Analysing Urban Tourism Accessibility Using Real-Time Travel Data: A Case Study in Nanjing, China

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Abstract: This study aimed to evaluate the spatial accessibility of tourism attractions in the urban destination city. An analytical framework for assessing urban tourism accessibility at different spatial scales was proposed to provide references on the interaction of urban transport and tourism systems. In addition to the travel time-based measure, a modified gravity model integrating the tourism destination attractiveness, urban transport system characteristics, and tourist demand distribution was developed to evaluate tourism accessibility in this study. Real-time travel data obtained from the Web Maps service were used to take the actual road network operation conditions into consideration and improve the accuracy of estimation results. Taking Nanjing as an example, the analysis results revealed the spatial heterogeneity of tourism accessibility and inequality in tourism resource availability at different levels. Road transport service improvement plays a dominant role in increasing tourism accessibility in areas with insufficient tourism resources, such as the outskirts of the destination city. As for areas with abundant attractions, authorities could pay attention to destination attractiveness construction and demand management in addition to the organization and management of road network operations around attractions during holidays. The results of this study provide a potentially valuable source of information for urban tourism destination management and transport management departments.

Keywords: accessibility; urban tourism attractions; Web Map API; real-time travel data; spatial heterogeneity; Nanjing

1. Introduction

Urban tourism is an important form of leisure and recreation for residents that has grown rapidly over the last two decades as a result of improved mobility through transportation and advanced technology [1]. In recent years, with the popularity of short-term tourism trips on weekends, self-drive tourism has become the mainstay of domestic tours in China [2]. This phenomenon has become even more pronounced with the restriction of long-distance travel due to the COVID-19 pandemic. In 2021, the number of self-drive tours in China accounted for 77.8% of the total number of domestic trips, an increase of 14% over 2020. The self-driving tours within residents’ home cities or nearby in the countryside have become a dominant form of tourist activity for urban residents and an important component of urban tourist flows.

The tourist travel process from the origin to the final destination is an important component of the overall urban tourism process. Mobility provisions between tourist attractions and tourist origins are fundamental preconditions for tourism activities, which means that the quality and the level of tourism travel services dramatically influence tourist satisfaction and loyalty. The increasing use of cars for urban tourism has put substantial pressure on limited urban road network capacity [3]. This problem further manifests as congestion during non-weekdays on the road networks around tourist attractions, leading to extra air pollution, noise and difficulties in urban tourism and transport management.
Understanding the relationship between urban transport and tourism systems can not only guide the optimization of tourism attractions layout and the improvement of road networks and sustainable transport systems, but also provide references for tourist travel arrangement, including the selection of starting time, visiting order, travel route, etc., to access their destinations more efficiently. In this paper, we try to answer the following questions: How do we quantify the interaction between tourists and destinations? What factors may influence the interaction between tourists and tourism destinations? How easily can tourists reach their expected tourism products and services with acceptable travel cost constraints using an urban transportation system? How can urban tourism accessibility analysis function as a decision-making basis for transport and tourism destination management? This paper tries to analyse the ease of self-driving tourists’ movement between origins and tourist attractions within a destination city as the reference for tourism transport problem diagnosis and the precondition for developing sustainable transport policies and management strategies for urban tourism.

Accessibility has been used widely as an essential indicator in spatial interaction and equity studies. Although the definition and estimation model of accessibility may vary from different research perspectives [4–6], the essence of accessibility studies is consistent; it is the relationship between people, activity, and mobility [7]. Commonly used measures in existing accessibility research include the distance-based methods [8], the container method, gravity-based models [9], and the cumulative opportunities method [10]. As for the strengths and weakness of each model, the shortest distance method is relatively straightforward and convenient, but neglects externalities regarding neighbourhoods. The traditional gravity model takes distance effects into consideration and can overcome the spatial spillover problem, but ignores the competition between different facilities. Some modified versions of the gravity model have been proposed to make up for this defect [11,12]. The two-step floating catchment area method (2SFCA) has been widely applied recently. It integrates the supply and demand side of opportunities, but different time thresholds might yield very different results, and the model neglects the distance decay effect within the catchment [13].

Some studies have researched tourism accessibility as the accessibility or transportation infrastructure as one of the crucial destination factors that affect tourist satisfaction and loyalty [14]. For example, Hooper [15] integrated distance and price factors in a modified location rent model and showed the spatial effect of the friction of distance on tourism patterns. Tomej and Liburd [16] developed a spatial network model of sustainable mobility for tourists in rural areas and focused on the spatial and temporal aspects of transport services for tourism. Uchiyama and Kohsaka [17] analysed the cognitive value of tourism resources and their accessibility, introducing tourism resources into the analysis of destination accessibility. It is noticeable that there are some flaws in existing studies on tourism accessibility that may need further exploration. First, distance, speed, and travel time estimate as impedance measures are predominantly applied for estimating tourism accessibility. Now, the availability of real-time travel data from online platforms can provide new insights into travel behaviour and improve estimation accuracy [18,19], which can also be applied to tourism accessibility research. Second, most tourism accessibility studies have been conducted at the tourism destination city level to improve the destination city competitiveness, and the analysis method is relatively unidimensional. It is necessary to examine tourism accessibility on a finer scale to enhance the transport service quality and tourism satisfaction within the urban destination city. What is more, factors other than the distance factor should be further studied in estimating tourism accessibility.

