

Article

Comprehensive Public Transport Service Accessibility Index—A New Approach Based on Degree Centrality and Gravity Model

Ruqin Yang ^{1,2}, Yaolin Liu ^{1,*}, Yanfang Liu ¹, Hui Liu ² and Wenxia Gan ³ 

¹ School of Resource and Environmental Sciences, Wuhan University, Wuhan 430079, China; yangruqin667788@163.com (R.Y.); yfliu610@whu.edu.cn (Y.L.)

² Wuhan Natural Resources and Planning Information Center, Wuhan 430014, China; huixing@whu.edu.cn

³ School of Civil Engineering and Architecture, Wuhan Institute of Technology, Wuhan 430074, China; ganwenxiagw@gmail.com

* Correspondence: yaolin610@whu.edu.cn

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Abstract: Public transport accessibility (PTA) is an essential index for evaluating the efficiency of urban public transport resource and public service. Improving public transport accessibility is considered as the most effective way of alleviating urban congestion and promoting urban sustainability. PTA can be divided into three types, which are access to stations, accessibility of networks and access to activities. This paper focuses on evaluating access to public transport service at stations, considering walking time to stations and waiting time for services at stations. Numerous studies have been carried out on evaluating the accessibility of public transport stations. When building accessibility evaluation model, rare has seen different public transport modes as an integrated system. Hence the topological structure and geometrical layout of the system are not considered. In this paper, factors like the configuration of the public transport system and the surrounding environment of stations are included for the evaluation. The centrality of station index (COS) is presented to describe the importance of stations in the integrated public transport system. The COS index is an improved combination of the gravity model and degree centrality index of the complex network. This index improves the degree centrality index by replacing the number of nodes with weighted connections between stations. By modeling public transport operation, configuration and surroundings of stations, a comprehensive public transport service accessibility index (CPTAI) is formulated to quantify accessibility at the community level. To compute this index, a network analysis model is firstly applied to find the nearest station for each point of interest (POI) by using ArcGIS desktop 10.2, and the transport service frequency at the nearest station is measured. Then Baidu Map API is employed to measure the impedance indexes between stations in the integrated public transport network. Activities covered by stations within a given distance are seen as the generation and attraction of trips in between the stations. Then a weighted gravity model and COS is presented to calculate the integrated service frequency (ISF) for each POI afterward. In the end, the index is converted to the community level, which is CPTAI. The experiment is carried out in Wuhan metropolitan area, Hubei, China. Smart card data (SCD) is utilized to evaluate CPTAI and examine the association between commuting trips by public transport and accessibility level within Wuhan metropolitan area. Experimental results show that CPTAI has a significant statistical association with trips by public transport.

Keywords: public transport; accessibility; centrality; CPTAI; Baidu Map API; SCD

1. Introduction

The common use of public transport has great effects on energy conservation, the reduction of air pollution and the mitigation of traffic congestion. The accessibility of transportation is generally defined as the ease of access to activities by overcoming impedance between locations [1]. Studies have shown that the promotion of public transport accessibility (PTA) could effectively boost transport economy, enhance the protection of urban environment and facilitate the improvement of public health [2–5]. A well-organized transport system should be capable of undertaking different modes of traffic and promoting urban mobility to meet various traffic demands [6]. Hence, factors such as access to transport stations, the mobility of transport routes, connectivity of different transport modes and diversified traffic demand should be considered for building such transport systems [7–9]. Constructing efficient public transport systems with high accessibility is one of the main focuses for urban planners and decision-makers throughout the world [10]. With the rapid urbanization process in recent decades, a series of problems have become prominent because of the increasingly use of private cars, such as traffic congestion and urban environmental pollution [11–13]. On the one hand, increasing the accessibility of public transport can encourage the transition of private transport to public transport, which hence helps to mitigate the problems mentioned above. On the other hand, from the perspective of users, an active transport service can be defined as low cost of the whole journey, low impedance to access public transits, less walking distance, or even good travel experience. The cost of travel is normally measured in time, distance, or money [14–19].

Among the four essential functions of a city, traffic is the link of the other three, work, residence and recreation, which builds a bridge for people's demand and activities. People use transport facilities to go to offices and factories for work, to their homes for sleep, to shopping centers for food and clothing, to schools for education, to hospitals for nursing, to stadiums for sports and theaters for recreation. Better accessibility of traffic facilities can benefit more people. Similarly, good traffic accessibility ensures people's access to public services. Thus, the level of PTA is adopted to evaluate the social and economic equity by assessing the construction and distribution of public services. Poor public transport accessibility may result in social exclusion with the increasing cost of living for the inefficiency of public facilities. Studies show that access to public transport services has been the main factor for suburban areas to access public services and jobs [17,19]. People living in urban periphery and new city clusters face the challenge of easy access to work, education, shopping centers, cultural and sports facilities and other activities [15,16,18,20,21].

Meanwhile, poor accessible facilities like parks, shopping centers and sports centers, are not able to satisfy citizens' needs and not attractive to citizens, which is a waste of public resource [22,23]. Besides accessibility, another concern is traffic congestion. Highly congested traffic and the inefficient configuration of networks could lead to a poor experience. To tackle this problem, China has been carrying out the policy of "Giving Priority to Public Transport" in recent years [24,25]. With the rapid construction of public transport facilities, the evaluation of PTA based on the level of activities can provide a comprehensive measure covering the majority of travel needs and potentials.

This paper presents a review of numerous studies carried out on the evaluation of PTA [10,26,27]. Different modes of transport are regarded as independent systems in the previous studies of multimodal public transport accessibility. A weighted sum is then applied to measure the access level of PTA [7,10,28]. For daily trips usually involve more than one trip mode, and there are correlations between different modes, public transport modes should be integrated. Studies have shown the configuration of public transport networks is a success factor for public transport. Higher number of convenient transfer points, more choice of routes, higher degree of overlap with activity centers lead to a great role for public transport [29,30].

In this study, a new index is presented to measure multi-modal public transport service accessibility. Public transport service frequencies, the configuration of transport networks in terms of topological structure and geographical layout, and potential travel demands and attraction are taken into consideration. This approach is applied in evaluating the accessibility level of public transport

for communities in Wuhan metropolitan area, including public bus/tram and metro services. The remainder of this paper is organized as follows. The following section introduces the related work on the evaluation of public transport service accessibility (PTSA). Section 3 introduces the methodology and the computation of the new index. Section 4 presents the results of the proposed approach in Wuhan metropolitan area, compares the results of the new index with the existing approaches, and test the effectiveness of the approach using smart card data. In Section 5, we draw conclusions, and outline future research.

