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Analyzing the accessibility of Rome's healthcare services via public transportation: a complex network approach

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Access to healthcare services is vital for urban public health, significantly influencing life expectancy, equity, and economic development. This study investigates the spatial accessibility of healthcare services in Rome through public transportation, emphasizing system resilience during disruptions. We explore transport poverty, emphasizing that individuals without cars often rely solely on public transit for medical access. Our methodology integrates network analysis with spatial accessibility assessments. We constructed a graph model of Rome's transit system, where nodes represent stops and edges connect neighborhoods to healthcare facilities. This model incorporates actual travel times from the city's official public transport timetables. We applied centrality metrics to identify crucial transit hubs and evaluated how their removal impacts travel times to healthcare facilities. The findings reveal significant disparities in accessibility resilience, influenced primarily by network redundancy and the strategic importance of high-centrality nodes. To enhance resilience, it is essential to monitor critical transit nodes and implement real-time flow monitoring to respond to disruptions. Collaboration among local authorities, transport agencies, and healthcare providers is crucial for risk assessment and identifying vulnerable populations. Developing targeted interventions and strengthening network redundancy will ensure more equitable and reliable access to healthcare, particularly for those dependent on public transportation.

Keywords Network analysis, Public transport, Healthcare accessibility, Resilience and vulnerability

Access to healthcare facilities is a crucial component of urban planning. An accessible healthcare system increases citizens' life expectancy, improving overall quality of life[1]. According to various studies, human development depends on equal access to essential services such as healthcare[2]. From this perspective, the literature identifies accessibility to these services as a fundamental pillar for positively influencing economic growth, social equity, and the well-being of communities and territories[3–5]. To assess access to healthcare facilities, it is important to first identify the population groups with the greatest need[2–6]. For example, older adults and people with disabilities exhibit a high demand for medical care and, lacking private means of transport, depend almost exclusively on public transit to reach hospitals[7–9]. As a result, fully understanding access to medical facilities means looking at both how easy they are to reach and how available public transport is. Designing a public transport system that works well is essential for fair access to healthcare, since transport problems can strongly affect people's quality of life and the economy[6,10].

In general terms, accessibility of the public transport system represents the ease with which destinations can be reached. It is expressed through cost-time or cost-distance functions[11,12]. Conversely, service availability represents the system's scheduled offering (lines, frequencies, hours of operation, and stops). It is measured using indicators such as the number of trips per hour or the density of stops in an area[13].

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In terms of socio-economic planning of the transport system to healthcare facilities, it is therefore essential to combine, on one hand, high service availability-ensured by an adequate number of scheduled trips, stops, and frequencies—and, on the other hand, high transport accessibility, understood as the actual travel and waiting times recorded by users. This integrated approach is particularly crucial for the most vulnerable groups of citizens who rely almost exclusively on public transit to access healthcare services. In this sense, coordinated management of the public transport network not only reduces disparities in service provision and actual use but also promotes more inclusive, sustainable, and resilient urban planning, capable of responding equitably to the health needs of all population segments while helping to mitigate complex phenomena such as poverty and healthcare inequalities[1].

The need for a robust public transport system focused towards healthcare facility access highlights the importance of designing resilient networks capable of ensuring continuity and reliability even in the event of disruptions or external shocks. A resilient network is characterized by the presence of redundancies—that is, alternative routes and connections—which allow for the timely restoration of operational performance and minimize the impact of any service disruptions on users[14].

At the empirical level, network analysis emerges as one of the most relevant and widespread methodologies for investigating and measuring transport accessibility and availability to essential services[15–17]. The network analysis enables efficient modeling of networks as graphs composed of nodes (e.g., bus stops or healthcare centers) and edges that illustrate their connections (e.g., distances between services and travel times), allowing for accurate analysis of network structural properties, efficient identification of critical nodes, and precise assessment of system resilience[7,10,14–18].

Although several studies have examined spatial access to health facilities and public transport networks separately, there is still a lack of research exploring their interaction. In particular, how accessibility to health facilities is affected in areas characterized by limited public transport provision and low resilience to external shocks remains little explored[19–21].

This study aims to fill this gap by offering an integrated analysis, combining network analysis with spatial accessibility measures, to comprehensively assess disparities in access to health services through public transport and its resilience to external disruptions. In particular, similar to analyses such as Guida et al.[7], which examine public transport accessibility for the elderly population in need of health services, we focus on measuring accessibility to health facilities in the Municipality of Rome through the public transit network in ordinary and disruption scenarios. We exploit the availability of daily scheduled data on Roman transit lines, which allows us to model with detail and precision timetables, stops, and pre-established routes. In our study, ”public transport” (PT) therefore means the public transit services composed of bus, tram and metro lines. This methodological choice is motivated by the relevance of PT as the main vector of urban mobility and by their widespread use by the elderly population without private means, as highlighted in several works, for example, Gimie et al.[22], Gao et al.[8], Ravensbergen et al.[23], Zhang et al.[24].

The research uses quantitative methods and advanced computational tools to analyze the structural properties of the PT network, assess access to health services, and evaluate the resilience and reliability of the network. The network topology analysis uses centrality and connectivity metrics to identify critical nodes and paths, while spatial accessibility measurements integrate geographic and public transport data to assess travel times to health facilities. Resilience assessments explore the network response to disruptions and the implications for health accessibility. The results highlight the main transport hubs, classify stations within the complex network, and measure spatial accessibility to health services in both baseline and disruption scenarios, providing valuable insights into the impact of public transport on equity and providing recommendations to improve the resilience and reliability of the urban public transport system. In pursuing these objectives, the research provides guidance essential to strengthen public transport, promoting a more sustainable and equitable health system.

