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Evaluation of accessibility disparities in urban areas during disruptive events based on transit real data

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ABSTRACT

The main motivation of this paper is to emphasize the necessity of assessing the actual performance of public transportation (PT), rather than relying on schedules, when assessing accessibility and equity in the provision of PT services. Real conditions are reflected in datasets such as the outcomes of Automatic Vehicle Monitoring (AVM) systems, whereas schedules are usually provided as General Transit Feed Specification (GTFS). In light of the dissimilar characteristics of central and peripheral neighborhoods, it is crucial to consider the operational conditions that users encounter, particularly in the context of unexpected disruptions that alter regular service. By examining a real-world case study in Bologna, Italy, the research combines well-known measures and innovative methods and demonstrates notable variation in accessibility and equity in the provision of PT services when comparing results based on real-time data with those based on schedules. This work contributes to a more nuanced understanding of urban accessibility and highlights the need for public stakeholders and transport authorities to incorporate actual service conditions into their evaluations.

1. Introduction

Accessibility is a pivotal factor in several disciplines, as it reflects the convenience with which individuals can reach locations of interest, including public facilities, employment sites, and commercial areas. In general, the common practice is to refer to accessibility as the potential of opportunities for interaction (Hansen, 1959) or the ease with which any activity can be reached from a location (Dalvi and Martin, 1976). Debates on accessibility have given rise to a comprehensive discussion of the appropriate methodology and metric (Klar et al., 2023; Wang and Loo, 2024). In addition to accessibility, equity represents another concept worthy of attention within the domain of transportation planning and operations (Conway and Stewart, 2019; Lucas et al., 2016; Tabascio et al., 2024). Equity entails ethical considerations (van Wee et al., 2011) and the necessity for decision–making, given the imperative task of finding and implementing a balance between the competing demands of various users (Ramjerdi, 2006). This issue intensifies when a large proportion of the population has limited access to private vehicles or poor public transportation (PT) services, and this phenomenon has been observed in several countries with different socioeconomic backgrounds (Pinto et al., 2023).

In light of the significant role of PT in the modal share, the assessments of accessibility enabled by PT and equity in PT provision are critically important. These evaluations have improved in recent years, eased by the use of several systems, such as the Automatic Vehicle Monitoring (AVM) sensors or the General Transit Feed Specification (GTFS) datasets. These data sources frequently inform evaluations of PT agencies, particularly when discrepancies between scheduled and actual services are identified over an extended period. In fact, PT agencies are in charge of monitoring the evolution of PT service over time and implementing measures that enhance its attractiveness. In this context, unexpected events, regardless of their different origins (Mo et al., 2022; Papilloud and Keiler, 2021; Tao et al., 2018), may have considerable impacts on schedules, resulting in delays that vary depending on the magnitude of the event. Consequently, when viewed in a broader context, the discrepancies between planned and actual travel times (Braga et al., 2023) have the potential to distort effective and perceived accessibility, thereby impacting equity in transit provision (Carleton and

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Porter, 2018). This can ultimately contribute to the increase in social and economic disparities across neighborhoods and populations (Basso et al., 2020), which in turn may lead to a reduction in the attractiveness of PT.

Notably, it is crucial to consider the conditions that users experience during the use of PT, particularly in the context of unexpected disruptions that alter regular service. On the basis of these premises, the object of this research is intended to quantify the discrepancies in the accessibility and equity of PT provision by comparing actual (i.e., real data from AVM) and planned or scheduled (i.e., GTFS only) scenarios in the context of long-term disruptions affecting PT services in urban areas. As a case study, prolonged closure on a main urban road in Bologna, Italy, was taken into account. For the proposed methodology, the delays registered by the AVM sensors were incorporated into the original GTFS dataset, creating an 'adherent–to–reality GTFS' or, following the definition of Lee and Qian (2024), 'retrospective GTFS', where the timetables corresponded to actual times registered by the AVM sensors rather than the a priori defined schedules. Public facilities such as healthcare, schools, and universities have been considered opportunities in computations at different travel time thresholds. From a policy standpoint, the rationale behind this methodology is to provide an effective case study that can be replicated to assess the impact of significant disruptive events. This is facilitated by the use of well-known techniques such as the Gini coefficient (Gini, 1912) and Moran *I* (Shekhar et al., 2017) and standardized data sources, namely, the GTFS and AVM, thus enabling PT agencies and public authorities to develop effective recovery strategies in the event of long-term changes that affect regular services. The rest of the paper is organized as follows: Section 2 provides a review of the background and related works. Section 3 describes the materials and methods employed in the research, while Section 4 delves into the results and the related discussion. Conclusions and possible future developments are presented in Section 5.

2. Theoretical background

Accessibility has gained recognition as a valuable metric for evaluating the benefits associated with transportation and land use systems (Boisjoly and El-Geneidy, 2017; Braga et al., 2023; Condeço-Melhorado, 2021; Salih and Lee, 2022), and it is related to the space–time prism model (Qin and Liao, 2022). Despite the absence of a comprehensive definition (Handy, 2005) and heterogeneity across countries (Handy, 2020) in the concretization of the concept, discussions about accessibility have been conducted with assiduity since the seminal work of Hansen (1959) and have involved several disciplines, including transportation (Cascetta et al., 2016; Conway et al., 2018; Geurs and van Eck, 2001) and urban planning (Levine et al., 2012). Geurs and van Wee (2004) identified four components that influence accessibility, i.e., the individual, the land-use, the transportation, and the temporal components (Lucas et al., 2016). These factors are recognized as the main drivers in defining accessibility, and an interdependency between them has been acknowledged (van Wee et al., 2011). For example, the accessibility for some social groups (individual component) can be constrained by external factors such as the lack of a private car, the significant distance between the job location and the residence (land-use component) or the lack of adequate PT service (transportation component) at some hours (temporal component).

In addition to the theoretical approach, a more practical evaluation of accessibility can be addressed in accordance with the measures that can be used in accounting for it, and each of them should ideally take all the aforementioned components into account (Geurs and van Wee, 2004). Among them, cumulative opportunities and gravity-based models have been widely used (Tomasiello et al., 2023). The former is intended to be the sum of opportunities reachable within a given travel time or distance (Geurs and van Eck, 2001; Lee and Qian, 2024; Verduzco Torres and McArthur, 2024), whereas the latter introduces a decay function, which implies that the greater the distance (i.e., the farther the facility), the lower the accessibility to that opportunity. The strengths and weaknesses of the two methods have been discussed and compared elsewhere (Kapatsila et al., 2023; Siddiq and Taylor, 2021), and the derived accessibility has been compared with divergent results (Kapatsila et al., 2023; Klar et al., 2023; Santana Palacios and El-geneidy, 2022). In general, calculation based on cumulative opportunities has been acknowledged as an easy and straightforward method, whereas gravity models are able to account for accessibility more realistically, even if it is more difficult to use in practice (Klar et al., 2023).

In addition to accessibility, equity represents a pivotal topic in transportation matters. Equity is related to social justice and fairness (Kitchin and Thrift, 2009), and it is closely related to accessibility, as it concerns the manner in which it is distributed across the population (Martens, 2021). Equity can be defined as either horizontal, whereby individuals or groups are provided with the same transport supply, or vertical, which recognizes the need for an enhanced supply in favor of disadvantaged people (Zhou et al., 2018). Among several measures (Ramjerdi, 2006), the Gini coefficient or index (Gini, 1912) is one of the most employed techniques. The application of the Gini coefficient, which can be ascribed among horizontal equity measures (Zhou et al., 2018), can be found in several fields (Sitthiyot and Holasut, 2020), especially in urban studies (Neutens et al., 2010) and transportation research (Delbosc and Currie, 2011; Qin and Liao, 2022). In this latter domain, the Gini coefficient has been employed mainly to determine and quantify the level of (in)equity of a given resource, e.g., the PT supply in urban areas (Hörcher and Graham, 2021; Jang et al., 2017; Raza et al., 2023; Stępniak and Goliszek, 2016), walking accessibility (Tiznado-Aitken et al., 2018; Vale and Lopes, 2023), accessibility to healthcare facilities (Gu et al., 2023), high-speed rail supply in relation to income disparity (Di Matteo and Cardinale, 2023), or tourism seasonality (Boto-García and Pérez, 2023).