2. Related Work

PTA is an important research field for traffic policy making and urban planning. Public transport service accessibility (PTSA) is different from PTA by considering transport service frequency at the station, in addition to access time to the station. Poor PTSA to education, health, cultural facilities, and the uneven distribution of public transport facilities may seriously affect people, especially for the low-income group. Similarly, poor accessibility of public service may lead to a waste of public resource by not attracting enough people. Accessibility can be measured by the distance to stations or the distance of the whole journey from the origin to the destination [28]. Study shows that the measure of PTA/PTSA can be categorized to the following four types. The first one is physical access to public transport facilities/service. The second one is the access to specified social and economic activities. The third type is based on personal needs. The fourth one is based on utility theory. While users are considered as customers, and public traffic modes are their choice set [4,31]. Accordingly, the measure of PTA/PTSA can be categorized into three types, which are the access to public transport stops/service, the duration of the whole journey and the access to activities [32,33].

Most studies, which focus on physical access, take the access to public transport stations or travel time into consideration [3,34]. Substantial researches have created indexes to measure the quality of public transport service [10,18,19]. A part of them evaluates the quality of public transport service in terms of accessibility, mobility and connectivity [9,32,35]. The most utilized approach for evaluating accessibility is the index of public transport accessibility level (PTAL), which has been well developed and widely used in the UK [6,19]. This approach has become essential for urban and rural transport planning in the UK. The PTAL index considers walking time to access stations, transport service frequency. Access to public transport stations of all point of interests (POIs) are evaluated in this approach, and the results are categorized into six main levels. This approach measures the accessibility level for each census collector district by considering transport service frequency and walking distance to stations [7,19]. Public transport service accessibility index (PTAI) is derived from PTAL by considering the factor of population density covered by service area of stations. The population is assumed to be evenly distributed within the census area [10]. Another index is land use and public transport accessibility level (LUPTAL), which is established based on both origin and destination, and measures accessibility in terms of walking distance and travel time.

The indexes above have modeled different transport networks as independent ones, which should be modeled as an integrated system. The integrated system is a complex network composed of a group of nodes and routes. As well, degree centrality is a primary measure for evaluating the importance of nodes in a network. Studies show that the higher the centrality of facilities, the more efficiency of public transport networks [30]. The degree centrality of a public transport facility is the number of connected facilities [36]. In the complex transport system, the number of traffic routes connected to the station, population or activities covered by stations, or potential traffic flow between stations can be factors for measuring connections between nodes [37,38]. According to Tobler's first law of geography, near things are more related to each other [39,40]. Connections should consider the effect of distance attenuation. Hence the gravity model is integrated to optimize the connections. The gravity model is a measure for the relationship between two nodes, which is positively correlated with links of two nodes, and inversely correlated with impedance in terms of time, distance and other costs [41,42].

Geographical indexes are the common measures for travel cost. Studies show that the topological structure is also essential, especially in evaluating transport by rail. Stations with higher connectivity, ranking the higher degree of centrality and integration are more attractive for public trips [29,43]. Space syntax theory is popular in evaluating the topological structure of a network. Li et al. (2014) regard a transport line as a node to evaluate the access level of starting station and transfer station of the metro line [44]. While Zhou et al. (2015) treat stations as nodes and the routes between stations as routes [45]. The topological distance is presented to measure accessibility, while the distance between adjacent stations or connected routes is one step. The average depth, connectivity, degree of integration are the typical indexes utilized in previous methods [44,45]. While in reality, both topological and geographical distances are factors which affect the choice of traffic modes. The defects of existing measures are the separation of different public transport modes and the neglect of either topology or geography [7,10,41,42]. In response, this approach is based on demands and activities, and focuses on measuring access to different types of public transport stations in an integrated public transport system, while considering walk time, service frequency and network configurations.

3. Methodology

This study constructs an index to assess public transport accessibility at the community level. Community is the smallest administrative unit for urban management in China. Factors of transport service frequencies and the centrality of stations in the integrated public transport system are calculated to measure the CPTAI for each community. This study deals with transport service frequency in terms of access time to public transport service. The higher service frequency at the station, the higher accessibility levels for the POIs surrounding the station. COS is the weighted average of potential trips from the station to the other stations. The denser POIs surrounding the station shows higher access to activities and more potential trips of the station. While the less cost from the station to other stations shows the easier access to the station. Less cost can be shorter distance, less travel time, more options for travel and less depth, or a combination. Stations with higher centrality, namely higher connectivity, more travel choices, shorter distance and depth, show higher attraction for traffic flow. In this section, methods and the process for calculating the index are presented.

3.1. Framework

The CPTAI approach consists of two main procedures. The first step is to find the nearest stations for each POI and calculate the service frequency of the specified station. The second step is to measure the centrality of stations in the integrated public transport network. The COS index improves the degree centrality index by replacing the number of nodes with weighted connections between stations. The weighted connections are calculated using a gravity model, where connections are the number of POIs covered by stations in a given walking distance, and impedance is an integration of topological and geometrical factors. Connections stand for the traffic generation and attraction of both stations. While cost is a comprehensive expression of average distance, travel time, depth, transfers and options of travel from the station to the other stations. Then a weighted sum of the transport service frequency and COS is calculated for each mode, namely the integrated service frequency (ISF) for each POI. In the end, ISF for single POI is converted into community level, which is CPTAI. Figure 1 shows the framework for calculating the CPATI.