In summary, the contribution of our work is twofold. Firstly, we assess territorial sustainability by analyzing the equitable distribution and accessibility of health facilities via public transport across Rome's municipal districts, identifying disparities in areas with limited or difficult connections to hospitals. Methodologically, we combine network analysis with rigorous real-time travel time estimation, integrating the topological complexity of Rome's PT network and its daily GTFS schedules, to construct a transit-network-based healthcare accessibility index that delivers precise, realistic measures for both direct and connecting trips. Secondly, we integrate disruption sensitivity directly into our accessibility framework by simulating targeted removals of high-centrality nodes to evaluate how external shocks compromise network integrity and affect users' ability to reach essential services, thus providing robust insights, both for research and future urban policy.

The structure of this work is organized as follows. In Sect. "Literature background" a critical review of the literature is presented, with particular attention to spatial inequalities in access to health services, consolidated methodological approaches (gravity models, 2SFCA, network analysis), and the existing gaps in terms of integration between accessibility and resilience. Section "Empirical approach and methodology" describes in detail the empirical approach adopted, illustrating the data sources, the pre-processing phases, the construction of the multi-layer database, and the analytical methods, such as travel time calculation, betweenness centrality, and interruption simulations. In Sect. "Results" the main results are presented, divided into: (a) analysis of ordinary spatial accessibility; (b) evaluation of the variations in access times following targeted removals of high-centrality nodes; (c) identification of the most vulnerable and most resilient areas. Finally, in Sect. "Discussion and policy implications" we discuss the implications of the results for urban and health planning, proposing recommendations to improve network redundancy and service continuity, and outline possible future developments. The overall workflow of the study is illustrated in Fig. 1.

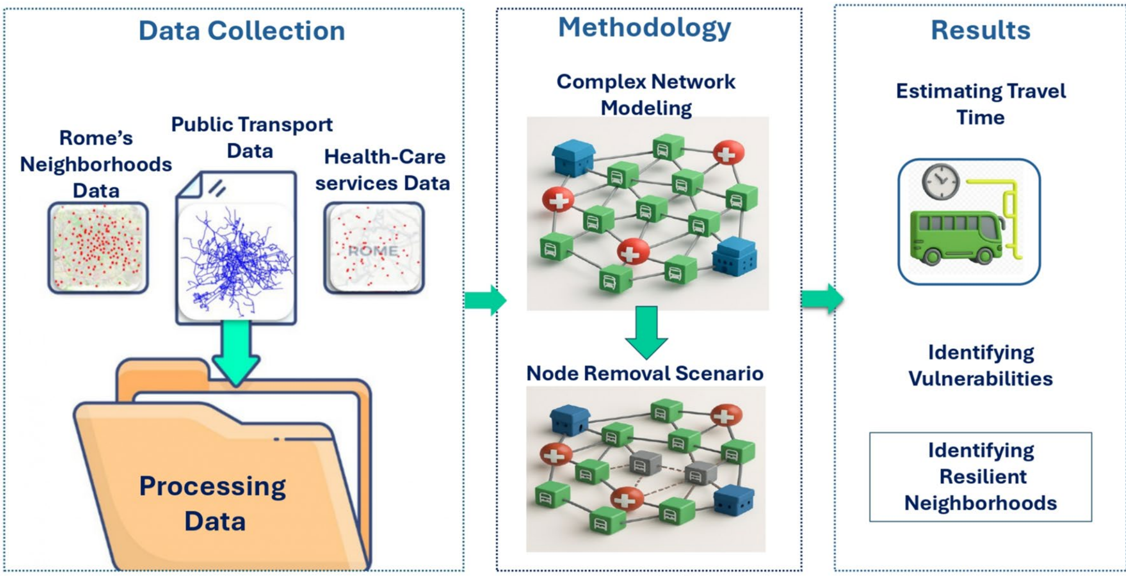

Fig. 1. Overall workflow of the research.

Literature background

As discussed in the "Introduction" section, strengthening access to essential services is crucial to promoting social equity, as these services influence the quality of life of citizens and their ability to fully participate in society[1,2,5,25]. In general, spatial accessibility refers to the ease with which individuals can reach desired destinations, such as healthcare facilities, workplaces, or educational institutions[26,27]. It plays a critical role in urban planning, transportation modeling, and equity assessments[12,28].

The economic and quantitative literature shows that there are two theoretical frameworks to calculate accessibility:(i) Place-based (potential) location-based accessibility counts destinations reachable within a certain distance or time[12,27]; (ii) Person-based (individual) accessibility considers personal constraints (time budget, daily travel, mobility resources), assessing the actual ability of each person to reach destinations[28].

In many works, accessibility and availability to health facilities were assessed using GIS methodologies that include travel times or distance estimates (usually as an impedance factor), such as the 2-step floating catchment area method (2FSCA)[29–33], gravity models[34,35] robust space-time accessibility assessments[36], and network analysis[37–39].

Network analysis mainly uses estimated or self-reported travel times on a network (e.g., a road or public transport network) to calculate the number of points of interest (in our case, e.g., healthcare facilities) that can be reached within a time threshold[37–39]. A similar framework is also present in gravity models[34,35] and 2SFCA methods[7,29–33], but they feature integrated systems. Comparatively, although all three methods rely on travel time or distance as a central component, they differ in how accessibility is conceptualized. Network analysis focuses on reachability within a time threshold. Although it does not explicitly account for spatial interactions and is sensitive to arbitrary distance or time thresholds, which may neglect variations just outside the defined limits, it remains one of the most widely used methodologies in the literature due to its operational clarity and ease of computation, especially in the presence of large amounts of data, which allow for immediate interpretation of the results[12,40]. Gravity models calculate the number of reachable opportunities within a given time or distance threshold by applying a continuous decay function that gives greater weight to the closest destinations[34,35]. A notable example is Hansen's[11] formulation, which integrates destination density with a distance decay term. However, because they typically treat all service locations as equally "attractive", these approaches may overlook spatial heterogeneity in service provision, a crucial issue when studying inequalities in access to care[41,42]. The 2SFCA method partially overcomes these limitations since it calculates for each origin the ratio between available opportunities and reachable population inside a defined catchment area. However, the definition of the catchment areas is often based on arbitrary time or distance thresholds, and this can lead to over- or underestimations of users in very heterogeneous contexts[7,29–33]. Furthermore, the model considers the opportunities' capacity as a fixed value and does not take into account daily and hourly variations in personnel and resources.

