and the influence of external environmental factors [82, 83] are the criteria for classifying the urban residents' travel modes. Martins et al. [76] and Wang et al. [74] classified travel modes based on the residents' willingness to travel non-motorised distances. This study approaches the classification of travel modes from two dimensions: subjective willingness and objective travel modes. In terms of subjective willingness, the relationship between the residents' actual travel intensity and the assumed willingness travel intensity is judged, reflecting the subjective willingness of residents to choose travel modes at that intensity. In terms of objective travel modes, different modes of travel result in different carbon emissions. The study categorises travel modes by different transportation modes and ranks them according to the average carbon emissions per person per kilometre for each mode, which mainly includes walking, cycling, rail transit, buses and cars.

Considering that walking and cycling are quite similar in terms of travel choice, encountered difficulties and per capita carbon emissions, we categorise walking and cycling together as non-motorised travel. Similarly, buses and rail transit are combined into public transportation for further analysis. This is because both share similar travel logic, face similar travel issues and require transfers and connections during trips. Additionally, buses often extend and complement rail transit, frequently appearing together in multimodal transport systems. Public transportation travel exhibits marginal effects in the reduction of carbon emissions, as the transportation process always involves some level of carbon emission. Non-motorised mode travel should be more vigorously promoted for short-distance trips [86, 87], as it can achieve true zero carbon emissions. Within the stratified assessment system for urban low-carbon travel potential, two types of travel mode classification systems are constructed, respectively, based on non-motorised travel and public transportation travel, along with their corresponding evaluation indicators.

*Travel mode classification based on non-motorised travel distance*

In the process of constructing the urban Tier 1 low-carbon travel potential assessment, non-motorised travel intensity is used as the basis for classifying the residents' subjective willingness, while the use of non-motorised modes for daily travel is taken as the objective basis for classifying travel modes. The Maximum Non-Motorised Travel Intensity (MNI) represents the maximum intensity of non-motorised travel that residents are willing to accept. On the subjective willingness level, it is assumed that the residents are willing to travel by non-motorised modes if the actual non-motorised travel intensity does not exceed this threshold. When the actual non-motorised travel intensity exceeds the threshold, the residents are unwilling to travel by non-motorised modes. On the travel mode level, walking and cycling are collectively referred to as non-motorised travel modes, while any motorised vehicle, including public transportation, is referred to as motorised travel modes. In the Tier 1 low-carbon travel potential assessment for cities, the residents' travel modes are classified into four categories: Active Tier 1 low-carbon travel, passive Tier 1 low-carbon travel, non-convertible motorised travel and convertible motorised travel, as illustrated in *Figure 3*.

Active Tier 1 low-carbon travel is when the residents' non-motorised travel intensity is below their acceptable maximum intensity and they have chosen to travel by non-motorised means; this indicates that the residents are suitable for choosing non-motorised travel.

Passive Tier 1 low-carbon travel is when the residents' non-motorised travel intensity exceeds their acceptable maximum intensity, yet they still opt for non-motorised travel; this suggests that the residents are compelled to travel non-motorised due to personal or objective reasons, making this a passive choice.

Non-convertible motorised travel is when the residents' non-motorised travel intensity is below their acceptable maximum intensity, but they have chosen motorised travel; this indicates that the choice of motorised travel is unrelated to non-motorised travel intensity and even with improvements in the residents' travel environment, the travel choices of this group cannot be changed.

Convertible motorised travel is when the residents' non-motorised travel intensity exceeds their acceptable maximum intensity and they have chosen motorised travel; the travel mode of these residents may change due to improvements in the pedestrian system and this group represents the low-carbon travel population that cities can target.

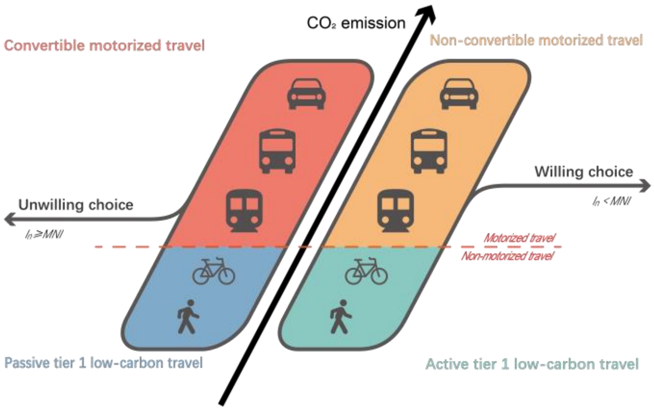



*Figure 3 – The Tier 1 low-carbon travel assessment model classification for cities*

Therefore, the proportion of Convertible Motorised Travel samples in the total sample is defined as the Urban Tier 1 Low-Carbon Travel potential, reflecting the potential reduction in the total carbon emissions of the urban transportation system following the city's measures to improve the non-motorised travel environment.

*Travel mode classification based on public transportation connection, delay and transfer*

In the process of constructing the Tier 2 low-carbon travel potential assessment for cities, the choice of public transportation by the residents for their daily travel is used as the objective basis for classifying travel modes, with the corresponding evaluation metric being the public transportation intensity threshold. The maximum public transportation intensity that the residents are willing to accept during travel is represented by three indicators: Maximum Connection Intensity (MCI), Maximum Delay Intensity (MDI) and Maximum Transfer Intensity (MTI). This study assumes that if the actual connection intensity, delay intensity and transfer intensity of residents do not exceed the threshold, their public transportation intensity is below the threshold and they are willing to travel by public transportation. Conversely, if any of these three indicators exceeds the corresponding threshold, the residents are subjectively unwilling to travel by public transportation. On the travel mode level, motorised travel is further divided into two categories: public transportation and non-public transportation. Public transportation includes low-carbon travel modes such as buses and rail transit, while non-public transportation includes car travel, ride-hailing and taxis. In the urban Tier 2 low-carbon travel potential assessment, the residents' travel modes are similarly classified into four categories: active Tier 2 low-carbon travel, passive Tier 2 low-carbon travel, non-convertible car travel and convertible car travel, as illustrated in *Figure 4*.

Active Tier 2 low-carbon travel refers to the situation where the residents' public transportation intensity is below their acceptable maximum intensity, meaning that the connection, delay and transfer intensities are all below their acceptable maximum and the residents have actively chosen non-motorised or public transportation modes.

Passive Tier 2 low-carbon travel occurs when the residents' public transportation intensity exceeds their acceptable maximum intensity, with at least one of the connection, delay or transfer intensities surpassing the acceptable maximum, yet residents still choose non-motorised or public transportation modes; this may be due to personal reasons such as economic status or travel philosophy, leading them to opt for low-carbon travel modes despite discomfort.

Non-convertible car travel indicates that the residents' public transportation intensity is below their acceptable maximum, but they have not chosen non-motorised or public transportation modes; this suggests that the choice of car travel is not due to the connection, delay and transfer factors of the public transportation system, but rather due to personal travel choices, including time, travel philosophy and public transportation safety, among other factors. Therefore, even when the public transportation system's connection, delay and transfer conditions are improved, the travel mode will not shift from car to public transportation.

Convertible car travel refers to the situation where residents choose car travel because their public transportation intensity exceeds the acceptable maximum; these residents face deficiencies in the public transportation system's connection, delay and transfer aspects and may shift to public transportation when the system is improved.

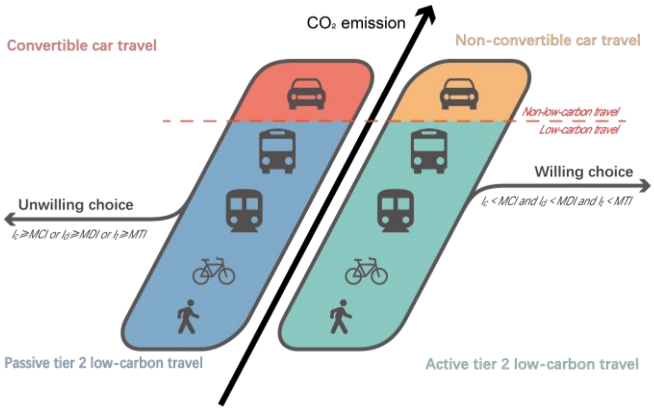



*Figure 4 – The Tier 2 low-carbon travel assessment model classification for cities*

Like the Tier 1 low-carbon travel potential model mentioned earlier, the proportion of convertible car travel samples in the total sample is defined as the Urban Tier 2 low-carbon travel potential, reflecting the potential reduction in total urban transportation carbon emissions as the city takes measures to improve public transportation connection, delay and transfer conditions.

### 3.4 Calculation of urban low-carbon travel potential indicators and construction of the evaluation system

*Calculation of the urban Tier 1 low-carbon travel potential indicators and construction of the evaluation system*

The urban Tier 1 low-carbon travel potential model is divided into four categories: active Tier 1 low carbon travel, passive Tier 1 low carbon travel, non-convertible motorised travel and convertible motorised travel. The calculation methods are as follows:

$$P_{a1} = \frac{card(A_{T1})}{T} \times 100\% \tag{5}$$

$$P_{p1} = \frac{card(P_{T1})}{T} \times 100\% \tag{6}$$

$$P_{n1} = \frac{card(N_M)}{T} \times 100\% \tag{7}$$

$$P_{c1} = \frac{card(C_M)}{T} \times 100\% \tag{8}$$

where $T$ represents the total number of effective samples. $P_{a1}$ indicates the proportion of active Tier 1 low carbon travel samples in the total samples, with $A_{T1}$ Being the set of Active Tier 1 low carbon travel samples, which includes samples where $I_n < MNI$ and the travel mode is non-motorised. $P_{p1}$ indicates the proportion of passive Tier 1 low carbon travel samples in the total samples, with $P_{T1}$ being the set of passive Tier 1 low carbon travel samples, which includes samples where $I_n \geq MNI$ and the travel mode is non-motorised. $P_{n1}$ represents the proportion of non-convertible motorised travel samples in the total travel samples, with $N_M$ being the set of non-convertible motorised travel samples, which includes samples where $I_n < MNI$ and the travel mode is motorised. $P_{c1}$ represents the proportion of convertible motorised travel samples in the total travel samples, with $C_M$ being the set of convertible motorised travel samples, which includes samples where $I_n \geq MNI$ and the travel mode is motorised. As described in Section 3.3.2 of this paper, the proportion of convertible motorised travel samples in the total travel samples represents the urban Tier 1 low-carbon travel potential and $P_{c1}$ is the value of the Tier 1 low-carbon travel potential.