The impact of some key factors other than travel time on the decision-making process of tourists in choosing and traveling to their destinations should also be considered. For example, destinations providing competitive advantages for tourists can still attract a significant number of tourists even with relatively higher travel costs. Therefore, the destination attractiveness factor is also important in tourism accessibility modelling. This factor corresponds to the facility capacity factor that is often considered in general accessibility
For most public facilities, such as urban parks, green spaces, and hospitals, facility capacity is always considered a pull factor for residents because a larger capacity means a greater number of opportunities can be taken advantage of and a greater number of residents can be accommodated [18]. However, in the context of tourism research, other factors, such as the popularity of a destination, the uniqueness of tourism resources, and singular events and activities also have an influence on the decision-making process of tourists rather than the facility capacity alone, which means that tourists do not always select the destination with the highest capacity given the specific purpose and needs of their visits. Although some studies have posited that it is meaningless to discuss destination attractiveness without the motivations or goals of tourists [21,22], researchers can still use a variety of models and calculation methods to measure destination attractiveness in a general sense. In addition to the distance and destination attractiveness as push and pull factors, the competition effect should not be ignored [23,24]. Thus, it is necessary to build a tourism accessibility model that can reflect the real travel time costs of tourists and integrate other important characteristics of transportation systems and tourism.

Analysing urban tourism accessibility can not only help assess the ease with which tourists can acquire their desired tourism products, allowing urban planners to pinpoint the disparity of tourism availability in the destination city, but also evaluate the service quality of road transport for tourism attractions and find out potential areas that may need further transport management, providing a valuable source of information for the destination management and the urban transportation departments. A more comprehensive and integrated analysis framework for tourism accessibility research may support the implementation of different management strategies to offer better transportation services for tourism destination development.

2. Study Area and Data

2.1. Study Area

Nanjing, as the provincial capital of Jiangsu Province, is a typical urban tourism destination city in the lower Yangtze plain in China (Figure 1). By 2021, Nanjing had an administrative area of about 6587.02 km² and a resident population of about 9.3 million. Considering the abundant tourism resources and large volume of tourist demand, Nanjing was taken as the study area in this study. Although influenced by COVID-19, the number of tourists of Nanjing had recovered to 82.2% of the same month in 2019 by the National Day Holiday of 2021, and a total of $182.2 billion US dollar in tourism revenue was achieved in 2021. The concentration of tourist demand in temporal and special dimensions brings a lot pressure on urban traffic management. In this study, the selected study area was defined as the city area of Nanjing, which covers 11 districts, including Xuanwu (XW), Qinhuai (QH), Jianye (JY), Gulou (GL), Pukou (PK), Qixia (QX), Yuhuatai (YHT), Jiangning (JN), Liuhe (LH), Lishui (LS), and Gaochun (GC).

2.2. Data Preparation

2.2.1. Classification of Tourist Attractions

As the main components in the urban tourism system, tourist attractions (TA) play an essential role in tourism resource protection and urban landscaping, providing spaces and opportunities for sightseeing, recreation, and outdoor activities. In this study, 47 major TAs in Nanjing were considered (Table 1). These TAs were divided into four types: History and culture (H), Natural scenery (N), Museum (M), and Leisure (L). The history and culture type is the predominant type in Nanjing city, and includes various historical monuments, ancient architectures, ethnographic landscapes, etc. The natural type refers to natural resource-based attractions, and the leisure type mainly refers to recreational facilities. The distribution of different types of attractions are shown in Figure 2a. We collected the information of TAs from the Nanjing Urban Planning Bureau and field surveys, including their names, sizes, capacities, locations, and ratings.
Table 1. Tourist attraction attributes in Nanjing.

<table>
<thead>
<tr>
<th>Attraction Name</th>
<th>Type</th>
<th>Maximum Daily Carrying Capacity (Ten Thousand Visitors)</th>
<th>Rating</th>
<th>Attraction Name</th>
<th>Type</th>
<th>Maximum Daily Carrying Capacity (Ten Thousand Visitors)</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Sun Yat-sen Mausoleum</td>
<td>H</td>
<td>40.0</td>
<td>5</td>
<td>Hongshan Forest Zoo</td>
<td>N</td>
<td>8.0</td>
<td>4</td>
</tr>
<tr>
<td>Fuzimiao-Qinhuai Scenic area</td>
<td>H</td>
<td>41.2</td>
<td>5</td>
<td>The President Palace in Nanjing</td>
<td>H</td>
<td>3.4</td>
<td>4</td>
</tr>
<tr>
<td>Xuanwu Lake Park</td>
<td>N</td>
<td>18.0</td>
<td>4</td>
<td>Chaotian palace</td>
<td>H</td>
<td>1.7</td>
<td>4</td>
</tr>
<tr>
<td>Nanjing Museum</td>
<td>M</td>
<td>0.2</td>
<td>4</td>
<td>The Yuhuatai Martyr Memorial Park</td>
<td>H</td>
<td>8.0</td>
<td>4</td>
</tr>
<tr>
<td>Tangshan Hot spring</td>
<td>L</td>
<td>1.5</td>
<td>4</td>
<td>Gaochun Ancient Street</td>
<td>L</td>
<td>9.0</td>
<td>4</td>
</tr>
<tr>
<td>Muyan Riverside Park</td>
<td>N</td>
<td>10.0</td>
<td>3</td>
<td>Yanzijin Scenic Area</td>
<td>N</td>
<td>1.8</td>
<td>2</td>
</tr>
</tbody>
</table>

Figure 1. Location of Nanjing city.

