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# Understanding the interplay between public transport travel time variability and jobs competition on accessibility inequalities

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ABSTRACT

Recent studies have examined socio-spatial inequalities in public transport accessibility in Global South cities, consistently showing that lower-income groups face reduced access. However, most rely on scheduled GTFS data to estimate travel times, ignoring day-to-day travel time variability caused by congestion or service disruptions. This oversight limits our understanding of how such variability impacts accessibility levels and inequalities – especially when using more robust indicators that account for competition over opportunities. Emerging research points to a complex interplay between travel time variability and competition for activities, with potential to bias inequalities assessments. Yet, these effects remain underexplored. This study addresses such gap by integrating GPS and GTFS data to assess how daily fluctuations in transit performance affect job accessibility and inequality estimates using both cumulative and competition-based metrics. Using data from Fortaleza, Brazil, our findings show that day-to-day variability significantly influences both accessibility levels and inequalities – regardless of the indicator used. When jobs competition is considered, socio-spatial inequalities widen, as variability is generally lower in central areas and higher in the periphery. Moreover, competition-based measures – adding the interaction between the population distribution, the location of job opportunities, and the level-of-service of the public transport system – amplify the effects of variability, leading to greater observed disparities than cumulative metrics. These findings highlight a critical link between transit reliability and accessibility inequalities, underscoring the need for future studies and policy evaluations to consider travel time variability and competition effects when assessing equitable access to opportunities in Global South metropolises.

## 1. Introduction

In recent years, researchers have paid more attention to accessibility by public transport, largely due to the increasing availability of data such as General Transit Feed Specification (GTFS) (Farber and Fu, 2017; Pereira, 2019). Because of the nature of static GTFS feeds, these studies calculate accessibility estimates based on scheduled public transport services. As a result, most of the literature neglects the issue of day-to-day variability in transit services, which relates to how travel times for any given origin-destination pair might vary across different days and times of the day. Such variations may generate large uncertainties as they impact individuals' abilities to consistently access opportunities. Different studies have proposed methodologies to evaluate the impact of this issue on accessibility estimates (see section 2), revealing that travel time variability can significantly impact different neighborhoods and socioeconomic groups, raising serious inequality concerns especially in the Global South context (Arbex and Cunha, 2020; Braga et al., 2023). However, these studies have exclusively relied on simple cumulative accessibility indicators, overlooking the demand aspect that could result in competition for activities (Cheng and Bertolini, 2013; Merlin and Hu, 2017). An expanding body of literature suggests the existence of intricate socio-spatial aspects concerning the interplay between travel time variability and competition for activity opportunities (Chen et al., 2020), but this relationship has not yet been examined in detail, especially considering job accessibility in the Global South context.

Therefore, this study aims to understand the interplay between transit day-to-day travel time variability, competition for job opportunities, and accessibility inequalities with a focus on understanding its socio-spatial implications. Using the city of Fortaleza (Brazil) as a case study, representative of high socio-spatial segregation in Latin American metropolises, we investigate how access to employment and its inequalities are impacted when utilizing accessibility metrics that consider

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competition for job opportunities in a context of high travel time variability in public transport services. We use GPS data to create GTFS feeds representing both a median and a dispersion scenario. Subsequently, we calculate accessibility from those feeds for both cumulative and competition measures, comparing the influence of transit day-to-day travel time variability on accessibility estimates and socio-spatial inequalities.

Previous studies have found that not accounting for day-to-day variability in transit travel times can overestimate accessibility conditions (Lee and Kim, 2023; Lee and Miller, 2020), reaching more than 50 % in peripheral regions of large Global South cities and underestimating accessibility inequalities by 35 % (Braga et al., 2023). Nonetheless, these findings were primarily based on accessibility metrics that do not incorporate competition effects which result from the potential demand for activity opportunities (Hu, 2014; Merlin and Hu, 2017; Soukhov et al., 2023). Competition adds another layer of complexity to accessibility assessment, with some studies that have evaluated its impact on socio-spatial inequalities indicating that it might underestimate or have little impact on accessibility income inequalities (Allen and Farber, 2020; Giannotti et al., 2021; Kelobonye et al., 2020). Moreover, emerging evidence suggests that travel time variability tends to impact competition-based accessibility in complex ways, with heterogeneous positive and negative effects across space (Chen et al., 2020). However, from the best of our knowledge, no study has investigated the extent to which this interplay between the variability of public transport services and the effects of competition for job opportunities could influence socio-spatial inequalities in accessibility to employment. This can be particularly important in cities in the Global South, where job opportunities are usually concentrated near the city center, and most of the low-income population lives in the periphery.

Therefore, this paper makes two main contributions to the existing literature. First, by comparing different accessibility metrics that incorporate competition with those that do not, we can isolate demand effects and gain further evidence into the intricate relationship between transit travel time variability across urban areas, socioeconomic groups, and the interplay between demand for and supply of job opportunities. Second, our study generates new evidence of the substantial socio-spatial effects of day-to-day variability in public transport travel times on estimations of accessibility levels and inequalities, particularly in the context of competition for job opportunities in a Latin American metropolis. We believe our findings will provide evidence to researchers when making decisions regarding accessibility metrics to be used on equity-based policy evaluations.

## 2. Literature review

In this literature review analysis, we cover the issue of public transport reliability focusing specifically on day-to-day travel time variability and its implications for accessibility assessments. We then review recent studies on competition-based accessibility and its inequalities implications. Lastly, we establish connections between these two topics and detail the research gaps in the literature.

### 2.1. Public transport travel time reliability issues in assessing accessibility

Recent research has assessed public transport (PT) accessibility conditions and analyzed the impact of transportation policies, particularly within the context of the Global South, and have highlighted significant socio-spatial inequalities in access patterns (Bittencourt et al., 2020; Boisjoly et al., 2020; Pereira et al., 2019a; Pinto et al., 2022). However, a key issue is that the estimation of PT accessibility in those assessments has relied on scheduled travel times, more recently from General Transit Feed Specification (GTFS) data. Two main PT travel time reliability issues can result from this practice: inaccuracy and variability. Travel Time Inaccuracy (TTI) refers to how the scheduled levels of PT service might differ from what is delivered to the population (Liu et al., 2022). Different studies have focused on this problem, showing that travel time estimates calculated based on transit scheduled times can significantly differ from those based on actual times (Mandelzys and Hellinga, 2010; Palm et al., 2020).