Generally, transport equity is a function of several factors, such as transport availability[9], mode-specific access[7], supply heterogeneity[43], and regional disparities[35].

As regards mode access, Guida et al.[7] found that using only the transit network and assuming no car access for older people, peripheral areas of Milan had significantly lower accessibility to healthcare facilities for this user group compared to central areas, noting spatial accessibility patterns. Similarly, Noh[9] detailed transport equity for older adults as the spatial interaction between transit availability and the share of the older population living in the communities of the study area in Florida. To consider heterogeneity in supply, Shao and Luo[43] utilized a doctor-specific attraction score inside the 2SFCA framework to control for the fact that the different attractiveness of doctors to patients can influence patients' choice and, as a consequence, individual accessibility to doctors. Also regional disparities matter. Raza et al.[35] using 4-step modeling, the Lorenz curve, and the Gini Index, found significant transit accessibility disparities among urban and rural Chinese areas in the Wuhan region. Algaidan et al.[44] developed an analytical framework to measure gaps between private and public transit stations using three common methods—cumulative opportunity, potential access, and gravity metrics—across multiple travel time thresholds and peak periods. Incorporating both spatial and temporal variables, the study assessed how accessibility disparities vary by method and time of day. Such examples help us understand that accessibility measures should be tailored to the user class studied (e.g., older adults without car access), considering, depending on the research focus, spatial disparities, heterogeneity in preferences, and/or disparities in mode availability, with particular attention to the needs of the target group. Taking a step further into network science, complex network analysis can be combined with more traditional approaches for travel time estimations.

A complex network comprises a set of nodes representing the system's constituents of interest and links representing the physical connections between node pairs[45,46]. Several properties and indices of the network can be used to describe its composition[47,48]. Complex network frameworks and tools are also helpful in analyzing the network's integrity when external disruptions occur, detailing the resilience properties of the network. Resilience is generally defined in the literature as the ability of transport networks to resist shocks, maintain functionality, and recover as quickly as possible to a whole level of service[49]. In the static part of resilience, at the moment of disruption, robustness defines the amount of performance the network can maintain. On the other hand, redundancy refers to the set of infrastructural and modal alternatives the system provides users[50]. Vulnerability, the opposite of robustness, indicates the amount of performance loss at the moment of disruption, serving as an index of susceptibility to loss[51].

Important investigations on resilience and vulnerability in transportation studies include, for example, the works of Jenelius and Mattsson[52], Reggiani et al.[49], and Gu et al.[53]. Resilience analysis can be system-based or topology-based[52], with the former more focused on the performance of the network (in terms of flows, speeds, etc.), while the latter focuses on the topological features of the networks, i.e., nodes, edges, and their connections. Several studies have built upon a framework combining both system-based and topology-based approaches. Using data from taxi trips, Wang et al.[54] showed that nodes with high centrality significantly influence network vulnerability and that travel time is directly related to flow loss. Similar studies have also been conducted on rail transit networks[55] and urban bus networks[56]. Focusing on transit, an efficient and effective Urban Public Transport System (UPTS) ensures that passenger transfer runs smoothly and stations are adequately distributed to businesses and residents[57,58]. Starting from this framework, Baggag et al.[59] used the public transport network (PTN) model to represent nodes, which are the stations and stops of a public transport system, and edges, which connect subsequent stations along a route. The critical nodes identified through the single-modal analysis cannot accurately represent the actual state of public transport. Therefore, it is useful to explore methods to identify pivotal nodes from a topological perspective within multimodal public transport networks[7,19,60]. Murray-Tuite[61] introduces the concept of quantitative metrics to measure the resilience of the transport system, analyzing the four dimensions of transport resilience and exploring the influence of traffic assignment on resilience.

This study integrates transportation network resilience analyses with accessibility measurements, generating an index that reflects both the topological structure and operational performance of the transit network to healthcare facilities. Differently from other relevant studies in the literature employing gravity models and 2SFCA methods, this paper adopts origin-to-specific-opportunity travel time estimates as the main measure of accessibility: our main objective is to build a complex transit network framework that integrates complex network geometry and scheduled timetables to minimize travel times between specific origin-opportunity pairs, identifying, through rigorous and realistic travel time estimation, the optimal opportunity among those reachable. By incorporating rigorous, data-driven travel time estimates alongside the underlying network geometry, our approach captures both the topological and performance dimensions of the transit system, providing realistic and disruption-sensitive estimates of accessibility. Building on the reviewed literature on resilience, we consider both dimensions and evaluate the transit-network-based healthcare accessibility index under both normal and disrupted conditions. Our travel-time-based method serves as a practical proxy for spatial reach and system performance, enabling more accurate assessments of urban service resilience in the face of disruptions. This integration of resilience into accessibility analysis represents a novel contribution to the field, addressing an aspect that remains underexplored in current research.

Empirical approach and methodology

Data processing

We use three datasets in this study. The first dataset contains georeferenced information about Rome's public transport network, provided in GeoJSON format and sourced from Kujala et al.[62]. This dataset represents the network as a multi-line string object and is illustrated in a simplified origin-destination (O-D) form in Fig. 2.

In our model, nodes correspond to PT stops, links are the segments of PT lines connecting consecutive stops, and routes consist of a sequence of these links that define the full path of a PT line. The overall public transport network is formed by the interconnection of these individual lines at shared stops.

The second dataset contains the georeferenced coordinates of the centroids of Rome's 66 neighborhoods, used to spatially represent population locations. The third dataset includes the geolocations of public and private healthcare facilities across the city[63]. In total, 36 healthcare facilities are mapped. Among them, 11 public facilities are classified by the Italian Ministry of Health's DEA system[64]. These classifications are "First Aid (PS)," offering basic emergency services; "First-level DEA (DEA1)," with essential emergency care; and "Second-level DEA (DEA2)," equipped for full-spectrum emergency care[26,27]. These public facilities are the primary focus of our analysis, as we aim to assess the ease with which residents can reach them via public transport. Private healthcare centers, mostly offering ambulatory services, are included in a supplementary analysis to provide a broader picture of service reachability. Figure 3 illustrates the spatial distribution of origins and destinations.