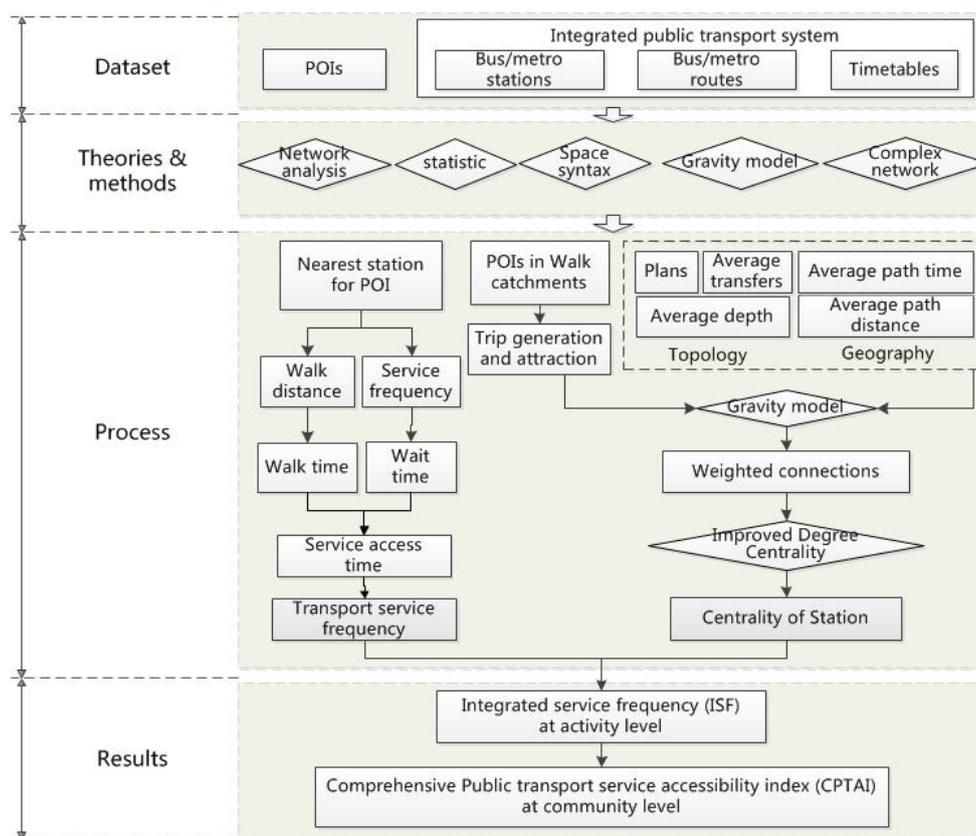


Figure 1. The framework.

3.2. Service Frequency

Service frequency is derived from service access time (SAT). SAT is the sum of the following two parts: (1) Walking time from each POI to the closest public transport stops, (2) waiting time at the station.

(1). Walking time to the nearest station (Walk_T)

The walking time is calculated from specified POI to the nearest public transport stop for all modes by applying network analysis. Distance from POI to the station is converted to time assumed at an average walk speed of 80 m/min. According to Guideline Standards for Public Facilities allocation in Newly Built Areas of Wuhan (Trial), maximum walking time to bus/tram stations is 5 min while for train stations is 15 min.

(2). Average waiting time (Wait_T)

The average waiting time (Wait_T) is the duration from arriving at the station to boarding. The fixed schedules of public transportation operation time lead to service availability gap. In our study, it is assumed that the average waiting time is half of the average traffic interval for all lines passing through the station in an hour. For instance, two routes, namely line A and line B, are passing the same Station *s*. The service interval of line A is 10 min, and 15 min of line B. Thus, the frequency of line A is 6 and 4 for line B per hour. For station *s*, the total service frequency is 10. Therefore, traffic interval at station *s* is 6 min, and the average waiting time (Wait_T) at station *s* would be 3 min. Wait_T is estimated as half of the average headway of all the bus lines, as shown in Equation (1).

$$Wait_{T_s} = 0.5 \times \left(60 / \sum_{k=1}^n F_{sk} \right) \quad k = 1, 2, 3 \dots n \tag{1}$$

where $Wait_{T_s}$ is the average waiting time (minutes) of the station *s*, F_{sk} is the service frequency of the transport line *k* passing through station *s*, and *n* is the number of routes passing through station *s*.

When more frequent routes pass through the station, the waiting time at the station for the service is shorter. This indicates the activities around would take less waiting time for access the transport service at the station.

(3). Service access time (SAT)

Service access time is the duration of walking from the activity site to getting on bus/metro. The SAT of a selected POI to the nearest public transport station is calculated as the sum of the *Walking time to the closest station* (Walk_T) and *Average waiting time* (Wait_T), shown in Equation (2).

$$SAT_{is} = Walk_T_{is} + Wait_T_s \quad i = 1, 2, 3, \dots m \quad (2)$$

where SAT_{is} is the service access time of POI_i to the closet stop/station s as explained above, $Walk_T_{is}$ is the walking time from POI_i to the closet stop/station s , $Wait_T_{is}$ is the average waiting time in station s , and m is the number of POIs.

(4). Service Frequency (SF)

The Service Frequency (SF) is derived from SAT. SF means the equivalent service times at the stop/station available per hour for POI_i . The higher service frequency, the more service is available for the activity. SF is calculated as Equation (3).

$$SF_{is} = 0.5 \times (60/SAT_{is}) \quad i = 1, 2, 3, \dots m \quad (3)$$

where SF_{is} is the *Service Frequency* for POI_i , SAT_{is} is the service access time of POI_i , m is the number of POIs.

3.3. Centrality of Station (COS)

It is assumed that the geographical distribution and topological level of station have significant effect on the access level of station. To quantify the effect, we proposed the centrality of station, which is an index to measure the importance of the station in integrated public transport network. The index is a weight for the service frequency at station s for each POI. COS is derived from the degree centrality index. The higher COS of the station has, the more important in transport network system the station is. By using weighted potential trips instead of the number of nodes connected to the station, the calculation of COS is as Equation (4).

$$COS(s_i) = \sum_{j=1}^n \log(W_Conn_{ij}) / (n - 1) \quad i \neq j \quad (4)$$

where $COS(s_i)$ is the centrality of station i , W_Conn_{ij} is potential traffic flow between station i and station j , and n is the total of stations. When calculating ISF, COS is a weight for transport service frequency. As the number of covered POIs is large, a log function is applied to normalize the weighted connections after calculation.

The gravity model is introduced to calculate the connections between the station and the other stations. The connections are the potential trips that may take place at the station. The model assumes that the potential trips between two regions is in proportion to both the demands of the original region and the attractions of the destination, while inversely proportional to the traffic impedance. The calculation of weighted connections using the gravity model is as Equation (5).

$$W_Conn_{ij} = Trip_gen(s_i) * Trip_attr(s_j) / f(Cost_{ij}) \quad i \neq j \quad (5)$$

where $Trip_gen(s_i)$ is the trip generation of station i , $Trip_attr(s_j)$ is the trip attraction of station j , $f(Cost_{ij})$ is the impedance of travel from station i to station j .

3.3.1. Trip Generation and Attraction

The amount of activities covered is applied to differentiate the demand and attraction of stations by considering activity distribution in walking distances. POIs are utilized to describe the distribution of activities. POIs taken for urban functions are chosen for the calculation of trips in both bus/tram and metro modes. Service area analysis model of GIS is applied to find the service area of stations, and spatial overlap function is applied to count the number of POIs covered by walking catchments, giving a walking time of 15 min for metro and 5 min for bus.

