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Research Article

Dynamic public transit accessibility analysis using actual transit operation data

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ABSTRACT

Understanding temporal variability in public transit accessibility is crucial for improving mobility and service quality in public transit systems. To accurately measure this variability in actual traffic conditions, this study utilized General Transit Feed Specification (GTFS) and the Advanced Public Transportation System (APTS) to calculate door-to-door travel time based on real public transit operation data. Recognizing that recurring and non-recurring congestion can co-occur, this study proposed two distinct metrics, Standardized Integral Accessibility (SIA) and Rate of Integral Accessibility Change (RIA), to independently identify temporal variability caused by recurring and non-recurring congestion. By using Integral Accessibility, this study effectively represented the regional public transit accessibility in Busan Metropolitan City, South Korea, revealing variations based on geographical location and the extent of the public transit network. Furthermore, the SIA metric allowed for the identification of accessibility changes during commuting times due to adverse weather conditions. Additionally, the study investigated the impact of heavy rain on accessibility variability using the RIA metric. It was found that variability caused by heavy rain occurs unpredictably at different times and locations, sometimes interacting with recurring congestion. The RIA metric proposed in this study has the potential to monitor real-time variations in accessibility caused by unexpected events. These findings can significantly contribute to the continuous improvement and management of public transit systems to better serve passengers' needs in various traffic conditions.

KEYWORDS

Public transit, dynamic accessibility, real-time analysis, General transit feed specification

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1. Introduction

The concept of smart city management has recently garnered significant interest, emerging as a new paradigm of intelligent urban governance (Alshuwaikhat et al., 2022; Neirotti et al., 2014). A key characteristic of this approach lies in its heavy reliance on big data, derived from the Internet of Things (IoT) sensing network. The availability of vast amounts of data from diverse sources offers cities remarkable opportunities to extract valuable insights (Zulkarnain & ZulkarnainPutri & , 2021). Notably, the Internet of Things (IoT) plays a pivotal role in this context, seamlessly integrating sensors, radio-frequency identification, and Bluetooth technology into the real-world environment through highly networked services (Hashem et al., 2016).

While big data presents the potential for cities to glean valuable insights from vast amounts of data collected through various sources, monitoring real-time traffic conditions and making decisions to maintain stable traffic flow remain challenging tasks. The rapid increase in urban traffic results in significant temporal uncertainties in traffic conditions, making accurate real-time traffic condition predictions under unforeseen events more complex (Y. Y. Zhang et al., 2022).

Nevertheless, ensuring the mobility of public transit holds paramount importance in smart city management, as it plays a crucial role in facilitating mid- to long-distance travel for all citizens, including those from low-income groups (Abulibdeh & Mansour, 2022). Public transit accessibility is influenced not only by traffic conditions, such as congestion during commuting hours, unforeseen events, and weather-related disruptions, but also by temporal variability arising from transit operators' scheduling and their responses to congestion. Understanding the temporal variability in public transit accessibility is pivotal for guiding decision-making in transit operations and planning (Curtis & Scheurer, 2010). This understanding allows for adjustments in vehicle routes, service frequencies, and overall efficiency improvements through real-time information systems. As a result, travel-time based public transit accessibility becomes an invaluable resource to design and construct a user-centered public transit network system.

The travel time of public transit is subject to dynamic fluctuations influenced by road traffic, headway, and transfer time in transit networks (D. J. Martin et al., 2008; Lei & Church, 2010; Salonen & Toivonen, 2013). Accurate calculation of travel time necessitates detailed data on public transit networks and specialized software to determine the shortest route (D. Martin et al., 2002). Recent advancements in the General Transit Feed Specification (GTFS) and spatial analysis have increased the potential for studying public transit accessibility by providing a metric to compute travel time between each origin and destination (Prommaharaj et al., 2020). Consequently, there has been a growing number of studies analyzing travel-time based accessibility since the introduction of GTFS (El-Geneidy et al., 2016; Farber & Fu, 2017; Farber et al., 2014; Fayyaz et al., 2017; Owen & Levinson, 2015; Salonen & Toivonen, 2013; Widener, 2017). However, most of these prior studies have not effectively reflected actual public transit accessibility concerning its temporal variability, primarily due to their reliance on scheduled travel times provided by transit operators, rather than actual travel times.

We recognize that Automatic Vehicle Location (AVL) technology (Cathey & Dailey, 2003) utilizing GPS and Advanced Public Transportation System (APTS) (Casey et al., 1991; Levine et al., 2000) can provide essential information to address the limitations of prior studies. APTS, as a typical technology of Intelligent Transport Systems (ITS), gathers real-time information on public transit vehicles, including their locations and arrival times at stops. Leveraging APTS data allows for real-time travel time calculations that vary with traffic conditions. This study introduces an analytical framework that identifies the temporal variations in public transit accessibility based on APTS data. Moreover, our investigation aims to explore variations in public transit accessibility resulting from unpredictable events. Specifically, we propose a distinctive methodology to examine the impact of non-recurring congestion caused by adverse weather conditions on public transit accessibility. Additionally, we develop several indicators to effectively explain spatio-temporal variations in public transit accessibility.

2. Background

Public transit accessibility refers to the ease with which users can reach desired destinations using public transit (Wachs & Kumagai, 1973). With the development of GIS technology, it became feasible to compute travel costs through road networks, leading to numerous studies applying public transit accessibility metrics (Azar et al., 1994; Polzin et al., 2002; Schuurman et al., 2006; Zhao et al., 2003). However, establishing a unified definition of public transit accessibility remains challenging, as each study employs distinct metrics based on specific objectives and costs.

Lei and Church (2010) categorize public transit accessibility metrics from prior studies into six categories, with system-facility accessibility and integral accessibility being particularly suitable for describing public transit accessibility based on travel time. System-facility accessibility estimates a user's ability to reach their destination, factoring in the travel time or cost spent on the public transit network (Djurhuus et al., 2016; El-Geneidy et al., 2009; Ford et al., 2015; Lei & Church, 2010). In the advanced model of system-facilitated accessibility metrics, additional variables such as walking time, departure and arrival times, and scheduled transfer times are taken into account to calculate door-to-door travel time (Benenson et al., 2011; Salonen & Toivonen, 2013). To address the inclusion of travel mode transfers, Dijkstra's algorithm (1959) is employed to identify the shortest route in a multimodal transport network (J. J. Zhang et al., 2011; Modesti & Sciomachen, 1998). Furthermore, ArcGIS Networks analysts leverage Dijkstra's algorithm (Curtin, 2007) to compute the travel cost between origin and destination.