The other relevant PT reliability issue is Travel Time Variability (TTV), understood here as day-to-day travel time variability, which refers to how the delivered travel times from the same location, at the same departure time, might vary across different days, mainly caused by traffic interruptions, fluctuations in demand, and extreme weather (Lomax et al., 2003). This subject has been extensively analyzed in the literature (Kieu et al., 2015; Mazloumi et al., 2010), showing that PT performance can substantially vary between days and potentially impact people's ability to reach opportunities consistently. High variability in transit travel time leads travelers to add a 'safety margin' to their expected O—D travel time, increasing the likelihood of arriving on time (Hall, 1983). Variability has also been shown to influence route selection more than the actual travel time, resulting in PT users preferring routes with less variability compared to lower mean travel times (Bates et al., 2001).

To assess the effects of reliability issues on public transport accessibility, methodologies bring actual travel times (usually through GPS) into static GTFS feeds to calculate transit travel times and compare accessibility estimates. For TTI, they compare schedule-based with observed travel time-based (coming from real-time GTFS or GPS) accessibility levels (Liu and Shalaby, 2024; Nalin et al., 2025; Nichols et al., 2024). Studies have shown that inaccuracies in schedule-based measures can have an inconclusive effect on job accessibility estimations in urban spaces, tending to either overestimate or underestimate accessibility. On average, scheduled-base accessibility was shown to overestimate access levels to job opportunities by 5–15 % in North American cities (Wessel and Farber, 2019), and by only 1.5 % in Fortaleza, Brazil (Braga et al., 2023), without a clear spatial pattern impact.

To address the TTV issue, accessibility studies have adopted different approaches. A prominent line of research uses space-time prisms to capture traveler behavior under uncertain travel times, allowing for the incorporation of different levels of risk tolerance while choosing origin-destination travel times (Lee and Miller, 2020; Zhang et al., 2018), with more recent research using static GTFS and real-time GTFS to model route choice (Lee and Kim, 2023; Lee and Miller, 2020). Other stream is based on using historical GPS data to reconstruct multiple static GTFS feeds to evaluate the impact of TTV on location-based accessibility, more focused on Global South cities where real-time GTFS is not available. These reconstructions enable comparisons between median-based and dispersion-based accessibility, helping to evaluate the impact of variability on access measurements. Looking at the city of São Paulo, Brazil, Arbex and Cunha (2020) found that the number of accessible jobs was on average 6.2 % smaller when TTV was accounted for. Braga et al. (2023), in turn, found that TTV can reduce average job accessibility by 50 % in Fortaleza, Brazil. More importantly, this latter study shows that the impact of TTV varies significantly across space, with a pronounced impact in urban peripheral areas rather than near the city center. Consequently, the authors found that, in a Latin American metropolis, accessibility inequalities between high and low-income groups were 35 % higher when TTV was accounted for.

In conclusion, our literature review highlights the importance of considering reliability issues when assessing public transport policies and socio-spatial inequalities, with particular emphasis on transit travel time variability as compared to travel time inaccuracy.

### 2.2. Competition for activity opportunities

Competition indicators incorporate the potential demand for activity opportunities by factoring in the population that could simultaneously access them. This concept is especially crucial when: (i) demand for available opportunities is unevenly distributed across different areas; and (ii) the activities have capacity limits, as is the case with job opportunities (Shen, 1998). The incorporation of competition in accessibility became significant with Shen's work, which laid the foundation for comprehensively implementing it into accessibility calculations. The author introduced a multi-stage method to measure accessibility that accounts for competition by adjusting the number of opportunities available at a location based on the potential demand within the surrounding area. This approach also involved using a travel impedance function to represent the friction of movement between origin and destination pairs, particularly for job opportunities.

Building upon Shen's work, the Two-Step Floating Catchment Area (2SFCA) metric was introduced by Luo and Wang (2003), which has been widely used ever since, primarily for healthcare opportunities (Wan et al., 2012). This indicator provides a different interpretation of Shen's approach, calculating a location accessibility by: first, calculating the level of service for each job location, by dividing the number of opportunities by all the population that will be competing for opportunities within that location catchment area; and second, from each origin, identifying all the locations it can access and summing the level of services within its catchment area.

The 2SFCA, in its original formulation, presents two main drawbacks: i) it employs a binary function for delineating catchment areas, working as a cumulative indicator; ii) it overestimates demand and supply in cases of overlapping areas of influence. Recent advancements have addressed these issues by enhancing the measurement of the area of influence using stepwise and Gaussian functions (Luo and Qi, 2009), while other studies have tackled the problems of demand inflation (Wan et al., 2012). More recently, researchers proposed an indicator able to address the issues of demand and supply inflation and showcased how the new indicator tackles both issues in comparison with the traditional 2SFCA (Paez et al., 2019). This indicator would later be called the Balancing Float Catchment Area (BFCA), being applied to access to healthcare opportunities (Pereira et al., 2021a, 2021b).

Lately, several studies have explored how accounting for competition in the analysis of access to jobs can impact estimates of accessibility inequalities. Allen and Farber (2020) proposed and applied a competition-based metric to eight Canadian cities, showing that levels of inequalities (measured by Gini index) are 30 % lower for a competition-based metric in contrast to a cumulative one. In the Global South context, Giannotti et al. (2021) conducted a study in which accessibility inequality assessment, measured by the Gini coefficient, remained relatively consistent when competition was integrated using the 2SFCA method.

### 2.3. The interplay between transit travel time variability, competition for activities, and accessibility socio-spatial inequalities

As discussed above, the existing body of research studying the impact of transit travel time variability on location-based accessibility has predominantly focused on cumulative accessibility metrics (Arbex and Cunha, 2020; Braga et al., 2023). However, relying solely on cumulative indicators provides a limited understanding of the overall impact of variabilities in PT travel times, especially because this type of measure does not incorporate the potential demand for opportunities. Moreover, accounting for job competition in accessibility assessment is important because of two factors. Firstly, it generates a more realistic view of the job opportunities people can reach, given that demand for jobs is not evenly distributed in the space and there is a limited capacity issue (one job per person). Empirically, accessibility with job competition has been shown to have stronger associations with employment outcomes when compared to accessibility without competition (Merlin and Hu, 2017); and it should be better suited to compare accessibility from different cities since it accounts for population size and distribution (Allen and Farber, 2020).

Most importantly, emerging evidence suggests that incorporating competition can have pronounced effects on socio-spatial inequalities, particularly when travel time variability is considered. Focusing on accessibility by car to health services, Chen et al. (2020) conducted a study in Shenzhen, China, on the impact of travel time variability on accessibility considering competition. Using a probabilistic approach, the authors proposed an adaptation from the 2SFCA, incorporating the uncertainty of reaching opportunities under travel time variability. They found that it can have positive and negative effects depending on the distance to activities. The authors noted that, within the 2SFCA framework, as the variability negatively impacts travel times, people tend to reach fewer opportunities, but the competition from other locations for the closer opportunities also decreases. They also stated that travel time variability may exacerbate spatial inequalities in healthcare accessibility when competition is considered, but they have not calculated any inequality measure.