3.3.2. Impedance

The impedance is calculated from the perspective of both topological and geographic by applying space syntax theory and network analysis model. As space syntax measures spatial relations in terms of topological depths, which ignores the geographical distance [46,47], both topological and geographical relationships are considered in this study [45]. Intermediate indexes such as average topological depth, available travel plans, route distance, route time and transfer times from the station to all other stations are calculated by utilizing Baidu Map API. Public transport networks are organized as an integrated system, real-time congestion is included, and rules like shortest Euclidean distance/time/walking distance or least transfer times can be set when processing Baidu Route Planning API. In this study, we choose the shortest travel time as a rule for the model.

For calculating the impedance, a series of topological and geographical figures are put forward, namely average topological depth, number of travel plans, transfers, average route distance, and average route time.

(1). Average Topological Depth

Average topological depth refers to the average steps of the current station to all other stations. This index describes the topological distance between stations and ignores geometric distance. If the average topological depth is shorter, the topological location of the station is better in the public transport system. This means the impedance from the station to the other stations will be smaller. By the application of Baidu Route Planning API, topological distances from the station to all reachable stations are measured, the distance for adjacent stations is counted as one step, and transfer is counted as one step as well.

$$Dt_{is} = \sum_{k=1}^n Dt_{sk} / (n-1) \quad k \neq s, s = 1, 2, 3, \dots, n \quad (6)$$

where Dt_{is} represents the average topological depth for the closest station s of POI_i , Dt_{sk} represents the topological distance of the station s to any other station k , n is the number of stations.

(2). Number of Travel Plans

Connectivity is a typical morphologic index of space syntax, which stands for the number of spaces connected to the specified one. In this study, the options of travel plans stand for the connectivity of the station in the public transport network. A higher number means higher connectivity, which also means higher spatial permeability.

(3). Average Route Distance

The average route distance means the average geographical distance from the station to all other stations. Higher index shows the geographical advantage of the station in the public transport system. The smaller the index is, the cost of activity from the station to other stations would be less. The index is estimated by Baidu Route planning API, including the walking distance of transfer.

$$D_{is} = \sum_{k=1}^m D_{sk} / (m-1) \quad k \neq s, s = 1, 2, 3, \dots, m, \quad (7)$$

where D_{is} represents the average route distance from the closest station_s of POI_i to all other stations, D_{sk} represents the route distance from station s to any other station k , and m is the number of stations.

(4). Average Route Time

Similar to the index of average route distance, the average route time is also an index to measure the geographical configuration of the station in the public transport network. For the significant speed difference between travel modes, travel cost here is measured by equivalent time. The travel speed is set as the real-time travel speed extracted from Baidu Map API, and the road congestion in the morning rush hours is also included in the calculation.

$$T_{is} = \sum_{k=1}^m T_{sk} / (m - 1) \quad k \neq s, s = 1, 2, 3, \dots, m \quad (8)$$

where T_{is} is the average route time from the closest station s of POI_i , T_{sk} represents the route time from station s to any other station k , and m is the number of stations.

(5). Cost

By applying stepwise regression analysis, indexes with high correlated coefficient are eliminated. The indexes, finally chosen to calculate the impedance of travel, are normalized into a comprehensive cost index for the calculation of weighted connections.

3.4. Comprehensive Public Transport Service Accessibility Index (CPTAI)

The Integrated Service Frequency is the equivalent transport service frequency weighted by COS for each POI. The calculation of ISF is as shown in Equation (9). SF_{is_Bus} and SF_{is_Metro} consider the transport operation of both public bus and metro modes, and COS_{is} embodies not only the distribution of activities but also the topology and geometry of the network. As people may choose either bus or metro, both conditions are considered for the specified POI. We apply the same weight for both modes of POI_i .

$$ISF_i = (COS_{is_Bus}) \times (SF_{is_Bus}) + (COS_{im_Metro}) \times (SF_{im_Metro}) \quad (9)$$

where ISF_i stands for the integrated service frequency for POI_i , SF_{is_Bus} denotes the equivalent service frequency of bus station s for POI_i , SF_{im_Metro} denotes the equivalent service frequency of metro station m for POI_i , COS_{is_Bus} represents the comprehensive topology weight of bus station s for POI_i , and COS_{im_Metro} stands for the comprehensive topology weight of metro station m for POI_i . The ISFs calculated for POIs are converted into community level. Database converters of FME are employed to assign the maximum ISF figure of the POI inside the community to the specified community. Communities with no POI will be assigned the ISF of the nearest community within 15 min' walking distance. Only when the surrounding communities are not accessible, the ISF for the community is Zero.

For each community/enclave, we set rules shown in Equation (10).

$$CPTAI_i = \begin{cases} \max(ISF_{iu}) & \text{Has POI in community}_i \\ CPTAI_{i_near} & \text{No POI in community}_i \end{cases} \quad (10)$$

where $CPTAI_i$ is the public transport accessibility index of community i , ISF_{iu} is the maximum integrated service frequency of POI_u in community i , $CPTAI_{i_near}$ is the index of neighborhood community within a certain distance of community i .

4. Study Area and Experimental Result

As the index is introduced to evaluate the development of regional public traffic integration. A dataset of Wuhan metropolitan area is chosen to test the performance of the proposed index.

4.1. Data and Study Area

Wuhan metropolitan area has been the centralized construction area according to the urban master plan of Wuhan city. Within the 3261 km², the dataset of public transport construction and operation, socioeconomic facilities and the planning boundaries is introduced as follows.

(1) Two modes of public transport facilities including bus/tram and metro/light rail. Public transport facilities include stations and routes of each mode. These data are obtained from Baidu Map open platform. By the end of 2015, 746 directed routes and 4459 stations of bus/tram, three routes and 76 stations of metro/light rail are in operation in Wuhan metropolitan area. Figure 2 shows the distribution of the routes and stations within this area. Bus/tram stations cluster in the central area while dispersing in new city clusters.

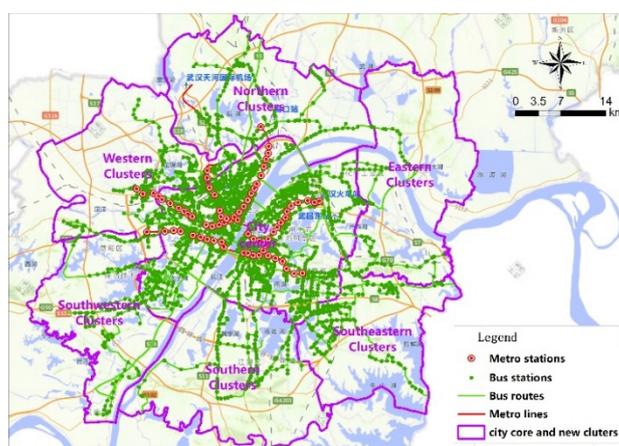


Figure 2. Spatial distribution of bus and metro routes and stations.