The advent of the 'Big Data era' in transportation analyses (Nalin et al., 2024b, 2024c; Ulrich et al., 2023; Zia et al., 2022) and the growing efficiency of simulation software and Geographic Information System (GIS), have improved the assessment of accessibility and equity (Montero-Lamas et al., 2023; Moya-Gómez et al., 2018; Park and Goldberg, 2021). Information such as the number of facilities (i.e., potential destinations) or scheduled public transportation (PT) services can now be accessed and measured with greater ease (Stępniak et al., 2019), and the combined use of disparate data sources can enhance the predictability of demand behaviors (Peled et al., 2021; Zhong et al., 2023). The wide-ranging term 'Big Data' (Chen et al., 2014) is used here to refer to specific terms, such as AVM and GTFS (Google, 2024). AVM sensors are installed on the PT fleet and collect real-time spatiotemporal information for the purposes of fleet management and monitoring service performance (e.g., delays and average speed) (Moreira-Matias et al., 2015). The GTFS was introduced in 2006 by Google as a complementary service to Google Maps (Hadas, 2013); it is currently the standard for PT operators and, by extension, for users. It is adopted by most PT agencies for the collection and distribution of service characteristics, status and, in the case of the GTFS, real-time, updated information about the service. As a consequence, from the users' perspective, the GTFS provides the status of PT services, enabling the evaluation of alternative routes. Moreover, the implementation of the GTFS has been recognized as a key factor in facilitating the communication of PT features and characteristics (Prommaharaj et al., 2020) and as a pivotal tool in improving reliability and accessibility analysis (Lee and Qian, 2024). Along with users' needs, the proliferation of the GTFS has enabled academia and practitioners to produce a plethora of accessibility assessments (Conway et al., 2017; Lee and Qian, 2024). In addition, the GTFS data framework allows researchers to investigate several topics related to accessibility with a level of accuracy and scale that would have been unreachable prior to its advent (Park et al., 2020; Wessel et al., 2017).

A review of the literature reveals that accessibility and equity are topics that have been widely analyzed with different sources, including some typologies of Big Data, such as AVM and GTFS. As transit is a universal service in several countries (Nalin et al., 2024a), it should be updated and attractive, especially when major disruptions occur. Nevertheless, to the best of the authors' knowledge, previous research efforts have not focused on the evaluation of variations in accessibility and equity when regular PT service is affected by longstanding disruptions. With regard to the latter, the authors consider this topic to be of paramount importance, as the management of PT requires quick and effective measures to be adequately implemented. In particular, PT agencies typically adapt and adjust schedules with the aim of balancing users' requests and organizational needs (e.g., crew rotation, fleet maintenance), taking into account potential changes in routes. Consequently, they should assess whether the measures are adequate or whether additional changes are needed.

To achieve the objectives of the research, this research combines well-known methodologies, such as the cumulative opportunities measure of accessibility, the Gini coefficient (Ceriani and Verme, 2012; Gini, 1912) and Moran's *I* (Shekhar et al., 2017), to account for the inequality in PT with innovative approaches, including the use of a corrected GTFS dataset improved with AVM data and the use of Rapid Realistic Routing with R5 in R (R5R), an open-source package on a multimodal transport network for the calculation of accessibility measures (Braga et al., 2023; Pereira et al., 2021; Tomasiello et al., 2023; Verduzco Torres and McArthur, 2024). In fact, analyses of accessibility and equity based either on schedules (GTFS) or real-time information only (AVM, GTFS real-time) can lead to erroneous estimates and a misrepresentation of actual travel behaviors (Lee and Qian, 2024). With respect to this latter point, the aim of this study is to contribute to accessibility debates following Basso et al. (2020) and Braga et al. (2023) in the evaluation of scheduled and actual accessibility and inequality. In addition to these motivations, the use of an open-source platform such as R5R and the incorporation of standardized datasets, including AVM and GTFS, are acknowledged as relevant components of this research, thus facilitating the replicability of the proposed methodology and allowing prompt formulation of the recovery strategy that has been previously proposed.

3. Materials and methods

3.1. Context description

The proposed methodology was tested in Bologna, Italy. The city is located in the Po valley, immediately north of the Apennine Mountains, and serves as the administrative capital of the Emilia–Romagna region. With a population of approximately 390,000 inhabitants, Bologna is among the 10 most populated Italian cities. The road closure introduced in Section 1 is located in the center of Bologna, Italy, and it is specifically related to San Vitale (Fig. 1). The closure was imposed on October 31, 2023 and was necessitated by imperative rehabilitation works to Garisenda Tower, one of the most prominent Bolognese historical landmarks and tourist attractions. At the time of this writing, the closure and deviations are still in effect and are expected to persist in the near future (Comune di Bologna, 2024b). As a consequence of the construction work, several open spaces and roads in the vicinity of the site were temporarily closed, necessitating the diversion of regular bus lines from San Vitale. Notably, the majority of the trunk lines of the Bolognese bus network were affected by this disruption, resulting in longer routes with increased travel distances and time spent onboard. Furthermore, given that the new routes diverged to a road with promiscuous traffic, massive delays and bus bunching were expected.

To achieve homogeneous and comparable results and in accordance with the method proposed in Basso et al. (2020), Tomasiello et al. (2023), and Vergel-Tovar et al. (2022), a regular tessellation method based on a hexagonal grid (distance between hexagon centroids: 400 m) was created in a GIS environment and adopted as a spatial unit. With respect to the population density reported in Fig. 2, there is considerable variation across the city, with the majority of the population concentrated in the plain areas. The PT network, made up of regular urban and interurban bus and trolleybus lines, is operated by TPER SpA (TPER SpA, 2024) and is outlined in Fig. 2 with respect to both the density of bus stops and lines at the hexagon level. The network is denser in the most populated areas, whereas some peripheral areas are supplied by low-frequency lines or demand-responsive transit (DRT). Therefore, to avoid biases related to the inhomogeneous level of service, some of the peripheral hexagons not served by regular PT services were excluded. However, since the adopted procedures are intended to be scalable and easily replicable, the authors argue that further implementation should also consider the discarded areas.

With respect to opportunity, schools, university facilities, and healthcare facilities, were selected. Their locations were extracted from the official open data portal of the municipality (Comune di Bologna, 2024a) and are plotted in Fig. 3. The selection of these three facilities is supported by several justifications. Indeed, education and healthcare are

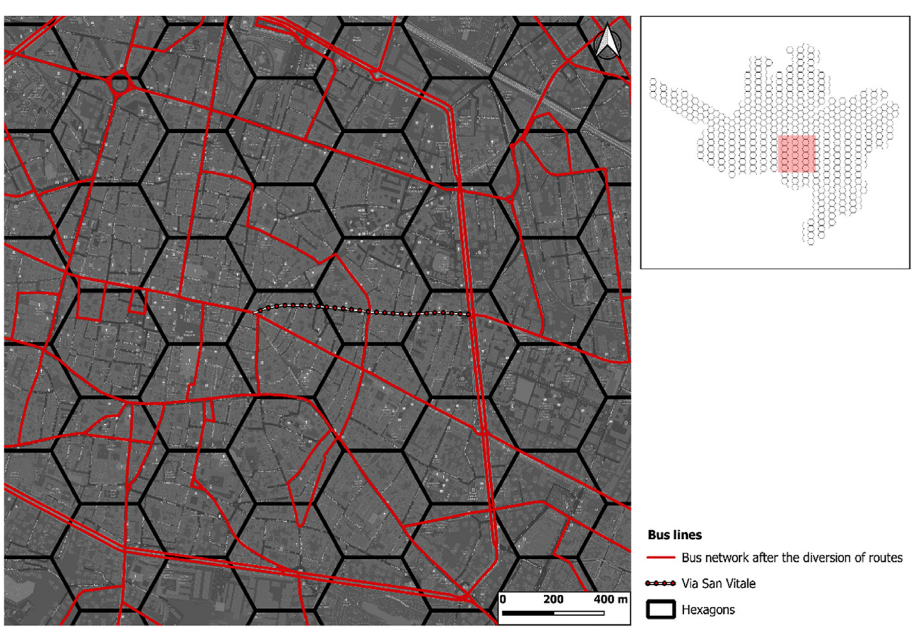

Fig. 1. Location via San Vitale.