While the evidence presented by Chen et al. (2020) pertains to a specific Chinese city and its healthcare services accessed by car, it may be reasonable to expect that similar patterns of competition for other activities can be observed using public transport, particularly in Global South cities. Moreover, the interplay between competition for job opportunities and the variability of public transport services within a Latin American context may be even more intricate. In such a socio-spatial segregation scenario, most of the low-income population resides a considerable distance from the city center, where employment opportunities are concentrated. It is well-established that these low-income locations suffer a greater impact when considering transit travel time variability; therefore, we can anticipate a worsening of socio-spatial inequalities within this context as well.

## 3. Study area: Fortaleza, Brazil

Fortaleza, capital of the state of Ceará, ranks as the fourth most populous city in Brazil, with an estimated population of 2.4 million inhabitants (IBGE, 2022). Like most large Latin American cities, it is marked by high levels of social inequalities, especially in income. In 2022, the city had a Gini coefficient of 0.64 (Salata and Ribeiro, 2023), similar to countries such as South Africa and Namibia. This income inequality has a strong spatial character in the city (Pinto et al., 2023), with a clear concentration of higher-income groups near its central area, where there is also a greater concentration of employment activities and opportunities, and a clustering of low-income groups predominantly in its West and South regions (Fig. 1).

Public transportation is central to mobility in Fortaleza, accounting for about 20 % of daily trips in the city, according to the 2019 Household OD Survey. The system carries more than 500,000 passengers per day, most of them on bus services. These are structured around 318 lines and supported by an expanding network of dedicated infrastructure. Since 2013, Fortaleza has implemented more than 130 km of exclusive bus lanes, which have significantly improved travel speeds and service efficiency. In addition to buses, the city operates three low-to-medium frequency LRT/metro routes, which complement the network and provide additional capacity on key corridors. The full public transport network is presented in detail in Fig. 2. The urban bus system is structured to encompass feeder, trunk, and circular routes. Feeder routes serve to connect outlying neighborhoods to major terminals, while trunk routes link terminals to the city center. Circular routes facilitate connectivity between terminals. The rail system includes: the West Line, which departs from the Central region and cuts through the Northwest region, extending to the municipality of Caucaia; the South Line, which also starts from the Central region, crosses the Northwest region, and travels through the entire Southwest region towards the municipality of Maracanaú; and the Parangaba-Mucuripe LRT line, which connects the Southwest and the Northeast regions (still under assisted operation).

One of the outcomes of the land use and transport configuration in the city is a marked socio-spatial inequality in access to employment in Fortaleza, a condition that has worsened over the past two decades (Castro et al., 2025). Results from the Access to Opportunities project (Pereira et al., 2019b) estimate that the richest have on average twice as

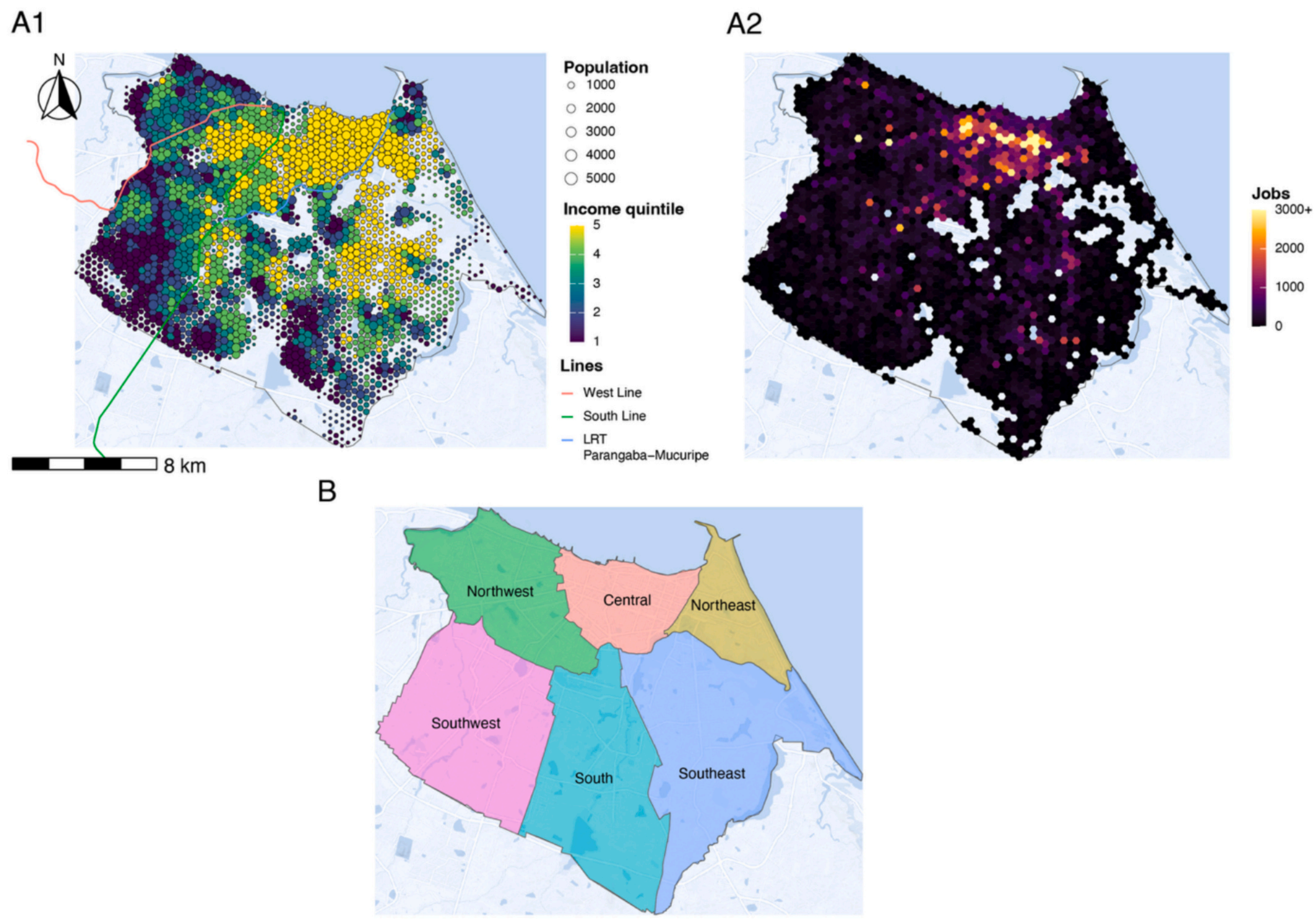


**Fig. 1.** Fortaleza's population and income distribution from 2010 (A1) and formal jobs distribution from 2019 (A2); Fortaleza's analysis regions (B).
Source: Adapted from Braga et al. (2023).