Figure 2. Spatial distribution of key elements in transport and tourism system of Nanjing. (a) Major roads and 47 tourist attractions. (b) Population density (2021 estimated).
2.2.2. Origin and Destination Points of Urban Tourists

In this study, the focus was on tourist trips within the destination city, so we assumed that both local and nonlocal tourists departed from locations in Nanjing, including hotels, transport hubs for nonlocal tourists, and residential areas for local tourists. The study area was divided into 8609 grids and georeferenced in ArcGIS as the starting point for urban tourists.

The destinations were the 47 selected TAs. In Figure 2a, historical TAs and museums are concentrated in the central urban area, especially in QH and XW districts, while natural and leisure types are in suburban areas. The geographic information of origins and destinations was obtained on 1 March 2021 through Baidu Maps.

2.2.3. Population Data

The population grid dataset was from the Resource and Environment Science and Data Centre [25]. Figure 2b reflects the population distribution and displays the estimated total number of people using 1 km × 1 km grid cells across the city.

2.2.4. Travel Time Data

The Baidu Maps Route Matrix API offers open access to acquire actual travel distance and time data under several independent or mixed transportation modes, reflecting travel conditions more accurately. According to the coordinates of ODs and the designed driving preference rule, the corresponding distance and real-time duration were returned. The routes with the shortest distance considering real-time road network conditions under driving mode were selected in this study. Considering the fluctuations in travel data over time, the data in this study were acquired during the tourist peak travel period from 9:30 a.m. to 10:30 a.m. between 24 April and 30 April 2021, covering both workdays and weekends. The API returned results for this study that reflect the entire path time and distance cost.

3. Methodology

3.1. Analytical Framework and Indicators for Tourism Accessibility

An analysis framework for assessing urban tourism accessibility was proposed in this study. Figure 3 illustrates the flowchart for measuring urban tourism accessibility characteristics.

Two types of measurements were adopted in this paper. The direct measure mainly reflects accessibility in relation to the urban transport system with the travel time cost for tourists moving between origins and destinations. This is also the most commonly used accessibility measure. The indirect measure takes the destination attributes and tourist demand into consideration, thus allowing related departments to investigate the relationship between the urban transport system, destination system and tourists. Based on these measures, some analysis indicators were established to evaluate the spatial differentiation of urban tourism resource availability and the service radiation capability of different tourist attractions.

The tourist service radiation capability analysis can reflect the efficiency and catchment of its service and help identify tourist attractions where accessibility constrains the development. The characteristic of the service radiation capability of tourist attractions has been defined by indicators, destination average tourism accessibility and tourism destination service capability. These indicators focus on the area and the population that can reach the destination for a certain travel time threshold, indirectly reflecting the service area of the tourist attraction as well as the operational conditions of the road transportation system around a tourist attraction. The destination average tourism accessibility index has its importance as it is the average value of tourism accessibility from a tourist attraction to other locations in the destination city (Equation (1)), measuring the general access to a tourist attraction. Tourism destination service capability is described as the tourist demand that can
be served within a given threshold. The selection of the threshold is related to the tourism marketing positioning for different destinations and their tourism-generating regions.

\[ A_j = \frac{\sum_{i=1}^{n} A_{ij}}{n}, \]  

(1)

Here, \( A_j \) is the average accessibility to tourist attraction \( j \), and \( n \) is the number of locations in the city. \( A_{ij} \) can be either the direct accessibility indicator or calculated by the modified gravity-based model.

**Figure 3.** Flowchart for tourism accessibility characteristic analysis.

Tourism resource availability analysis can evaluate the distribution of tourism facilities, assess the spatial equity of tourism resource availability, and provide a reference to urban planners from the perspective of social equity. In this paper, we discuss the availability of tourism resources on both the grid level and the district level. The grid-level accessibility indicator is the average value of tourism accessibility of a specific location to all tourism resources in the destination city (Equation (2)). The spatial distribution of this grid-level indicator depicts the ease of tourists in different areas in acquiring tourism services, reflecting the tourism service equity in the destination city.

\[ A_i = \frac{\sum_{j=1}^{k} A_{ij}}{k}, \]  

(2)

The measurement \( A_i \) represents the grid-level tourism availability indicator. \( i \) represents the specific location in the destination city and \( k \) is the number of tourist attractions to be considered.

When analyzing the grid-level indicator, locations in the destination city are regarded as points without attributes, which ignores the distribution of tourist demand. Therefore, we introduced the district-level indicator, the tourist demand weighted availability indicator (Equation (3)). First, the estimated tourist demand weight \( w_{p_{ij}} \) was the ratio of potential tourists who might travel from location \( i \) to tourist attraction \( j \) to total potential tourists.
within the district Z (Equation (4)). This weight was used to multiply tourism accessibility. The multiplied values for all grids in the district were summed to obtain the estimated tourist amount weighted accessibility $A_{Zj}$ for each target district separately.

$$A_{Zj} = \sum_{i=1}^{Z} w_{pij} \cdot A_{ij},$$  \hspace{1cm} (3)

$$w_{pij} = PT_{ij} / \sum_{i=1}^{Z} \sum_{j=1}^{k} PT_{ij},$$  \hspace{1cm} (4)

### 3.2. Direct Tourism Accessibility Measure

The travel distance and time cost indicator are often used as the accessibility measure (Equation (5)). This measurement derives from the distance-based method and is relatively intuitive and easy to interpret, reflecting the travel cost for tourists to access different attractions and revealing the quality of road transport service for urban tourists. In general, tourists tend to choose the closest tourism destination that can satisfy their purpose and needs. The traveling probability of tourists may be reduced with the increase in travel time, and longer travel time indicates lower tourism accessibility. In this study, we adopted the actual time-consuming data obtained from the Baidu Maps API to represent the direct tourism accessibility indicator and to take the actual traffic conditions into consideration. The time cost between different locations with related distances and routes under different modes can be precisely obtained, improving the validity and convenience of the time cost estimation process.

$$A_{ij}^{t} = T_{ij},$$  \hspace{1cm} (5)

where $A_{ij}^{t}$ is the direct tourism accessibility between location $i$ and tourist attraction $j$, and is represented by the actual travel time data, $T_{ij}$.