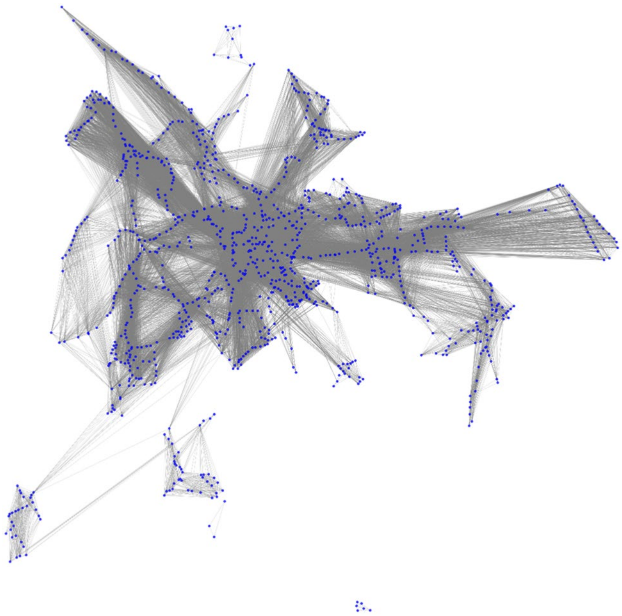

Fig. 2. Complex network graph, with blue circles denoting selected PT stops and gray lines representing PT routes.

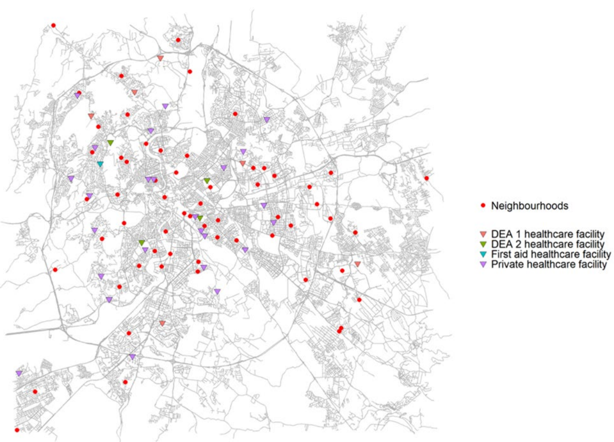

Fig. 3. Spatial distribution of origins (centers) and destinations (hospitals) in the Municipality of Rome. *Source*: Author's elaboration on the Italian Ministry of Health. This map was generated in R v4.4.2[65], with the `ggplot2` v3.5.1 package[66], and the road network was extracted from `osmdata` v0.2.5[67].

In our database, the service availability component includes PT schedule data (lines, stops, frequencies), while the transport accessibility component comes from the calculation of travel times between origins (centroids) and destinations (hospitals).

The GeoJSON point data for the healthcare facilities also indicates the closest PT stop to them, allowing us to evaluate the accessibility of healthcare facilities through the public transport network. The third data set that we use is the General Transit Feed Specification (GTFS) for public transportation in Rome, obtained from the website of the City Government Department of Transportation. This comprehensive dataset contains detailed scheduling information for Rome's public transportation system. It provides a complete record of all PT routes, including the precise sequence of stops along each path and the scheduled arrival and departure times for every service throughout the day. The data structure allows for detailed travel planning as it contains the complete timetable of the city's PT network. With this information, users can calculate the optimal travel routes between two points in the city at any time, including trips that require transfers between multiple lines. The temporal and spatial precision of the dataset makes it valuable for everyday travel planning and advanced transportation analysis, enabling accurate estimation of travel times across Rome's entire public transit network.

Fig. 4. Example of a directed route between O-D. *Source*: Author's elaboration on Municipality of Rome. This map was generated in R v4.4.2[65], with the `leaflet` v2.2.2 package[71], and the road network was extracted from `osrm` v4.2.0[72].

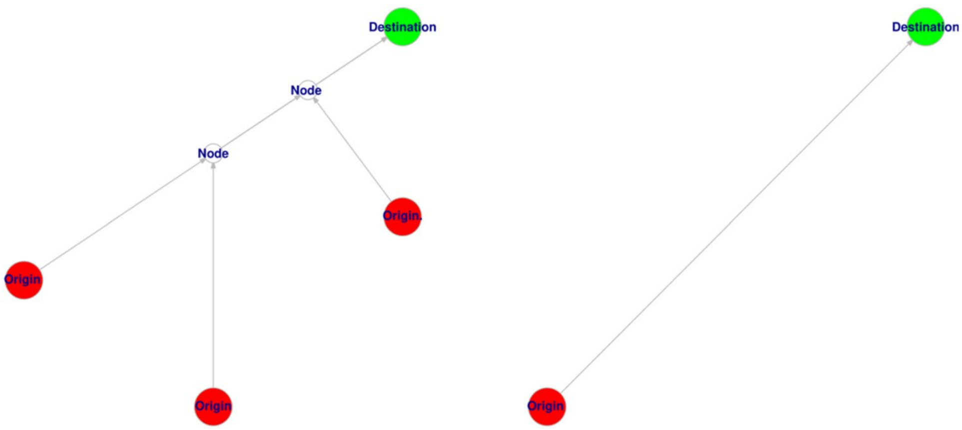

Fig. 5. Illustrates the undirected (on the left) and directed (on the right) lines between origin and destination.

Datasets

We construct our multi-layer database[68,69] by combining relational, geospatial, and temporal components that comprehensively reflect service availability (scheduled lines, stops, frequencies) and separately compute transport accessibility (travel-time-based reach) from the centroids of Rome's neighborhoods to hospitals via a public PT lines network. To achieve this, we develop a complex model structure that integrates two key components: on one side, the availability of geographical data, which includes the coordinates of PT stops closest to Rome's neighborhood centers and hospitals; and on the other side, the travel time information for the routes, along with the scheduled service times of the Municipality of Rome's fixed-route PT.