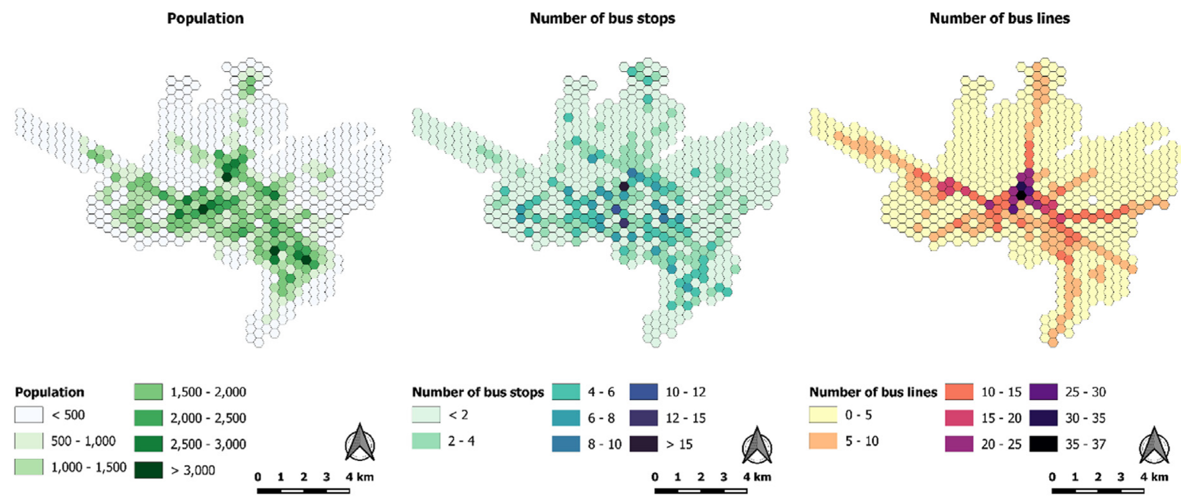

Fig. 2. Population density and PT coverage. Own elaboration on the basis of Comune di Bologna (2024a) and TPER SpA (2023).

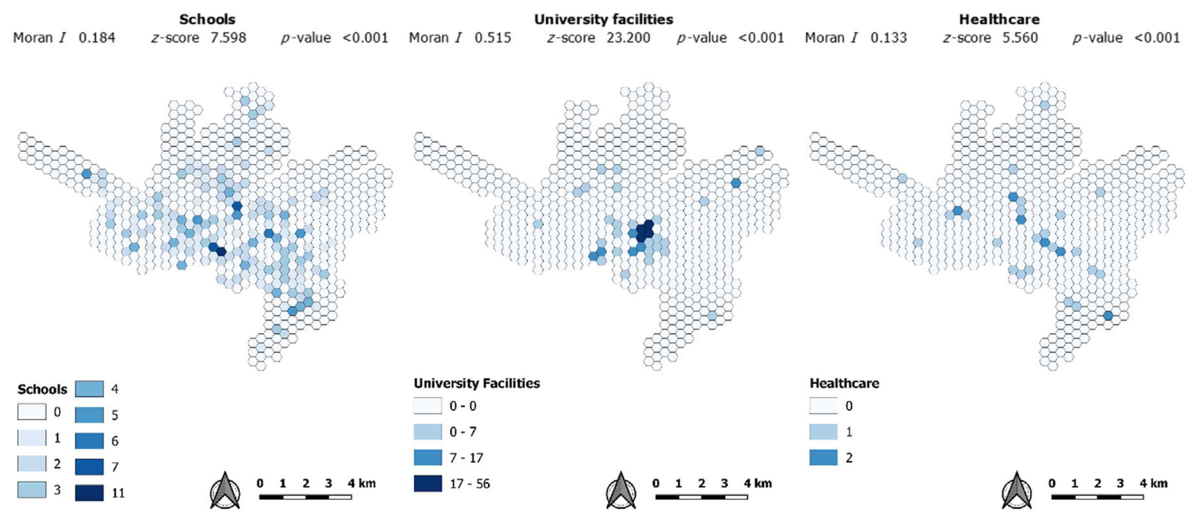

Fig. 3. Number of opportunities per hexagon and statistics about the distribution of opportunities. Own elaboration is based on Comune di Bologna (2024a).

services that should meet the essential needs of residents (Iamtrakul et al., 2024) and represent two of the main trip purposes (Bittencourt and Giannotti, 2023), particularly for user categories such as students and the older population, who often lack private vehicles or rely on public transport for their daily journeys (Beirão and Sarsfield Cabral, 2007). Furthermore, accessibility to these major facilities can influence human behavior (Bittencourt and Giannotti, 2023). Therefore, the analysis of travel time and the number of reachable opportunities within different time windows (Verduzco Torres and McArthur, 2024) is highly important in evaluating public and private decisions, as the considered facilities are typically used by all social groups. In addition to the graphic representation, Moran's I was calculated. This indicator is employed to quantify spatial autocorrelation and detect the presence of clusters, as it estimates the strength of interdependence between observations of the variable of interest in relation to the distance. Given its characteristics, the inclusion of Moran's I in this methodology was intended to facilitate the detection of patterns of homogeneity in the distribution of the phenomena under analysis. It is computed as Eq. (1):

$$I = \frac{\sum_i \sum_{j \neq i} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_i \sum_{j \neq i} w_{ij}} \tag{1}$$

$$S^2 = \frac{1}{n} \sum_i (x_i - \overline{x})^2 \tag{2}$$

where I is the Moran index, x_i denotes the observed value at location i, $\overline{x}$ is the mean of the x variable over the n locations, and w_{ij} is the element of the spatial weights matrix for locations i and j, defined as 1 if location i is contiguous to location j and 0 otherwise (Shekhar et al., 2017). It ranges from −1 to 1, where the null hypothesis is a random distribution, positive and statistically significant values indicate that the distribution tends to be clustered, and negative and statistically significant values indicate that the distribution tends to be dispersed. As illustrated by the maps and the Moran I values, the selected opportunities have different spatial distributions. Schools and healthcare facilities are widespread across the city, since the data concerning the former comprises elementary, middle, and high schools, whereas healthcare comprises public and private hospitals and clinics. With respect to the facilities, aulas, administrative offices, and collateral facilities (e.g., libraries, museums, and canteens) have been taken into account. In fact, Bologna is a well-known university city with a consistent number of students (>80,000 enrolled) and personnel whose mobility behaviors have already investigated (Battistini et al., 2022a, 2022b; De Angelis et al., 2021). Most of the locations are located within the city center, in the so-called "University area" (dark blue hotspot in Fig. 3 – "University Facilities").

3.2. Overview of the Gini index and the opportunity formulation

As previously described, this research is based on the Gini index or coefficient, a well-known method introduced in the early 1900s (Ceriani and Verme, 2012; Gini, 1912) that is able to synthetically account for inequalities. It is based on the Lorenz curve plotted in Fig. 4, which graphically represents the disparity in the distribution of a given resource across a population. The 45-degree line represents the perfectly equitable distribution of the resource (Y-axis) across a given population (X-axis) and should be considered a theoretical scenario only (Delbosc and Currie, 2011), whereas any line below this reference represents an inequitable distribution.