### 3.3. Gravity-Based Model for Tourism Accessibility

The limitation of the direct travel cost indicator is the absence of other vital factors that may change the willingness and ease of reaching destinations. To build a more realistic model, we compared commonly used accessibility measures in recent years, including cumulative opportunity measures, utility measures, gravity-based measures, and 2SFCA measures. Utility measures take into account individual differences in perceived utility. However, this measure gives insufficient consideration to location information, and requires large amounts of data that are relatively difficult to obtain practically. The cumulative opportunity approach assumes that people outside the given time threshold have no accessibility and that those within the area have the same accessibility, but tourists living outside the area can still visit the destination. In comparison, the gravity-based models can avoid the loss of accessibility outside a one-size catchment area. However, the influence of demand is ignored in these traditional gravity-based models. The 2SFCA method is a dichotomous version of the gravity model. Although it integrates the distance-decay function and takes both the supply and demand of opportunities into consideration, the problem of locations outside the given catchment having no accessibility still exists. Because many tourist attractions in this study were scattered in the urban area and outside the given time thresholds, we chose to revise the gravity model to examine the degree to which different tourism destinations could be accessed for a certain location.

The original gravity model measured accessibility by weighing the attraction of opportunities using travel impedance, as shown in Equation (6).

$$A_{ij} = C_j \cdot d_{ij}^{-\beta}$$  \hspace{1cm} (6)

where $C_j$ is the capacity of the public facility $j$ and $d_{ij}$ is the distance between locations $i$ and $j$. This model assumed that destination accessibility increased with a decrease in the travel distance and an increase in the facility capacity. Thus, the more attractions that are
distributed, the better the road network operation condition and transport system are, the higher the tourism accessibility. We replaced the capacity factor with the attractiveness of tourism destinations as the major pull factor in the revised model. The statement that urban tourists will go to the nearest tourist attraction is only valid when the attractiveness of all the destinations is equal to a tourist. In reality, all the tourist attractions in the destination city can be alternatives for tourists, and the attractiveness can have a significant impact on their access to the destination. Under the premise of fulfilling a tourism purpose (such as recreation, education, training, or health care), the tendency of accessing a destination increases with the increase in attractiveness of a tourist attraction. Thus, the basic form of the gravity-based tourism accessibility model is as follows:

$$A'_{ij} = \text{Att}_j \cdot d^{-\beta}_{ij}, \quad (7)$$

where $d_{ij}$ can be represented by travel costs. $\beta$ is the travel friction coefficient. The larger this coefficient is, the larger the travel friction to the closer tourism attraction can be. Although some previous research set this coefficient to be 2 [12], excessive coefficient values may overestimate the impact of the gravity model in calculations. Based on the gravity models in most previous travel simulations [24], this coefficient is set to 1.5 as travel times and distances are based on the highway network in this paper. $\text{Att}_j$ indicates the attraction of tourist attraction $j$ to tourists at grid $i$. A larger impedance between an origin and a tourist attraction means higher travel costs and inconvenience in accessing destinations. In contrast, the higher attractiveness of a destination indicates more potential tourists and higher tourism accessibility. Although it is difficult to calculate a tourism destination’s attractiveness to every tourist owing to their different preferences, it is reasonable to assume that the overall attractiveness of a destination among all tourist attractions in the city can be calculated as the relative popularity-weighted capacity:

$$\text{Att}_j = w_p^j \cdot C_j, \quad (8)$$

$$w_p^j = r_j / \sum r_j, \quad (9)$$

where $w_p^j$ is the relative popularity weight calculated by the percentage of tourist attraction $j$’s rating in the sum of all tourist attraction’s rating in the city, and $C_j$ is the capacity of the tourist attraction $j$, indicating the maximum number of tourists that a scenic area can accommodate under certain conditions. In this study, the carrying capacity was adopted to represent the maximum number of tourists that could be served in the tourist attraction with the premise of ensuring the personal safety of tourists and the environmental safety of tourism resources. $r_j$ is the rating of a tourist attraction. The $r_j$ term adopted in this paper refers to the standard of the rating for the quality of tourist attractions made by the Ministry of Culture and Tourism of China, which is widely accepted by the domestic tourism management department and tourists. The ratings were divided into five levels (one to five), where five represents the highest attractiveness. Many factors, including tourism resource attractiveness, market attractiveness, tourist satisfaction, and quality of service facilities, are comprehensively considered in this rating system.