(2) Transport service frequency is scraped from websites and Apps like Tuba and Intelligent public transport. We obtained timetables in morning rush hours from 7:00 to 9:00. The schedules for 365 routes out of the 378 undirected routes are collected.

(3) POIs are bought from the company of *Siweituxin* at the beginning of 2016. By data classification and cleaning, we delete the non-functional POIs, remove redundant data, such as addresses, crossroads. Finally, a dataset with 134.8 thousand POIs is obtained. These POIs are categorized into catering, public service, jobs, residents, commercial, living service and leisure facilities. Table 1 shows the distribution of different POI categories and the average distances of each category to bus and metro stations. Most functions are within 5 mins' walking distance to bus stations, while none of them are within 15 mins' walking distance to metro stations. Figure 3 shows the spatial distribution of POIs. Highly dense POIs cover the central area. While in the new city clusters, POIs exist mainly in town centers and distribute along the main roads.

Table 1. Points of interest in Wuhan Metropolitan area.

Categories	Number	Percentage	Average Distance to Closest Bus/Tram Stations (m)	Average Distance to Closest Metro Stations (m)
Catering	16,431	12.11%	295	3284
Public service	12,283	9.05%	377	3546
Infrastructures	2584	1.90%	534	23772
Jobs	20,505	15.11%	496	4565
Residents	7307	5.39%	334	3444
Commercial	49,720	36.65%	281	3903
Living service	20,867	15.38%	305	5455
Leisure	5981	4.41%	360	3623

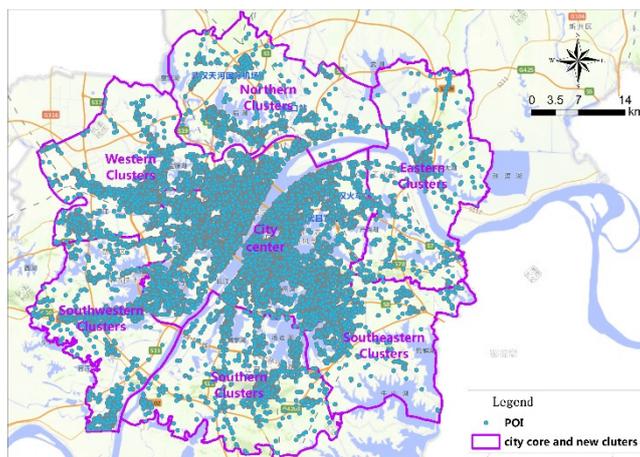


Figure 3. Spatial distribution of POIs.

(4) The Administrative boundaries dataset includes community boundaries and the “1+6” boundary within the metropolitan area. The “1+6” is respect to the one city center and six new city clusters around the center. Community boundaries are obtained from digital Wuhan open platform, and the latter is acquired from the urban master planning. With the rapid construction and renewal of Wuhan metropolitan area, community boundaries are adjusted accordingly. For the investment and resettlement policies, land of some communities is enclosed by the other communities. Enclaves existing in some communities lead to the complexity of calculation, so we separate them from the main community part. Then 1924 communities are separated into 2505 parts.

4.2. Results of PTAL, PTAI and CPTAI

Our proposed approach extends the commonly used indexes, including the index of PTAL which is devised by Transport for London and is widely adopted. PTAL considers walking time, waiting time, and service frequency in accessibility measurements. It calculates equivalent frequencies of all public transport modes. Another index derived from PTAL is the PTAI, which takes public transport service frequency and population density as important distribution indicators [10]. In this study, we choose activities as the distribution factor when calculating PTAI and CPTAI. Both indexes are calculated by summing up the accessibility indexes for different modes of public transport. The results are calculated and categorized into six levels based on Quantile Method except for zero accessible communities.

Results for PTAL and PTAI are shown in Table 2. According to the table, 67.35% of the community/enclaves or about 33.41% of activities have zero to moderate access to public transport modes based on PTAL. While referring to PTAI, 60.56% of the community/enclaves or about 26.32% activities have zero to moderate access to public transit. The results are quite similar. By considering activity distribution, the index of PTAI obtains much better accessibility in communities with high access and worse accessibility in communities with poor access than PTAL. The result shows that POIs are more concentrated near stations at a highly accessible location, and dispersed at a poorly accessible location.

Table 3 shows the results of CPTAI. According to the results, zero access is provided for 2685 POIs, which is 1.99% of all POIs. Overall, near 13.7% of the POIs in half of communities/enclaves in the metropolitan area have poor access levels of public transport service. 64.55% of POIs concentrated in 31% of communities/enclaves have relatively good access to public transport services. Figures in different CPTAI categories show high consistency with figures in PTAL and PTAI categories in Table 2. While compared to PTAL, CPTAI shows quite consistent results. There are slightly more communities with poor access from 46.26% to 48.78%, and a bit more communities with extreme high access from 1.92% to 2.12%. The result shows that higher centrality of the station has a positive effect on accessibility.

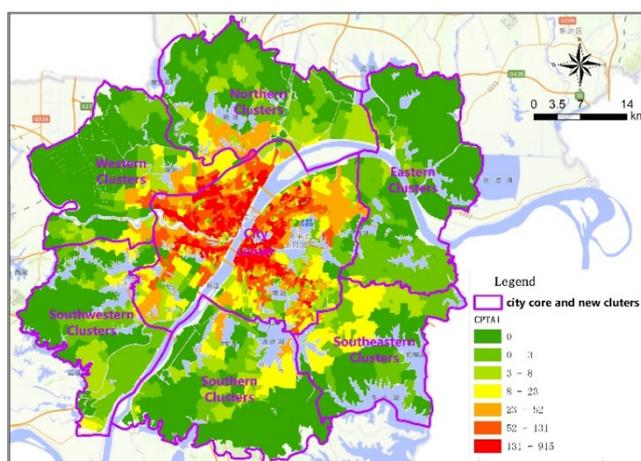
Table 2. Public transport accessibility level (PTAL) and public transport accessibility index (PTAI).