In its easiest formulation, the Gini coefficient G can be reported by Eq. (3):

$$G_1 = 1 - \sum_{k=1}^{n} (X_k - X_{k-1})(Y_k - Y_{k-1}) \tag{3}$$

where X_k is the cumulative proportion of the population variable, for $k = 0, \dots, n$, with $X_0 = 0$, $X_n = 1$, and Y_k is the cumulative proportion of the analyzed variable, for $k = 0, \dots, n$, with $Y_0 = 0$, $Y_n = 1$ (Delbosc and Currie, 2011). When the Gini coefficient is used, the perfectly equal distribution is equal to 0, whereas the perfectly unequal distribution is equal to 1 (Rey and Smith, 2013). Any other scenario falls within the 0–1 interval, where the closer the value is to 1, the higher the inequality. According to Jang et al. (2017), Gini coefficients $<$0.20 denote low inequality, whereas values between 0.20 and 0.50 indicate medium inequality, and values $>$ 0.50 are considered high inequality. The use of the Gini coefficient in the proposed methodology is justified by its main characteristics, i.e., it is scale independent (Lucas et al., 2016). This property is highly important for ensuring that the analysis is not biased by the scale of the data, thus enabling researchers and policymakers to draw valid conclusions about inequality and assess the effectiveness of interventions aimed at reducing disparities. By relying on this feature, the proposed methodology can focus on the relative distribution of resources, thereby providing a clearer picture of inequality dynamics over time or across different parts of a city. Furthermore, the Gini coefficient is able to overcome a major limitation of the Lorenz curve, namely, the latter does not allow for easy spatial comparisons or interpretations of equality within an analysis area (Carleton and Porter, 2018). In this research, the variable of interest is accessibility, here accounting for cumulative opportunity, i.e., the number of facilities that can be reached in a given amount of time, which is defined by Eq. (4):

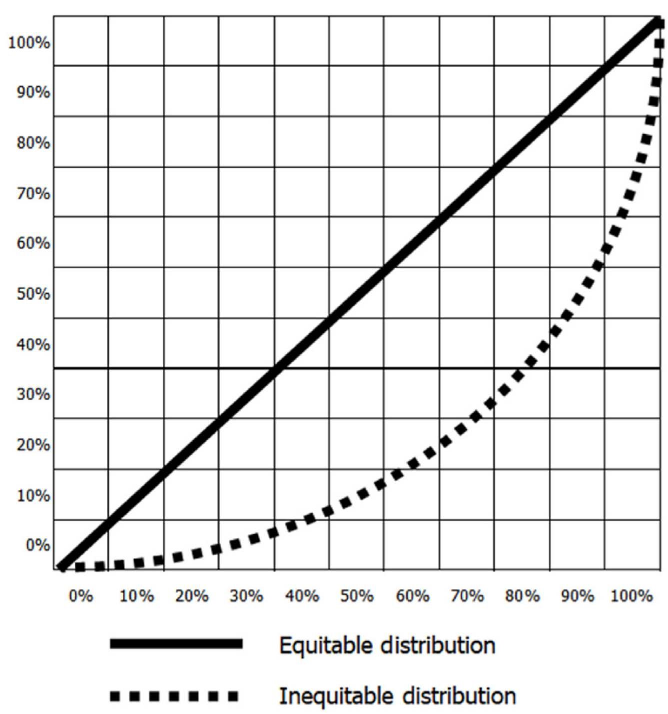

Fig. 4. Lorenz curve.

$$A_i = \sum_{j=1}^{n} O_j f(t_{ij});\ f(t_{ij}) = \begin{cases} 1 \text{ if } t_{ij} \leq T \\ 0 \text{ otherwhise} \end{cases} \tag{4}$$

where A_i is the accessibility at origin i, O_j is the number of opportunities at destination j, t_{ij} is the travel time from i to j and $f(t_{ij})$ is an indicator function for whether destination j is reachable within the time threshold T (Lee and Qian, 2024). In this research, the computation of O_j was carried out primarily on each opportunity, i.e., schools, university facilities, and healthcare, as described in Section 3.1. The output of the computation is hence related to the number of opportunities reachable from each hexagon i to each hexagon j at different time cutoffs, as described in Section 3.4.

3.3. GTFS and AVM data

Following what has been introduced in Section 1, GTFS datasets represent a valuable source for studying PT characteristics with associated geographical information (GTFS static) on the basis of the use of global positioning systems (GPSs) and real-time status (GTFS real-time). Given their main features (Hadas, 2013; Prommaharaj et al., 2020; Wessel et al., 2017; Wu et al., 2023), this research focuses on the GTFS static datasets. A GTFS feed is composed of several.txt files. Each file models a particular aspect of transit information, such as the locations of stops, the characteristics of routes and trips, and information about schedules. The main features of each file, as well as the additional and optional files, are available at Google (2024). The description of the main.txt files is reported in Table 1, whereas the general framework of the GTFS dataset and the relationships among files are outlined in Fig. 5.

In addition to the GTFS data, AVM data have been employed. AVM data are based on the automatic and continuous collection of information about vehicle location and performance with the objective of monitoring transit services. The high spatial and temporal resolution of AVMs can reduce the uncertainty in the operation and assessment of PT services

Table 1
Description of the main GTFS files.

File	Attribute	Description
agency.txt	agency_id, agency_name, agency_url, agency_timezone, agency_lang, agency_phone	Information about the PT agency
calendar.txt or calendar_dates.txt	service_id, date, exception_type	Information about the days when the service is scheduled
routes.txt	route_id, agency_id, route_short_name, route_long_name, route_type, route_color, route_text_color	Information about the lines and the routes
shapes.txt	shape_id, shape_pt_lat, shape_pt_lon, shape_pt_sequence	Information about the geographical location of the graphical element, e.g., to draw it in a GIS-like environment
stop_times.txt	trip_id, arrival_time, departure_time, stop_id, stop_sequence	Information about the schedules of each trip and service
stops.txt	stop_id, stop_name, stop_lat, stop_lon, location_type, parent_station	Information about the location and the characteristics of each stop
trips.txt	route_id, service_id, trip_id, trip_headsign, direction_id, shape_id	Information about trips and their routes. A trip is a sequence of two or more stops that occurs at specific time

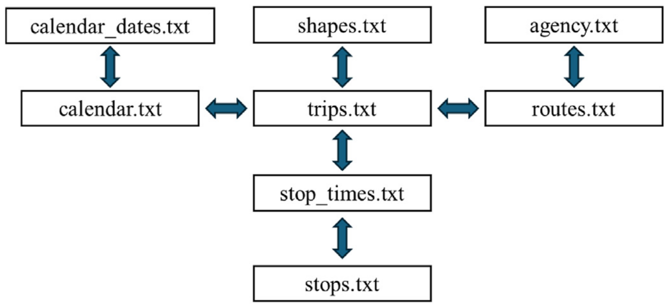

Fig. 5. GTFS general framework. Own elaboration.

(Ibarra-Rojas et al., 2015). With respect to the Bolognese fleet, AVM devices have been installed on the fleet since the early 2000s (TPER SpA, 2023a). As a consequence of the significant disruptions to the regular service introduced in Section 3, several GTFS datasets have been created and made available as open data (TPER SpA, 2023b). The main changes in services consisted of two phases and were put into operation every two weeks (27 November and 4 December, 2023). Consequently, distinct GTFS datasets have been created and employed in the analysis. In addition to GTFS, delay data from the AVM system were provided by the PT company and used to create a 'real-time AVM-corrected GTFS', 'adherent-to-reality GTFS' or 'retrospective GTFS' (Lee and Qian, 2024). In this method, the stop_times.txt file was modified in accordance with the actual times registered by the AVM sensors at each bus stop, thus aligning the GTFS data with the real-world operational context. To incorporate the real-time data collected by the AVM sensors into the GTFS framework, a separate GTFS dataset for each day of the study period was generated. The key file modified was stop_times.txt, where the scheduled arrival times were replaced with the actual arrival times recorded by the AVM sensors. For each bus trip, the real-time arrival data from the AVM to the corresponding service and trip IDs in the GTFS dataset were matched. In cases where a bus arrives early at a stop (which is especially common at the first stop of the route), the scheduled departure time was retained, as it was assumed that the bus would wait until its scheduled time to depart. Gaps in the AVM data, such as missing arrival times for specific stops, were addressed through linear interpolation on the basis of the available delay data and the stop sequence. For trips with no AVM data, we assumed a delay of zero. The workflow for updating the GTFS data was implemented in Python via the pandas library (The Pandas Development Team, 2024), supplemented by the gtfs_kit wrapper for handling GTFS data (MRCagney, 2024), and was automated with Snakemake (Mölder et al., 2021) to ensure consistency and reproducibility.