To compensate for the lack of consideration of tourist demand in the gravity model, a modified version was adopted to incorporate tourist demand. The competition effect considered in Equation (10) comes from the fact that tourist competition for limited tourism resources can affect the degree of crowdedness and the number of opportunities at a tourism destination, thus influencing tourist decisions. Because tourists have high expectations of the level of service, they prefer a destination with less potential competition provided that their tourism purpose can be met. Excessive potential tourists might lower tourists’ willingness to access a tourism attraction.

$$A^p_{ij} = \frac{\text{Att}_j \cdot d^{-\beta}_{ij}}{\text{PT}_j}, \quad (10)$$
Due to the difficulty of obtaining accurate tourist OD and travel data, the estimated total potential tourist amount was introduced here. \( PT_j \) is the estimated total potential tourist amount for tourist attraction \( j \). Based on the population-weighted opportunities model for measuring mobility patterns [26], the potential tourist amount could be estimated as follows:

\[
PT_{ij} \propto \frac{Pop_i \cdot Att_j}{S_{ji}},
\]

(11)

where \( PT_{ij} \) is the potential tourist amount from origin grid \( i \) to tourist attraction \( j \); \( Pop_i \) is the population size of origin grid \( i \); and \( S_{ji} \) indicates the population potential of tourist attraction \( j \) from the surrounding region, which is the circle area centred at the tourism destination, with the radius being the distance between the origin grid \( i \) and destination \( j \).

A more specific formula is as follows:

\[
PT_{ij} = \frac{Pop_i \cdot R_j \cdot C_j \left( \frac{1}{S_{ji}} - \frac{1}{M} \right)}{\sum_{k \neq i} R_k \cdot C_k \left( \frac{1}{S_{ki}} - \frac{1}{M} \right)},
\]

(12)

\[
R_j = R_{min} \cdot \frac{r_j}{r_{min}},
\]

(13)

where \( R_j \) represents the relative rating of tourist attraction \( j \), and \( n \) is the number of locations in the city. The tourist attractions studied here had a minimum rating of two and a maximum of five, so we set \( r_{min} = 2 \) and \( R_{min} = R_2 = 1 \). \( C_j \) as the carrying capacity of the tourist attraction \( j \). \( M \) is the total potential population in the city.

4. Results

4.1. Accessibility of Tourist Attractions in Different Districts

Figure 4a shows that the average travel time for tourists to access a TA on weekends is between 0.86 to 1.43 h. Nearly 60% of the TAs can be accessed in less than 1.1 h, while only two TA adjacent to the southern border of the central urban area can be reached in an average time of 1 h. Although the results for weekdays are not precisely the same as on weekends, they show a similar spatial pattern. Tourists spend less time on average on their way to the TAs in the central part of Nanjing, while TAs in northern suburban areas are harder to access. However, the percentage of TAs with higher accessibility increases, and 26% of TAs have an average travel time of less than 1 h (Figure 4b). The portion of TA with less than a 1.1-h average travel time climbs slightly to 64%. Historical and cultural TAs have relatively higher accessibility; tourists can reach 55% of this type of TAs in 1 h.

The cumulative histograms of the population covered in different travel time catchments are displayed in Figure 5a,b. TAs in districts located in the urban area can obviously serve more population within the same given travel time. In contrast, LS, LH, and GC in the suburban areas can only offer tourism service to less than half of the people within a 1-h catchment. Only 18.3% of the total population are found in a 1-h travel catchment of TAs in GC.
Figure 4. The average travel time to different tourist attractions during different periods: (a) on weekends; (b) on weekdays.

Figure 5. The average percentage of the population that can access TAs in different districts within a given travel time catchment during different periods: (a) on weekends; (b) on weekdays.

To consider the match between tourist demand and supply of TAs, in Figure 6, the cumulative percentage of estimated tourist demand curves of some typical TAs are displayed. All of the TAs fully cover the tourist demand within 30 to 90 min. The change rule of these curves is slightly different and is related to the attributes of TAs. The well-known Sun Yat-sen Mausoleum curve climbs slowly as the travel time increases and meets the entire tourist demand within around 90 min. Possible reasons for this discrepancy are that the fame and iconicity of the Sun Yat-sen mausoleum make it more attractive, leading to a larger span of travel time.

Figure 6. Cumulative frequency curves between travel time from each TA and estimated tourist demand.
4.2. Grid-Level Tourism Accessibility

To explore the ease of accessing tourism services from different locations in the city, the tourism accessibility of each origin grid calculated by travel time (direct tourism accessibility) and the gravity-based model (relative tourism accessibility) were conducted. The average direct tourism accessibility of 8609 origin grids in Nanjing is 1.12 h, with a standard deviation of 0.208. The maximum and the minimum value of direct tourism accessibility in the study area are 2.16 h and 0.66 h, respectively. Only 32% of the locations have relatively higher direct accessibility, with less than 1-h average travel time to tourism services.

A hot spot analysis was conducted in Arcgis 10.6, revealing the clusters of the accessibility indicator and identifying the locations of statistically significant hot spots and cold spots. As a higher direct accessibility value indicates a longer average time to reach tourism services and worse accessibility, the cold spots here are areas with lower direct tourism accessibility values and better accessibility. Combining Figures 7 and 8, the urban core areas containing GL, JY, QH, and XW are the cold spots clustered with better tourism accessibility locations. In contrast, the periphery areas of the city, especially GC and LH districts, are hot spots with longer average travel times and worse accessibility conditions. Other regions do not show any obvious spatial patterns.

![Figure 7](image1.png)

**Figure 7.** The spatial distribution of average travel time from an origin grid to different type of TAs: (a) Historical type; (b) Natural type; (c) Museums; (d) Leisure type; (e) All TAs in Nanjing.