To investigate the trend of $P_{c1}$ with changes in MNI and to identify the key stages of change in the urban Tier 1 low-carbon travel potential, a series of scenarios were constructed based on the variation of MNI values. The range of MNI values was determined by considering the distribution of the sample and supported by existing research data. In this study, MNI was set to range from 0 to 50, with uniform intervals of 1, resulting in 51 scenarios. For example, scenario number 49 has an MNI value of 48, which is referred to as scenario N48. The overall scenario numbering and corresponding MNI values are shown in *Table 1*:

*Table 1 – Series of scenarios constructed based on the changes in the MNI*

| **MNI** | **0** | **1** | **2** | **……** | **48** | **49** | **50** |
|---|---|---|---|---|---|---|---|
| **Scenario number** | 1 | 2 | 3 | …… | 49 | 50 | 51 |

After constructing the 51 scenarios for the Tier 1 low-carbon travel potential, the non-motorised travel intensity limit $I_n$ was set for each scenario in both cities. Based on the actual travel patterns of the statistical samples, $P_{a1}$, $P_{p1}$, $P_{n1}$ and $P_{c1}$ were calculated, yielding the Tier 1 low-carbon travel potential $P_{c1}$ for each city. With MNI as the independent variable and the Tier 1 low-carbon travel potential value as the dependent variable, a curve fitting was performed to obtain the overall change in the urban Tier 1 low-carbon potential. This curve reflects the level of the city's overall Tier 1 low-carbon travel potential, i.e. the change in non-motorised travel potential, which can be used to analyse the overall differences in non-motorised travel environment and the residents' travel philosophy between different cities. Selecting characteristic points with significant representation from the function curve serves as key scenarios for horizontal comparison within the city, evaluating the Tier 1 low-carbon travel potential in different areas of the same city, analysing the causes of the different residents' willingness to choose non-motorised travel and corresponding measures to address these differences.

*Calculation of the urban Tier 2 low-carbon travel potential indicators and construction of the evaluation system*

The Tier 2 low-carbon travel potential model is divided into four categories: active Tier 2 low carbon travel, passive Tier 2 low carbon travel, non-convertible car travel and convertible car travel. The calculation methods are as follows:

$$P_{a2} = \frac{card(A_{T2})}{T} \times 100\% \tag{9}$$

$$P_{p2} = \frac{card(P_{T2})}{T} \times 100\% \tag{10}$$

$$P_{n2} = \frac{card(N_C)}{T} \times 100\% \tag{11}$$

$$P_{c2} = \frac{card(C_C)}{T} \times 100\% \tag{12}$$

where $T$ represents the total number of effective samples. $P_{a2}$ indicates the proportion of active Tier 2 low carbon travel samples in the total samples, with $A_{T2}$ being the set of active Tier 2 low carbon travel samples, which includes samples where $I_c < MCI$, $I_d < MDI$, $I_t < MTI$ and the travel mode is either non-motorised or public transportation. $P_{p2}$ indicates the proportion of passive Tier 2 low carbon travel samples in the total samples, with $P_{T2}$ being the set of passive Tier 2 low carbon travel samples, which includes samples where $I_c \geq MCI$ or $I_d \geq MDI$ or $I_t \geq MTI$ and the travel mode is either non-motorised or public transportation. $P_{n2}$ represents the proportion of non-convertible car travel samples in the total travel samples, with $N_C$ being the set of non-convertible car travel samples, which includes samples where $I_c < MCI$, $I_d < MDI$, $I_t < MTI$ and the travel mode is car travel. $P_{c2}$ represents the proportion of convertible car travel samples in the total travel samples, with $C_C$ being the set of convertible car travel samples, which includes samples where $I_c \geq MCI$ or $I_d \geq MDI$ or $I_t \geq MTI,$ and the travel mode is car travel. As described to Section 3.3.3 of this paper, the proportion of convertible car travel samples in the total travel samples represents the urban Tier 2 low-carbon travel potential and $P_{c2}$ is the value of the Tier 2 low-carbon travel potential.

To investigate the trend of $P_{c2}$ with changes in MCI, MDI and MTI and to identify the key stages of change in the urban Tier 2 low-carbon travel potential, a series of scenarios were constructed based on the variation of these values. The range of MCI, MDI and MTI values was determined by considering the sample distribution, related research and reports from government and corporate departments. In this study, MCI was set to range from 0 to 5.0 with uniform intervals of 0.1, MDI from 0.50 to 3.00 with uniform intervals of 0.05 and MTI from 0 to 4 with uniform intervals of 1, resulting in a total of 13,005 scenarios. For example, scenario number 305 has MCI = 0, MDI = 2.95 and MTI = 0, which is referred to as scenario C0.1D2.95T0. The overall scenario numbering and corresponding MCI, MDI and MTI values are shown in *Table 2*:

*Table 2 – Series of scenarios constructed based on changes in MCI, MDI and MTI*

| **MCI** | **MDI** | | | | | | | **MTI** |
|---|---|---|---|---|---|---|---|---|
| | **0.50** | **0.55** | **0.60** | **……** | **2.90** | **2.95** | **3.00** | |
| **0** | 1 | 2 | 3 | | 49 | 50 | 51 | 0 |
| | 52 | 53 | 54 | | 100 | 101 | 102 | 1 |
| | 103 | 104 | 105 | | 151 | 152 | 153 | 2 |
| | 154 | 155 | 156 | | 202 | 203 | 204 | 3 |
| | 205 | 206 | 207 | | 253 | 254 | 255 | 4 |
| **0.1** | 256 | 257 | 258 | | 304 | 305 | 306 | 0 |
| | | | | | | | | ⋮ |
| | 460 | 461 | 462 | | 508 | 509 | 510 | 4 |
| ⋮ | | | | …… | | | | ⋮ |
| **4.9** | 12496 | 12497 | 12498 | | 12544 | 12545 | 12546 | 0 |
| | | | | | | | | ⋮ |
| | 12700 | 12701 | 12702 | | 12748 | 12749 | 12750 | 4 |
| **5.0** | 12751 | 12752 | 12753 | | 12799 | 12800 | 12801 | 0 |
| | | | | | | | | ⋮ |
| | 12955 | 12956 | 12957 | | 13003 | 13004 | 13005 | 4 |

By integrating connection intensity, delay intensity and transfer intensity, 13,005 scenarios for the Tier 2 low-carbon travel potential were simulated and constructed. Following the same approach as for the Tier 1 low-carbon travel potential scenarios, connection intensity $I_c$, delay intensity $I_d$ and transfer intensity $I_t$ limits were set for each scenario in both cities. Based on the actual travel patterns of the statistical samples, $P_{a2}$, $P_{p2}$, $P_{n2}$ and $P_{c2}$ were calculated, yielding the Tier 2 low-carbon travel potential $P_{c2}$ for each city. With MCI, MDI and MTI as independent variables and the Tier 2 low-carbon travel potential as the dependent variable, due to the complexity of the multi-factor function, separate curve fittings were performed for each independent variable. Similarly, three curves were constructed to explore the overall changes in the Tier 2 low-carbon travel potential from the aspects of public transportation connection distance, delay distance ratio and transfer times, reflecting the differences in public transportation infrastructure and the residents' public transportation philosophy between the two cities. Key points were selected from each curve and critical scenarios were formed to evaluate the differences in Tier 2 low-carbon travel potential across different regions of the city, identifying differences in the city's internal public transportation system construction, analysing the causes and proposing urban construction improvement plans.

## 4. ASSESSMENT RESULTS AND DISCUSSION

### 4.1 Travel characteristics of respondents

In daily travel, the OD distance is an important characteristic shared by residents [88], which directly affects the volume of traffic carbon emissions [89]. The OD distribution reflected in the survey questionnaire is shown in *Figure 5*. The OD distance distribution indicates that the vast majority of the respondents' daily travel is within a range of 10 km, which is similar to the characteristics reflected by the data from Beijing taxi statistics [90]. After the travel distance exceeds 15 km, the change in the number of respondents becomes more gradual. Among Shanghai respondents, those with travel distances less than 5 km account for 35.9% of all respondents, while in Wuhan, this proportion is 38.8%. For respondents with travel distances less than 5 km, considering only the travel distance, using non-motorised modes of travel is already within an acceptable range [91].

The urban built-up area of Shanghai is larger than that of Wuhan and the difference in urban scale is also reflected in the distribution of respondents' travel distances. Compared to Wuhan, the proportion of Shanghai respondents whose daily travel is within 10 km is smaller. After the travel distance exceeds 30 km, especially after 50 km, the proportion of Shanghai respondents gradually exceeds that of Wuhan respondents.

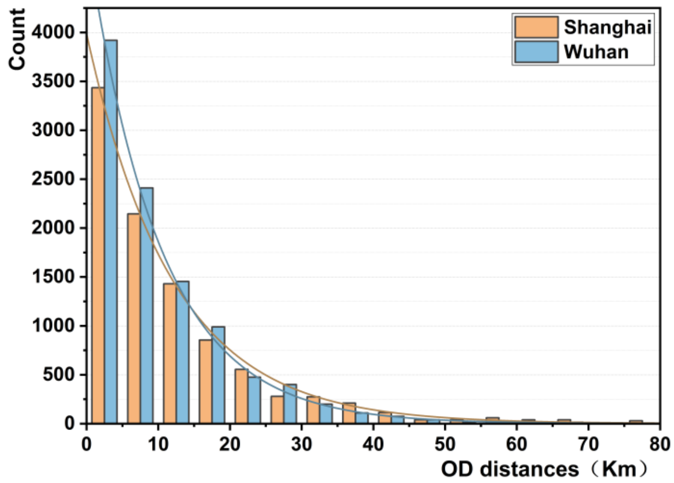



*Figure 5 – Distribution of the respondents' daily travel OD distances*

The proportions of various travel modes in the daily travel of the Shanghai and Wuhan respondents are shown in *Figure 6*. Overall, the proportions of different modes in both cities are very close. More than 50% of respondents in both cities travel by public transportation, which still has a certain gap compared to Singapore's public transportation travel ratio of over 60% [84]. In addition to public transportation, the proportion of non-motorised modes is about 27% and the proportion of car travel is 20–21%.