The main objective is to calculate, from the PT arrival and departure times of lines at stops, the travel times from every neighborhood centroid to any reachable hospital, including a maximum of one line change, to put a threshold on the individual travel times.

In this framework, municipal centroids, defined by latitude and longitude, serve as the network's origins, while the nearest stops to each hospital act as the destinations. Hospitals are classified according to the DEA classification system, which helps to calculate accessibility in terms of travel time from each neighborhood centroid to specific types of hospitals. In our dataset, each PT line connecting neighborhoods to hospitals is represented as a distinct data block. Within this block, travel times are calculated based on the scheduled timetables from origin to destination, reflecting the availability of PT services at those times, as illustrated in Fig. 4. There are two possible scenarios: In the first, a single line directly connects the origin and destination. In the second, the origin and destination are connected through one transfer stop. Figure 5 provides a graphical representation of both cases. In the second scenario, the accessibility is calculated as the sequential sum of time differences between consecutive stops, with the addition of a 20-min waiting time at the transfer stop, as estimated by Moovit[70].

Formally, in the case of a direct connection, it is assumed that a single PT line provides available service linking the stop associated with a given centroid to one or more stops located near hospitals. In tabular terms, this is represented by the creation of entries that indicate, for each centroid c_i, each line l_k passing through it, and each hospital h_j reachable by l_k, the presence of a direct connection: $(c_i \rightarrow h_j)$. This structure supports the calculation of accessibility, measured in terms of travel time, for direct routes. For indirect connections requiring a transfer, the dataset is structured to store the journey in two segments (see Eq. 1). In the first segment, the centroid is connected to an intermediate stop v_k via a direct line. In the second segment, the route continues from v_k to the hospital h_j. In such cases, the total travel time from c_i to h_j via v_k is calculated as:

$$T_{ikj} = t_{ik} + \Delta_t + t_{kj} \tag{1}$$

where:

- t_{ik} is the travel time from the centroid c_i to the intermediate stop v_k;
- Δ_t is a fixed waiting time (20 min), based on Moovit estimates, representing the time required for transferring between lines in Rome;
- t_{kj} Is the travel time from the stop v_k to the hospital h_j.

To accommodate cases where a line or a transfer segment is available to serve multiple hospitals, we introduced a mechanism that replicates data blocks for each hospital destination. Specifically, when a PT route (or a segment of it in the case of transfer-based routes) connects a centroid to more than one hospital, the original origin-destination data block, including intermediate stops and travel times, is duplicated for each hospital. Each duplicate represents a distinct travel path that originates from the same centroid and follows the same available route but ends at a different hospital. This ensures that each hospital is treated as a unique destination for accessibility evaluation, even when the travel segments overlap.

The final structure of the database used for estimating accessibility in terms of travel time between centroids and hospitals consists of the following components:

- *PT stops:* A list of all stops, including their geographical coordinates and the PT lines serving them.
- *Hospitals:* A list of target facilities, along with their coordinates and relevant attributes.
- *Lines and timetables:* Detailed information about PT routes, linking each line with its ordered list of stops and scheduled times of arrival at each stop.
- *Travel times:* Computed either from
  - Direct connections: $(c_i \rightarrow h_j)$;
  - Indirect connections with one transfer: $(c_i \rightarrow v_k \rightarrow h_j)$.

A table summarizing the sample of entries and the structure of our dataset, as well as a table summarizing the frequency distribution of the number of trips in our dataset for each origin-destination, is provided in the Supplementary Material.

Temporal transport accessibility to emergency care via public transit

Contrary to a purely geospatial approach—based on Euclidean distance, road distance, or abstract topological network structures—this study adopts a framework grounded in scheduled PT timetable data. Specifically, we utilize General Transit Feed Specification (GTFS) data made available by the Municipality of Rome. The objective is to derive an empirically informed estimate of transport accessibility, starting from service availability (GTFS schedules) to calculate actual access times to hospitals and hospital care via public transport, thereby avoiding geographical simplifications that overlook the actual functioning of the transportation network. Following the construction of the integrated database, travel times from centroids to hospitals are computed as the median and minimum values of observed travel durations between urban centroids (origin points) and hospitals classified under the DEA ("Dipartimento di Emergenza e Accettazione") category (destination points). The focus on DEA-classified hospitals ensures that the analysis prioritizes access to emergency medical services, which are critical for urgent healthcare needs. For each trip on a given line l_k connecting a centroid c_i to a hospital h_i, we calculate the travel time by summing the time intervals between consecutive PT stops along the route. Let the sequence of stops be denoted by $s_1, s_2, \ldots, s_n$, where s_1 is the first stop near c_i and s_n is the final stop near h_i. If $t_{\text{arr}}(l_k, s_{p+1})$ denotes the arrival time at the stop s_{p+1} and $t_{\text{dep}}(l_k, s_p)$ the departure time from the stops_p, then the total travel time t_n for a single trip is computed as:

$$t_n = \sum_{p=1}^{n-1} \left[t_{\text{arr}}(l_k, s_{p+1}) - t_{\text{dep}}(l_k, s_p) \right]. \tag{2}$$

This formulation captures the sequential nature of the trip, where each segment contributes a "gap time" reflecting actual service intervals. Since multiple trips are scheduled along the same route on a given day, we define the set of observed travel times as:

$$\check{T}_{ij}^{(l_k)} = \{t_1, t_2, \ldots, t_n\}. \tag{3}$$

Based on this set, three main computations are performed:

(a) Calculation of the median travel time : For each homogeneous route, defined as all trips on the same line l_k connecting the same centroid c_i to the same hospital h_i—we compute the median of travel times:

$$\check{T}_{ij}^{(l_k)} = \text{median}(\check{T}_{ij}^{(l_k)}). \tag{4}$$

This value provides a robust estimate of typical travel time, less sensitive to outliers.