![Figure 8](image2.png)

**Figure 8.** The hot spot analysis results from an origin grid to different types of TAs: (a) Historical type; (b) Natural type; (c) Museums; (d) Leisure type; (e) All TAs in Nanjing.

For historical and cultural TAs, the average direct tourism accessibility decreases to 0.93 h, with a minimum value of 0.3 h and a maximum value of 1.9 h, which may be related to the densely distributed historical TAs in the core area. The areas of cold spots spread northward to the outer urban space in LH, and the hot spots mainly occur on the western edge of the map. As for museums and natural types, they show similar spatial patterns, but more northern regions belong to hot spots with a confidence level greater than 95%. Also, the cold spots spread to JN in the south. The maximum, minimum, and average values in the leisure type scenario are all larger than these indicators in the overall scenario. The hot spots with a 99% confidence level are primarily located in the suburban area in GH.
The relative accessibility in each scenario is divided into five grades. The mean relative tourism accessibility in overall, historical and cultural, natural, museum, leisure scenarios is 1.51, 1.20, 1.54, 0.46, and 2.06, respectively (Table 2). This shows that tourists leaving from locations in Nanjing had relatively high accessibility to leisure tourist attractions and natural tourist attractions. In contrast, historical TAs and museums may be more difficult to access. As for the area with relatively higher accessibility to tourism services, although 60% of locations reach historical TAs within 1 h, the regions belonging to at least the medium relative accessibility type only take up 17.3%.

Table 2. Comparison between statistics of direct and relative tourism accessibility.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>Proportion of Area within 1-h Catchment (%)</th>
<th>Scenarios</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>Proportion of Area with at Least Medium Value (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>1.12</td>
<td>2.16</td>
<td>0.66</td>
<td>32.0</td>
<td>Overall</td>
<td>1.51</td>
<td>3.06</td>
<td>0.08</td>
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<td>Historical and cultural type</td>
<td>0.93</td>
<td>1.95</td>
<td>0.30</td>
<td>60.2</td>
<td>Historical and cultural type</td>
<td>1.20</td>
<td>4.48</td>
<td>0.05</td>
<td>17.3</td>
</tr>
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<td>35.8</td>
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<td>0.46</td>
<td>1.60</td>
<td>0.05</td>
<td>21.5</td>
</tr>
<tr>
<td>Leisure</td>
<td>1.16</td>
<td>2.37</td>
<td>0.70</td>
<td>27.1</td>
<td>Leisure</td>
<td>2.06</td>
<td>9.58</td>
<td>0.08</td>
<td>61.1</td>
</tr>
</tbody>
</table>

Regarding spatial pattern, the landscapes of relative tourism accessibility for different TAs have some differences compared to travel time indicators (Figure 9). In general, half of the locations in Nanjing had at least medium tourism accessibility, but only 17.5% are areas with relatively high accessibility. Regions in southern Nanjing with a longer average travel time to tourism services actually have acceptable relative tourism accessibility. A similar situation can be noticed in the natural and leisure TA scenarios.

Figure 9. The spatial patterns of relative tourism accessibility for different type of TAs: (a) Historical type; (b) Natural type; (c) Museums; (d) Leisure type; (e) All TAs in Nanjing.

4.3. Estimated Tourist Demand Weighted District-Level Tourism Accessibility

For 11 districts, the estimated tourist demand weighted accessibility is 0.615, with a weighted travel time of 0.93 h and a weighted speed of 48.2 km/h (Table 3). Regions with relatively higher weighted tourism accessibility mainly gather in the urban areas, which are also more economically developed and population concentrated (Figure 10). In contrast, districts with the highest weighted travel time also have a higher weighted average speed. It is noticeable that the weighted average speed is generally less than 50 km/h, which is considerably lower than the normal expected driving speed. This result is consistent with the traffic congestions experienced by tourists on weekends or holidays. Tourists in suburban areas had both longer average travel times and higher average travel speeds.
Table 3. Statistics of weighted travel speed, weighted travel time, and weighted relative tourism accessibility for different districts.

<table>
<thead>
<tr>
<th>District</th>
<th>Weighted Travel Speed (km/h)</th>
<th>Weighted Travel Time (hour)</th>
<th>Weighted Relative Tourism Accessibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xuanwu</td>
<td>39.1</td>
<td>0.79</td>
<td>0.050</td>
</tr>
<tr>
<td>Qinhuai</td>
<td>41.8</td>
<td>0.72</td>
<td>3.531</td>
</tr>
<tr>
<td>Jianye</td>
<td>42.8</td>
<td>0.78</td>
<td>0.011</td>
</tr>
<tr>
<td>Gulou</td>
<td>37.7</td>
<td>0.86</td>
<td>0.063</td>
</tr>
<tr>
<td>Pukou</td>
<td>44.5</td>
<td>0.99</td>
<td>0.075</td>
</tr>
<tr>
<td>Qixia</td>
<td>46.4</td>
<td>0.90</td>
<td>1.513</td>
</tr>
<tr>
<td>Yuhuatai</td>
<td>45.8</td>
<td>0.85</td>
<td>0.014</td>
</tr>
<tr>
<td>Jiangning</td>
<td>48.0</td>
<td>0.79</td>
<td>1.385</td>
</tr>
<tr>
<td>Liuhe</td>
<td>53.4</td>
<td>1.08</td>
<td>0.049</td>
</tr>
<tr>
<td>Lishui</td>
<td>62.5</td>
<td>1.01</td>
<td>0.051</td>
</tr>
<tr>
<td>Gaochun</td>
<td>68.7</td>
<td>1.42</td>
<td>0.023</td>
</tr>
<tr>
<td>Average</td>
<td>48.2</td>
<td>0.93</td>
<td>0.615</td>
</tr>
</tbody>
</table>

Figure 10. The spatial patterns of estimated tourist demand weighted district-level tourism accessibility for different type of TAs: (a) Historical type; (b) Natural type; (c) Museums; (d) Leisure type; (e) All TAs in Nanjing.