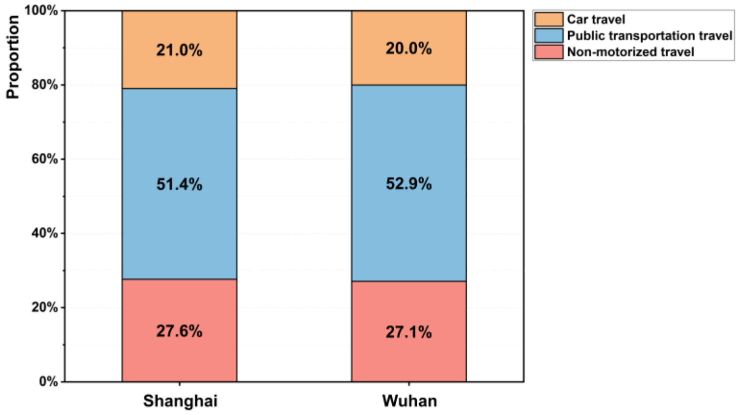



*Figure 6 – Proportion of different travel modes in daily travel of Shanghai and Wuhan respondents*

*Figures 7 and 8* further clarify the OD distance distribution of respondents using different travel modes. Given the overall sample characteristic that Shanghai respondents tend to have longer daily travel distances, the distribution of car travel among respondents in Shanghai and Wuhan is generally similar, with similar proportions across various distance segments. The difference in the overall sample's travel distance distribution is mainly concentrated among the public transportation user group. Travel distances of the Wuhan respondents' public transportation are concentrated within a range of 20 km, accounting for 84.4% of all respondents travelling on public transportation and the proportion drops rapidly after 10 km. Shanghai respondents can adapt to longer-distance public transportation travel, with the proportion of people travelling more than 10 km reaching 44.2%, while in Wuhan, this proportion is 52.1%. The construction of the rail transit system in the outer areas of Shanghai is superior to that of Wuhan, providing infrastructure conditions for residents to travel long distances by public transportation.

Shanghai has a significantly higher proportion of respondents who travel by non-motorised means within the 5–10 km range compared to Wuhan, where respondents tend to concentrate their non-motorised travel within the 5 km range. Shanghai respondents are more willing to accept longer non-motorised travel distances for their daily commutes. The OD distance of non-motorised travel for these respondents is also their non-motorised travel intensity value $I_n$.

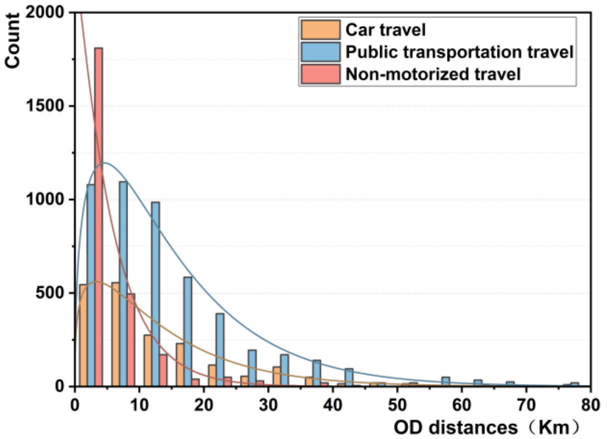



*Figure 7 – OD distance distribution of Shanghai respondents by different travel modes*

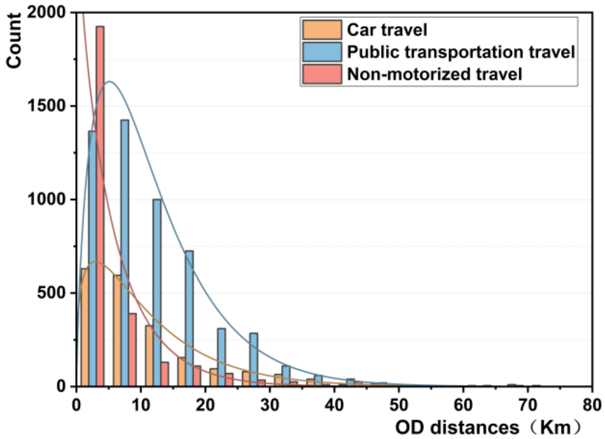



*Figure 8 – OD distance distribution of Wuhan respondents by different travel modes*

Further exploration of the travel characteristics of respondents using public transportation in both cities is shown in *Figures 9–11*, which depict the distribution of connection intensity $I_c$, delay intensity $I_d$ and transfer intensity $I_t$ values for respondents during their public transportation trips.

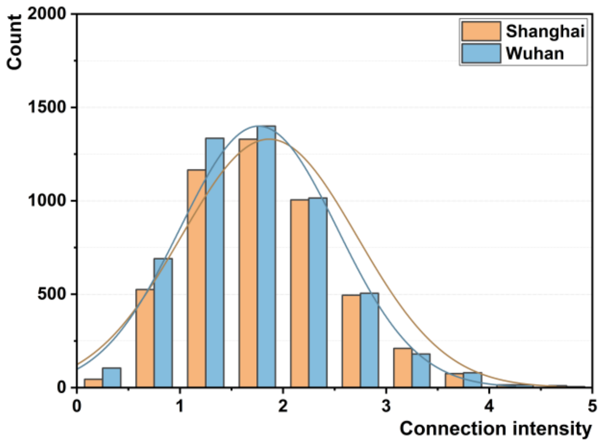



*Figure 9 – Distribution of connection intensity $I_c$ for public transportation respondents*

*Figure 9* illustrates the distribution of connection intensity $I_c$ for respondents using public transportation. It is evident that the distribution trends of connection intensity $I_c$ for respondents in Shanghai and Wuhan are highly similar, with Shanghai respondents having a higher connection intensity. If a connection intensity $I_c$ of 2 km is used as a dividing line, 62.3% of Shanghai respondents have a connection distance less than 2 km, while 66.0% of Wuhan respondents have a connection distance less than 2 km. This indicates that Shanghai respondents are willing to accept a higher connection intensity, which is also reflected in the non-motorised travel population. Improving the urban slow-travel system can not only increase the proportion of non-motorised travel in the city but also improve the proportion of public transportation travel.

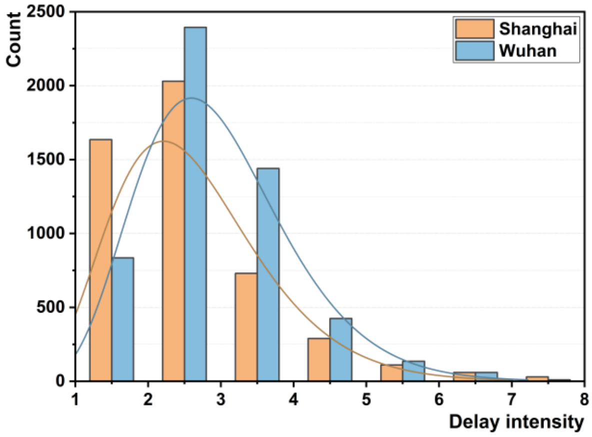



*Figure 10 – Distribution of delay intensity $I_d$ for public transportation respondents*

*Figure 10* illustrates the distribution of delay diversion intensity $I_d$ values among respondents using public transportation. The distribution trends of $I_d$ values for respondents in Shanghai and Wuhan are similar, but the peak values differ. Respondents in Wuhan face a higher proportion of time extension when using public transportation, indicating that the efficiency of Wuhan's public transportation system is lower than that of Shanghai's.

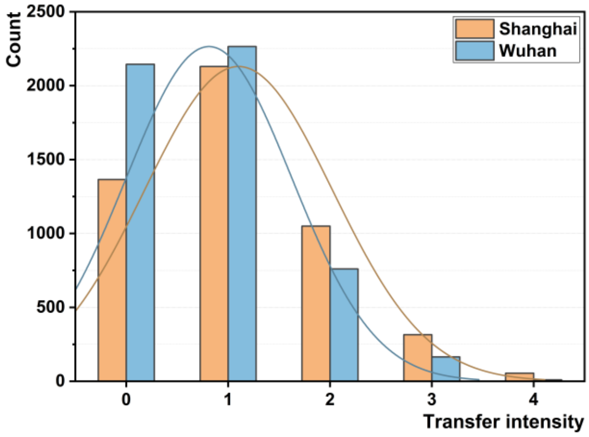



*Figure 11 – Distribution of transfer intensity $I_t$ for public transportation respondents*

*Figure 11* illustrates the distribution of transfer intensity $I_t$ for respondents using public transportation. Shanghai respondents using public transportation have a significantly higher transfer intensity $I_t$ compared to Wuhan respondents. In Shanghai, 71.0% of respondents using public transportation have 0 or 1 transfer, while in Wuhan, this proportion reaches 82.4%. Particularly, the proportion of respondents with no transfers is much higher in Wuhan than in Shanghai. When analysing the public transportation routes in both cities, especially the rail transit routes, Shanghai's network is more evenly distributed and respondents typically reach their destinations through transfers involving multiple lines. In contrast, Wuhan's distribution is uneven. For instance, Wuhan's Metro Line 2, which runs through densely populated areas and commercial centres such as Hankou, Wuchang and Optics Valley, allows many residents along its route to reach their destinations without the need for transfers.

In summary, Shanghai residents have a higher connection and transfer intensity in public transportation and considering the OD distance distribution of non-motorised travel residents, it is believed that Shanghai residents can accept a higher connection intensity. Additionally, due to the more advanced construction of Shanghai's rail transit, more residents are accustomed to transfer-based travel and the evenly distributed rail transit network provides practical conditions for such travel. Wuhan's rail transit network started later and geographical constraints limit the network layout, but the delay intensity has not increased, which is a relatively good setting under restrictions. However, the high population density along some lines leads to uneven metro traffic, revealing significant shortcomings.