Meanwhile, integral accessibility (Ingram, 1971; Morris et al., 1979; Pirie, 1979) calculates the number of destinations or service opportunities available from a specific location within a restricted travel cost, such as travel time or distance. This metric utilizes the cumulative opportunity measure (Kwan, 1998; Wachs & Kumagai, 1973) to determine accessibility. Unlike system-facilitated accessibility, which focuses on accessibility between a single route of origin and destination, integral accessibility considers accessibility to multiple destination facilities from a given location. Previous studies have effectively employed the integral accessibility metric to evaluate various aspects of accessibility in different regions. For instance, Luo and Wang (2003) used it to assess accessibility to medical services in Chicago counties, USA. Cheng and Bertolini (2013) utilized the metric in Amsterdam, Netherlands, to evaluate job opportunities. Additionally, Páez et al. (2010) applied integral accessibility in the city of Montreal to identify areas with limited access to food sources, commonly referred to as food deserts.

Travel time stands as a crucial metric when assessing public transit accessibility, directly influencing the convenience and reliability of the transit system (Curtis & Scheurer, 2010) and significantly impacting user behavior. A shorter travel time can make public transit a more attractive and appealing option for potential users. Studies conducted by Beiro & Cabral (2007) in Porto, Portugal, found that long waiting times and uncertainty about arrival times were considered inconveniences by public transit users. Similarly, De Oña (2013) identified travel time-related factors, such as punctuality and frequency, as having a significant impact on the assessment of public transit services in Granada, Spain.

The door-to-door trip time, encompassing waiting time, transfer time, and in-vehicle time, serves as a key metric for evaluating public transit service from the user's perspective, and it can be derived using public transit operation data (D. J. Martin et al., 2008; Lovett et al., 2002; Tribby & Zandbergen, 2012). An example of a metric that considers these factors is the Public Transit Accessibility Level (PTAL) (Shah & Adhvaryu, 2016; Wu & Hine, 2003), developed in the London Borough of Hammersmith and Fulham. PTAL estimates the level of public transit service by aggregating walking time to the stop and waiting time for public transit. In the case of Auckland, New Zealand, Mavoa et al. (2012) estimated the public transport accessibility to various facilities, including education, financial, health, shopping, social, and recreational facilities, based on factors like walking time and transit frequency.

The General Transit Feed Specification (GTFS) (McHugh, 2013) is a widely adopted format for storing public transit network data, encompassing crucial information on transit stops, routes, and schedules. Leveraging GTFS data, the ArcGIS Network Analyst toolbox accurately calculates door-to-door travel time across public transit networks, making it a valuable tool in recent studies that assess public transit accessibility (El-Geneidy et al., 2016; Salonen & Toivonen, 2013; Widener, 2017). For instance, Fransen et al. (2015) utilized GTFS to estimate accessibility to various facilities such as administrative centers, employment hubs, and supermarkets in Flanders, Belgium. Similarly, Farber et al. (2014) identified food desert areas in Cincinnati, Ohio, United States, based on travel time calculated using GTFS data. However, these studies rely on pre-planned schedules provided by transit operators to estimate travel time, which limits their ability to capture the temporal variability of public transit accessibility caused by local traffic conditions or unforeseen events.

The travel time of public transit is dynamically shaped by various elements within the public transit network, including the headway of transit, transfer processes, and the operating schedule of public transit (Cooke & Halsey, 1966; D. Martin et al., 2002). Beyond these internal factors, public transit travel time is affected by external traffic conditions such as traffic congestion and adverse weather (Mondschein et al., 2010; Schrank, 2012). The integration of public transit operation data within GTFS allows for the representation of temporal variability in public transit accessibility, as it accounts for travel time across public transit networks. By evaluating the temporal variations in travel-time-based accessibility, we can gain a deeper understanding of how factors such as peak-hour congestion, service disruptions, and changes in road and weather conditions influence accessibility.

The objective of this study is to propose an analytical framework capable of effectively identifying the temporal variability in public transit accessibility caused by two distinct types of congestion: recurring congestion and non-recurring congestion. Recurring congestion refers to the anticipated congestion caused by routine traffic conditions in a typical traffic environment (Hallenbeck et al., 2003), such as congestion during peak commuting hours. Conversely, non-recurring congestion arises from temporary disruptions, such as accidents, sports events, or adverse weather conditions (Sun et al., 2017). Non-recurring congestion, according to Hallenbeck et al. (2003), can result from events like lane-blocking accidents, construction lane closures, significant roadside distractions, and unfavorable weather conditions. Additionally, Mondschein and Taylor (2017) point out that adverse weather conditions can significantly impact ridership, frequency, travel time, and headway regularity. Given the sudden and unexpected nature of non-recurring congestion, it is crucial to have a real-time system in place to identify such temporal variations in traffic promptly.

3. Methods

3.1. Scope of the study

This study investigates the influence of traffic congestion on public transit accessibility during commuting hours in Busan Metropolitan City, South Korea. Busan is the second-largest metropolitan city in South Korea, spanning 770.04 km² with a population of approximately 3.4 million. Notably, 47% of its total area consists of mountainous terrain, and the city's coastal layout restricts road expansion. These geographical constraints, combined with a dense population and a significant floating population, contribute to frequent traffic congestion, particularly during peak commuting hours. Furthermore, Busan's mountainous topography and localized heavy rainfall in the summer further exacerbate traffic disruptions. Given these regional characteristics, establishing an effective traffic congestion monitoring system is a critical priority for the city.

Busan has an extensive public transit network, operating 289 bus routes and four subway lines, and has actively implemented policies to improve urban mobility through public transportation. Since December 2019, the city has introduced exclusive bus lanes as part of the Bus Rapid Transit (BRT) system to alleviate congestion. As a result, by 2018, the public transit mode share in Busan had reached approximately 44%, the second highest among South Korea’s metropolitan cities.

The study area, which includes key regions of Busan and its public transit network, is illustrated in Figure 1. In certain areas, traffic congestion is particularly severe due to geographical constraints. Dongnae-gu and Geumjeong-gu are among the city's traditional residential districts. Dongnae-gu has a high density of apartment complexes, while Geumjeong-gu features a mix of residential and commercial zones centered around universities. Due to their high population density, these areas experience significant congestion during commuting hours. Busanjin-gu, Busan’s largest commercial district, also faces severe traffic congestion. As a central hub for shopping malls, department stores, entertainment facilities, and financial institutions, the area attracts a high volume of vehicular and pedestrian traffic. Similarly, Saha-gu and Sasang-gu, where Busan’s maritime and logistics industries are concentrated, experience heavy congestion due to the influx of commuters and workers during business hours.

In this study, the city was partitioned into 760 grid areas of 1 km², resulting in 640 center points of grid areas as Origin-Destination (OD) points. Among these, 120 points were excluded due to the absence of bus stops or subway stations within a 1 km² radius. OD travel times were then calculated between each OD point at 5-minute intervals (192 temporal points) from 6:00 to 21:55 on the selected days. As Tarawneh (2001), the walking speed of men under 45 years old ranges from 4.64 km/h to 5.36 km/h. To calculate walking time, this study adopted a fixed walking speed of 5 km/h, obtained by dividing the walking distance by the walking speed. Additionally, the boarding time on the vehicle was fixed at 15 s, following the approach by Farber and Fu (2017).