The accessibility to historical TAs is generally low in most districts except for the urban core. Regions with higher accessibility to natural resources are mainly found in the less central urban area and the northern suburban areas. As for museums and leisure TAs, locations in the north part of Nanjing display a relatively higher value of accessibility.

4.4. Difference between Weekdays and Weekend

Understanding the temporal characteristic of tourism accessibility is essential for identifying congestions and overcrowding caused by tourism demand rather than regular fluctuation and help with developing targeted tourism and transport management policies to optimize the tourist travel experience.

Although the rate of change was not very significant, over 80% of regions in Nanjing experienced a decrease in tourism accessibility on weekends, increasing 3.05% travel time on average and dropping 2.17% travel speed and 3.5% tourism accessibility (Table 4). In addition, the value of these growth rates had considerable variation among different locations (Figure 11). Take tourism accessibility as an example. The minimum value of its growth rate on weekends is $-25.38\%$, meaning that the tourists departing from this origin might spend over 25% more time to access tourism services than they would on weekdays. The regions with lower accessibility are primarily located in the upper center of
the map. Instead, the tourism accessibility in most areas in northern Nanjing is improved on weekends.

Table 4. Growth rate of different accessibility measures statistics on the weekend.

<table>
<thead>
<tr>
<th>Growth Rate of Indicators</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>Std</th>
<th>The Proportion of Areas with Decreasing Accessibility</th>
<th>The Areas with a Growth Rate of Over 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel time</td>
<td>+3.05%</td>
<td>+20.09%</td>
<td>−12.73%</td>
<td>3.41</td>
<td>91.66%</td>
<td>22.71%</td>
</tr>
<tr>
<td>Travel speed</td>
<td>−2.17%</td>
<td>+99.37%</td>
<td>−14.49%</td>
<td>3.39</td>
<td>84.79%</td>
<td>39.09%</td>
</tr>
<tr>
<td>Tourism accessibility</td>
<td>−3.50%</td>
<td>+47.64%</td>
<td>−25.38%</td>
<td>6.39</td>
<td>87.57%</td>
<td>14.24%</td>
</tr>
</tbody>
</table>

Figure 11. The landscape of relative tourism accessibility growth rate on weekends.

5. Discussion

The study presented the characteristic analysis and visualization of tourism accessibility in a destination city. This information can help decide where there is potential to increase tourism to the destination and can be used to pinpoint marketing initiatives and travel promotions more efficiently. From the tourism attraction-based perspective, travel time measures showed that tourists had to spend more time on average accessing TAs in the city’s periphery. This tendency is also detected in other cities [27] and is determined by the spatial pattern of tourism resource development. This phenomenon also reflects that transport is one of the important factors restricting the development of tourism attractions in the outskirts of the city. It is consistent with existing conclusions in previous studies, which indicates that the more developed the road network is, the higher the accessibility of attraction is [28]. Meanwhile, the results of the proposed gravity-based model show a somewhat contrary spatial pattern, in that TAs in some suburbs had higher values of calculated accessibility. The possible explanation is that most of these suburban TAs are natural or leisure types, with larger capacities but less visibility. This may be appealing to those willing to trade travel costs for a more comfortable touring environment. On the contrary, the lowest value appeared in some well-known attractions in the urban core, which indicates that although destinations in the urban core may have more road transport supply nearby, they receive more potential visits simultaneously. From the perspective of tourism resource availability, the travel time indicator value of different origin locations decreased from the central urban area to northern and southern Nanjing, meaning that tourists departing from central regions can access tourism services quickly overall. The spatial pattern of tourism accessibility for different types of resources was consistent with the tourist attraction distribution pattern. Moreover, the gravity-based model results show that areas with higher tourism resource availability did not always concentrate in urban areas.

As for theoretical contributions, an analytical framework for assessing urban tourism accessibility was built, and two types of measurement for tourism accessibility were
adopted in this study. The direct tourism accessibility was represented by actual travel time, which focused on the relationship between tourism and transport. Different from most other tourism accessibility research that use road network distance and estimated travel speed to calculate travel time as the accessibility representation [29], here the actual time cost data from web map services further ensure the reliability of this model. Furthermore, a more refined model based on the conventional gravity function combining tourism destination attractiveness, actual time cost, and the tourism resource competition effect was established to explore the tourism accessibility of locations in Nanjing. On the one hand, the analysis was conducted at a finer scale—at district and grid level, rather than at a regional or national level as in most previous research; on the other hand, making a distinction between tourism accessibility by these different methods can indicate whether the tourist attraction attributes or competition for tourism resources plays a dominant role in tourism accessibility.

Specific implications for tourism and transport planning and management includes:

(1) For areas with less developed transport systems or insufficient tourism resources, the deficiency in self-driving accessibility can be made up by a multi-modal suburban transport system for tourism objectives. Instead of only expanding the size or capacity of the road transport network, local authorities may promote the development of environmentally friendly tourist travel modes and improve the overall tourism accessibility by suitable planning and management measures, including offering a variety of sustainable travel mode choices, such as setting up dedicated tourist bus routes.