### 4.2 Assessment and comparison of urban Tier 1 low-carbon travel potential

Under the Tier 1 travel potential assessment system, considering the actual travel mode choices of all valid survey samples, the corresponding Tier 1 low-carbon travel potential $P_{c1}$ values for Shanghai and Wuhan in 51 scenarios were calculated. The statistical data are listed in *Table 3*:

*Table 3 – Urban Tier 1 low-carbon travel potential values in various scenarios*

| Scenario number | MNI | Shanghai $P_{c1}$ | Wuhan $P_{c1}$ |
|---|---|---|---|
| 1 | 0 | 66.83% | 67.13% |
| 2 | 1 | 65.67% | 65.95% |
| 3 | 2 | 62.68% | 62.45% |
| ⋮ | | | |
| 50 | 49 | 2.12% | 0.27% |
| 51 | 50 | 2.02% | 0.23% |

To determine the relationship between the urban Tier 1 low-carbon travel potential and MNI, a relationship curve was plotted with MNI as the independent variable and the Tier 1 low-carbon travel potential value $P_{c1}$ as the dependent variable. To compare the differences between Shanghai and Wuhan's Tier 1 low-carbon travel potential curves, the corresponding curves of both cities were plotted on the same coordinate system, resulting in the relationship curve between the urban Tier 1 low-carbon travel potential and MNI values shown in *Figure 10*.

To determine the relationship between Tier 1 urban low-carbon travel potential $P_{c1}$ and MNI, MNI is used as the independent variable and the Tier 1 urban low-carbon travel potential value $P_{c1}$ as the dependent variable to plot the relationship curve. The logistic four-parameter fitting algorithm is applied to fit the relationship curve, resulting in a reverse "S"-shaped fitted curve. The relationship curve and the fitted curve are shown in *Figure 12* and the fitting results are detailed in *Table 4*. The "S"-shaped curve consists of a significant rapid release zone in the middle of the curve and a flat stage at both ends. The point of fastest change, i.e. the point of maximum derivative, is selected as the midpoint of the rapid release zone, denoted as point B and the points where the derivative reaches 50% of its maximum value are selected as the start and end points of the rapid release zone, denoted as points A and C. Points A, B and C represent the Tier 1 low-carbon travel potential situation when the residents' maximum willingness non-motorised travel distance is at a low, medium and high level, respectively. The rapid release zone of the curve implies that as the residents' maximum willingness non-motorised travel distance increases from the low level at point A to the high level at point C, more residents will shift from motorised to non-motorised travel modes, indicating a rapid change in urban Tier 1 low-carbon travel potential. Selecting key points within this stage makes the subsequent regional analysis more representative.

*Table 4 – Fitting results of the relationship curve between urban Tier 1 low-carbon travel potential and MNI*

| MNI | $A_1$ | s.e. | $A_2$ | s.e. | $x_0$ | s.e. | p | s.e. | $R^2$(COD) | Adjusted $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Shanghai | 0.66554 | 0.00225 | -0.03957 | 0.00264 | 11200.99103 | 69.99977 | 1.66083 | 0.01879 | 0.99972 | 0.9997 |
| Wuhan | 0.66544 | 0.00354 | -0.0438 | 0.00317 | 9752.84045 | 85.38463 | 1.77389 | 0.02915 | 0.99933 | 0.99929 |

The fitting process of *Figure 12* conforms to the following:

$$P_c = \frac{A_1 - A_2}{1 + (x/x_0)^p} + A_2 \tag{13}$$

where $A_1$ is the value of the low-carbon potential when the independent variable approaches 0, $A_2$ is the value when the independent variable approaches infinity.

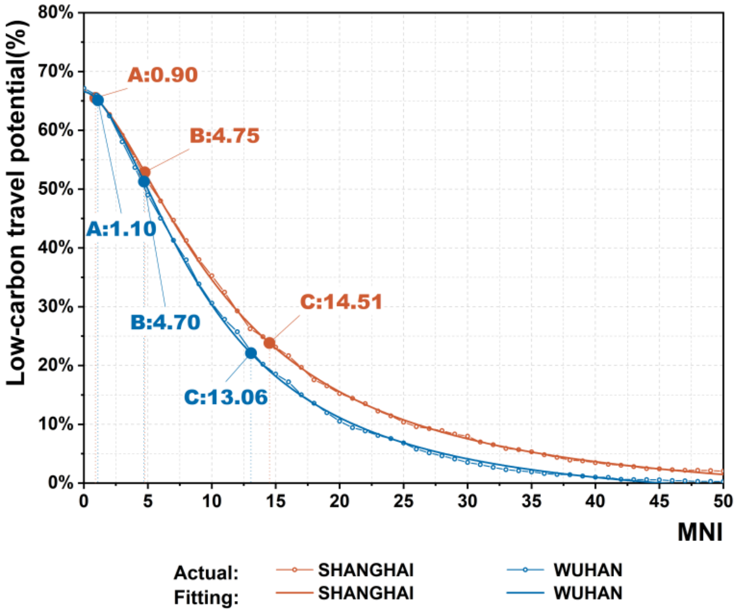



*Figure 12 – Fitting curve of urban Tier 1 low-carbon travel potential and MNI*

The rapid release zone of Shanghai's Tier 1 low-carbon travel potential curve corresponds to the starting point A, with an MNI of 0.90 km and a Tier 1 low-carbon travel potential value of 65.5%, the point of fastest change B corresponds to an MNI of 4.75 km, with a Tier 1 low-carbon travel potential of 52.9%, and the ending point C, with an MNI of 14.51 km and a Tier 1 low-carbon travel potential value of 23.8%. This indicates that as the Shanghai residents' willingness to travel non-motorised increases from 0.90 km to 14.51 km, 41.7% of the urban Tier 1 low-carbon travel potential can be released. For Wuhan, the starting point A of the rapid release zone corresponds to an MNI of 1.10 km, with a Tier 1 low-carbon travel potential of 65.1%, the point of fastest change B corresponds to an MNI of 4.70 km, with a Tier 1 low-carbon travel potential of 51.3%, and the ending point C corresponds to an MNI of 13.06 km, with a Tier 1 low-carbon travel potential of 22.1%. This indicates that as the Wuhan residents' willingness to travel non-motorised increases from 1.10 km to 13.06 km, 43.0% of the urban Tier 1 low-carbon travel potential can be released.

Combining the above analysis, the positions of the corresponding key points for the two cities are similar, with only minor differences. The range of the rapid release zone in Shanghai is slightly larger than that in Wuhan, but the points of fastest change are almost the same, indicating that the travel distance of 4.70 km–4.75 km has a significant impact on the residents' choice of non-motorised travel in different cities. The threshold for the residents' travel mode choice is concentrated in this range. For short trips within 5 km, the proportion of residents choosing non-motorised travel is high and further optimising the built environment has a relatively poor effect on reducing overall carbon emissions. For medium-short trips 5–10 km, non-motorised travel is still within an acceptable range and if the travel philosophy of this group of residents' changes, the city's carbon emission reduction effect will be most significant. However, it is too difficult for residents to travel by walking for 5–10 km [78, 79], which puts new requirements on the construction of urban non-motorised lanes, cycling safety and the deployment of shared bicycles [92, 93].

Summarising the information presented in this section, for Shanghai, the key points A, B and C correspond to MNI values of MNI = 0.90 km, MNI = 4.75 km and MNI = 14.51 km, respectively. The corresponding scenarios A, B and C are N1, N5 and N15, which are selected as key scenarios for regional analysis. For Wuhan, the key points A, B and C correspond to MNI values of MNI = 1.1 km, MNI = 4.70 km and MNI = 13.06 km, respectively. The corresponding scenarios A, B and C are N1, N5 and N13, which are selected as key scenarios for regional analysis.

### 4.3 Assessment and comparison of urban Tier 2 low-carbon travel potential

Under the Tier 2 travel potential assessment system, considering the actual travel mode choices of all valid survey samples, the corresponding Tier 2 low-carbon travel potential $P_{c2}$ values for Shanghai and Wuhan in 13,005 scenarios were calculated. The statistical data are listed in *Table 5*:

*Table 5 – Urban Tier 2 low-carbon travel potential values in various scenarios*

| Scenario number | MCI | MDI | MTI | Shanghai $P_{c2}$ | Wuhan $P_{c2}$ |
|---|---|---|---|---|---|
| 1 | 0 | 1.0 | 0 | 19.38% | 18.43% |
| 2 | 0 | 1.1 | 0 | 19.38% | 18.43% |
| 3 | 0 | 1.2 | 0 | 19.38% | 18.43% |
| ⋮ | | | | | |
| 2000 | 0.7 | 2.0 | 4 | 19.29% | 18.21% |
| ⋮ | | | | | |
| 4000 | 1.5 | 3.1 | 3 | 14.08% | 13.25% |
| ⋮ | | | | | |
| 6000 | 2.3 | 4.2 | 2 | 8.20% | 7.06% |
| ⋮ | | | | | |
| 8000 | 3.1 | 5.3 | 1 | 11.67% | 9.19% |
| ⋮ | | | | | |
| 10000 | 3.9 | 1.3 | 1 | 19.33% | 18.07% |
| ⋮ | | | | | |
| 13003 | 5.0 | 5.8 | 4 | 1.16% | 1.09% |
| 13004 | 5.0 | 5.9 | 4 | 1,16% | 1.05% |
| 13005 | 5.0 | 6.0 | 4 | 1.16% | 0.96% |

To determine the relationship between urban Tier 2 low-carbon travel potential and MCI, MDI and MTI, each was used as an independent variable, with the Tier 2 low-carbon potential value $P_{c2}$ as the dependent variable and function curves were plotted. To analyse the impact of one factor while disregarding the negative effects of the other two factors, the Tier 2 low-carbon potential values $P_{c2}$ corresponding to the maximum values of the other two factors were selected to plot the relationship curves. Like the Tier 1 low-carbon travel potential analysis, the corresponding curves for Shanghai and Wuhan were plotted on the same coordinate system, resulting in the relationship curves between urban Tier 2 low-carbon travel potential and MCI value (*Figure 12.a*), MDI value (*Figure 12.b*) and MTI value (*Figure 12.c*).