(b) Calculation of the minimum observed time : Next, for each (c_i, h_i, l_k) combination, we identify the minimum observed travel time:

$$\check{T}_{ij}^{(l_k)} = \min(\check{T}_{ij}^{(l_k)}), \tag{5}$$

representing the best-case scenario under optimal transit conditions.

(c) Minimum time grouped by DEA category : Assuming that hospitals within the same DEA category are interchangeable from the user's perspective, we compute the minimum travel time from each centroid to any hospital in the same DEA group:

$$\check{T}_{ij}^{(l_k)} = \min(\check{T}_{ijc}^{(l_k)}), \tag{6}$$

where the subscript *c* denotes the hospital category. This final result constitutes the first major output of the spatial accessibility analysis.

Network topology modelling

To quantify the importance of each node in facilitating access to the healthcare network via public transportation, we employ centrality analysis, a fundamental concept in network theory[15,16]. While numerous centrality metrics exist, each capturing a distinct aspect of node influence [73,74], we adopt betweenness centrality (BC), mathematically represented in Eq. 7, as the primary metric due to its demonstrated relevance in transportation networks [75,76]. The choice of betweenness centrality is motivated by its ability to identify transit hubs that facilitate movement between urban zones (origins) and healthcare facilities (destinations). As Barthélemy [77] highlights, BC is particularly effective in detecting bottleneck nodes whose removal would disrupt network connectivity—an essential concern in emergency healthcare contexts where timely access can be life-saving. Mathematically, the betweenness centrality of a node v_k is defined as:

$$BC(v_k) = \sum_{s \neq t} \frac{\sigma_{st}(v_k)}{\sigma_{st}}, \tag{7}$$

where:

- σ_{st} is the total number of shortest paths from node *s* to node *t*;
- $\sigma_{st}(v_k)$ is the number of those paths that pass through node v_k.

Nodes with high *BC* values often serve as structural checkpoints. Previous studies have used BC to assess geopolitical relevance and infrastructure vulnerability[78].

Resilience assessment

The resilience assessment component of this methodology addresses a critical aspect of access to healthcare: the robustness of the system in disruption scenarios. Drawing on the theoretical and empirical frameworks discussed in Jenelius and Mattsson[21], Ganin et al.[14], and Bergantino et al.[50], we define resilience as the network's ability to maintain healthcare accessibility when key nodes are compromised. This assessment focuses on how disruptions to high-centrality nodes impact healthcare accessibility across Rome's urban zones. To evaluate network resilience, we implement targeted node removal scenarios following the methodology of Albert et al.[79], refined for transportation networks by Berche et al.[80] The top three high-centrality nodes belonging to the section of the O-D between the 0.25 and the 0.75 quantiles of the bus routes, ranked by betweenness centrality, are removed altogether to simulate a widespread disruption. The decision to consider only the central segments of PT routes is based on the rationale behind the node selections. Since origins and destinations are always touched by the shortest paths, given that all routes ultimately lead to the 11 healthcare facilities, using all lengths of paths to select the nodes to remove would result in the hospital nodes being identified as the chosen ones. We then recalculate the minimum median travel time to the nearest hospital within the same DEA group, the number of urban zones that lost access, and the change in average healthcare accessibility.

If the optimal path is disrupted, the next-best alternative is selected within the one-line-change constraint. If no alternative exists, the travel time is recorded as infinite, indicating a complete loss of access due to the unavailability of a feasible transit route. This approach builds on the work of Jenelius et al.[52] and El-Adaway et al.[76], demonstrating that targeted disruptions to high-centrality nodes offer more meaningful insights into network vulnerability than random failures. In addition to analyzing the impact of targeted node removals on network-wide accessibility metrics, we also performed a focused evaluation of the spatial heterogeneity in travel-time variations between individual origin-destination pairs after node removal. This analysis illustrates how accessibility to healthcare facilities varies at an aggregate level and between specific urban zones and hospitals when the network is disrupted. Specifically, we compare the minimum travel time T_{ij}^{base} from the urban centroid c_i to the hospital h_j under normal, undisrupted conditions with the corresponding minimum travel time T_{ij}^{disr} after the removal of one or more high-betweenness centrality nodes. The spatial impact of the disruption for each origin–destination pair is quantified as:

$$\Delta T_{ij} = T_{ij}^{\mathrm{disr}} - T_{ij}^{\mathrm{base}} \tag{8}$$

where:

- T_{ij}^{base}: minimum travel time from centroid c_i to hospital h_j in the intact network;
- T_{ij}^{disr}: new minimum travel time for the same pair after network disruption;
- ΔT_{ij}: variation in travel time due to the failure.

A positive ΔT_{ij} indicates worsened accessibility for that specific origin–destination pair. If $\Delta T_{ij} = 0$, accessibility is preserved despite the disruption. In cases where no route remains within the one-line-change constraint, T_{ij}^{disr} is considered infinite, and ΔT_{ij} is marked as undefined to reflect complete inaccessibility.

This spatial heterogeneity analysis helps identify localized vulnerabilities and assess the uneven impacts of disruption across the urban area. By adopting a multi-scale heterogeneity perspective, we move beyond global resilience metrics and provide a more granular understanding of how disruptions reshape access to emergency healthcare spatially. We perform two analyses to compare healthcare accessibility under different scenarios. The first considers only the 11 DEA-classified healthcare facilities as defined in the baseline scenario. The second expands to include all 36 DEA and non-DEA classified facilities, treating each as a viable alternative.

This broader approach applies to less critical healthcare needs, where patients may seek care at any facility that is available and accessible for general check-ups or non-urgent consultations.

Results

To address the research question concerning the impact of network disruptions on access to healthcare, we estimate travel times under baseline and disruption scenarios. These estimates capture changes in healthcare accessibility across urban neighborhoods, accounting for direct routes and potential detours caused by targeted node removals in the transportation network. The results, presented in Tables 1, 2, and 3, reveal key outcomes.