(2) Through the comparison between the direct measure and the relative measure, it can be observed that the improvement of accessibility to attractions and locations in tourism resource concentrated areas should pay more attention to destination attractiveness and tourist demand management in addition to the transport factor. The high-density tourist demand and the concentration of high-reputation TAs in the urban core of Nanjing are breaking the balance between urban transport supply and tourism demand. Possible ways to improve the accessibility of TAs in the urban area include the intervention of tourism demand by encouraging reservation policies and advancing the itinerary of tourists; the enhancement of TAs’ attractiveness by joining different tourist attractions in the district; and the improvement of the collection and distribution capacity of the road network surrounding tourist attractions.

(3) The comparison between tourism accessibility on weekends and weekdays confirmed that although the change may not have been significant, the travel time on weekends from most regions to the tourist attractions increased, while travel speed decreased. Furthermore, the locations with declined tourism accessibility on weekends were mainly distributed in the central urban area. Thus, the improvement of tourism accessibility on non-workdays may focus on the transport management and road transport organization in the central urban area, especially on the road network around tourism attractions. The following measures are feasible ways to enhance the transport services for tourism on non-workdays: implementing transport system management measures, encouraging sustainable tourism travel modes, and developing intelligent guidance systems for tourists. These may provide potentially valuable sources of information for tourism planning authorities, destination marketers, and transport management departments.

Considering the influence of the COVID-19 pandemic in recent years, the findings in this study may differ from the traffic patterns in a regular situation before the pandemic. These differences were directly caused by the change in tourism destination management strategies and tourist travel characteristics, including travel demand, travel distance, and travel mode. Previous studies revealed that tourism patterns might change to be more elaborate and conservative after global health emergencies. For example, travelers may prefer wide-open, natural settings and choose to drive cars when traveling for tourism resumes after the COVID-19 pandemic [30]. Therefore, we focused on short-distance self-driving tours, a typical and preferred type of tourism that complied with the future tendency, to reflect these shifted preferences, and we tried to provide a practical reference for
urban tourism and transportation management in the post-pandemic era. Regarding travel demand and travel distance factors, these characteristics were considered in the calculation of tourism accessibility as the variables $PT_j$ and $d_{ij}$. After the COVID-19 pandemic, urban traffic volume was influenced by various management measures including work from home measures, reservation systems, and volume control measures for tourist attractions, leading to a reduction in tourist volume and congestion. Despite these differences, the analysis results in this study were a reliable reflection of urban tourism service availability during the post-pandemic period. Additionally, the real travel demand and distance data could be inputted into the model, and the proposed analysis framework could be applied to investigate the tourism accessibility in different scenarios.

The limitations of this study are as follows. The method integrates tourism demand into the traditional gravity model, but the estimated tourist demand model is relatively simple due to the lack of real tourism demand data after COVID-19. A more sophisticated estimation model may be needed for various tourism purposes and demands. Moreover, there are some aspects that can be further studied in the future. This study used the average value during a random week to represent the accessibility of different locations, and in the temporal dimension, we only distinguished between weekdays and weekends. Finer analysis of the temporal characteristics can be conducted in future research, including the changes in accessibility over different months or days. Meanwhile, although the results under a single mode can guide the improvement of the transport system for tourism, the tourism accessibility evaluation under a multi-mode scenario deserves further study.

6. Conclusions

Although many studies have explored the accessibility of public service facilities, urban tourism accessibility still needs further exploration. Tourism accessibility as a tool for understanding the interactions between tourism elements and tourists is essential for destination development and tourist satisfaction improvement.

The landscape of tourism accessibility in Nanjing showed obvious spatial differentiation. From the aspect of destinations, the tourist attractions with relatively high accessibility were mainly located in the southern parts of Nanjing. Those in the urban area mostly had lower accessibility, especially historical tourist attractions in the urban core. The spatial hot-spot analysis result of tourism accessibility, in which the estimated tourist demands were considered, reveals that urban areas in the central part of Nanjing had better tourism resource availability. Although the average growth rates are moderate, most regions showed lower accessibility on non-workdays owing to worsening traffic conditions. Urban core areas and the northern part of the city had a more significant loss in tourism accessibility than southern suburban districts, suggesting that extra effort into transport management and service improvement for tourists in the urban core of Nanjing may be required.

In general, the influencing factors of tourism accessibility mainly involve tourism destination attributes, transport supply and services, and tourist demand characteristics. The tourism resource distribution and unbalanced development of road transport networks may lead to the inequity of tourism accessibility in different areas. For districts with lower concentrative degrees of tourism or insufficient transport supply, the transport factor is dominant in the evaluation of accessibility, indicating that the planning, organization and management of transport systems for tourism objectives are still the critical factors for improving tourism accessibility in these areas. Building a sustainable transport system for tourists in peripheral areas can make up for the insufficiency of tourism accessibility and help achieve the goal of the sustainable development of urban tourism systems at the same time. Meanwhile, the improvement of tourism accessibility in central areas should not only include the organization and management of self-driving tourist flow on road networks around attractions on holidays, but also involves destination attractiveness construction and tourist demand management.

The proposed analytical framework of analyzing urban tourism accessibility helps with understanding the relationship between urban transport service, tourism attractions
and tourists, and provides an essential reference for the planning and management of tourism elements and transport systems. The improved method to evaluate tourism accessibility at a finer scale with accurate travel time data obtained from web map services can be further adapted in other tourism destination cities.

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References