To examine the temporal variability in public transit accessibility resulting from adverse weather conditions, specifically heavy rain, this study gathered hourly precipitation data on the designated days. The precipitation data were acquired from the Automatic Weather Stations (AWS) located in Busan. These AWS systems continually record various weather parameters, including temperature, precipitation, atmospheric pressure, wind speed, and humidity, with a frequency of every minute. A total of 14 AWS installations to monitor and collect this meteorological data exist in the Busan area.

This study conducted an analysis of spatial-temporal public transit accessibility during heavy rainfall and compared it to the accessibility on four non-rainy days. The specific rainy days selected for analysis were June 28, 2018, July 3, 2018, June 26, 2019, and August 6, 2019, during which the instantaneous precipitation exceeded 20mm/h. To conduct a comparative analysis between the results of rainy days and non-rainy days, control groups were selected with a one-week gap from the rainy days. Specifically, the days July 5, 2018, July 10, 2018, July 3, 2019, and August 13, 2019 were chosen as control groups for the study. Due to the substantial alteration of traffic flows in the city caused by the COVID-19 outbreak, the days following the pandemic were not included in this study.

Table 1 presents the hourly precipitation data for the heavy-rain days analyzed in this study. On July 3, 2018, and June 26, 2019, it rained continuously throughout the entire day. However, on June 28, 2018, and August 6, 2019, heavy rain occurred specifically during commuting hours. Notably, August 6, 2019, experienced a significant impact from typhoons resulting in intensified and severe rainfall intensity.

Figure 1. Public transit network of Busan and administrative districts.

3.2. Estimating travel time based on public transit operation data

To compute the travel time through Busan's public transit network, this study established a database by collecting actual public transit operation data through the Advanced Public Transportation System (APTS). APTS data tracks the real-time location of public transit vehicles based on GPS and records it on a data server. This enables the extraction of arrival and departure times of all public transit vehicles at each bus stop. The APTS data for buses in Busan was obtained from the government office of Busan Metropolitan City. The travel time for each origin-destination pair is then computed using the Network Analyst toolbox of ArcGIS 10.8.1 in conjunction with the GTFS data.

Figure 2. Structure of required GTFS data files.

While APTS data in Busan solely recorded the operation data of buses, the public transit operation data for subways were collected from operation schedule data. Unlike road vehicles, subways and railways are less susceptible to traffic environmental changes, including adverse weather conditions (Hofmann & O'Mahony, 2005; Khattak & De Palma, 1997). Consequently, the operation schedules of subways can reliably provide departure and arrival times of subway vehicles at stations with minimal errors. The operation schedule data used in this study were obtained from the Company of Busan Metro Operation Service.

In this study, GTFS data for 8 target days was constructed based on the collected APTS data. GTFS, which stores information about public transit operations in separate files, consists of various subcomponents as shown in Table 2. The essential components required for the composition of GTFS data include Agency, Routes, Calendar, Trips, Stops, and Stop times. Figure 2 depicts the connection structure of these required data. The Agency file stores information about public transit institutions. The Routes file contains a comprehensive list of all public transit routes, along with the type of public transit associated with each route. The Calendar file reflects the changes in trip operation schedules depending on the day of operation. Within the GTFS data, the Trips file includes a list of trips corresponding to each route. The Stops file comprises the stop ID and location information of all stops. Additionally, the Stop times file records the trip ID and the respective arrival and departure times at each stop.

Figure 3. Framework of travel time calculation using GTFS.

Travel time calculations were performed using Esri's ArcGIS Network Analyst Development and Mmorang's Add GTFS to the Network Dataset toolbox of ArcGIS, following the methodology outlined by Farber et al. (2014). Utilizing ArcGIS Network Analyst, the lowest door-to-door travel time between the origin and destination was computed based on the GTFS data through the OD-cost matrix. ArcGIS's GTFS toolkit allowed us to calculate travel time at specific departure times with 5-minute intervals, enabling the assessment of travel time variations accordingly. The road network data utilized in ArcGIS was collected from the Korea Transport Database, ensuring accurate and reliable results in the analysis.

Figure 3 illustrates the framework employed for calculating travel time using ArcGIS's GTFS toolkit. The travel times between the origin and destination are determined following Equation 1 and Equation 2.

represents the door-to-door travel time from the starting point to the destination at departure time . When there are transfers in the route, public transit segments are generated. is the travel time taken through public transit on a specific transit segment . And it consisted of walking time , boarding time , and in-vehicle time at transit segment k. represents the walking time between the departure location and the starting bus stop and represents the walking time between the ending bus stop and the arrival location. represents the walking time between the arrival bus stop of transit segment and the departure bus stop of transit segment *.* The GTFS toolkit in ArcGIS calculates the minimum travel cost between an origin and a destination within an operational public transit network system. This implies that the travel time is calculated based on the optimal route among various public transit travel routes available, including single trip or trips involving multiple transfers.

3.3. Measurements

The hourly Integral Accessibility for each of the 640 OD points in Busan is calculated based on the door-to-door travel time. Integral Accessibility is determined by using a cumulative opportunity measure. Additionally, two metrics, namely the Standardized Integral Accessibility (SIA) and the Rate of Integral Accessibility change (RIA), are proposed to distinguish the temporal variability in accessibility resulting from recurring congestion and unexpected events. Previous studies have proposed methodologies to identify recurring congestion and non-recurring congestion to track changes in traffic flow on roadways. Gall and Hall (1989) distinguished between recurring and non-recurring congestion based on vehicle volumes and occupancy measured at downstream and upstream points on the road. Kallem (2011) analyzed GPS data from freight trucks, calculating speed at five-minute intervals and detecting non-recurring congestion using the Standard Normal Deviate of speed for each segment. Gall (1989) also defined a threshold for identifying non-recurring congestion based on the historical mean and standard deviation of vehicle speed across road segments. However, as these studies primarily identify recurring and non-recurring congestion based on the movement of private and freight vehicles, they exhibit a fundamental limitation in capturing the impact of congestion from a public transit perspective. Unlike private vehicle travel, public transit mobility is influenced not only by traffic congestion but also by factors such as bus route concentration, transfer conditions, vehicle waiting times, and peak-hour operational strategies by transit agencies. The two metrics we propose effectively identify the locations and time periods in which recurring and non-recurring congestion occur from a public transit perspective, as well as their impact on public transit accessibility. SIA highlights periods of low accessibility caused by recurring congestion, offering insights into its effects on transit accessibility. On the other hand, RIA captures the temporal variation of Integral Accessibility over specific periods relative to an average of ordinary days. By minimizing the influence of regular congestion, RIA effectively represents the temporal variability in accessibility caused by unexpected events.