3.4. Accessibility computation

Accessibility analysis in PT requires a combination of spatial data and transit information to estimate how easily individuals can reach key destinations. In this study, three primary datasets were utilized: a hexagonal grid representing the spatial distribution of origins and destinations, as described in Section 3.1; an OpenStreetMap (OSM) layer for the road infrastructure, downloaded from OpenStreetMap (2024); and GTFS datasets (both planned and real-time) to model PT schedules, as described in Section 3.3. The R5R package in R (Conway et al., 2018; Pereira et al., 2021; Saraiva, 2024) was used to calculate the accessibility from each hexagon to every other hexagon within the city, employing the OSM-based road network and PT as the only transport options. This approach was adopted with the objective of modeling the number of opportunities accessible via the most straightforward modal chain and to provide evidence of any variations in accessibility and equity after the route diversion described in Section 3.1. Walking was included to model access and egress legs (Conveyal, 2024), as it is the typical complementary mode in modeling the behavior of PT demand (Kujala et al., 2018). The resulting travel times are idealized, as the routing algorithm of R5 assumes that travelers choose the options that minimize their overall travel time. The procedure was conducted considering early morning peak hours (06:45–08:00). For each O/D pair, a travel time matrix was generated via real-time AVM-corrected GTFS data. The analysis accounted for maximum walking times of up to 15 min.

In consideration of the aforementioned temporal threshold, PT has the potential to be utilized by users with diverse statuses and physical abilities. Factors such as gender, age, and disability have been identified as influencing walking distance in accessing or egressing transit (van Soest et al., 2020). Similarly, the built environment can play a crucial role in either enhancing or reducing walkability (Wang and Cao, 2017). Furthermore, considering the heterogeneous PT coverage illustrated in Fig. 2, some areas (identified as hexagons in Fig. 2) in Bologna require longer access and egress walking times to complete the journey. Consequently, the authors have deliberately opted for a more flexible time threshold, diverging from the conventional, more restrictive values (El-Geneidy et al., 2014; van Soest et al., 2020), with the aim of more accurately modeling the real-world behavior of users.

The cumulative opportunity measure introduced was then applied in different scenarios, accounting for how many destinations were reachable from each hexagon within specified travel time cutoffs (e.g., 15, 30, and 60 min). With respect to the cutoffs, they have been chosen to account for reasonable travel times in urban areas comparable to those in Bologna and in light of solicitation in Stępniak et al. (2019) regarding the particular focus on temporal resolution. In particular, the '15 min' time window has recently become a popular threshold for accounting for facilities reachable at the neighborhood level (Moreno et al., 2021), whereas the '30 min' threshold has been acknowledged as a reasonable travel time, particularly for healthcare facilities (Gu et al., 2023) or jobs (Vale and Lopes, 2023). The '60 min' time window is narrowly equal to the maximum travel time of the longest Bolognese PT lines (TPER SpA, 2024), so it has been considered a valid threshold considering that transfers have been excluded. Moreover, the latter two have been tested elsewhere in accounting accessibility at the urban level (Pinto et al., 2023).

The accessibility measures were calculated for each day of the study period, with the results exported to CSV files for further analysis. A typical output is outlined in Table 2, where real values from the computation R5R have been reported in relation to Hexagon number 23 (latitude of the centroid: 44.53315, longitude of the centroid: 11.24040), the opportunities and the cutoffs. While the absolute value of facilities increases with increasing travel time equal to the cutoff, when the edited GTFS is used, this value typically decreases, reflecting the impacts of actual travel times and bus arrival data. Section 4 details these relationships and values on a city-wide scale.

4. Results and discussion

Sections 4.1 and 4.2 delve into the results. On the basis of the methodology described in Section 3, the Gini coefficients are presented and discussed. The Gini coefficients referring to schools are reported in

Table 2
Sample data from the R5R computation.

Hexagon ID	Opportunity	Cutoff	Number of facilities	
			Non edited GTFS	Edited GTFS
23	School	15	6	7
23	School	30	64	61
23	School	60	300	295
23	University	15	0	0
23	University	30	100	100
23	University	60	334	333
23	Healthcare	15	1	2
23	Healthcare	30	9	9
23	Healthcare	60	31	30

Table 3
Gini coefficients – opportunity: schools.

Week	Cutoff (min)	Gini, non-edited GTFS	Gini, edited GTFS	Δ_{Gini}
27 November–3 December 2023	15	0.673	0.671	−0.002
	30	0.608	0.612	0.004
	60	0.411	0.421	0.010
4–10 December 2023	15	0.672	0.671	−0.001
	30	0.613	0.617	0.004
	60	0.421	0.430	0.009

Table 3, whereas those related to universities and healthcare are reported in Tables 4 and 5, respectively. Tables 3–5 report the Gini coefficients in relation to the set of used data (i.e., edited and non-edited GTFS), the week and the cutoffs (15, 30, and 60 min), and the difference between values, expressed as Δ_{Gini}. In addition, the relative cumulative proportion of accessibility to each opportunity q_i obtained from the calculation of Gini coefficients is plotted in Figs. 6–8, with the aim of facilitating a comparison of the results for each opportunity at the hexagon level, whereas Moran I values for q_i are reported in Tables 9–11. Notably, the authors deliberately avoided the visualization of results with Lorenz curves, given that the differences in values were too small to be adequately represented by plotting the values in graphs similar to what is reported in Fig. 4.

4.1. Gini coefficients

In general, the values related to edited GTFS are generally greater than those related to the non-edited GTFS. The results are homogeneous across all three opportunities, indicating that the proposed methodology is effective in identifying differences between scheduled and real data in terms of accessibility, although the computations exclusively consider the PT mode during the morning peak hours. In this context, the results are aligned with those of Basso et al. (2020), Lee and Qian (2024), and Wessel et al. (2017) in relation to the role of this typology of Big Data in this research field. Furthermore, the application of the Gini coefficient and the introduction of multiple cutoffs represent a partial solution to the issue of relying on a single indicator for evaluating results, as highlighted by Lucas et al. (2016). Additionally, the criticism of the cumulative opportunity method discussed in Giannotti et al. (2022) and Klar et al. (2023) is addressed by computing comparisons across different opportunities and time windows and standardized values.

The wider ranges between the highest and lowest Gini coefficients are reported for University (Table 4), which is consistent with the Moran I values (Fig. 3), given that the location of university facilities is more clustered than the other opportunities are. None of the Gini coefficients are below 0.2 (Jang et al., 2017), which suggests that, despite the analysis being based on different cutoff times, several parts of Bologna lack an adequate PT supply or cannot be reached in a 60-min trip without transfers. In addition to these general observations, the authors acknowledge the results as a noteworthy contribution to the literature on the comparison of GTFS and real data in accessibility assessment. The differences among the results, here defined as Δ_{Gini}, are $\leq 1\%$, indicating that the accessibility based on scheduled services has been moderately overestimated. Nevertheless, the degree of overestimation is less

Table 4
Gini coefficients – opportunity: university.

Week	Cutoff (min)	Gini, non-edited GTFS	Gini, edited GTFS	Δ_{Gini}
27 November–3 December 2023	15	0.931	0.931	0.000
	30	0.705	0.714	0.009
	60	0.371	0.376	0.005
4–10 December 2023	15	0.930	0.932	0.002
	30	0.713	0.719	0.006
	60	0.378	0.385	0.007

Table 5
Gini coefficients – opportunity: healthcare.