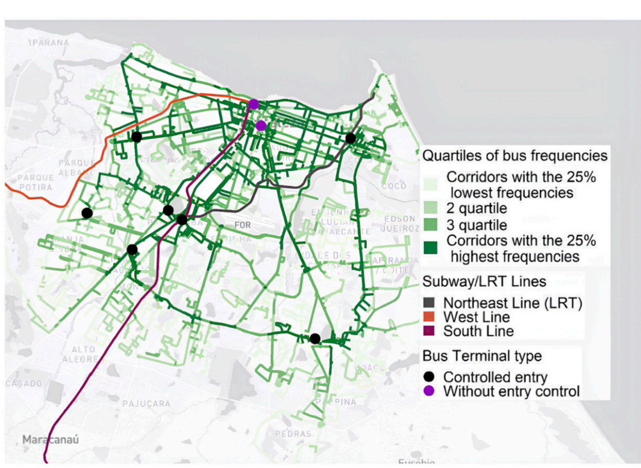


**Fig. 2.** Fortaleza's public transport system.
Source: Adapted from Lucas Albuquerque-Oliveira et al. (2024).

much accessibility to jobs as the poor by public transport in Brazilian metropolises.

## 4. Data and methods

This study aims to assess the impact of incorporating transit travel time variability and competition for job opportunities on accessibility levels and inequalities. To answer our research question, the proposed methodology is organized in two main steps. Firstly, we calculate travel times that represent both the median performance of the PT network as well as travel times that capture the day-to-day variability of its level of service. To do this, we use historical GPS data to replace travel times in the scheduled GTFS. We compare the median-corrected accessibility (based on a version of GTFS corrected by the median of real speeds) with the dispersion-corrected accessibility (based on a version of GTFS corrected by a dispersion measure of real speeds).

The second methodological step consists of comparing the transit travel time variability impact on accessibility estimates when using cumulative and competition indicators. This comparison aims to provide further evidence on how each measure may be impacted differently by transit travel time variability. We examine the impact of travel time variability on the cumulative indicator (as a representation of non-competition-based measurement) and then on both the Two Step Floating Catchment Area (2SFCA) and the Balanced Floating Catchment Area (BFCA) metrics (representing competition-based measures). The methodology for calculating and comparing the accessibility indicators is detailed in section 4.3.

### 4.1. Data sources

Population and income data came from Brazil's 2010 Census, with formal employment data being extracted from the Ministry of Labor's Annual List of Social Information (*Relação Anual de Informações Sociais -*

RAIS) for the year 2019. The final dataset, containing geolocated population, formal job counts, and income deciles, was aggregated over a hexagonal grid with a short diagonal of 357 m and an area of 0.1 km$^2$. It was obtained using the R package *aopdata* (Pereira et al., 2022). GPS and GTFS data of the bus system were provided by Fortaleza's Urban Public Transport Agency (ETUFOR). GTFS data of the metro/LRT system were obtained from the state public transport agency, METROFOR. Both data sets referred to scheduled services planned for September 2018. According to the GTFS data, a typical business day in Fortaleza's public transport system had around 35,000 vehicle trips distributed across 318 routes.

GPS records registered the timestamp and the spatial coordinates of each bus every 30 s in most cases. On average, there were approximately 4 million data points per day during the 19 business days of September 2018. Approximately, 85 % of the bus fleet was covered in the GPS dataset. The other 15 % missing from the GPS dataset consisted of smaller vehicles running on feeder routes with low capacity and passenger demand. Because of these characteristics, the missing vehicles are assumed to be on links that are less affected by travel time variability, making their absence less critical. Moreover, vehicles within the 85 % coverage that crossed these links likely provided sufficient travel time information, helping to capture conditions on such links.

Due to the unavailability of fully consolidated 2022 Census data, this study relies on the 2010 Census as the most comprehensive demographic source. Transport data from 2018 and employment data from 2019 were selected as they represent the most recent and reliable datasets available for the corresponding periods.

### 4.2. Reconstructing GTFS with historical GPS data

The process of reconstructing travel times in a GTFS based on historical GPS data was conducted in two steps. Firstly, the process involved converting raw GPS data into a timetable format resembling the GTFS *stop_times.txt* file. For each vehicle and day, trips were delimited by creating a buffer around the start and endpoints of each route, with trip direction determined by snapping GPS points to the corresponding GTFS inbound route sequence. The method then estimates the moment each vehicle passes through each stop by calculating cumulative distances and linearly interpolating timestamps, generating a table similar to GTFS *stop_times.txt* file.

In the second step, travel times of all vehicles between consecutive stops (what we refer to as the links in the PT network) were aggregated over 15-min intervals. This resulted in a travel time distribution for each link during each interval along the day. The number of observations in each link depends on the frequency of the routes operating on it. To enhance measurement reliability, travel time estimates for links with less than 10 observations per 15-min interval were considered unreliable and replaced with travel times from the scheduled timetable. This aggregation process created approximately 120 thousand combinations of links and 15-min intervals (5400 segments × 22 time-intervals between 6 am and 8 am). Approximately only 17 % of these combinations had fewer than 10 data points, related to links mostly situated in peripheral areas with low bus traffic. This minimizes concerns about data exclusion, as these regions tend to have less variability in travel times. One advantage of this approach is that it generates reliable travel times between PT stops for routes that eventually have no GPS records, as is the case for low-capacity vehicle services like minibuses and vans in the city of Fortaleza. A detailed version of the method is presented by Braga et al. (2023).

To understand the impact of travel time variability, we adopted the methodology proposed by Braga et al. (2023) which calculates travel times for a median scenario and compares it to travel times calculated from a dispersion scenario. We chose this approach because it has been demonstrated to effectively assess the impacts of transit travel time variability on accessibility levels without relying on complex simulations, while allowing us to use existing methods that estimate travel times and accessibility from GTFS feeds. Therefore, based on the distribution of transit travel times for each PT network link and interval, we constructed two new GTFS feeds. The “P50 GTFS” feed considers the median travel times in each link (P50) to represent the median performance of the PT system; and the “P85 GTFS” feed considers the 85th percentile (P85) to represent the state of dispersion performance. The P50 GTFS and P85 GTFS are built by replacing the travel time values from the GTFS *stop_times* file with those values estimated with GPS records in each network link for the same time interval. P85 GTFS is used to calculate accessibility to be compared to accessibility calculated by P50 GTFS. While various percentiles can be used to represent a dispersion scenario (Mazloumi et al., 2010), we adopted the 85th percentile as it approximates one standard deviation above the mean, assuming travel times follow a normal distribution – a common assumption supported by studies on travel time variability (Abkowitz et al., 1987).