Categories	PTAL				PTAI			
	Communities		POIs		Communities		POIs	
No access	570	22.75%	2619	1.94%	570	22.75%	2619	1.94%
Very poor	125	4.99%	1853	1.37%	231	9.22%	8009	5.94%
Poor	464	18.52%	12,074	8.95%	352	14.05%	9445	7.00%
Moderate	528	21.08%	28,509	21.14%	364	14.53%	15,414	11.43%
Good	444	17.72%	37,985	28.17%	313	12.50%	19,821	14.70%
Very good	326	13.01%	44,684	33.14%	350	13.97%	33,135	24.57%
Excellent	48	1.92%	7116	5.28%	325	12.97%	46,397	34.41%
Total	2505	100%	134,840	100%	2505	100%	134,840	100%

Table 3. CPTAI categories and distribution at the community scale.

Categories	Ranges	Community/Enclaves		POI	
		Number	Percent	Number	Percent
Zero	0/NULL	582	23.23%	2685	1.99%
Very poor	0–3	222	8.86%	2874	2.13%
Poor	3–8	418	16.69%	12918	9.58%
moderate	8–23	506	20.20%	29325	21.75%
Good	23–52	427	17.05%	37048	27.48%
Very good	52–131	297	11.86%	41964	31.12%
Excellent	>131	53	2.12%	8026	5.95%
Total		2505	100.00%	134840	100.00%

Figure 4 shows the distribution of CPTAI categories in Wuhan Metropolitan area. Most of the communities/enclaves are accessible to public transport. High levels of accessibility from good to excellent are most concentrated in city center and the core areas of six new city clusters, while there are still communities with low accessibility in the city center.

**Figure 4.** Spatial distribution of CPTAI in Wuhan metropolitan area.

4.3. CPTAI Assessment

Smart card data of public transport is adopted to evaluate the approach. The dataset includes data of bus and metro of Wuhan in May 2015. The database has the hourly swiping data of smart card for both check-in and check-out. We calculate the daily average swipes for each station and allocate the trips of stations to reachable communities by applying the weight of POI number within each community. By allocating, a total of 2.48 million trips by metro and 6.16 million trips by bus

are allocated to communities, including both check-in data and check-out data. Trips by metro make up less than a quarter of public transport flow. Therefore, public bus is still the most popular public transport mode.

By applying cross-tabulation analysis with Chi-square and Cramer’s V test, the association between CPTAI indexes and public transport modes are tested. Table 4 shows the results of cross-tabulation analysis between the six levels and two commuting modes. The CPTAI index is categorized from very poor to excellent. The rows present trips and percentage of trips for each mode. The columns are the figures for each access level. The results indicate that the number of trips shows an upward trend with the increasing accessibility of public transports. For the very poor to poor accessibility level, trips by metro are quite few and fewer than trips by bus. This may be because metro stations on the periphery area are within longer walking distance and with low connectivity for the metro facilities are scarcer than bus facilities.

Table 4. Cross tabulation results for public transport modes and PTAI categories.

		CPTAI Categories						Total	
		Excellent	Very Good	Good	Moderate	Poor	Very Poor		
Modes	metro	Observed	300,121	1,139,169	622,783	384,839	35,721	114	2,482,747
		Expected	200,778.5	999,703.3	736,382.1	431,583.3	100,838.2	13,461.6	2,482,747.0
	% in mode	12.1%	45.9%	25.1%	15.5%	1.4%	0.0%	100.0%	
Modes	bus	Observed	398,493	2,339,324	1,939,477	1,116,866	315,148	46,726	6,156,034
		Expected	497,835.5	2,478,789.7	1,825,877.9	1,070,121.7	250,030.8	33,378.4	6,156,034.0
	% in mode	6.5%	38.0%	31.5%	18.1%	5.1%	0.8%	100.0%	
Total	Observed		698,614	3,478,493	2,562,260	1,501,705	350,869	46,840	8,638,781
		Expected	698,614.0	3,478,493.0	2,562,260.0	1,501,705.0	350,869.0	46,840.0	8,638,781.0
	% in mode	8.1%	40.3%	29.7%	17.4%	4.1%	0.5%	100.0%	

Quantitative statistics of trips by public transport modes based on different transport access levels are shown in Figure 5. It shows that in places with poor accessibility, public bus is dominant. While with the increase of accessibility, the number of trips by metro rises more rapidly than by bus according to Figure 5.

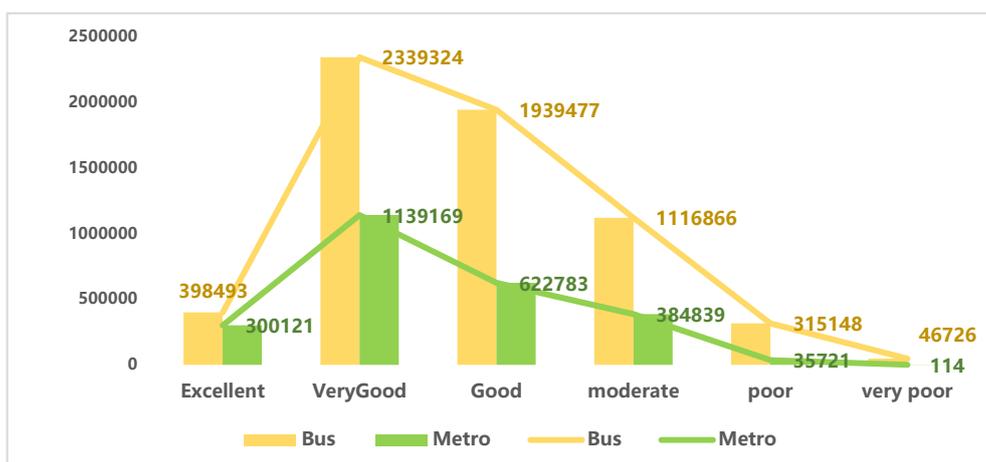


Figure 5. PTAI categories and public transport modes in Wuhan Metropolitan area.

According to Table 5, the Pearson Chi-square is 205558.167 with the p-value less than 0.001. Accessibility level is significantly associated with accessibility levels and commuting by public transport modes.

Table 5. Chi-square test of the association for CPTAI categories and travel modes.

	Value	df	p-Value
Pearson Chi-square	205558.167a	5	0.000
Likelihood ratio	225294.220	5	0.000
N of validate cases	8638781		

a. 0 cells (0.0%) expected count < 5. The minimum expected count is 13461.61.

Cramer's V test is used to explore the strength of association between public transport modes and the CPTAI categories. The value is in range of 0 to 1. The closer to 1 the stronger relationship there is. Seen in Table 6 the relationship between public transport modes and access levels is weak as the index of Cramer's V is 0.154. This is in consistency with the result of Table 4. The distribution of trips in each CPTAI category is similar for each mode, and the difference between the two modes is small. However, the number of trips in each category of both modes varies greatly. One reason is the lack of metro facilities in urban periphery where the accessibility level is poor, and using of bus is more common. Another reason can be the congestion in urban center where the accessibility levels of both modes are good, people choose metro more for time-saving. However, for the traffic capacity variation for each mode, the overall choice of bus is more than that of metro.