Furthermore, using the logistic four-parameter fitting algorithm (*Equation 13*), the functional relationships between Tier 2 urban low-carbon travel potential and MCI, MDI and MTI are fitted. The fitted curves are shown in *Figure 13* and the fitting results are detailed in *Table 6*. Similar to the Tier 1 low-carbon travel potential analysis, the curves were divided into a significant rapid release zone and a flat section, with points A, B and C identified as key points. Points A and C represent the start and end points of the rapid release zone, while point B represents the point of fastest change. The determination of the rapid release zone and the point of fastest change helps urban managers and builders to identify efficient areas for construction and improvement in the urban public transportation field.

*Table 6.a – fitting results of the relationship curve between urban Tier 2 low-carbon travel potential and MCI*

| MCI | $A_1$ | s.e. | $A_2$ | s.e. | $x_0$ | s.e. | p | s.e. | $R^2$(COD) | Adjusted $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| **Shanghai** | 0.19123 | 0.00104 | -0.0029 | 0.00101 | 1605.8919 | 0.01136 | 3.52449 | 0.08769 | 0.99849 | 0.9984 |
| **Wuhan** | 0.18314 | 0.00070 | -0.0013 | 0.00066 | 1618.21987 | 0.0079 | 3.61806 | 0.06203 | 0.99942 | 0.99939 |

*Table 6.b – Fitting results of the relationship curve between urban Tier 2 low-carbon travel potential and MDI*

| MDI | $A_1$ | s.e. | $A_2$ | s.e. | $x_0$ | s.e. | p | s.e. | $R^2$(COD) | Adjusted $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| **Shanghai** | 0.19689 | 0.00080 | 0.00698 | 0.00063 | 1.22252 | 0.00797 | 10.7326 | 0.06271 | 0.99727 | 0.9971 |
| **Wuhan** | 0.18725 | 0.00107 | 0.00821 | 0.00096 | 1.23344 | 0.01279 | 9.96983 | 0.11894 | 0.99791 | 0.99778 |

*Table 6.c – Fitting results of the relationship curve between urban Tier 2 low-carbon travel potential and MTI*

| MTI | $A_1$ | s.e. | $A_2$ | s.e. | $x_0$ | s.e. | p | s.e. | $R^2$(COD) | Adjusted $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| **Shanghai** | 0.19375 | 0.0054 | -0.0185 | 0.01644 | 1.23307 | 0.13646 | 1.90417 | 0.40671 | 0.99878 | 0.9951 |
| **Wuhan** | 0.18433 | 0.00229 | -0.0025 | 0.00385 | 0.9134 | 0.02452 | 2.44001 | 0.29178 | 0.99978 | 0.99913 |

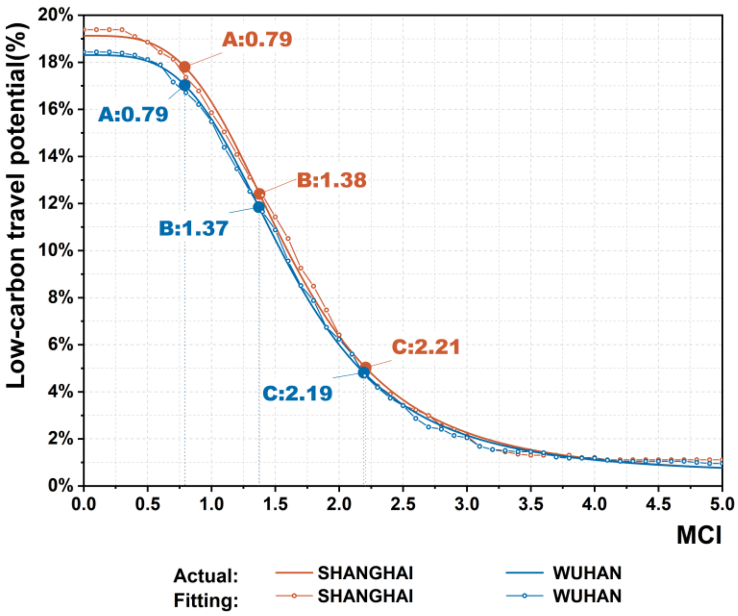



*Figure 13.a – Fitting curve of urban Tier 2 low-carbon travel potential and MCI value*

For Shanghai, the starting point A of the rapid release zone corresponds to an MCI of 0.77 km, with a Tier 2 low-carbon travel potential of 17.8%, the point of fastest change B corresponds to an MCI of 1.38 km, with a Tier 2 low-carbon travel potential of 12.4% and the ending point C corresponds to an MCI of 2.20 km, with a Tier 2 low-carbon travel potential of 5.0%. Therefore, it can be seen that as the acceptable public transportation transfer distance for Shanghai residents increases from 0.79 km to 2.21 km, 12.8% of respondents may switch to public transportation. For Wuhan, the starting point A of the rapid release zone corresponds to an MCI of 0.79 km, with a Tier 2 low-carbon travel potential of 17.0%, the point of fastest change B corresponds to an MCI of 1.37 km, with a Tier 2 low-carbon travel potential of 11.8% and the ending point C corresponds to an MCI of 2.19 km, with a Tier 2 low-carbon travel potential of 4.8%. Therefore, it can be seen that as the acceptable public transportation transfer distance for Wuhan residents increases from 0.79 km to 2.19 km, 12.2% of respondents may switch to public transportation.

The connection key points of the two cities are almost the same, indicating that the impact of the urban public transportation connection distance on the residents' travel mode choices is similar across different cities, with no significant inter-city differences. If the public transportation connection distance is greater than 1.4 km, most citizens cannot accept public transportation travel. If the connection distance can be kept within 1 km, the practical difficulties of residents using public transportation in terms of connection distance are eliminated. Both cities should focus on optimising the public transportation connection distance within the range of 1 km to 1.4 km.

For Shanghai, the starting point A of the rapid release zone corresponds to an MDI of 1.55, with a Tier 2 low-carbon travel potential of 18.2%, the point of fastest change B corresponds to an MDI of 2.38, with a Tier 2 low-carbon travel potential of 12.1% and the ending point C corresponds to an MDI of 3.48, with a Tier 2 low-carbon travel potential of 4.9%. Therefore, as the acceptable public transportation delay proportion for Shanghai residents increases from 1.55 to 3.48, 13.3% of the urban Tier 2 low-carbon travel potential can be released. The potential changes fastest when the residents' delay proportion is 2.38. For Wuhan, the starting point A of the rapid release zone corresponds to an MDI of 1.77, with a Tier 2 low-carbon travel potential of 16.9%, the point of maximum change B corresponds to an MDI of 2.58, with a Tier 2 low-carbon travel potential of 11.5%, and the ending point C corresponds to an MDI of 3.61, with a Tier 2 low-carbon travel potential of 4.8%. Therefore, as the acceptable public transportation delay proportion for Wuhan residents increases from 1.77 to 3.61, 12.1% of the urban Tier 2 low-carbon travel potential can be released. The potential changes fastest when the residents' delay proportion is 2.58.

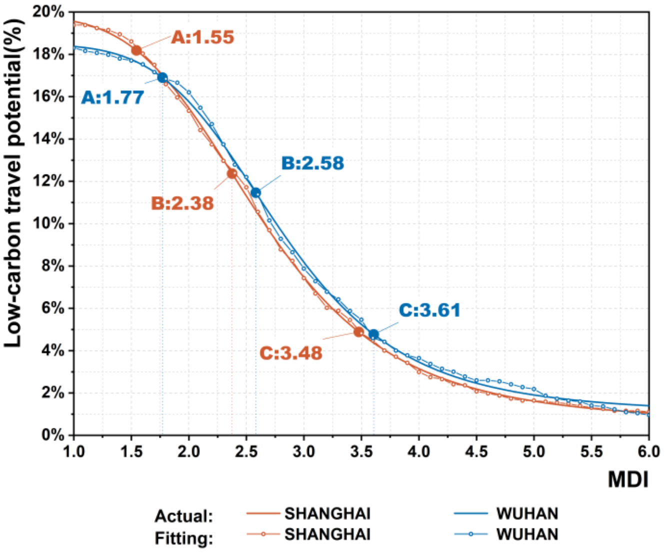



*Figure 13.b – Fitting curve of urban Tier 2 low-carbon travel potential and MDI value*

Based on the above analysis, Shanghai outperforms Wuhan in terms of public transportation delay. The key points and rapid release zones in Shanghai are all shifted further left, indicating higher efficiency in public transportation transfer. Interestingly, while Shanghai's public transportation transfer efficiency is already superior to that of Wuhan, it is also more sensitive to optimising travel delays. This sensitivity enables Shanghai to achieve greater rapid release of potential for optimising low-carbon travel.