3.3.1. Integral accessibility calculated by **cumulative opportunity measure**

The cumulative opportunity measure is a metric that accumulates the outcomes of a binary function, considering a specific threshold. It can be flexibly applied to construct Integral Accessibility based on diverse travel purposes, such as job, school, and health accessibility (Ingram, 1971; Morris et al., 1979). Integral Accessibility assesses the number of destinations reachable within a designated threshold time through public transit. To calculate Integral Accessibility at a specific OD point during a specific period H, denoted as , the following Equation 3 and Equation 4 are used.

where is Integral Accessibility at OD point at departure time , is the travel time between origin point and destination point at departure time , is the travel time threshold, and is the number of departure times in period H.

To accommodate the temporal variability of public transit accessibility concerning departure time, we computed Integral Accessibility with 5-minute intervals. Public transit travel time can significantly differ based on the departure time, impacting waiting time for public transit vehicles and transfer time (D. Martin et al., 2002; Lei & Church, 2010; Luan et al., 2021). To minimize the impact of waiting time for public transit vehicles, the Integral Accessibility calculated at 5-minute intervals was aggregated into one-hour intervals. In this study, a threshold travel time of 60 minutes was set to define the accessibility boundaries.

3.3.2. Standardized integral accessibility (SIA)

The SIA metric is employed to identify periods when public transit accessibility regularly decreases due to recurring congestion. It standardizes Integral Accessibilities for one day, computed by hourly periods. The SIA at a specific OD point during a specific period H, denoted as , is determined using the following Equation 5.

where is the average of Integral Accessibility at OD point over all periods on the target day and is the standard deviation of Integral Accessibility at OD point over all periods on the target day.

SIA enables us to assess the relative level of accessibility during a specific period compared to other periods of the day at a given point of origin. Since SIA standardizes the integral accessibility values for specific time periods, it is particularly effective for analyzing predictable, recurring traffic congestion that follows daily patterns. When accessibility variations are examined across multiple typical days, the influence of regularly occurring congestion can be effectively isolated. In this study, by analyzing SIA variations across four ordinary days without adverse weather conditions, we can identify periods when public transit accessibility decreases due to recurring congestion. Furthermore, SIA enables a comprehensive comparison of the temporal variation in public transit accessibility across all origin points on a uniform scale. This standardized approach ensures a consistent and reliable assessment of accessibility variations in different scenarios.

3.3.3. Rate of integral accessibility change compared with ordinary day

To gain deeper insights into the impact of non-recurring congestion resulting from unpredictable events on the variation of public transit accessibility, we employ the Rate of Integral Accessibility Change (RIA) metric. This measurement quantifies the change in Integral Accessibility during specific periods when traffic events occur, relative to the same periods on ordinary days. The RIA at a specific OD point during a specific period H, denoted as , is calculated by using the following Equation 6.

where is the average of Integral Accessibility at OD point during a specific period H on ordinary days. This study determined for each year by categorizing the four days of ordinary into two-day groups for each year.

RIA serves to identify unexpected variations in accessibility by distinguishing them from recurring congestion, which occurs regularly. Unlike SIA, which captures daily congestion patterns, RIA quantifies non-recurring congestion caused by unpredictable external factors such as sudden weather changes. By comparing accessibility during specific traffic events to ordinary days, RIA isolates the impact of these disruptions, offering a complementary perspective on accessibility analysis. This metric is particularly valuable for understanding how sudden weather changes unexpectedly affect public transit accessibility.

By employing both SIA and RIA, this study effectively differentiates between two distinct types of congestion. SIA is designed for analyzing accessibility variations due to predictable, recurring congestion, while RIA is specifically designed to capture accessibility variations caused by unpredictable, non-recurring congestion. These metrics ensure a comprehensive understanding of how both regular and irregular congestion impact public transit accessibility.

4. Result

4.1. Spatial disparities In public transit accessibility In Busan

Figure 4a illustrates the Integral Accessibility during four ordinary days with a 60-minute threshold, measured using the Cumulative Opportunity Measure. It represents the spatial disparities in public transit accessibility between OD points in Busan. The values of Integral Accessibility at each OD point indicate the number of destinations accessible from the center point of each grid. In the central part of Busan (Dongnae-gu, Sasang-gu, Buk-gu, and Yeonje-gu), the local average of Integral Accessibility exceeds 200, indicating that residents in these areas can access at least 31% of OD points within 60 minutes through public transit. Conversely, in regions such as Yeongdo-gu, a southern island area, Gangseo-gu, a western suburban area, and Gijang-gun, an eastern suburban area, the local average of Integral Accessibility falls below 105, signifying that residents in these areas can access at most 16.4% of OD points within an average travel time of 60 minutes.

Figure 4b displays the number of transit routes in each grid area, indirectly indicating the local level of public transit networks. An examination of the correlation between the Integral Accessibility of each OD point and the number of transit routes revealed a correlation coefficient of 0.59, showing a significant positive correlation. This suggests that the Integral Accessibility of the Busan area is influenced not only by its geographical location but also by the extent and quality of its public transit network.

Figure 4. (a) Integral accessibility of Busan during ordinary days with 60 minutes threshold, (b) number of transit routes In OD points .

4.2. Temporal variation of public transit accessibility

While Integral Accessibility can effectively represent cross-sectional spatial disparities, it falls short in describing temporal variability. To overcome this limitation, SIA provides a means to represent the relative value of Integral Accessibility during specific periods that vary with time at each OD point. Figure 5 visually demonstrates the variability in public transit accessibility on both ordinary days and heavy-rain days by averaging the SIA values of all OD points in Busan.

Figure 5. (a) Local average of standardized integral accessibility (SIA) In Busan on ‘not rainy days’, (b) local average of standardized integral accessibility (SIA) In Busan on ‘heavy-Rain days’ .

On 'not rainy days', the temporal patterns of accessibility exhibit minimal variations (Figure 5a). The local average of SIA in Busan experiences a rapid decrease between 7:00–8:00 and 17:00–18:00, followed by a gradual recovery to normal levels. During the morning commuting time, the local average of SIA is −0.58, while during the afternoon commuting time, it drops to −1.27. This indicates a substantial decrease in public transit accessibility during commuting hours due to recurring congestion, which is a regular occurrence on ordinary days. However, the patterns of variability in accessibility on Heavy-Rain days were not similar to those on ordinary days (Figure 5b). Increased and decreased accessibility were observed even outside of commuting hours on Heavy-Rain days. This suggests that public transit accessibility is influenced not only by heavy rain but also by factors beyond recurring congestion during commuting hours. The impact of heavy rain on accessibility is evident, leading to noticeable fluctuations in public transit accessibility throughout the day.