Table 6. Chi-square based measures of association for CPTAI categories and travel modes.

		Value	p-Value
Nominal by nominal	Phi	0.154	0.000
	Cramer's V	0.154	0.000
	Contingency coefficient	0.152	0.000
N of validate cases		8,638,781	

4.4. Comparison between CPTAI, PTAI and PTAL

Chi-square test is applied for each index with trip modes to make a comparison of the new index CPTAI with PTAL and PTAI. Cross-tabulation results of the six accessibility levels of three indexes and the two trip modes are as shown in Table 7. All indexes show consistency in the correlation between trips and access levels. Trips increase as the access level increase except for the excellent level of PTAL and CPTAI. This is mainly because the percentage of communities with excellent access level is relatively low in these two approaches, according to Tables 2 and 3.

For further analysis, most trips are in moderate to excellent access level, only 4.6% of trips share poor access in PTAL index, 3.3% of PTAI and 3.7% of CPTAI. This implies the insufficient supply of public transport facilities in the study area. As for different traffic modes, compared with the typical PTAL, CPTAI has slightly more trips in good access levels by bus and a bit more trips in good access levels by metro. The result suggests that centrality of station affects the metro more than the public bus, especially when the metro network is still under construction and not completely developed.

Table 7. Cross tabulation results for public transport modes and PTAL, PTAI and PTAI categories.

		PTAL						PTAI						CPTAI						Total
		Exc	VG	Good	Mod	Poor	VP	Exc	VG	Good	Mod	Poor	VP	Exc	VG	Good	Mod	Poor	VP	
bus	Observed	39.8	233.9	193.9	111.7	31.5	4.7	277.4	187.3	75.0	50.0	17.4	8.5	36.6	242.0	198.9	109.1	26.1	2.9	615.6
	expected	49.8	247.9	182.6	107.0	25.0	3.3	308.9	175.6	72.8	38.1	14.2	6.1	44.7	259.4	184.6	103.9	20.9	2.1	615.6
	% mode	6.5	38.0	31.5	18.1	5.1	0.8	45.1	30.4	12.2	8.1	2.8	1.4	6.0	39.3	32.3	17.7	4.2	0.5	100
metro	Observed	30.0	113.9	62.3	38.5	3.6	0.0	156.1	59.1	27.1	3.4	2.5	0.1	26.1	122.0	60.2	36.8	3.2	0.0	248.3
	expected	20.1	100.0	73.6	43.2	10.1	1.3	124.6	70.8	29.4	15.4	5.7	2.5	18.0	104.6	74.5	41.9	8.4	0.8	248.3
	% mode	12.1	45.9	25.1	15.5	1.4	0.0	62.9	23.8	10.9	1.4	1.0	0.0	10.5	49.1	24.2	14.8	1.3	0.0	100
total	Observed	69.9	347.8	256.2	150.2	35.1	4.7	433.5	246.4	102.2	53.4	19.9	8.6	62.8	364.0	259.1	145.9	29.3	2.9	863.9
	expected	69.9	347.8	256.2	150.2	35.1	4.7	433.5	246.4	102.2	53.4	19.9	8.6	62.8	364.0	259.1	145.9	29.3	2.9	863.9
	% mode	8.1	40.3	29.7	17.4	4.1	0.5	50.2	28.5	11.8	6.2	2.3	1.0	7.3	42.1	30.0	16.9	3.4	0.3	100 ^a

a: Exc is the abbreviation for Excellent, VG for very good, Mod for moderate, VP for very poor.

Results of Chi-square based measures are shown in Table 8. The correlation between index categories and transport modes is significant. The reason is that the chi-squares are large, and p values are less than 0.001. For the Phi value and Cramer's V are not large, the correlation of accessibility levels and transportation modes is not strong accordingly. PTAI categories have a relatively stronger relationship with transport accessibility among the three indexes, for the maximum likelihood ratio and Phi value of PTAI.

Table 8. Chi-square measures of association for PTAL, PTAI and CPTAI categories and trip modes.

	PTAL		PTAI		CPTAI	
	Value	<i>p</i> -Value	Value	<i>p</i> -Value	Value	<i>p</i> -Value
Pearson Chi-square	195,527.372 ^a	0.000	329,470.499 ^b	0.000	205,558.167 ^c	0.000
Likelihood ratio	208,888.081	0.000	387,990.103	0.000	225,294.220	0.000
Phi	0.150	0.000	0.195	0.000	0.154	0.000
Cramer's V	0.150	0.000	0.195	0.000	0.154	0.000
Contingency coefficient	0.149	0.000	0.192	0.000	0.152	0.000
N of validate cases	8,638,873		8,638,873		8,638,781	

a. 0 cells (0.0%) expected count < 5. The minimum expected count is 8338.12. b. 0 cells (0.0%) expected count < 5. The minimum expected count is 24577.23. c. 0 cells (0.0%) expected count < 5. The minimum expected count is 13461.61.

As PTAI considers the activities covered by the station, stations with similar socioeconomic environment and schedules would share similar PTAI value, no matter the station is on the periphery or in city center. This index may be suitable for measuring the physical access level to facilities without considering the quality of services, such as less transfer, fewer steps and more available choice of travel plans. Hence, CPTAI is more suitable and flexible to evaluate accessibility from a systematic and comprehensive perspective.

The results show a relative relationship between trip modes and PTAI access levels, reflecting that the integrated public transport system of Wuhan metropolitan area is immature. Further construction needs to consider not only the generation and attraction of traffic but also the efficiency of the public transport system.

5. Discussion

This paper proposes an approach to evaluate the accessibility of public transport service in Wuhan metropolitan area. It brings out the index of CPTAI in community level to see the accessibility pattern of public transportation. A statistical test is applied to see the correlation between accessibility levels and trip modes. The results of CPTAI show consistency with the existing indexes and have a significant association with choices of traffic modes.

By calculating CPTAI, results show that 582 communities/enclaves out of 2505 communities have no access to public transport service, which means 1.99% of POIs have no access to public transport service. While 2.13% and 9.58% of activities are with very poor to poor access to public transport services, which are mainly located in the periphery of Wuhan metropolitan area. 33.5% of activities located in near half of the communities/enclaves have zero to moderate access to public transport services. However, these below-good community parts are not only in the suburban area. In the central area, there are still 22.6% of the communities have below-good accessibility levels to public transport services. These communities cover 16345 POIs, which may bring out 5% of activities.