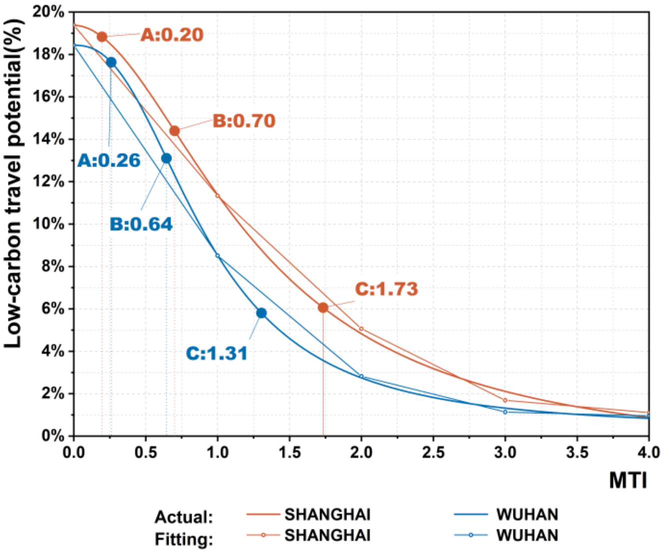



*Figure 13.c – Fitting curve of urban Tier 2 low-carbon travel potential and MTI value*

For Shanghai, the starting point A of the rapid release zone corresponds to an MTI of 0.20, with a Tier 2 low-carbon travel potential of 18.8%, the point of fastest change B corresponds to an MTI of 0.70, with a Tier 2 low-carbon travel potential of 14.4% and the ending point C corresponds to an MTI of 1.73, with a Tier 2 low-carbon travel potential of 6.1%. Therefore, as the acceptable number of public transportation transfers for Shanghai residents increases from 0.20 to 1.73, 12.7% of the urban Tier 2 low-carbon travel potential can be released. The potential changes fastest when the number of transfers is 0.70. For Wuhan, the starting point A of the rapid release zone corresponds to an MTI of 0.26, with a Tier 2 low-carbon travel potential of 17.6%, the point of fastest change B corresponds to an MTI of 0.64, with a Tier 2 low-carbon travel potential of 13.1%, and the ending point C corresponds to an MTI of 1.31, with a Tier 2 low-carbon travel potential of 5.8%. Therefore, as the acceptable number of public transportation transfers for Wuhan residents increases from 0.26 to 1.31, 11.8% of the urban Tier 2 low-carbon travel potential can be released. The potential changes fastest when the number of transfers is 0.64. However, since the number of transfers must be an integer, the subsequent analysis considers that the rapid release area of Tier 2 low-carbon travel potential for both Shanghai and Wuhan falls within the range of MTI=0 to MTI=2, with the point of fastest change occurring at MTI=1.

Based on the analysis above, Shanghai residents are more willing to accept a higher number of transfers compared to Wuhan residents and are more accustomed to reaching their destinations through transfers. The impact of transfer times on potential changes varies between the two cities, with Shanghai's rapid release zone being broader and the potential value change being greater. Wuhan's rapid release zone is narrower, indicating a faster change. However, as mentioned earlier, the difference of less than one transfer between the two cities is concealed in actual operations. Both Shanghai and Wuhan should aim to control the number of transfers to 0 or 1 to increase the proportion of public transportation travel among city residents. From an economic perspective, reducing the number of transfers is valuable when it is within two times, but it is challenging to change people's travel mode choices when the number of transfers exceeds two.

*Table 7 – Key scenarios for assessing urban Tier 2 low-carbon travel potential*

| Scenarios | A | B | C |
|---|---|---|---|
| Shanghai | C0.8D1.6T0 | C1.4D2.4T1 | C2.3D3.5T2 |
| Wuhan | C0.8D1.8T0 | C1.4D2.6T1 | C2.2D3.7T2 |

Summarising the information provided in this section, for Shanghai, the key points A, B and C correspond to MCI of 0.79 km, MDI of 1.55 and MTI of 0, MCI of 1.38 km, MDI of 2.38 and MTI of 1, and MCI of 2.21 km, MDI of 3.48 and MTI of 2, respectively. The corresponding scenarios A, B and C are C0.8D1.6T0, C1.4D2.4T1 and C2.3D3.5T2, which are selected as key scenarios for regional analysis. Points A and C and their corresponding scenarios A and C represent the start and end of the rapid release zone in the assessment of Shanghai's Tier 2 low-carbon travel potential.

For Wuhan, the key points A, B and C correspond to MCI of 0.79 km, MDI of 1.77 and MTI of 0, MCI of 1.37 km, MDI of 2.58 and MTI of 1, and MCI of 2,19 km, MDI of 3.61 and MTI of 2, respectively. The corresponding scenarios A, B and C are C0.8D1.8T0, C1.4D2.6T1 and C2.2D3.7T2, which are selected as key scenarios for regional analysis. Points A and C and their corresponding scenarios A and C represent the start and end of the rapid release zone in the assessment of Wuhan's Tier 2 low-carbon travel potential, as shown in *Table 7*.

### 4.4 Regional Assessment and comparison of urban low-carbon travel potential

The content discussed in Section 4.3 of this paper focuses on the overall differences between Shanghai and Wuhan, and does not provide an in-depth analysis of the differences within various regions of a single city or the levels of construction differences. Overall urban analysis is not conducive to identifying the weaker parts of urban slow-travel systems and public transportation systems. Therefore, further regional analysis within the city can help urban managers and urban planners to carry out urban planning and construction work. Through the assessment and construction of the two-tier low-carbon travel potential system for the entire city as described in the previous sections, three key scenarios A, B and C were selected for the assessment of the two-tier low-carbon travel potential in each city. In this section, further analysis will be carried out based on the key scenarios mentioned in the previous text.

As described earlier, the division of TAZs mainly considers the following factors: First, it is necessary to ensure that each TAZ has enough effective samples, so the city cannot be divided into too many TAZs. Second, the urban population distribution is not uniform and the sample statistics roughly conform to the population density distribution. If TAZs are divided according to the grid method, it would lead to significant differences in the population distribution of the analysis areas, inevitably resulting in some analysis areas with too few samples. Finally, during the urban construction process in China, district-level administrative units are important decision-makers. Overly detailed division of TAZs would make it difficult for the corresponding administrative agencies to play a decisive role in urban construction within their areas. Therefore, considering the above factors, urban district-level administrative regions were selected as the TAZs for this study.

*Regional assessment and comparison of Shanghai's low-carbon travel potential*

Shanghai has a total of 16 administrative districts, as detailed in *Figure 14*. The central urban areas include the Huangpu District, Xuhui District, Changning District, Jing'an District, Putuo District, Hongkou District, Yangpu District and the inner part of Pudong New Area. The outer urban areas include the Minhang District, Baoshan District, the outer part of Pudong New Area, Jinshan District, Songjiang District, Qingpu District, Fengxian District and Chongming District. Among them, Pudong New Area has a vast area, which includes a larger part of the city centre. The Chongming District, mainly consisting of the Chongming Island, has relatively limited connections with other parts of Shanghai.

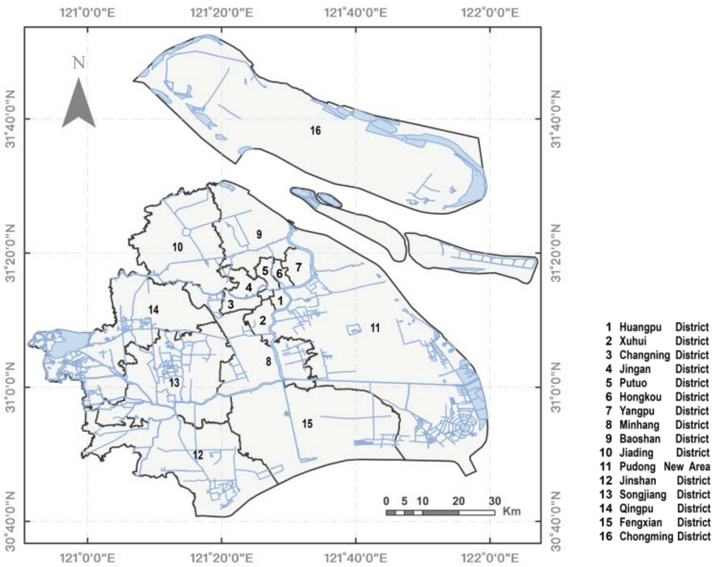
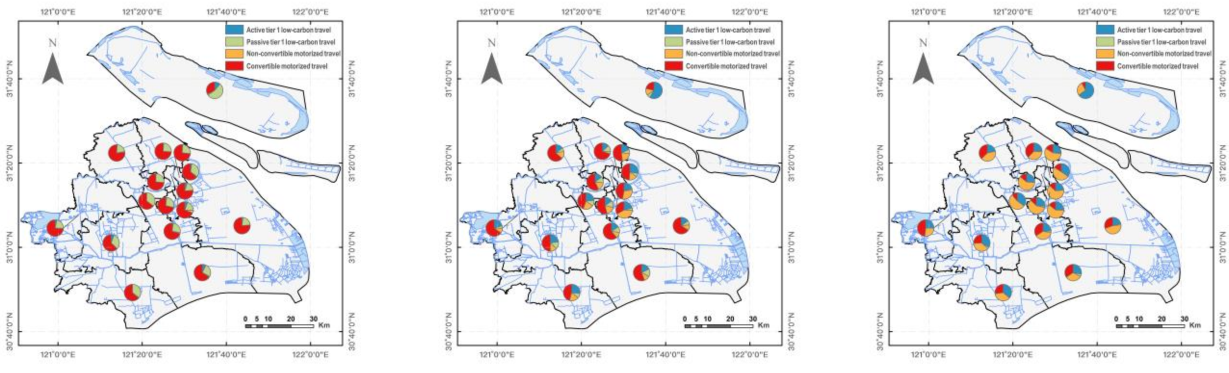



*Figure 14 – Shanghai district map*

*Figure 15* illustrates the distribution and proportion of the four types of resident travel modes within each TAZ in Shanghai's Tier 1 low-carbon travel potential assessment system for the three key scenarios corresponding to N1, N5 and N15.




*(a)* *(b)* *(c)*

*Figure 15 – Shanghai Tier 1 low-carbon travel potential assessment key scenario corresponding district map: a) Key scenario A: N1; b) Key scenario B: N5; c) Key scenario C: N15*

Regarding the urban Tier 1 low-carbon travel potential assessment system, the differences between key scenarios A-C can divide the urban areas into three categories.