Figure 6 shows the spatial distribution of the SIA at specific periods on four ordinary days. The SIA metric represents the relative magnitude of Integral Accessibility at a particular period compared to other periods within a day. Figure 6a and Figure 6c illustrate the SIA values during 7:00–8:00 and 17:00–18:00, respectively, while Figure 6b and Figure 6d display the SIA values during 10:00–11:00 and 19:00–20:00, respectively. These visualizations provide a detailed view of the temporal variability in public transit accessibility during different periods of the day.

Figure 6. (a) Standardized integral accessibility (SIA) during morning commuting time, (b) standardized integral accessibility (SIA) In daytime, (c) standardized integral accessibility (SIA) during afternoon commuting time, (d) standardized integral accessibility (SIA) In evening.

During morning and afternoon commuting hours, significant decreases in the SIA were observed in the central part of Busan (Saha-gu, Sasang-gu, Busanjin-gu, and Dongnae-gu). These districts experience a high influx of over 500,000 floating populations during commuting times. The decrease in accessibility observed in these south-central regions of Busan is likely caused by the increase in commuters and traffic flow on roadways during commuting time, resulting in traffic congestion. On the other hand, during the morning commuting hours, SIA increased in the northeastern part (Gijang-gun). Unlike other districts, this area was relatively less affected by traffic congestion during the afternoon commute. This can be attributed to the presence of a beltway surrounded by mountains, which does not generate significant commuting demand during peak hours. These findings suggest that different regions of Busan may exhibit distinct accessibility patterns depending on the commuting period.

Furthermore, the observed increase in accessibility in the northeastern part during the morning commute may be linked to public transit policies that adjust service frequencies based on commuting demand. In Busan, most public transit routes operate with varying headways between peak and off-peak hours, with vehicle intervals shortened by approximately 1–3 minutes during peak times. Consequently, this area appears to benefit from increased service frequency without experiencing congestion-related delays. This implies that transit resources aimed at mitigating accessibility declines during commuting hours may be allocated to areas where they are not critically needed.

4.3. Temporal variability In public transit accessibility caused by heavy-Rain

The SIA metric represents variability in accessibility caused by both recurring and non-recurring congestion, making it challenging to identify accessibility changes caused by unpredictable events. However, the RIA metric provides a solution to distinguish variations in accessibility caused by unpredictable rainfall from those influenced by commuting time. By minimizing the impact of recurring congestion, the RIA metric efficiently quantifies the influence of abrupt weather changes on public transit accessibility.

Figure 7. (a) Local average of rate of integral accessibility change (RIA) In Busan on heavy-Rain days, (b) average precipitatioin of Busan on heavy-Rain days.

Figure 7a illustrates the local average of RIA in Busan aggregated by hourly periods for each Heavy-Rain day, while Figure 7b shows the hourly precipitation for each Heavy-Rain day. We identified the periods during which public transit accessibility was affected by heavy rainfall, which were 07:00-08:00 on June 28, 2018; 19:00-20:00 on July 3, 2018; 18:00-19:00 on June 26, 2019; and 15:00-16:00 on August 6, 2019. One of the common patterns observed in the figure is the clear inverse relationship between rainfall and SIA. Notably, on July 26, there were two distinct rainfall peaks. During the first peak around 10 AM, RIA decreased by approximately 2%, then returned to normal levels after 11 AM. However, during the second peak around 6 PM, RIA dropped again by about 5%. This pattern was also evident on June 8 and August 6. In contrast, on July 3, the decline in RIA was not as pronounced. Unlike the other days, rainfall on July 3 was not concentrated at specific times but persisted throughout the entire day across the study area.

Figure 8a, Figure 8b, Figure 8c, and Figure 8d depict the distribution of RIA in Busan during the hourly periods of heavy rainfall on June 28, 2018, July 3, 2018, June 26, 2019, and August 6, 2019, respectively. The changes in SIA during heavy rainfall reveal several interesting patterns. Significant declines in RIA were observed in the southestern industrial and logistics districts of the city, as well as in the city center during commuting peak hours. Notably, during the morning peak hour (Figure 8-a), RIA in the industrial zones dropped by more than 10%, showing a greater impact compared to the afternoon peak hour (Figure 8-c), when travel demand is more evenly distributed over time. In contrast, after the afternoon peak period (Figure 8-d), the decline in SIA was more pronounced in coastal residential areas and mountainous regions rather than in industrial districts. On the other hand, on July 3 (Figure 8-b), when rainfall persisted throughout the entire day, there was no significant decrease in RIA, and some areas even showed an increase. This suggests that continuous rainfall may have led people to forgo or reduce travel, resulting in minimal reductions in road travel speed.

Figure 8. (a) Rate of integral accessibility change (RIA) during heavy-Rain period on june 28, 2018, (b) rate of integral accessibility change (RIA) during heavy-Rain period on july 3, 2018, (c) rate of integral accessibility change (RIA) during heavy-Rain period on june 26, 2019, (d) rate of integral accessibility change (RIA) during heavy-Rain period on august 6, 2019.

Figure 8 illustrates that the decrease in public transit accessibility during adverse weather conditions with hourly precipitation of 20mm or more occurred differently by region and period. This illustrates the difficulty of predicting public transit accessibility change from unexpected events, which depends on the characteristics of the incident, the terrain, and the time of occurrence. The variability in the impact of adverse weather on public transit accessibility underscores the need for flexible and adaptive transportation planning and management strategies to mitigate the effects of unpredictable events on the transit system.

4.3.1. Ⅵ. discussion & conclusion

This study presents a comprehensive methodological framework for measuring public transit accessibility using actual transit operation data and understanding the impact of traffic environments on accessibility in real-time. The key contributions of this research are as follows: Firstly, Integral Accessibility, calculated using the Cumulative Opportunity Measure, serves as a robust metric to quantify public transit accessibility across different regions of Busan. The analysis reveals that spatial disparities in accessibility are influenced by both geographical location and the level of development of the public transit network. Secondly, we propose the Standardized Integral Accessibility (SIA) metric to assess the relative impact of recurring congestion on public transit accessibility at specific origin points. Through SIA, we identify the spatiotemporal periods during which public transit accessibility is significantly reduced due to recurring congestion during commuting hours. Thirdly, the Rate of Integral Accessibility Change (RIA) is introduced to identify the spatiotemporal areas where public transit accessibility is affected by non-recurring congestion, specifically heavy rainfall. By mitigating the effects of recurring congestion, RIA allows us to focus on variations caused by unpredictable events.

Our findings demonstrate that the impact of heavy rainfall on public transit accessibility is not consistent across locations and periods. Variability due to adverse weather conditions occurs unpredictably and can overlap with recurring congestion. RIA proves to be an effective tool for real-time observation of temporal variations in public transit accessibility.