Firstly, in some cases, the minimum median travel time remains unaffected despite network disruptions. This indicates a high degree of redundancy in the transportation network, as specific node removal did not affect the connection between a given centroid and its closest DEA-specific hospital. In other areas, disruptions result in significantly longer travel times to specialized hospitals. This occurs when the closest facility becomes

Neighborhood	Minimum travel times (base analysis)	Minimum travel times (disruption analysis)	Pre- and post disruption differences
11B Valco San Paolo	10.43	–	–
20B Acquatraversa	13.57	–	–
Marconi	5.63	–	–
11A Ostiense	6.03	21.83	5.80
16X Villa Pamphili	8.47	8.52	0.05
15B Portuense	13.25	13.25	0
15D Trullo	31.90	31.90	0
16B Buon Pastore	29	29	0
16X Villa Pamphili	45.92	45.92	0
17A Prati	38.60	38.60	0
1A Centro storico	28.13	28.13	0
1D Testaccio	10.50	10.50	0
1G Celio	6.35	6.35	0
1X Zona archeologica	10.03	10.03	0
2X Villa Borghese	13.80	13.80	0
3Y Verano	57	57	0
5B Casal Bruciato	37.33	37.33	0
5C Tiburtino Nord	60.93	60.93	0
9E Latino	13.67	13.67	0
Aurelio Nord	35.77	35.77	0
Tuscolano Nord	7.70	7.70	0

Table 1. Minimum travel times: DEA2.

Neighborhood	Minimum travel times (base analysis)	Minimum travel times (disruption analysis)	Pre- and post disruption differences
1A Centro storico	32.97	–	–
2C Flaminio	16.68	–	–
2X Villa Borghese	22.00	–	–
Medaglie d'Oro	16.77	–	–
Tomb of Nerone	7	40.23	33.23
17B Della Vittoria	19.03	43.17	24.13
20X Foro Italico	19.03	43.17	24.13
20H La Storta	21.90	24.80	2.90
10F Osteria del Curato	17.70	17.70	0
10I Barcaccia	8.78	8.78	0
10L Morena	18.33	18.33	0
10X Ciampino	17.07	17.07	0
12G Spinaceto	15.23	15.23	0
16X Villa Pamphili	75.37	75.37	0
19B Primavalle	16.98	16.98	0
19C Ottavia	8.63	8.63	0
20L Prima Porta	17.55	17.55	0
20M Labaro	17.55	17.55	0
5B Casal Bruciato	12.90	12.90	0
5C Tiburtino Nord	4	4	0
5G Pietralata	7.70	7.70	0
7B Alessandrina	23.00	23.00	0
7C Tor Sapienza	32.20	32.20	0
8C Giardinetti-Tor Vergata	4.53	4.53	0
8F Torre Angela	14.80	14.80	0
Centro Direzionale Centocelle	30.60	30.60	0
Grotta Rossa Est	8	8	0

Table 2. Minimum travel times: DEA1.

Neighborhood	Minimum travel times (base analysis)	Minimum travel times (disruption analysis)	Pre- and post disruption differences
20B Acquatraversa	18.93	–	–
16X Villa Pamphili	39.65	39.65	0

Table 3. Minimum travel times: First aid (PS).

unreachable due to hub disruption, requiring residents to travel to more distant hospitals offering the same specialization. Thirdly, the most concerning outcome is observed in certain urban centroids where specialized hospital types become entirely inaccessible following network disruptions. These areas experience a complete loss of access to essential healthcare services, which has the most severe impact on the healthcare system's resilience. This last scenario is particularly critical for affected area residents when the designated hospital provides highly specialized emergency services, as for level 2 DEA facilities (see Table 2).

Several instances of these vulnerabilities emerge from our results, where travel times can increase by more than 30 min. In extreme cases, access to essential healthcare facilities becomes entirely unfeasible following the removal of key nodes, leaving residents without viable routes to specialized emergency care. For instance, in the baseline scenario, residents of the Marconi district can reach San Camillo Forlanini, a Level 2 DEA hospital providing specialized emergency care, in just 5.63 min under normal, undisrupted conditions. However, our analysis revealed that if the 'Maiorana-Fornetto' transportation node is disrupted, Marconi residents lose all accessible routes to Level 2 DEA hospitals. A similar situation arises in Acquatraversa, where the Policlinico Universitario Fondazione Gemelli is the closest DEA2 hospital under normal conditions. However, after the elimination of the "Trionfale-Tenuta Sant'Agata" stop, no DEA2 hospitals are reachable from this location.

Furthermore, our analysis also identifies numerous intermediate scenarios where transportation disruptions caused increases in travel time to specialized hospitals. An example of these intermediate impacts can be seen in the Tomb of Nerone district (as shown in Table 1). Under normal conditions, residents can reach a Level 1 DEA hospital within just 7 min. However, our analysis reveals that if the 'Cassia-Pareto' transportation node is interrupted, the travel time to the nearest alternative Level 1 DEA hospital increases dramatically to 40.2 min, nearly a six-fold increase, although access to the hospital remains possible. While this situation does not result in total inaccessibility, the delays can significantly impact urgent medical access, particularly in areas with high mobility demand. In contrast to these vulnerabilities, our analysis also identifies areas with high resilience in healthcare accessibility. Several central urban districts—including Zona Archeologica, Verano, and Villa Borghese—maintain consistent access to key hospitals even when high-centrality transportation nodes are disrupted. These areas benefit from redundant transportation options that provide multiple pathways to healthcare facilities.

Our broader analysis, which considers all healthcare facilities (both specialized DEA and non-specialized non-DEA hospitals) as potential destinations, reveals a much more robust healthcare accessibility network. In this case, many origin-destination paths show only marginal changes in travel times (see the third Table in the Supplementary Material), suggesting that simply removing three nodes, given the wide range of alternative destinations, does not have a significant impact.

Discussion and policy implications

By comparing travel times under normal and disrupted conditions, we identified key weaknesses in Rome's public transport system in maintaining access to emergency care, addressing the research question we posed on how disruptions in the transport network affect access to healthcare services.

To understand the impact of these disruptions, we removed specific PT stations identified as key hubs using complex network analysis. This allowed us to examine how taking out central nodes—and the routes linked to them—affects people's ability to reach healthcare facilities.