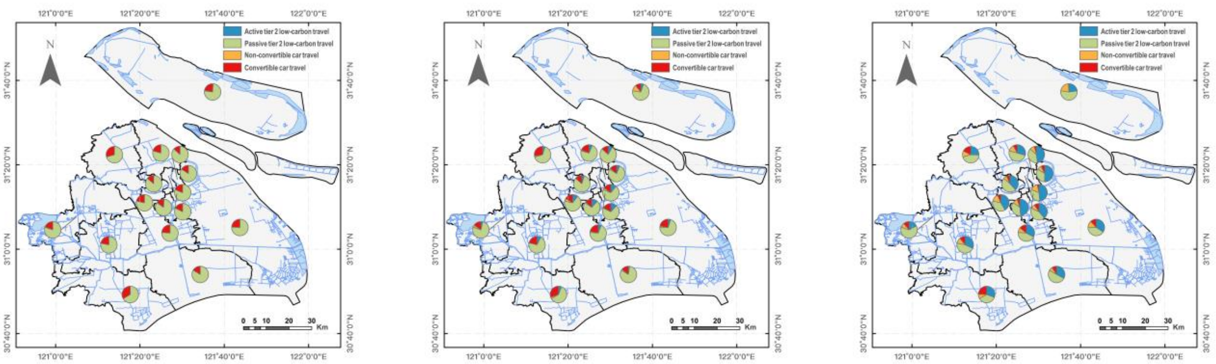
First, the central urban area, including districts 1–7 and the parts of district 11 close to the city centre, has a common characteristic of high convertible motorised travel proportion at the starting point of the rapid release zone, Scenario A. However, as MNI increases, the Tier 1 low-carbon travel potential is rapidly released and the convertible motorised travel proportion decreases rapidly, indicating that the travel distances of most residents are relatively short, with most daily travel distances within 15 km.

Second, in the western and northern parts of the city, including districts 9, 10 and 14, the convertible motorised travel proportion does not decrease to a sufficiently low level from Scenario A to Scenario C and the Tier 1 low-carbon travel potential value is not fully released, indicating that a considerable proportion of residents in these areas have travel distances greater than 15 km, especially in the Qingpu District, where nearly half of the residents have daily travel distances greater than 15 km. Especially in district 14 are daily travel distances exceeding 15 km. The residents in the far urban areas work in the city centre, and the large distance between the workplace and residence is a significant factor.

Finally, in the southern parts of the city, including districts 8, 12, 13 and 15, the convertible motorised travel proportion is relatively low in Scenario A, indicating that a considerable proportion of the residents travel by non-motorised modes. During the transition from Scenario A to Scenario C, nearly 30% of the Tier 1 low-carbon travel potential remains unreleased, indicating that some residents have short travel distances, but there is also a significant proportion with longer travel distances, possibly due to the presence of independent urban sub-centres in the area, where some residents only need to reach the sub-centre for daily life.

District 16, due to its special geographical location, weak connections with other parts of the city, coupled with its agricultural production focus, sees most residents travelling shorter distances. As the MNI increases, its Tier 1 low-carbon travel potential is quickly unleashed.

*Figure 16* illustrates the distribution and proportion of the four types of resident travel modes within each TAZ in Shanghai's Tier 2 low-carbon travel potential assessment system for the three key scenarios corresponding to C0.8D1.6T0, C1.4D2.4T1 and C2.3D3.5T2.




*(a)* *(b)* *(c)*

*Figure 16 – Shanghai Tier 2 low-carbon travel potential assessment key scenario corresponding district map: a) Key scenario A: C0.8D1.6T0; b) Key scenario B: C1.4D2.4T1; c) Assessment key scenario C: C2.3D3.5T2*

For the Tier 2 low-carbon travel potential assessment system, the differences between key scenarios A–C can also categorise the regions of Shanghai into three levels.

Firstly, the areas with a well-developed public transportation system are mainly the central urban areas, including districts 1–7 and district 9. Among them, districts 3 and 5 show the fastest release of Tier 2 low-carbon travel potential, while district 1 is relatively the worst.

Secondly, the areas with a developed public transportation system are mainly the peripheral urban areas, including districts 8, 11 and 13–15. The Tier 2 low-carbon travel potential in these areas is within 25% in Scenario A and as the scenario changes from A to C, the potential is released to some extent, placing them at a mid-level in the city's overall context.

Lastly, the areas with a weak public transportation system are mainly district 10 in the north and district 12 in the south. They have the highest Tier 2 low-carbon travel potential in Scenario A and only a small part of the potential is released during the transition from Scenario A to C, indicating that their public transportation systems are lagging the city's average level in terms of connection, delay and transfer.

### *Regional assessment and comparison of Wuhan's low-carbon travel potential*

Wuhan has a total of 13 administrative districts, as detailed in *Figure 17*. The central urban areas include the Jiang'an District, Jianghan District, Qiaokou District, Hanyang District, Wuchang District, Qingshan District and Hongshan District. The outer urban areas include the Dongxihu District, Hanshan District, Caidian District, Jiangxia District, Huangpi District and Xinzhou District.

*Figure 18* illustrates the distribution and proportion of the four types of resident travel modes within each TAZ in Wuhan's Tier 1 low-carbon travel potential assessment system for the three key scenarios corresponding to N1, N5 and N13.

For the Tier 1 low-carbon travel potential assessment system, the differences between key scenarios A-–C can roughly divide Wuhan into three regions.

Firstly, the urban core area led by district 2, mainly including the central urban areas of districts 1–3 and 5, has a core feature that its Tier 1 low-carbon travel potential is rapidly released as MNI increases, especially during the process from MNI=1km to MNI=5km and at MNI=13km, the convertible motorised travel proportion has dropped to a low level. This indicates that the most residents' travel distances are within the 13 km range and even a considerable part is within the 5 km range. Improving the non-motorised travel environment in this area and constructing dedicated non-motorised travel roads can help residents choose more low-carbon walking or cycling modes.

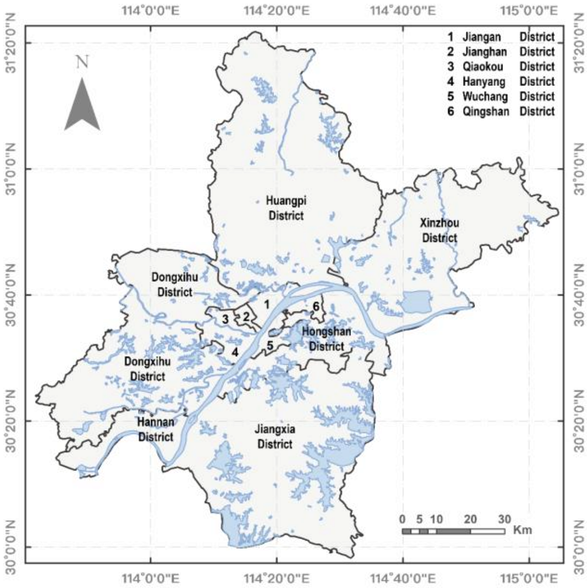
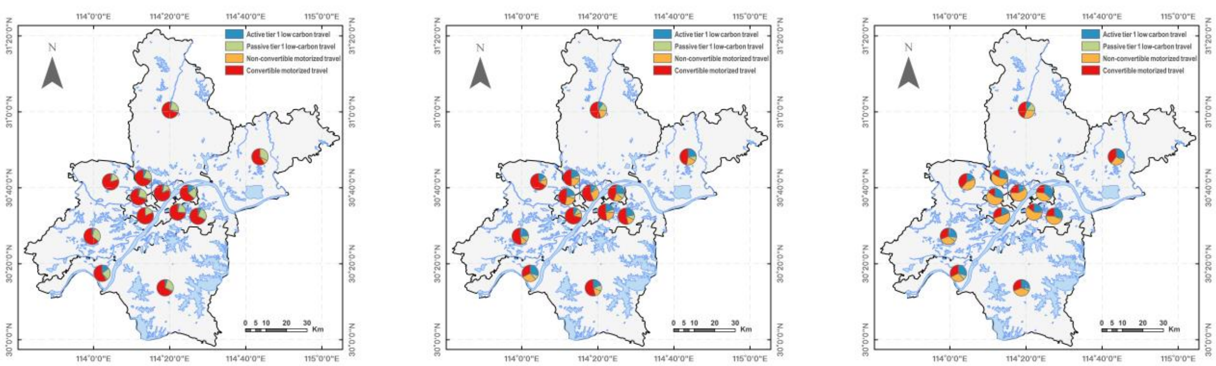



*Figure 17 – Wuhan district map*

Secondly, the urban peripheral area led by districts 4 and 7, including the central urban areas of districts 4, 6 and 7, as well as the outer urban areas of districts 8, 10 and 11, has a significant feature that the Tier 1 low-carbon travel potential is released less during the process from Scenario A to Scenario B, and the release of Tier 1 low-carbon travel potential is relatively considerable during the process from Scenario B to Scenario C. This indicates that the most residents' travel distances are beyond the 5 km range and from the perspective of travel mode itself, walking distances of more than 5 km are already difficult to be used as a daily commuting mode. To increase the proportion of non-motorised travel in this area, more consideration should be given to bicycle modes and more bicycle lanes should be planned and constructed.

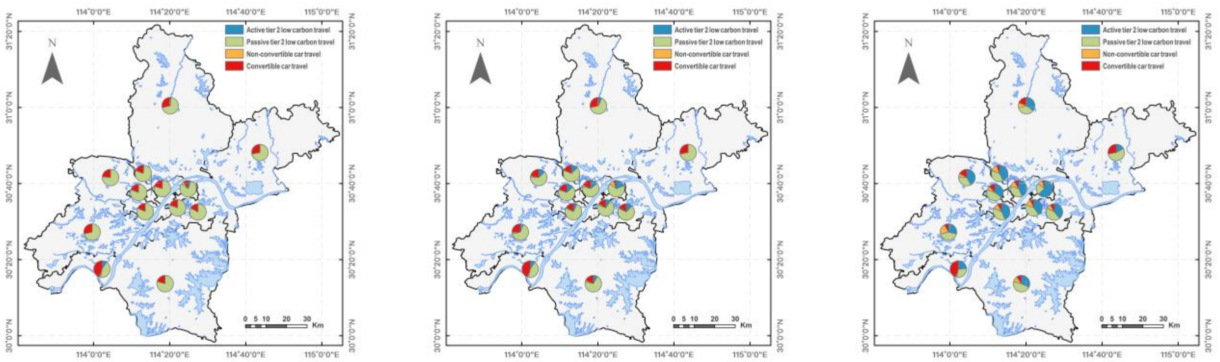


*(a)* *(b)* *(c)*

*Figure 18 – Wuhan Tier 1 low-carbon travel potential assessment key scenario corresponding district map: a) Key scenario A: N1; b) Key scenario B: N5; c) Key scenario C: N13*

Finally, the urban satellite cities composed of districts 9, 11 and 12 have a characteristic that some Tier 1 low-carbon travel potential has been released during the process from Scenario A to Scenario B, but there is little change during the process from Scenario B to Scenario C. This indicates that there is a severe polarisation in the travel distances of residents in this area, with some residents commuting within the area without the need to reach the central urban area, and their daily travel distances are within 5 km, which is conducive to the conversion from motorised to non-motorised travel modes. However, another part of the residents has travel distances of more than 13 km and there are practical obstacles to converting their travel modes to non-motorised travel, so public transportation construction should be sought to solve this problem.