As discussed by Braga et al. (2023), the proposed method has some limitations. Firstly, it corrects for speeds between consecutive PT stops, but it does not account for differences between planned and actual service frequencies. This assumption may be problematic if there is a significant discrepancy between scheduled and observed trip frequency, though this is not expected to be an issue for Fortaleza according to its city officials. Additionally, the approach assumes that all links of the PT network would simultaneously operate under 50th or 85th percentile conditions, which may overestimate travel times. However, we argue that if a link exhibits low variability, assuming it operates at the 85th percentile is less problematic since that would be less variation in its distribution. Moreover, the primary objective of our research is not to quantify the absolute impact of travel time variability, but to examine its spatial distribution within the city and how this impact differs across income groups. Finally, the study mitigates this by averaging travel times over 20 days to improve robustness. The following sections describe the methodological step related to the accessibility indicators.

### 4.3. Accessibility levels calculation and comparison

To assess the impact of travel time variability on accessibility inequalities while accounting for competition for job opportunities, we calculated and compared three distinct metrics. As a baseline reference, we used a traditional cumulative opportunities indicator, which is one of the most widely used metrics in the literature. Two other accessibility indicators were considered to account for competition: the Two Step Floating Catchment Area (2SFCA) and the Balanced Floating Catchment Area (BFCA) indicators. The 2SFCA was chosen due to its widespread use and established analysis in the literature, making it easier to compare to other studies. The 2SFCA calculation started by allocating the potential demand from each origin (population) to all the destinations within its catchment area - therefore each destination has a potential demand (Eq. 1). Next, we calculated the level of service of each destination, which divides the potential demand by the number of jobs at the employment center (Eq. 2). The final step identifies and sums all the levels of service(s) from each origin to calculate the accessibility level (Ai) at origin i (Eq. 3).

$$P_j = \sum\nolimits_{i=1}^{n} P_i w_{ij} \tag{1}$$

$$L_j = \frac{S_j}{P_j} \tag{2}$$

$$A_i = \sum\nolimits_{j=1}^{J} L_i w_{ji} \tag{3}$$

Where:

$P_i$ is the population at population center i ($i = 1,\cdots$,n);

$S_j$ is the number of jobs at j;

$L_j$ is the level of service at j;

$w_{ij}$ is a weight for location pair i j (j = 1,⋯,J). In our case, we are using a cumulative function, therefore:

$w_{ij} = 0$ if *travel time*$_{ij}$ > *time threshold*.
$w_{ij} = 1$ if *travel time*$_{ij} \le$ *time threshold*

As discussed in section 2.2, an important shortcoming of the 2SFCA formulation is that it inflates both the potential demand and the level of service. The demand inflation happens at the first step when the population from each origin is simultaneously assigned to all the destinations. The level of service inflation happens when the same level of service from one destination is considered multiple times in the catchment area of multiple origins. These inflation issues have been shown to cause misinterpretation of the indicator and to be unevenly distributed in space, which could bias analysis concerned with socio-spatial inequalities (Paez et al., 2019). Therefore, the BFCA indicator was also chosen to capture competition effects because it is relatively a novel approach that addresses the issues of inflation of both demand and level of service inherent to the 2SFCA indicator, providing a more theoretically robust metric. This approach replaces the weights in Eqs. 1 and Eq. 3 and uses instead a set of weights normalized by travel costs on the demand side (Eq. 4) and on the supply side (Eq. 5). These weights are then applied when calculating the accessibility level (Ai) at origin i (Eq. 6).

$$w_{ij}^{i} = \frac{w_{ij}}{\sum_{j=1}^{J} w_{ij}} \quad (4)$$

$$w_{ij}^{j} = \frac{w_{ij}}{\sum_{i=1}^{n} w_{ij}} \quad (5)$$

$$A_i = \sum_{j=1}^{J} \frac{S_j w_{ij}^{i}}{\sum_{i=1}^{n} P_i w_{ij}^{i}} \quad (6)$$

After the selection of the indicators, the next step was to calculate accessibility levels for the multiple indicators, and for both the P50 and P85 GTFS feeds. We estimated travel times between origin-destination (OD) pairs by public transport using the R5 routing engine through the r5r package in R (Pereira et al., 2021a, 2021b). This application provides comprehensive travel time estimates, considering various aspects of the door-to-door transit journey, including walking time to the stop, waiting time, time spent in the vehicle, and waiting time for potential integrations. OD pairs were formulated based on the centroids of the H3 hexagonal spatial index with a short diagonal of 357 m and area of 0.1 km$^2$.

For P50 GTFS and P85 GTFS feeds, we computed the median travel time between 6 am and 8 am, considering multiple departure times every minute within that time frame, which has become a common practice to avoid significant differences in the overall trip duration due to slight variations in each trip's start time (Conway et al., 2018; Stepniak et al., 2019). Building these estimated travel time matrices, we used the package Accessibility (Pereira and Herszenhut, 2024) to compute job accessibility for each one of the indicators and for each GTFS feed. We considered job opportunities within travel time thresholds of 45, 60, and 90 min – representing, respectively, the first quartile, median, and third quartile of public transport commute times in Fortaleza, based on its latest 2019 household OD travel survey.

Finally, to evaluate the impact of travel time variability on each indicator (cumulative vs competition), we calculated the relative difference (%) between the accessibility level estimated with the P50 GTFS vs the one estimated with the P85 GTFS in each hexagon. To assess the effect of competition, we compared the relative impact across the territory using two approaches: cumulative opportunity measures versus 2SFCA and BFCA indicators.

### 4.4. Accessibility inequalities assessment

To explore how transit travel time variability impacts PT accessibility inequalities for both cumulative and competition-based indicators, we examined the distribution of accessibility levels across income deciles and use the Palma Ratio as our measure of inequality. The Palma Ratio compares the average accessibility of the wealthiest (decile 10) to that of the poorest (deciles 1 to 4). It has been extensively used in the literature (Freiberg et al., 2024; Geurs, 2020; Pritchard et al., 2019) because it offers a straightforward way to calculate and to interpret inequalities of access to opportunities. Unlike traditional measures such as the Gini coefficient, the Palma Ratio facilitates direct comparisons between income groups and is easier to interpret. However, as shortcomings it overlooks disparities within income groups and excludes consideration of middle-income categories (Karner et al., 2023).

## 5. Results and discussions

This section is structured in three subsections. First, we analyze the spatial effects of considering day-to-day transit travel time variability on accessibility estimates, contrasting the outcomes when utilizing cumulative and competition indicators. Then, we discuss the impact of travel time variability on inequalities for each one of the accessibility indicators and evaluate how differently each indicator is impacted by variability. Finally, we provide practical examples of how those impacts happen in space.