The results show that some neighborhoods in Rome depend heavily on just a few key transit hubs to reach healthcare services, making them particularly exposed to disruptions. In certain cases, when a central hub is lost, it leads to a total loss of access to specific types of hospitals because no alternative routes are available. The impact of disruptions is not evenly spread across the city. While many routes between neighborhoods and healthcare services remain mostly unaffected, some neighborhoods experience significant delays. For instance, certain routes to more advanced emergency care facilities face major increases in travel time, which could seriously hinder timely medical assistance. On the other hand, some routes, like the one to Villa Pamphili, experience minimal delays, showing that parts of the network benefit from good redundancy. One of the most affected routes connects the Tomb of Nerone area to a basic emergency facility and shows a drastic increase in travel time. These contrasts highlight how vulnerability within the network varies by location, and in the most affected neighborhoods, disruptions can entirely cut off access to hospitals, leaving residents without timely public transport options for emergency care.

The spatial distribution of disruption impacts reveals important patterns about Rome's transportation network resilience. The concentration of significant travel time increases in specific areas (particularly northern and western zones like Tomb of Nerone, Della Vittoria, and Foro Italico) suggests localized vulnerabilities in the transportation infrastructure. This pattern may reflect areas where alternative routes are limited or where the transportation network lacks sufficient redundancy. The research methodology revealed the most vulnerable neighborhoods and pinpointed critical hubs in the transport network whose failure could isolate entire neighborhoods from essential healthcare services. These findings emphasize the need to enhance redundancy within the public transport system to ensure continuity of access during unexpected disruptions. On the other hand, the absence of disruption impacts across most origin-destination pairs (17 out of 21 for DEA2 facilities and 21 out of 28 for DEA1 facilities) indicates substantial resilience in Rome's overall transportation network. This resilience is particularly evident in central and eastern areas of the city, suggesting more robust transportation infrastructure or greater route alternatives in these regions.

The observed patterns have significant implications for healthcare accessibility, particularly in emergencies, that can translate into direct policy implications. The data reveals that disruptions can create substantial inequities in healthcare access across different neighborhoods. This highlights the role of redundant transit connections, i.e., alternative routes that, while slower, serve as viable substitutes when primary routes are disrupted. These substitutes play a critical role in safeguarding healthcare access during emergencies, especially in areas with limited baseline service options. Conversely, areas with lower redundancy are significantly more vulnerable, facing a risk of complete isolation from hospital facilities in the event of hub failures. In today's rapidly changing environment, where infrastructure modifications, traffic patterns, and healthcare facility operations can shift unexpectedly, static analyses are insufficient, particularly in identifying which communities face total or partial disconnection from healthcare services during such events. To mitigate this vulnerability, it is advisable to identify and continuously monitor critical structural hubs through dynamic monitoring systems that can adapt to evolving urban conditions. Such systems can promptly detect interruptions or congestion and suggest real-time diversions or reinforcements of the service. Strategies should include temporary lines, emergency shuttle services, and real-time travel information systems, all of which would enhance the resilience of the healthcare transport network.

The analysis also highlights the unequal burden such disruptions place on certain populations. Many of the most affected residents depend exclusively on public transportation, often due to financial or social constraints that limit access to private vehicles or more flexible mobility options. As a result, any interruption in service disproportionately impacts these communities, particularly when timely access to emergency or specialized healthcare is essential. Our approach can help policymakers identify where resilience interventions are most urgently needed to protect the health and mobility of vulnerable residents. This analysis should inform targeted infrastructure planning, prioritizing new transport nodes, increased service frequencies, and preferential lanes in the most affected areas. We recommend that authorities also engage citizens and local stakeholders through participatory consultations and targeted communication campaigns. This would support the co-creation of transport services and improve public awareness of alternative routes during emergencies.

Overall, the use of daily GTFS data and a "real" travel time model, combined with network analysis, showed potential in identifying strategic nodes and mapping the most vulnerable areas. The phase of collecting and processing GTFS data into a single dataset represented the main challenge, in particular to ensure the correct temporal alignment of trips. The comparison with the literature confirms the importance of major public transport hubs in maintaining redundancy and continuity of service and extends previous resilience analyses by introducing more granular disruption simulations than those proposed by Jenelius et al.[52] or Wang et al.[54]. This operational approach, which combines methodological rigor and empirical details, opens new perspectives for future studies on the robustness of urban transport networks.

We acknowledge that this study has limitations. While our focus on rigorous travel time estimation and complex network construction represents a significant methodological contribution, we did not account for other important factors that influence accessibility. These include, for example, spatial dynamics of supply and demand, user perceptions, and behavioral heterogeneity. Further extensions of this paper addressing such dimensions will contribute to our understanding of accessibility to healthcare services and transportation equity. On-field experiments, behavioral data collection, and population surveys could validate the results of our empirical application. Other streams of future research are worth exploring: implementing a multi-scenario monitoring framework, including rush-hour conditions, holidays, and unexpected emergencies such as extreme weather events or traffic incidents, would allow for the development of more effective response strategies. Additionally, integrating epidemiological and clinical data into transport accessibility studies could provide valuable insights into the direct relationship between travel times and health outcomes, particularly for medical emergencies such as strokes, heart attacks, and severe trauma, where timely hospital arrival is crucial.

Data availability

The data used in the study comes entirely from public sources and is accessible to the public domain. In particular, the georeferenced data relating to the public transport network of Rome (GeoJSON and GTFS formats) were obtained from the open data portal of the Municipality of Rome and from the database made available by Kujala et al. (2018). The information on the classification of healthcare facilities comes from open datasets of the Ministry of Health. The procedure described in the article for the construction of the database (including the association between stops, lines, timetables, municipal centroids, and hospitals) is therefore entirely replicable, being based on open data sources that can be freely consulted and downloaded. Any additional details on the processing or direct links to the data publication platforms can be provided, upon request, by the authors.

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Author contributions

All the authors contributed equally to the paper.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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