Nearly 73.4% of communities/enclaves are within walking catchment areas of bus transits and 33.4% communities within walking catchments of metro stations. There are 4459 bus stops and 96 metro stations in this area, with an average bus frequency of 26.8 and metro frequency of 3.7 in morning rush hours. However, the trips by bus is only 2.4 times of trips by metro. According to the Wuhan Transportation Annual Report, the percentage of trips by Metro among all public mode is increasing year by year. The mode of metro is more attractive for daily trips. This is because there is more uncertainty of travel time with bus than metro because of above-ground traffic congestion.

By applying a Chi-square test, results imply that there is a statistically significant correlation between the index categories of accessibility levels and mode choices of traffic. Most of the trips by metro are with above-average levels of accessibility. While by bus, 5.9% of trips are with accessibility below-average level. Considering the number of facilities, the mode of metro is more productive. As metro stations are located in urban core areas, communities with no access to metro service tend to choose the mode of public bus for the availability of bus facilities in the suburban areas. While the fact is that efficient bus services do not cover the urban periphery area. Stations in the outer city area are often with low service frequency, and bus stations are often in poor connection to other stations in the integrated transport network. In other words, from those stations, the choices of travel plans are quite limited, and the cost to activities is relatively high. Vulnerable groups like old, poor-educated, low-income and unemployed ones, who have high demands for public transport services, are not able to easily access efficient public transport services. It leads to informal transport modes like electric motorcycles and unlicensed taxis, which may bring out safety problems [48,49].

The comparison of the indexes of PTAL, PTAI and CPTAI shows how the distribution of activities and the centrality of stations affect the accessibility level of public transport services at the community level. By comparing PTAL with PTAI, trips with high access levels of PTAI increase rapidly by 12.4%, while trips with poor access levels decrease by 1.3%. For the mode of bus, the trips with high access levels increase dramatically by 11.7%, while trips with poor access levels decrease by 1.7%. For the mode of metro, the trips with high access levels increase by 14.5%, while trips with poor access levels decrease by 0.4%. To test the impact of the centrality of stations, we compare PTAI with CPTAI. Results indicate that trips with high access levels of CPTAI decrease by 11.1%, and trips with poor access levels increase by 0.3%. For the mode of bus, trips decrease by 10.1% with high access level, and increase by 0.5% with poor access levels. For the mode of metro, trips decrease by 13.8% with high access levels and increase by 0.3% with poor access levels.

The discussions above show that in general, the centrality of stations has a slightly positive correlation with the accessibility level in the immature integrated public transport system. Among the two factors of COS, the factor of connections has a strong positive impact on accessibility. Activities are densely distributed in areas with high access levels and sparsely distributed in areas with poor access to public transport mode. By contrast, the cost has a robust negative effect on accessibility. Stations with fewer travel options and more travel steps would attract fewer trips. The compensation of these two factors on accessibility leads to the slight difference between PTAL and CPTAI, while the difference between PTAL/CPTAI and PTAI is more significant.

Public transport facilities are evaluated to be more accessible by utilizing PTAI index without considering the quality of public transport service. By following the PTAI index, people have to sacrifice comfort to pursue public transport service. By comparing the two modes, the bus network is better integrated into the public transport system than the metro network.

Overall, the new index can be seen as a measure for evaluating the locational difference. It considers the distribution of activities particularly from the perspective of land use plan, and public transport network configuration with respect to public transport plan. Poor access to public transport services leads to difficulties with accessing public services and job chances, and also brings about isolation for vulnerable residents. This approach measures accessibility to both residential spaces and living activities. The analysis demonstrates that the operation and configuration of the integrated public transport system are closely associated with the service accessibility and quality of public transport. The output of this research can provide the urban planners and decision-makers with the public transport access level information. More efficient public transport plan and rational land use plan can be made accordingly, hence to improve the allocation of public transport and facilities.

6. Conclusions

In this study, we present a novel approach to measure the rush-hour accessibility of public transport services for all community/enclaves in Wuhan metropolitan area. The approach models

different public transport networks as an integrated system, and considers the geographic distribution and topological degree of stations in the integrated transport system. The dataset of SCD is employed to evaluate the usefulness and effectiveness of the index in assessing the use of public transport. Results imply that CPTAI is an effective method for assessing the accessibility of integrated public transport service in Wuhan metropolitan area.

Results of the index show that there are still communities in urban fringe with no access to public transport service. In these areas the activities are sparsely distributed, and there are inadequate public transport facilities. While less than one-third of the communities which are covered by near two-thirds of the activities have fine access to public transport service. There are still activities in central city with poor access to public transport services. This is because of unproper urban planning from the municipality or difficulties of building transport facilities around such areas. The problem should be further analyzed before the municipality makes decisions. The association between accessibility levels and transport modes is significant but the association is not very strong. In places with poor accessibility, the mode of bus is dominant for the availability of facilities. With the increase of accessibility level, the choice for metro rises more rapidly than bus, and the increasing rates varies in each mode. However, the number of trips by bus is larger than metro for the capacity of existing facilities. The comparison of the three indexes shows consistency. The centrality of station has slight impact on the choice of available facilities. This index is more suitable for cities with even public transport networks, especially rail transit. The approach can be easily applied in a city to evaluate the public transport construction with consideration of the rational allocation of urban functions. As public transport is regarded as one of the most effective ways to alleviate urban congestion, promote the eco-environment, and mitigate the extremely uneven development of different areas. Promoting the proper development of public transport is of great importance to meet various needs of different groups of people at a lower cost. Therefore, it helps to build a resource-saving and environment-friendly society, and achieve sustainable urban development.

A weakness of this approach is the measure focuses on morning rush hours and does not consider the difference of activities between periods of time. Activities vary in time. For example, trips for leisure activities often gather in the afternoon and catering gather at dawn. In this study, the POIs we count for are mainly distributed along the roads, for the dataset is collected for traffic navigation. Consequently, the distances may be less considered. There are also limitations for the estimation of average waiting time and walking time in our model. Waiting time at station can be random, very long or short, and walk speed varies among different groups. Moreover, because of the lack of public transport survey data within the communities, the reallocation of smart card data by weight of the number of activities in communities may result in bias from reality. Furthermore, the traffic capacity and travel experience are omitted in this study, which may have a significant influence on people's choice. Future researches will be investigated on the temporal difference of traffic demand, traffic capacity and other factors which may affect people's choice. In the future, when evaluating the accessibility of public transport services, we will also try to seek for more compatible data to test the accuracy and reliability of the proposed approach.

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