### 5.1. Travel time variability impacts when accounting for competition

Accessibility measured by the Cumulative, 2SFCA, and BFCA indicators were initially calculated for the P50 GTFS feed, for a time threshold of 60 min. Fig. 3 depicts the current accessibility conditions for the three metrics, with the maps showing no clear differences in spatial patterns, even between the two competition indicators. The Central region appears to be slightly lighter in the cumulative measure compared to the competition ones, indicating higher accessibility in the city center in comparison to its peripheral regions. 2SFCA and BFCA indicators have very similar spatial patterns and range of values, which may suggest that the correction of inflation of demand and supply proposed by the BFCA may be offsetting the accessibility levels, considering the level of spatial complexity with several catchment areas overlapping. This issue requires further investigation for other case study's urban contexts.

To assess the impact of travel time variability considering distinct metrics, we then calculated the relative percentage difference (%) between the P85 GTFS and P50 GTFS job accessibility levels at each hexagon, for each indicator and the 45-, 60-, and 90-min time thresholds (Fig. 4). A negative variability impact (in red) indicates where job accessibility levels estimated by the P85 GTFS are lower than the ones estimated by the P50 GTFS. For the Cumulative indicator (first column), job accessibility levels at all regions are negatively impacted by transit travel time variability, which is expected given that P85 travel times are always equal or higher than P50 travel times (Braga et al., 2023). The Central region is the least impacted by variability in PT service, especially for 45- and 60-min thresholds, because comprises the most important employment centers and its residents are less affected as they lose access to other regions. The Southwest and Northwest regions are the most impacted because transit travel time variability plays a big role in limiting their residents' access to the city center. Overall, for the 45- and 60-min thresholds, spatial accessibility patterns remain similar across most regions. However, at the 90-min threshold, the impact is concentrated primarily in the most peripheral areas. Despite the high variability in travel times, 90 min represents a relatively generous time budget for reaching the city center, therefore causing little impact on most regions. It is also important to highlight the positive impact of the metro South Line, which we assume doesn't have variability in its service.

The incorporation of jobs competition through the 2SFCA and BFCA indicators changes the variability impact in some regions of the city (respectively, second and third columns in Fig. 4). The Central region presents the most prominent changes when compared to the scenario

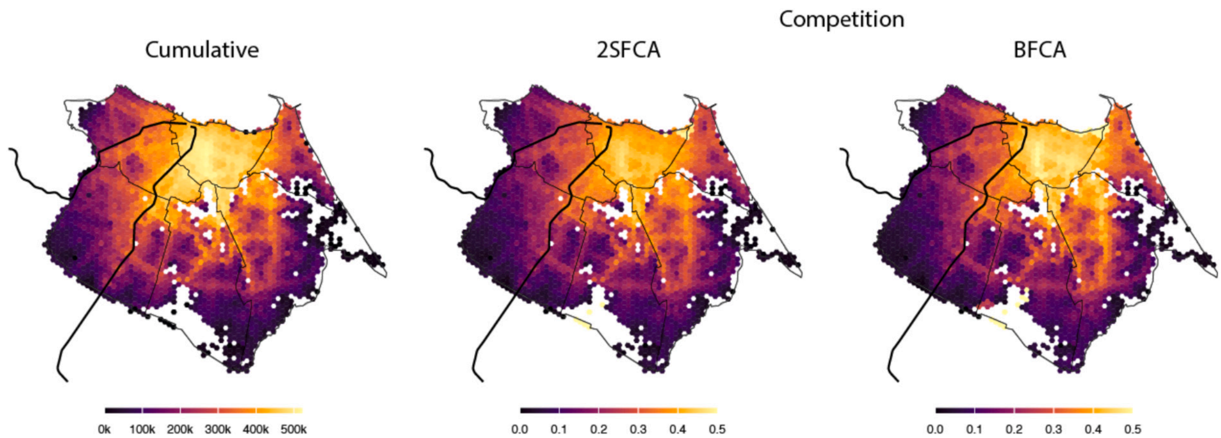


**Fig. 3.** Employment Accessibility for 60-min time threshold by public transport calculated with P50 GTFS. Fortaleza, 2019.

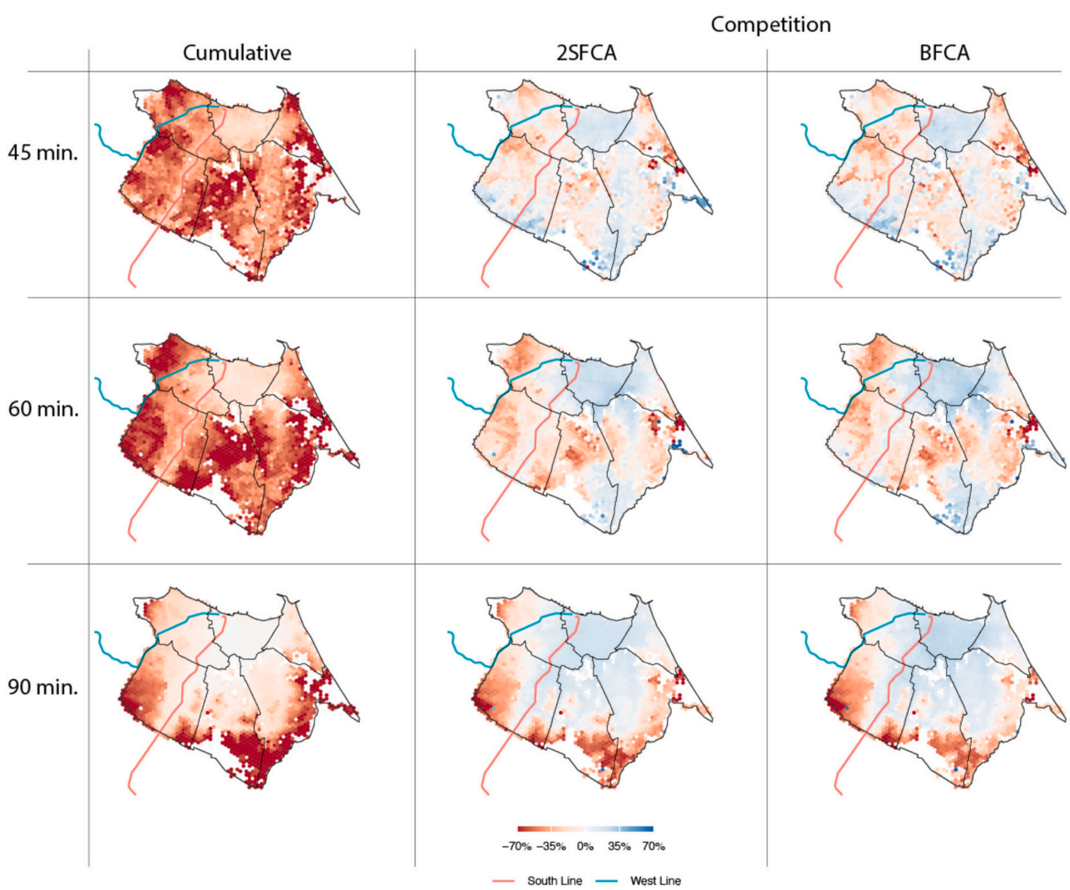


**Fig. 4.** Relative difference (%) between P85 GTFS and P50 GTFS accessibility estimates for 45, 60 and 90 min time thresholds.
Note: In red (negative impact) are the locations where P85 accessibility level is lower than P50 estimate.
Note: P85/P50 GTFS accessibility: accessibility calculated with corrected GTFS from P85 and P50 travel times from each transport link, respectively