In conclusion, this study's methodology provides valuable insights into the dynamic nature of public transit accessibility and its relationship with traffic environments. The proposed metrics, Integral Accessibility, SIA, and RIA, offer a comprehensive approach to understanding and responding to the temporal variations in public transit accessibility, ultimately aiding in the development of more efficient and resilient transit networks.

Previous studies on public transit accessibility, which relied on predetermined operating schedules of public transit, had limitations in accurately reflecting the variability in accessibility based on actual traffic environments (El-Geneidy et al., 2016; Farber & Fu, 2017; Farber et al., 2014; Salonen & Toivonen, 2013; Widener, 2017). In this study, we address these limitations by utilizing Advanced Public Transportation System (APTS) data, which records the real-time location of public transit vehicles. By estimating actual travel time through APTS data, we present a robust framework for identifying variations in public transit accessibility. Currently, real-time urban spatial information, such as weather conditions, is actively observed and analyzed. However, transportation information, specifically public transit accessibility, has not yet been analyzed in real-time. Our study fills this gap by introducing a metric that allows real-time monitoring of accessibility variations. These variations in accessibility indicate that users' perceptions of accessibility change dynamically. The metric proposed in this study provides public transit management with the ability to promptly identify real-time fluctuations in accessibility and respond effectively to changes caused by non-recurring congestion from the perspective of the user. With the implementation of this framework, public transit authorities can gain valuable insights into how various factors, such as heavy rainfall, accidents, or special events, impact public transit accessibility in real-time. By addressing accessibility fluctuations promptly, transit agencies can improve service reliability and enhance the overall user experience, ultimately leading to a more efficient and user-centric public transit system.

The study has certain limitations that need to be acknowledged. Firstly, building the database for calculating travel time from APTS data was time-consuming due to the absence of specialized software. The extensive data for Busan also posed challenges in determining precise temporal accessibility in minute units, leading us to select OD points at a 1km² spatial scale and calculate travel times in 5-minute intervals. While this approach provides valuable insights, it may not capture all temporal variations at finer time scales. Moreover, the focus on traffic conditions during heavy rain days restricted the number of study days to four, limiting the generalizability of the findings. As spatial and temporal weather conditions varied on each study day, it was difficult to identify a consistent influence of adverse weather conditions on public transit accessibility. Additionally, it is important to note that this study did not account for other traffic environmental variables beyond adverse weather conditions, despite the potential influence of various factors on public transit accessibility variability. Factors such as hourly floating population, average road width, and traffic volume can significantly impact public transit accessibility.

To improve future research, developing specialized software for calculating travel time from APTS data would streamline the database-building process. Additionally, expanding the study to include more diverse weather conditions and a larger number of study days could provide a more comprehensive understanding of the impact of weather on public transit accessibility. Considering finer time intervals for calculating travel time could also lead to more detailed insights into temporal variations. Addressing these limitations will enhance the accuracy and applicability of future studies exploring public transit accessibility in diverse traffic and weather conditions. To conduct a more comprehensive and statistically significant analysis, future research should consider analyzing the influence of these additional traffic environmental variables. By incorporating a broader range of factors, we can gain a deeper understanding of the complex dynamics affecting public transit accessibility in real-time scenarios.

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Table 1. Hourly precipitation of heavy-Rain days.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Precipitation | Mean | | | | Max | | | | Min | | | | |
| 2018 | | 2019 | | 2018 | | 2019 | | 2018 | | 2019 | | |
| **Time** | **June 28** | **July 3** | **June 26** | **August 6** | **June 28** | **July 3** | **June 26** | **August 6** | **June 28** | **July 3** | **June 26** | **August 6** |
| **06:00** | 24.9 | 0.5 | 0.0 | 0.0 | 34.5 | 1 | 0 | 0 | 7 | 0 | 0 | 0 |
| **07:00** | 20.8 | 1.3 | 0.0 | 0.0 | 49 | 2.5 | 0 | 0 | 9.5 | 0.5 | 0 | 0 |
| **08:00** | 17.4 | 2.6 | 0.2 | 0.0 | 22 | 5 | 1.5 | 0 | 13 | 1 | 0 | 0 |
| **09:00** | 14.1 | 2.1 | 2.0 | 0.0 | 17.5 | 3 | 7 | 0 | 10.5 | 1 | 0 | 0 |
| **10:00** | 3.0 | 2.8 | 11.5 | 0.0 | 4.5 | 4 | 19.5 | 0 | 2 | 1.5 | 6 | 0 |
| **11:00** | 2.3 | 4.3 | 10.3 | 0.0 | 3 | 6.5 | 26 | 0 | 1.5 | 2 | 4.5 | 0 |
| **12:00** | 2.2 | 5.1 | 3.0 | 0.0 | 4 | 7 | 6.5 | 0 | 1.5 | 2.5 | 2 | 0 |
| **13:00** | 5.0 | 9.6 | 5.5 | 0.4 | 17 | 17 | 12 | 1.5 | 3 | 4 | 3.5 | 0 |
| **14:00** | 2.4 | 10.8 | 3.8 | 8.0 | 4 | 17 | 5 | 17 | 1.5 | 2 | 2.5 | 2 |
| **15:00** | 0.5 | 9.2 | 3.5 | 20.7 | 1 | 19 | 6.5 | 28 | 0 | 1.5 | 2.5 | 14 |
| **16:00** | 0.0 | 4.5 | 6.3 | 18.9 | 0.5 | 15 | 9 | 29 | 0 | 0 | 2.5 | 13.5 |
| **17:00** | 0.0 | 4.7 | 12.6 | 10.8 | 0 | 11.5 | 19 | 22.5 | 0 | 0.5 | 7.5 | 4 |
| **18:00** | 0.0 | 5.8 | 16.5 | 15.1 | 0 | 11 | 23.5 | 26.5 | 0 | 1.5 | 10.5 | 9 |
| **19:00** | 0.2 | 10.3 | 12.0 | 4.9 | 0.5 | 20 | 20.5 | 8 | 0 | 3 | 7 | 2.5 |
| **20:00** | 0.1 | 7.6 | 7.5 | 0.7 | 0.5 | 20.5 | 14 | 2 | 0 | 1 | 1.5 | 0 |
| **21:00** | 0.0 | 5.0 | 4.8 | 0.5 | 0.5 | 12.5 | 9 | 1.5 | 0 | 0 | 1.5 | 0 |

Table 2. Definition of required GTFS data files.

|  |  |
| --- | --- |
| File name | Definition |
| Agency | Agency offering feed (timetable) data |
| Stops | Name and Location of stop |
| Routes | List of Transit Line (Sequence of stops) |
| Trips | The order of trips in a specific route |
| Stop times | Arrive and departure time at the specific stop of each trip |
| Calendar | Schedule for service |