Week	Cutoff (min)	Gini, non-edited GTFS	Gini, edited GTFS	Δ_{Gini}
27 November–3 December 2023	15 min	0.804	0.807	0.003
	30	0.632	0.504[a]	−0.128[a]
	60	0.401	0.409	0.008
4–10 December 2023	15	0.806	0.808	0.002
	30	0.639	0.642	0.003
	60	0.410	0.419	0.009

[a] Due to an issue affecting the combination of GTFS and AVM data, this computation is considered by authors as an outlier.

pronounced than that observed in Braga et al. (2023). This can be attributed to the methodology employed by TPER SpA in the development of GTFS, namely, the utilization of a conservative schedule to minimize delays (Braga et al., 2023). Furthermore, it is noteworthy that Gini coefficients exceeding 0.5 at cutoffs below 60 min may indicate a lack of homogeneity in the provision of PT services across the city. Indeed, the Bolognese bus network comprises a number of trunk lines and several supplementary lines with a reduced scheduled service in terms of frequency (TPER SpA, 2023b, 2024). Consequently, it may be assumed that some neighborhoods are proportionately better served in terms of the number of lines and scheduled services than others are. Regarding the Gini coefficients in relation to each opportunity, it is notable that the accessibility in relation to schools at cutoff = 15 min is greater with the edited GTFS, as indicated by the lower Gini coefficients. Conversely, as the cutoff increases, the discrepancies between the edited and nonedited GTFS computations are observed to be greater on a global scale. As the computation considers only the PT mode during the morning peak hours, it can be concluded that students residing in proximity to their educational institutions are adequately served by the PT service. In light of the observed fluctuations across the weeks, particularly with regard to the assessment of accessibility in relation to the incidence of disruptions, a diachronic analysis of the coefficients presented in Tables 3 and 4, Table 5 is deemed relevant. As previously stated, the PT company was compelled to implement significant variations to the service, resulting in the alteration of numerous schedules and the diversion of multiple lines from the original route. With regard to the results, there is a slight, though notable, change in the majority of the Gini coefficients. Notably, the nonedited GTFS values at the cutoff = 15 min increased for healthcare, whereas a decrease was observed for schools and universities. Conversely, all values increased at cutoffs = 30 min and cutoff = 60 min. As a result, it can be posited that the ease of reaching more opportunities decreased for longer trips, even if the accessibility increased. Although this result was somewhat predictable, given that the new routes diverged from the city center, where several facilities are located (Fig. 3), the reduction in the Gini coefficient for shorter trips is a noteworthy result that suggests additional and more comprehensive investigations. Computations based on edited GTFS indicate that accessibility is generally lower following changes to schedules and routes, resulting in decreased accessibility. With respect to the variation in Δ_{Gini}, despite the aforementioned trends and results, it is possible to identify meaningful differences, given that the authors interpret this as evidence that, despite the overall reduction in accessibility, the revised PT service was generally able to meet the demand. It thus follows that the PT company is required to implement a rapid and effective recovery strategy.

4.2. Relative cumulative proportion of accessibility q_i

This supplementary analysis was conducted to facilitate a disaggregate examination, specifically at the hexagon level. While the Gini coefficient is an aggregated measure, the focus on q_i enables a comprehensive and detailed analysis, thus identifying variations in accessibility and equity in PT provision that may be overlooked by the

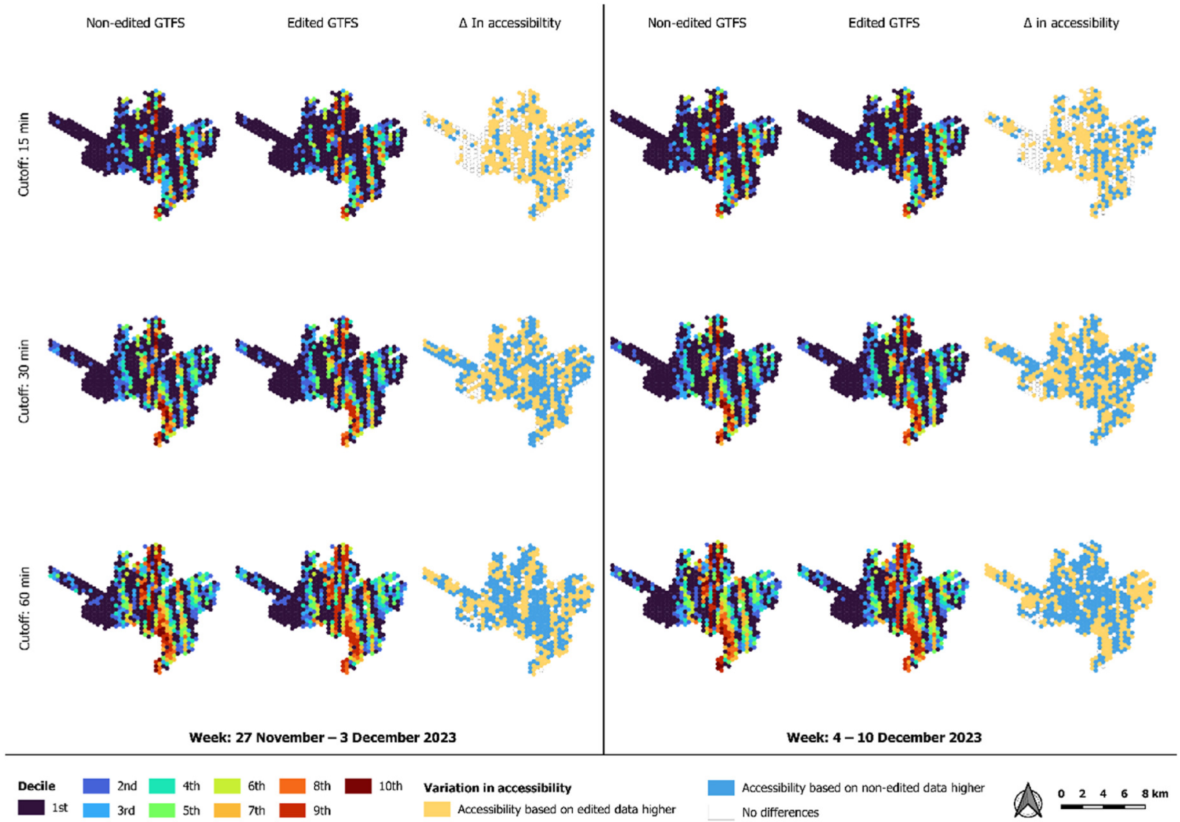

Fig. 6. Relative cumulative proportion of accessibility q_i – opportunity: schools.

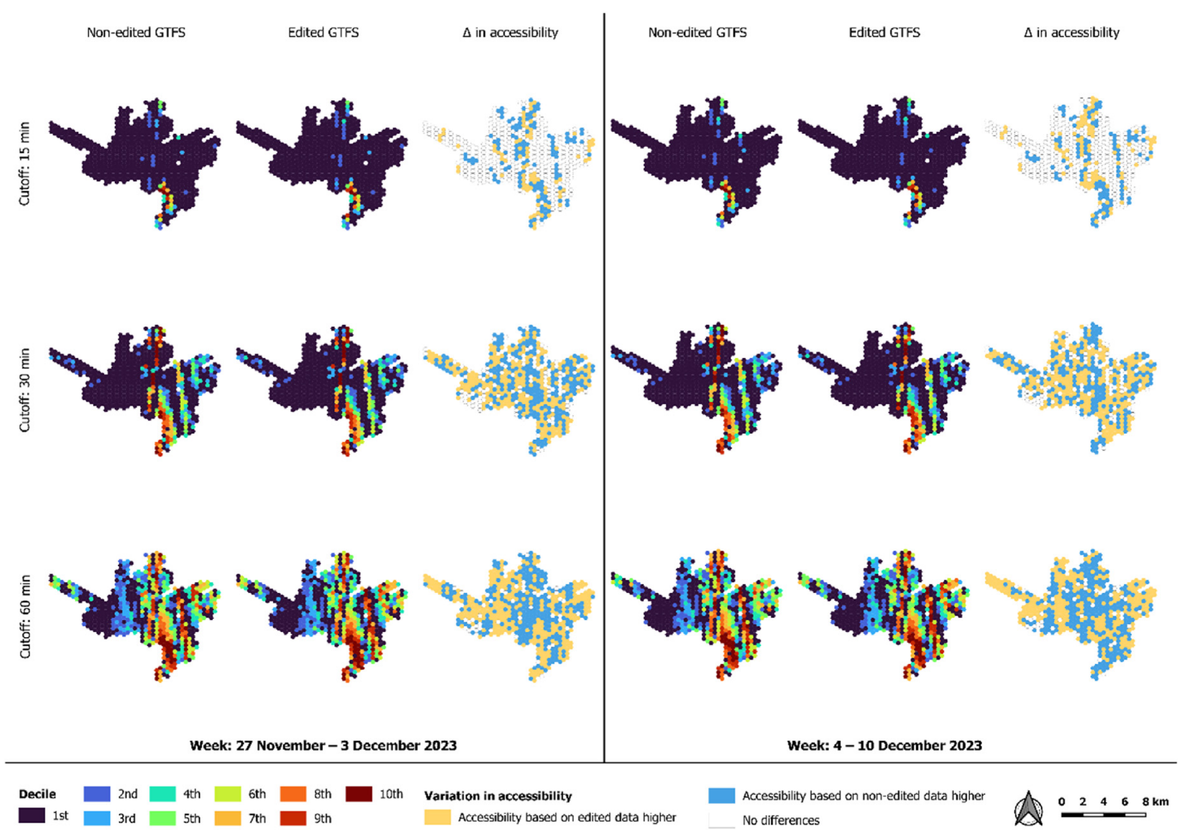

Fig. 7. Relative cumulative proportion of accessibility q_i – opportunity: university.