shown by the Cumulative indicator. When considering competition, the impact of variability is reversed in the Central region: P85 estimates portray a scenario of better accessibility levels then the P50 estimates. This can be explained by how competition is incorporated: while people in all regions are accessing less job opportunities due to higher transit travel times, fewer residents from peripheral regions are competing for the highest number of jobs located in the Central region. With less competition, accessibility increases for residents within or near the city center, which offsets the decrease of accessibility caused by worse PT levels of service to reach more distant job opportunities. In the Northwest and Southwest regions, where most of the low-income population resides, the impact of travel time variability (TTV) on accessibility estimates appears consistent across all indicators – TTV generally reduces accessibility. However, the negative impact tends to be less pronounced when competition-based indicators are considered. The average percentual impact of travel time variability for 60-min time threshold for the cumulative indicator is 50 %, while for the two competition indicators is around 6 %.

Another important finding is that the impacts of transit travel time variability tend to have very similar spatial patterns with both competition metrics. This indicates that the demand/supply inflation correction proposed by the BFCA indicator is little impacted by the different variability patterns in PT services.

### 5.2. Travel time variability impacts on accessibility inequalities

Our previous analyses assessed, from a spatial point of view, the different impacts of transit travel time variability on job accessibility levels when comparing the cumulative indicator to the two competition metrics: 2SFCA and BFCA. In this section, we aim to assess how these spatial differences could have an impact on the inherent social inequalities in accessibility estimates.

Fig. 5 showcases how transit travel time variability impact (the percentage difference between P85 and P50 GTFS accessibility estimates for each hexagon) is distributed throughout the income deciles, for each indicator. Our analysis focus on the 60-min accessibility threshold, considered the most representative as it reflects the median travel time in Fortaleza. For the cumulative indicator, as expected from the spatial distribution of the differences observed over Fortaleza's territory (first map in the second row of Fig. 4), all hexagons are negatively impacted by travel time variability, with the lower income deciles being the most impacted. Competition indicators, on the other hand, present a consistent scenario in which the variability impact for income deciles up to 7 is negative, but starts to switch (variability impacting positively) for hexagons representing the income deciles 8–10, which are usually located in the Central area. The impact on lower-income groups is also smaller when using competition metrics compared to the cumulative measure. This supports our spatial analysis, which found evidence that the poorest populations are less affected by TTV when competition is considered.

Additionally, we calculated the Palma Ratio for each accessibility indicator, comparing the differences on accessibility estimates deriving from a median (P50 GTFS) and a dispersion scenario (P85 GTFS) of PT services. The Palma ratio divides the average accessibility of the 10 % richest (income decile 10) by that of the 40 % poorest (income deciles 1 to 4). Therefore, a ratio exceeding 1.0 means greater accessibility for the richest compared to the poorest, with higher ratios indicating greater social inequalities.

Fig. 6 depicts the Palma Ratio values calculated for each accessibility

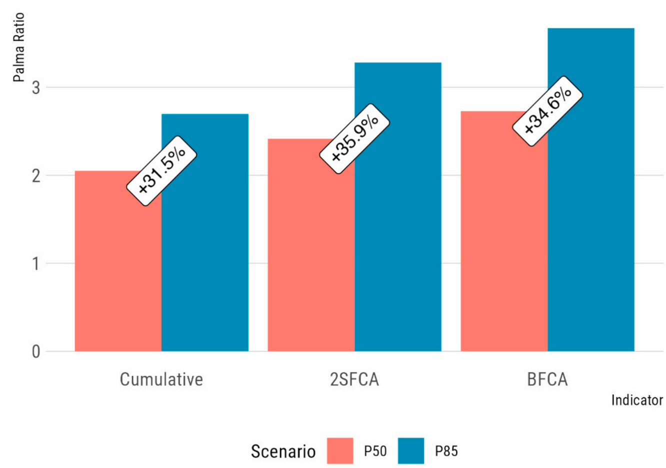


**Fig. 6.** Palma ratio for each PT service variability scenario, by accessibility indicator.
Note: P50 and P85: Accessibility calculated using the P50 GTFS and the P85 GTFS, respectively