* Uses real-time APTS and GTFS data to measure actual public transit travel times
* Proposes SIA and RIA metrics to capture recurring and non-recurring congestion
* RIA enables real-time monitoring for transit disruptions and planning

Disclosure statement

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[bib30]##AuthST##Levine, J.##AuthEN##, ##AuthST##Hong, Q.##AuthEN##, #dlST#Edward Hug, G., #dlEN#& ##AuthST##Rodriguez, D.##AuthEN## ##InstAuthST###inST#Edward Hug Jr.#inEN##inST#. #inEN###InstAuthEN##(2000). Impacts of an #inST#advanced public transportation system demonstration project#inEN##inST#.#inEN##dlST#Advanced Public Transportation System Demonstration Project.#dlEN# *Transportation Research Record: Journal of the Transportation Research Board*, 1735(1), 169#inST#–#inEN##dlST#-#dlEN#177. https://doi.org/10.3141/1735-20##CMST##Reference Type: journal -- Crossref##CMEN##

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[bib32]##AuthST##Luan, S.##AuthEN##, ##AuthST##Ma#inST#,#inEN##inST#,#inEN##dlST#,#dlEN# X.##AuthEN##, ##AuthST##Li, M.##AuthEN##, ##AuthST##Su, Y.##AuthEN##, & ##AuthST##Dong, Z.##AuthEN## (2021). Detecting and interpreting non#inST#‐#inEN##dlST#-#dlEN#recurrent congestion from traffic and social media data. *IET Intelligent Transport Systems*, 15(12), 1461#inST#–#inEN##dlST#-#dlEN#1477. https://doi.org/10.1049/itr2.12104##CMST##Reference Type: journal -- Crossref##CMEN##

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[bib35]##AuthST##Martin, D.##AuthEN##, ##AuthST##Wrigley, H.##AuthEN##, ##AuthST##Barnett, S.##AuthEN##, & ##AuthST##Roderick, P.##AuthEN## (2002). Increasing the sophistication of #inST#Access#inEN##dlST#access#dlEN# measurement in a rural healthcare study. *Health & Place*, 8(1), 3#inST#–#inEN##dlST#-#dlEN#13. https://doi.org/10.1016/S1353-8292(01)00031-4##CMST##Reference Type: journal -- Crossref Pubmed##CMEN##

[bib36]##AuthST##Mavoa, S.##AuthEN##, ##AuthST##Witten, K.##AuthEN##, ##AuthST##McCreanor, T.##AuthEN##, & ##AuthST##O’Sullivan, D.##AuthEN## (2012). GIS based destination accessibility via public transit and walking in Auckland, New Zealand. *Journal of Transport Geography*, 20(1), 15#inST#–#inEN##dlST#-#dlEN#22. https://doi.org/10.1016/j.jtrangeo.2011.10.001##CMST##Reference Type: journal -- Crossref##CMEN##

[bib37]##AuthST##McHugh, #inST#B#inEN##dlST#Bibiana#dlEN#.##AuthEN## (2013). Pioneering open data standards: The GTFS Story. In ##EdAuthST##Brett##EdAuthEN##. ##EdAuthST##Goldstein, L.##EdAuthEN## ##EdAuthST##Dyson, & A.##EdAuthEN## ##EdAuthST##Nemani##EdAuthEN## (Eds.), “*Beyond transparency: #inST#Open#inEN#*#dlST#open#dlEN# *data and the future of civic* #dlST#innovation.” Beyond transparency: open data and the future of civic innovation.#dlEN###CMST##Reference Type: Edited Book -- Grobid##CMEN####CMST##Please provide missing publisher name and page number for the "McHugh, 2013" references list entry.##CMEN##

[bib38]##AuthST##Modesti, P.##AuthEN##, & ##AuthST##Sciomachen, A.##AuthEN## (1998). A utility measure for finding multiobjective shortest paths in urban multimodal transportation networks. *European Journal of Operational Research*, 111(3), 495#inST#–#inEN##dlST#-#dlEN#508. https://doi.org/10.1016/S0377-2217(97)00376-7##CMST##Reference Type: journal -- Crossref##CMEN##

[bib39]##AuthST##Mondschein, A.##AuthEN##, & ##AuthST##Taylor, B. D.##AuthEN## (2017). Is traffic congestion overrated? Examining the highly variable effects of congestion on travel and accessibility. *Journal of Transport Geography*, 64, 65#inST#–#inEN##dlST#-#dlEN#76. https://doi.org/10.1016/j.jtrangeo.2017.08.007##CMST##Reference Type: journal -- Crossref##CMEN####CMST##Please provide missing issue number for the "Mondschein and Taylor, 2017" references list entry.##CMEN##

[bib40]##AuthST##Mondschein, A.##AuthEN##, ##AuthST##Taylor, B. D.##AuthEN##, ##AuthST##Brumbaugh, S.##AuthEN##, & ##AuthST##Org, E.##AuthEN## (2010). *Congestion and #inST#accessibility: What's#inEN#*#dlST#Accessibility: What’s#dlEN# *the #inST#relationship?#inEN#*#inST#.#inEN##dlST#Relationship?#dlEN# https://escholarship.org/uc/item/8135b0jh##CMST##Reference Type: book -- Grobid##CMEN####CMST##Please provide missing publisher name for the "Mondschein et. al., 2010" references list entry.##CMEN##

[bib41]##AuthST##Morris, J. M.##AuthEN##, ##AuthST##Dumble, P. L.##AuthEN##, & ##AuthST##Wigan, M. R.##AuthEN## (1979). Accessibility indicators for transport planning. *Transportation Research Part #inST#a#inEN#*#dlST#A#dlEN#*: General*, 13(2), 91#inST#–#inEN##dlST#-#dlEN#109. https://doi.org/10.1016/0191-2607(79)90012-8##CMST##Reference Type: journal -- Crossref##CMEN##

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[bib43]##AuthST##Owen, A.##AuthEN##, & ##AuthST##Levinson, D. M.##AuthEN## (2015). Modeling the commute mode share of transit using continuous accessibility to jobs. *Transportation Research Part #inST#a#inEN#*#dlST#A#dlEN#*: Policy and Practice*, 74, 110#inST#–#inEN##dlST#-#dlEN#122. https://doi.org/10.1016/j.tra.2015.02.002##CMST##Reference Type: journal -- Crossref##CMEN####CMST##Please provide missing issue number for the "Owen and Levinson, 2015" references list entry.##CMEN##