*Figure 19* illustrates the distribution and proportion of the four types of resident travel modes within each TAZ in Wuhan's Tier 2 low-carbon travel potential assessment system for the three key scenarios corresponding to C0.8D1.8T0, C1.4D2.6T1 and C2.2D3.7T2.




(a) (b) (c)

*Figure 19 – Wuhan Tier 2 low-carbon travel potential assessment key scenario corresponding district map: a) Key scenario A: C0.8D1.8T0; b) Key scenario B: C1.4D2.6T1; c) Key scenario C: C2.2D3.7T2*

For the Tier 2 low-carbon travel potential assessment system, the differences between key scenarios A–C can also categorise Wuhan's regions into three levels.

Firstly, the areas with well-developed public transportation systems primarily include the urban centre districts 1–7, along with the outer district 8. Among them, districts 2 and 6 have the fastest release of Tier 2 low-carbon travel potential during the transition from Scenario A to Scenario C, indicating that these are the areas with the most complete public transportation system construction in Wuhan. District 2, as the core area of Wuhan, has a high density of rail transit stations and many lines. Although district 6 does not have the same level of rail network density as district 2, its linear layout allows residents to travel conveniently by public transportation, especially by rail transit, due to the two subway lines extending along the long axis of the district.

Secondly, the areas with a developed public transportation system mainly include some peripheral urban areas, including districts 10 and 11. In Scenario A, the proportion of convertible car travel in these areas is at a mid-level in the city and during the transition from Scenario A to Scenario C, the Tier 2 low-carbon travel potential has been released to some extent. Both areas are outer urban areas with weak infrastructure, but both have rail transit lines extending to the core of the district, providing a rail transit solution for the residents' travel. With the increase in MCI, MDI and MTI, the low-carbon travel potential in these areas can also be released. However, the road network in these areas still needs to be further densified to build a connection system within the district, facilitating residents' travel to the city centre.

Lastly, the areas with a weak public transportation system mainly include district 9 in the southwest and districts 12 and 13 in the northeast. During the transition from Scenario A to Scenario C, the Tier 2 low-carbon travel potential in these areas is difficult to release, indicating that the public transportation system construction in these areas is too weak. Among them, district 9 still has rail transit lines reaching the central area, while districts 12 and 13, due to their long distance from the city centre, have not yet had rail transit lines reaching the core of the district. The lack of convenient public transportation solutions for cross-regional travel is the key factor limiting the release of their Tier 2 low-carbon travel potential.

## 5. CONCLUSIONS

The urban low-carbon travel potential stratified assessment method proposed in this study focuses on identifying the potential for residents of non-low-carbon travel to shift to low-carbon travel and it defines the proportion of the convertible non-low-carbon travel population as the urban low-carbon travel potential. To adapt to the actual conditions of many underdeveloped regions, we collect basic data through questionnaire surveys and conduct subsequent quantitative analyses. Based on the carbon emission levels of travel modes, a two-tier assessment system is constructed, which reveals the trends of urban low-carbon travel potential as the maximum acceptable travel distances for non-motorised travel, and the maximum acceptable connection, delay and transfer strengths for public transportation travel change. The curves obtained show an inverse “S” shape. The middle part of the curve is defined as the “rapid release zone,” with the starting and fastest change points defined as key points A, B and C and their corresponding scenarios defined as key scenarios A, B and C. The “rapid release zone” of the curve is the most critical, where the urban low-carbon travel potential value decreases rapidly with the increase in the residents’ thresholds for non-motorised travel intensity and public transportation connection, delay and transfer intensity. The determination of the non-motorised travel threshold interval and the public transportation connection, delay and transfer threshold interval corresponding to the rapid release zone is the core contribution of this study. This allows for the judgment of the extent of measures that can quickly release the urban low-carbon travel potential and increase the proportion of low-carbon travel. Measures to improve non-motorised travel and public transportation conditions mainly include two directions: one is to increase the residents’ acceptance thresholds for non-motorised travel intensity and public transportation connection, delay and transfer intensity, and the other is to reduce the actual non-motorised travel intensity and public transportation intensity in the residents’ travel. The former includes improving the urban slow-travel environment, optimising the public transportation experience and enhancing the convenience of public transportation transfers, while the latter includes adding public transportation lines, improving public transportation operation plans and constructing new public transportation facilities. The implementation of these measures is based on a significant cost investment and insufficient investment cannot achieve the expected benefits, while excessive investment may not necessarily yield proportional returns. The assessment method proposed in this study can clearly define where the cost investment for improving low-carbon travel conditions should start and stop, helping urban managers to formulate precise transportation policies and achieve an increase in the proportion of low-carbon travel at the lowest marginal cost.

This study applied this method to assess the Tier 1 and Tier 2 low-carbon travel potentials of Shanghai and Wuhan, finding that the rapid release zones of low-carbon travel potential in Shanghai and Wuhan are quite similar, with the same change patterns, but the potential values and details of the changes are different, which are related to the city’s scale and public transportation system, especially the rail transit system. Through regional analysis under key scenarios, significant differences in low-carbon travel potential are found in different urban areas, with both cities showing a huge difference between the core and outer areas, which is related to the imbalance in the construction of urban slow-travel systems and public transportation systems. However, the key challenges of urban development are concentrated in the middle zones of cities, which face longer commuting distances than the outer suburbs or satellite cities, as well as poorer travel conditions and less coverage by public transportation compared to the city centre areas.

Due to differences in their developmental stages and urban layouts, different cities face distinct development issues. Public transportation networks, especially rail transit networks, play a crucial role in inter-district travel. The density of the city centre affects the demand for public transportation among urban residents. Cities with more dispersed central areas or decentralised city centres place higher demands on public transportation systems. Dense urban construction in central areas presents fewer challenges but requires the development of more suburban routes to connect with the outer regions of the city. Each city has its own vulnerabilities and requires tailored development strategies and policy directions, as well as public education initiatives.

## 6. LIMITATIONS AND OUTLOOK

The urban low-carbon travel stratified assessment method proposed in this study uses the carbon emission levels of travel modes as the basis for grading, assessing the Tier 1 low-carbon travel potential corresponding to non-motorised travel and the Tier 2 low-carbon travel potential corresponding to public transportation travel. The main considerations are the impact of travel distance on the residents’ willingness to travel non-motorised and the impact of connection, delay and transfer on the residents’ willingness to travel by public transportation.

However, factors affecting the residents' willingness to travel non-motorised and public transportation are comprehensive and complex. Social development, industrial layout, economic level, population structure and other factors may also affect the residents' willingness to travel non-motorised and public transportation. However, these factors involve more than just urban transportation and the problems they cause cannot be solved solely by improving urban slow-travel conditions and public transportation travel conditions. Therefore, these factors are not considered in this study. Factors such as urban climate conditions, slow-travel comfort, urban air quality and public transportation efficiency will also affect the residents' willingness to choose non-motorised and public transportation travel. Therefore, constructing an urban low-carbon travel potential assessment system that considers more comprehensive factors is the direction of our research. Further expanding the assessment to more cities, enriching the assessment data, finding development patterns for different types and levels of cities and identifying universal indicators for the construction of urban slow-travel systems and public transportation systems are the expected outcomes. For regional assessment within the city, due to the limitation of sample size, it is not possible to refine the analysis to smaller administrative units. Considering that public transportation lines often cross regions, overly detailed TAZs do not have significant advantages. However, if the data volume is further increased, it is possible to identify the weak areas of urban development more accurately. In addition, based on the research, we plan to develop automation and visualisation using ArcGIS and Python to help promote the method to other cities, providing decision-making support for increasing the proportion of low-carbon travel and reducing urban transportation carbon emissions in various locations.

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丁科元，张妍，郭海旭，周旭，彭然

**城市低碳出行潜力的分级评估**

**摘要：**

非机动出行和公共交通出行被认为是低碳的出行方式，而驾车出行则是非低碳的出行方式。本文据此提出一种城市低碳出行潜力的分级评估方法，将可能转变为非机动出行的机动出行人群在全部出行人群中的数量占比定义为城市交通一级低碳出行潜力，将可能转变为公共交通出行的驾车出行人群在全部出行人群中的数量占比定义为城市交通二级低碳出行潜力，以此整体性呈现城市在控制交通碳排放方面的可进步空间。该方法考虑距离是非机动出行较之于机动出行的主要不利因素而影响居民非机动出行意愿，接驳、延迟、换乘是公共交通出行较之于驾车出行的主要不利因素而影响居民公共交通出行意愿，从而通过对居民实际出行距离以及公共交通出行模式下实际接驳、延迟、换乘强度值与假定居民最大可接受出行距离以及最大可接受接驳、延迟、换乘强度值的比较，识别假定场景中可能转变为相应等级低碳出行的人群数量并据此计算相应的低碳出行潜力值，然后进一步分析其值随居民对于非机动出行可接受距离以及公共交通出行可接受接驳、延迟、换乘强度阈值变化的

趋势并拟合其关系曲线，发现拟合曲线呈现反向“S”型态，由此识别了曲线的“快速释放区”及“关键点”。本文以中国上海市及武汉市为例，基于 19,732 份居民日常出行 OD 调查样本对两个城市的低碳出行潜力进行了分级评估，同时也对两个城市的低碳出行潜力进行了分区可视化呈现，由此分析了两个城市的低碳出行潜力特征并比较了两个城市的低碳出行潜力差异。

**关键词：**
城市低碳出行潜力；非机动出行；公共交通出行；接驳；延迟；换乘