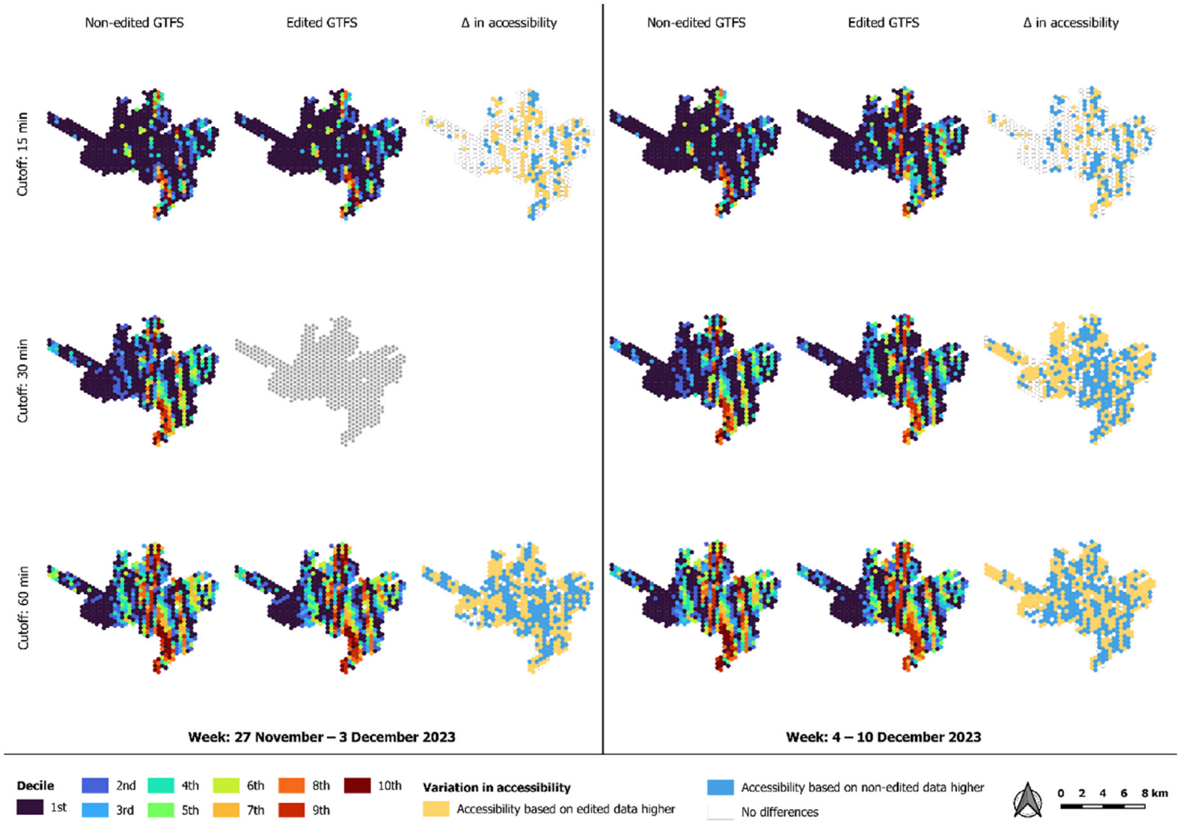

Fig. 8. Relative cumulative proportion of accessibility q_i – opportunity: healthcare. Owing to an issue affecting the combination of GTFS and AVM data, computation at the cutoff of 30 min is considered by the authors to be an outlier.

Table 6
Number of hexagons in relation to the variation in accessibility – opportunity: schools.

Week	Cutoff	Number of hexagons with accessibility based on edited data higher	Number of hexagons with accessibility based on non-edited data higher	Number of hexagons with no differences
27 November–3 December 2023	15 min	298 (50%)	120 (20.1%)	177 (29.7%)
	30 min	255 (42.8%)	289 (48.5%)	51 (8.5%)
	60 min	241 (40.5%)	311 (52.2%)	43 (7.2%)
4–10 December 2023	15 min	277 (46.5%)	149 (25%)	169 (28.4%)
	30 min	265 (44.5%)	277 (46.5%)	53 (8.89%)
	60 min	231 (38.8%)	320 (53.7%)	44 (7.3%)

Table 7
Number of hexagons in relation to the variation in accessibility – opportunity: university.

Week	Cutoff	Number of hexagons with accessibility based on edited data higher	Number of hexagons with accessibility based on non-edited data higher	Number of hexagons with no differences
27 November–3 December 2023	15 min	79 (13.2%)	117 (19.6%)	399 (67%)
	30 min	247 (41.5%)	242 (41.5%)	106 (17.8%)
	60 min	293 (49.2%)	259 (43.5%)	43 (7.2%)
4–10 December 2023	15 min	95 (15.9%)	108 (18.1%)	392 (65.8%)
	30 min	273 (48.8%)	217 (36.4%)	105 (17.6%)
	60 min	275 (46.2%)	276 (46.3%)	44 (7.3%)

analysis on the basis solely of the Gini coefficients. This focus is intended to partially overcome the intrinsic limitation of the Gini formulation, namely, the computation of the coefficient at the aggregate level (Rey and Smith, 2013), which forces the spatial entities to be split into different subgroups to obtain a comparative analysis (Raza et al., 2023). The analysis of q_i was reported in Figs. 6–8. Each figure is structured as follows: the q_i values per week, cutoff, and source (either edited or non-edited GTFS) are plotted with details on the deciles. Additionally, the variations are plotted as arithmetical differences between edited and non-edited q_i values. Importantly, the latter plots consider only the differences in values, and they could be below the interdecile difference. Therefore, a hexagon can be thematized with the same decile color in both plots, despite a variation in the q_i value. To provide a more comprehensive account of the variation in accessibility, Tables 6–8 are included. These tables present the number of hexagons in accordance with their status (i.e., whether the accessibility based on edited or non-edited data is greater or whether no differences are identified) and in relation to the scenario (week, cutoff).

From a general perspective, the results illustrate the heterogeneous distribution of accessibility across the city, as measured by the lowest deciles. This serves to corroborate the findings of Section 4.1, which indicated a lack of adequate PT supply in some areas of the city. This deficit is particularly pronounced in peripheral areas, whereas some isolated spots are located in central districts, particularly at cutoff = 15

Table 8
Number of hexagons in relation to the variation in accessibility – opportunity: healthcare.

Week	Cutoff	Number of hexagons with accessibility based on edited data higher	Number of hexagons with accessibility based on non-edited data higher	Number of hexagons with no differences
27 November–3 December 2023	15 min	151 (25.3%)	83 (13.9%)	361 (60.6%)
	30 min	—[a]	—[a]	—[a]
	60 min	269 (45.2%)	283 (47.5%)	43 (7.2%)
4–10 December 2023	15 min	103 (17.3%)	130 (21.8%)	362 (60.8%)
	30 min	263 (44.2%)	239 (40.1%)	93 (15.6%)
	60 min	286 (48%)	265 (44.5%)	44 (7.3%)

[a] Due to an issue affecting the combination of GTFS and AVM data, this computation was not possible.

min. Other notable outcomes are the positive variations in q_i values associated with the edited GTFS and the values related to Moran's *I*. The results in Tables 9–11 can be considered another indicator of the presence of clusters of inaccessibility and disparities in PT supply, since all the Moran's *I* values are positive and significant at the 99.9% confidence level ($p < 0.001$). A significant outcome of the results is related to some Moran *I* values for edited GTFS, which are lower than those of nonedited scenarios, and this is interpreted by the authors as an additional confirmation of the conservative approach adopted in creating GTFS. With respect to schools and healthcare, increasing Moran *I* values at increasing cutoffs are interpreted as an indirect confirmation of the adequate distribution of scholastic institutions and health-related facilities at the neighborhood level, as well as the PT supply, with noteworthy implications for policies related to urban planning (Logan et al., 2022; Moreno et al., 2021; Olivari et al., 2023; Staricco, 2022). With respect to University, this latter opportunity accounted for decreasing Moran *I* values at cutoffs >15 min, suggesting that most of the population needs a longer commute to reach those facilities.