[bib44]##AuthST##Páez, A.##AuthEN##, ##AuthST###inST#Gertes #inEN#Mercado, R#dlST#. G#dlEN#.##AuthEN##, ##AuthST##Farber, S.##AuthEN##, ##AuthST##Morency, C.##AuthEN##, & ##AuthST##Roorda, M.##AuthEN## (2010). Relative accessibility deprivation indicators for urban settings: Definitions and application to food deserts in #inST#Montreal#inEN##dlST#montreal#dlEN#. *Urban Studies*, 47(7), 1415#inST#–#inEN##dlST#-#dlEN#1438. https://doi.org/10.1177/0042098009353626##CMST##Reference Type: journal -- Crossref##CMEN##

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[bib46]##AuthST##Polzin, S. E.##AuthEN##, ##AuthST##Pendyala, R. M.##AuthEN##, & ##AuthST##Navari, S.##AuthEN## (2002). Development of Time-of-Day#inST#–#inEN##dlST#-#dlEN#Based #inST#transit accessibility analysis tool#inEN##inST#.#inEN##dlST#Transit Accessibility Analysis Tool.#dlEN# *Transportation Research Record: Journal of the Transportation Research Board*, 1799(1), 35#inST#–#inEN##dlST#-#dlEN#41. https://doi.org/10.3141/1799-05##CMST##Reference Type: journal -- Crossref##CMEN##

[bib47]##AuthST##Prommaharaj, P.##AuthEN##, ##AuthST##Phithakkitnukoon, S.##AuthEN##, ##AuthST##Demissie, M. G.##AuthEN##, ##AuthST##Kattan, L.##AuthEN##, & ##AuthST##Ratti, C.##AuthEN## (2020). Visualizing public transit system operation with GTFS data: A case study of Calgary, Canada. *Heliyon*, 6(4#inST#), #inEN##inST#e03729#inEN##inST#.#inEN##dlST#).#dlEN# https://doi.org/10.1016/j.heliyon.2020.e03729##CMST##Reference Type: journal -- Pubmed Crossref##CMEN##

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[bib49]##AuthST##Schrank, D.##AuthEN## (2012). *#inST#TTI's#inEN#*#dlST#TTI’s#dlEN# *2012 #inST#urban mobility report powered#inEN#*#dlST#Urban Mobility Report Powered#dlEN# *by INRIX #inST#traffic data#inEN#*#dlST#Traffic Data#dlEN#. http://mobility.tamu.edu##CMST##Reference Type: book -- Grobid##CMEN####CMST##Please provide missing publisher name for the "Schrank, 2012" references list entry.##CMEN##

[bib50]##AuthST##Schuurman, N.##AuthEN##, ##AuthST##Fiedler, R. S.##AuthEN##, ##AuthST##Grzybowski, S. C#dlST#. W#dlEN#.##AuthEN##, & ##AuthST##Grund, D.##AuthEN## (2006). #dlST#Defining rational hospital catchments for non-urban areas based on travel-time. #dlEN#*International Journal of Health Geographics*, 5#inST#(#inEN##inST#1#inEN##inST#), #inEN##inST#43#inEN#. https://doi.org/10.1186/1476-072X-5-43##CMST##Reference Type: journal -- Crossref##CMEN####CMST##Please provide missing article title for the "Schuurman et. al., 2006" references list entry.##CMEN##

[bib51]##AuthST##Shah, J.##AuthEN##, & ##AuthST##Adhvaryu, B.##AuthEN## ##InstAuthST###inST#Transport Planning Consultant, India#inEN##inST#, & #inEN###InstAuthST###inST#CEPT University#inEN##inST#. #inEN###InstAuthEN####InstAuthEN##(2016). Public #inST#transport accessibility#inEN##dlST#Transport Accessibility#dlEN# Levels for Ahmedabad, India. *Journal of Public Transportation*, 19(3), 19#inST#–#inEN##dlST#-#dlEN#35. https://doi.org/10.5038/2375-0901.19.3.2##CMST##Reference Type: journal -- Crossref##CMEN##

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[bib57]##AuthST##Wu, B. M.##AuthEN##, & ##AuthST##Hine, J. P.##AuthEN## (2003). A PTAL approach to measuring changes in bus service accessibility. *Transport Policy*, 10(4), 307#inST#–#inEN##dlST#-#dlEN#320. https://doi.org/10.1016/S0967-070X(03)00053-2##CMST##Reference Type: journal -- Crossref##CMEN##

[bib58]##AuthST##Zhang, J.##AuthEN##, ##AuthST##Liao, F.##AuthEN##, ##AuthST##Arentze, T.##AuthEN##, & ##AuthST##Timmermans, H.##AuthEN## (2011). A multimodal transport network model for advanced traveler information systems. *Procedia -#inST# #inEN#Social and Behavioral Sciences*, 20, 313#inST#–#inEN##dlST#-#dlEN#322. https://doi.org/10.1016/j.sbspro.2011.08.037##CMST##Reference Type: journal -- Crossref##CMEN####CMST##Please provide missing issue number for the "Zhang et. al., 2011" references list entry.##CMEN##

[bib59]##AuthST##Zhang, Y.##AuthEN##, ##AuthST##Li, Y.##AuthEN##, ##AuthST##Zhou, X.##AuthEN##, ##AuthST##Luo, J.##AuthEN##, & ##AuthST##Zhang, Z. L.##AuthEN## (2022). Urban #inST#traffic dynamics#inEN##dlST#Traffic Dynamics#dlEN# Prediction#inST#—#inEN##dlST# -#dlEN#A #inST#continuous spatial#inEN##dlST#Continuous Spatial#dlEN#-temporal Meta-learning #inST#approach#inEN##dlST#Approach#dlEN#. *ACM Transactions on Intelligent Systems and Technology*, 13(2#inST#), #inEN##inST#1#inEN##inST#–#inEN##inST#19#inEN##inST#.#inEN##dlST#).#dlEN# https://doi.org/10.1145/3474837##CMST##Reference Type: journal -- Crossref##CMEN##

[bib60]##AuthST##Zhao, F.##AuthEN##, ##AuthST##Chow, L#inST#.#inEN##inST# #inEN##dlST#.-#dlEN#F.##AuthEN##, ##AuthST##Li, M#inST#.#inEN##inST# #inEN##dlST#.-#dlEN#T.##AuthEN##, ##AuthST##Ubaka, I.##AuthEN##, & ##AuthST##Gan, A.##AuthEN## (2003). Forecasting #inST#transit walk accessibility#inEN##dlST#Transit Walk Accessibility#dlEN#: Regression #inST#model alternative#inEN##dlST#Model Alternative#dlEN# to #inST#buffer method#inEN##inST#.#inEN##dlST#Buffer Method.#dlEN# *Transportation Research Record: Journal of the Transportation Research Board*, 1835(1), 34#inST#–#inEN##dlST#-#dlEN#41. https://doi.org/10.3141/1835-05##CMST##Reference Type: journal -- Crossref##CMEN##

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