As a general remark, the results presented in Sections 4.1 and 4.2 can be interpreted as robust outputs of the analysis, thus constituting a topic of further discussion. As the mitigation of long-term unplanned disruptions has been identified as crucial for PT agencies (Mo et al., 2022), the capacity to rapidly restore an acceptable operational status is limited by the overall vulnerability and reliability of the system (Moylan et al., 2022) or the absence of sufficient redundancy (Boura and Ferguson, 2024). The argument presented here is applicable to numerous fields of transportation and is related to the broader theory of transportation system resilience (Zhou et al., 2019). In view of its distinctive status, these concerns are particularly pronounced in the domain of transit (Cats and Jenelius, 2015; Ge et al., 2022). In this context, the promptness with which information on changes to regular services is addressed may be a key factor in how users adapt their behaviors to the new situation (Leng and Corman, 2020), with direct effects on overall satisfaction. The spatial resolution of this analysis employs a regular tessellation made up of hexagons, and the selected metrics, namely, the Gini coefficient, are designed to serve as a robust instrument for PT agencies and public authorities, facilitating insights for further in-depth analyses. These may include the delineation of alternative scenarios involving alterations to the regular PT service, whether planned (Yap and Cats, 2022) or unplanned.

Table 9
Moran *I* (relative cumulative proportion of accessibility q_i) – opportunity: schools.

		Nonedited GTFS			Edited GTFS		
Week	Cutoff	Moran *I*	*z*-score	*p* value	Moran *I*	*z*-score	*p* value
27 November–3 December 2023	15 min	0.320	12.978	< 0.001	0.327	13.286	< 0.001
	30 min	0.432	17.500	< 0.001	0.430	17.398	< 0.001
	60 min	0.444	17.935	< 0.001	0.411	17.820	< 0.001
4–10 December 2023	15 min	0.328	13.327	< 0.001	0.331	13.425	< 0.001
	30 min	0.431	17.474	< 0.001	0.428	17.324	< 0.001
	60 min	0.437	17.674	< 0.001	0.435	17.587	< 0.001

Table 10
Moran *I* (relative cumulated proportion of accessibility q_i) – opportunity: university.

		Nonedited GTFS			Edited GTFS		
Week	Cutoff	Moran *I*	*z*-score	*p* value	Moran *I*	*z*-score	*p* value
27 November–3 December 2023	15 min	0.560	23.177	< 0.001	0.558	23.100	< 0.001
	30 min	0.480	19.458	< 0.001	0.475	19.249	< 0.001
	60 min	0.490	19.806	< 0.001	0.496	20.035	< 0.001
4–10 December 2023	15 min	0.554	22.942	< 0.001	0.551	22.826	< 0.001
	30 min	0.487	19.754	< 0.001	0.476	19.287	< 0.001
	60 min	0.490	19.805	< 0.001	0.475	19.199	< 0.001

Table 11
Moran *I* (Relative cumulative proportion of accessible q_i) – Opportunity: healthcare.

		Nonedited GTFS			Edited GTFS		
Week	Cutoff	Moran *I*	*z*-score	*p* value	Moran *I*	*z*-score	*p* value
27 November–3 December 2023	15 min	0.400	16.287	< 0.001	0.392	15.945	<0.001
	30 min	0.473	19.149	< 0.001	—[a]	—[a]	—[a]
	60 min	0.445	17.996	< 0.001	0.445	17.986	<0.001
4–10 December 2023	15 min	0.397	16.141	< 0.001	0.391	15.905	<0.001
	30 min	0.478	19.351	< 0.001	0.466	18.891	<0.001
	60 min	0.445	18.403	< 0.001	0.440	17.808	<0.001

[a] Due to an issue affecting the combination of GTFS and AVM data, this computation was not possible.

5. Conclusions

The advent of Big Data and advancements in GIS have revolutionized the field of accessibility assessment, enabling more precise evaluations through Big Data and ITS components, such as GTFS and AVM systems. These technologies increase the accuracy of accessibility analyses, thereby increasing awareness of the provided service. In fact, it is vital for public transportation (PT) agencies to identify and address discrepancies between scheduled and actual services, as these gaps can significantly distort accessibility evaluations and ultimately exacerbate inequities. Furthermore, the integration of equity into accessibility discussions is essential, as it addresses the ethical implications of transportation planning and the need for equitable resource distribution. This study explores the multifaceted concept of accessibility, emphasizing the critical role of delays in the evaluation of accessibility gaps. The impact of a disruptive event, namely, the persistent closure of a main urban road in Bologna, Italy, was examined to ascertain whether there were any variations in accessibility, here accounting for the cumulative opportunity approach, when regular PT service was affected by external factors. The findings are in accordance with the results of previous studies that investigated the discrepancies in accessibility estimation when real data (based on AVM) and scheduled data (based on GTFS only) are used. Thus, the purpose of the authors is to present the results as robust outcomes and as a valuable contribution to the ongoing debate on accessibility.

The proposed methodology has been positively tested, resulting in an effective tool for transportation planning and urban policies. In particular, the combined use of two well-known techniques, such as the Gini coefficient and Moran's *I*, as well as the implementation of de facto standard datasets, such as the AVM and GTFS, may be considered the main strength of the paper, thus being a significant factor in enhancing the replicability of this methodology, e.g., in other cities or in analyzing the variation in accessibility caused by other disruptions. Indeed, PT agencies and public authorities should adopt an informed multidisciplinary approach when integrating accessibility assessments into their policies. Additionally, optimizing service frequency, particularly in areas served by a poor supply, and conducting regular accessibility evaluations on real data can significantly improve the user experience, potentially resulting in increased demand stability over time (Nalin et al., 2024a). On the governmental side, incorporating equity assessments into transportation planning processes is essential, utilizing tools such as the Gini coefficient to identify and address disparities in access. Collectively, these strategies can lead to significant improvements in accessibility, ultimately fostering a more inclusive urban environment.

However, on the basis of the evidence presented by both Gini coefficients and Moran's *I*, the authors argue that a more comprehensive analysis is necessary to understand the differences in accessibility across the city's central and peripheral areas. This is because disruptions can have varying effects on accessibility, depending on supply-side factors, such as the number of lines or the frequency of scheduled services. It is evident that disruptive events can have varying effects. For example, areas served by multiple lines may demonstrate greater resilience to disruptions than areas where the regular PT is inadequate. For future analyses, the authors mention the use of different time windows (e.g., evening peak hours, off-peak hours) (Stępniak and Goliszek, 2016) and opportunities, such as leisure facilities, shops or job locations, to holistically account for accessibility in Bologna, as proposed in Vale and Lopes (2023), or the implementation of intermodal travel in R5R, e.g., the implementation of transfers between different PT lines, which can ultimately result in redundancy analysis of a PT network, or the combined use of PT and other modes.

CRediT authorship contribution statement

Alessandro Nalin: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Nir Fulman:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Emily Charlotte Wilke:** Writing – original draft, Formal analysis, Data curation. **Christina Ludwig:** Methodology. **Alexander Zipf:** Supervision, Investigation. **Claudio Lantieri:** Writing – review & editing, Visualization. **Valeria Vignali:** Writing – review & editing. **Andrea Simone:** Supervision, Investigation.

Replication and data sharing

The dataset used in this research is partially available upon request by emailing the corresponding author.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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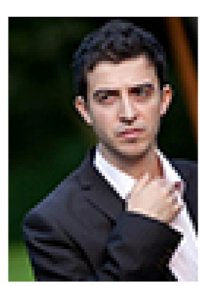

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