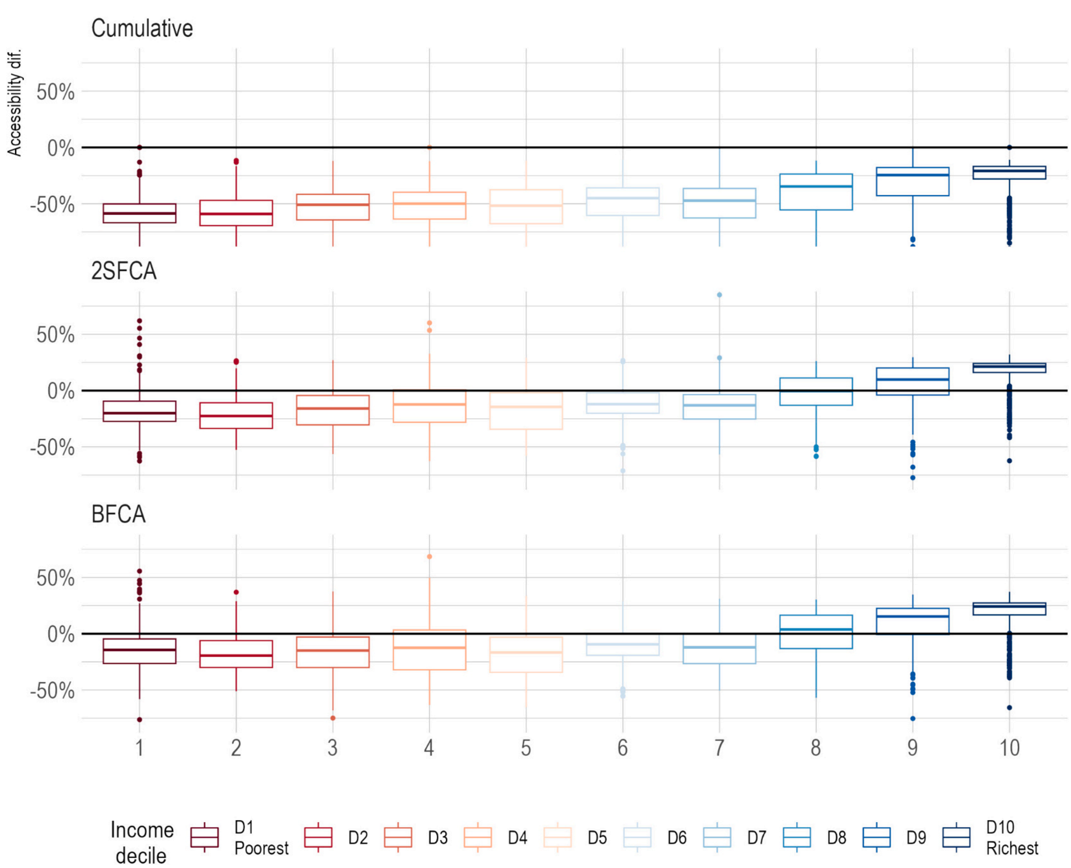


**Fig. 5.** Impact of PT travel time variability on income deciles, by accessibility indicator.
Note: Negative values denote locations where P85 GTFS accessibility is lower than P50 GTFS estimate

indicator, for the P50 GTFS (representing the median scenario) and for the P85 GTFS (representing the dispersion scenario). We also emphasize (in the white label) the percentage difference between the two accounts for each indicator, providing insight into how transit travel time variability can impact job accessibility inequalities.

Firstly, we can see that job accessibility estimates based on competition indicators tend to represent higher levels of socio-spatial inequalities over Fortaleza's urban territory. For example, if we compare the Palma Ratio values for the P85 GTFS estimates, we observe that job accessibility inequality is lower while measured by the cumulative indicator (2.7) compared to 2SFCA and BFCA metrics (3.3 and 3.7, respectively).

In terms of the effect of transit travel time variability on socio-spatial inequalities (the white label), there's a tendency for competition indicators to be more affected by service variability (averaging 35.3 %) compared to the cumulative indicator (31.5 %); although not by a significant margin. Within the competition indicators, there's a very similar degree of variability impact on inequalities, as illustrated by the corresponding boxplots in Fig. 5. These results showcase that the consideration of competition for job opportunities has the potential to portray higher socio-spatial inequality scenarios; and that PT service variability is even more important to consider when one is assessing accessibility accounting for competition for activities. The next section offers some clarification on why this is happening.

### 5.3. Understanding the interplay between variability and competition

One key finding from the preceding section is that TTV improved job accessibility in the city center for the competition indicators, which may seem counterintuitive given the travel times are lower when variability is accounted for. To better understand this outcome, we decompose the competition indicators and investigate in detail why they are differently impacted by travel time variability in comparison to the cumulative indicator.

As highlighted previously, the FCA family calculation in general involves the following steps:

1. Assign the potential demand to each destination, calculating for each location how many people could reach it given the time threshold;
2. Calculate the activity's level of service at each one of those locations, by dividing the total number of jobs by the potential demand;
3. Calculate the final accessibility from each origin, which sums the total level of service(s) within the catchment area.

We can identify that travel time variability impacts the 2SFCA/BFCA calculations by interfering in the calculations of steps 1 and 2, thus affecting the calculations of step 3. In step 1, travel time variability will reduce the potential demand at each destination, as people from further away will lose access to destinations. In step 2, the activity's level of service at each location will likely increase with variability, as fewer people will be competing for opportunities. In step 3, it decreases the catchment area that aggregates the level of service, reducing the locations that will be part of the indicator's calculation at each origin.

Although this is true for the entire city, as illustrated by the maps in Fig. 4, the travel time variability's effect on competition indicators varies across regions, with some regions even experiencing a positive impact, notably in the city center. To explore these findings, we sample two hexagons located in different areas of Fortaleza: one hexagon in the South region, affected negatively by variability; and another one in the Central region, positively impacted. In analyzing each example, we will explore how the calculations at each stage are influenced, ultimately producing the final accessibility impacts.

Firstly, we take a hexagon (black dot) located in the South region that was negatively impacted by variability when competition was considered (40 % decrease in accessibility due to variability) (Fig. 7, South Region). This origin zone lost access to locations in every region,


**Fig. 7.** Origin zones selected for analysis.

as the P85 catchment is smaller due to the higher travel times. The average potential demand for opportunities from this origin dropped by 36 % with the PT travel time variability impact (meaning that 36 % less people could compete for the same jobs at this location), while the total number of accessible jobs dropped by 63 %. As this origin zone lost access to the city center, it lost access to a significant proportion of jobs, and the decrease in the population competing for employment wasn't enough to offset the lost access to the jobs – resulting in an accessibility drop.

Secondly, we take a hexagon (black dot) located in the Central region that was positively impacted by transit variability when competition was considered (20 % increase in accessibility due to variability) (Fig. 7, Central Region). The total potential demand for opportunities from this origin zone dropped by around 27 % (meaning that 27 % less people could compete for the same jobs from this location) with the variability impact, but the total reachable jobs from the origin only dropped by 12 %. This explains how the competition indicator increased: this origin lost access to a significant part of the city, but it was to regions that proportionally had fewer jobs. On the other hand, fewer people could compete for those opportunities, and at a higher rate, people lost access to jobs, so an increase in accessibility is expected.

These findings underscore the critical need to enhance the reliability of public transport for accessing the city center, where most employment opportunities are concentrated. In a typical Latin American urban context – where low-income populations reside in peripheral areas and depend on trunk public transit lines to reach central opportunities – improving service reliability could help mitigate the effects of travel time variability on access inequalities. However, our case study also shows that demand for opportunities adds complexity to this relationship, as increased reliability may also lead to more competition for opportunities.

## 6. Conclusions and recommendations

This paper explored the interaction between day-to-day public transport travel time variability and competition for job opportunities in accessibility calculations, emphasizing their implications on socio-spatial inequalities. Our primary hypothesis was that day-to-day travel time variability tends to increase job accessibility inequalities, which get aggravated when we account for competition effects. To investigate this, we selected Fortaleza, Brazil, as a case study and computed accessibility estimates using cumulative and competition-based metrics (2SFCA and BFCA) for both median and dispersion scenarios of transit service. We then compared these scenarios to assess the impact of jobs competition under travel time variability.

Overall, regarding the impact of day-to-day travel time variability, we observed that competition-based accessibility indicators showed a different spatial pattern compared to cumulative measures. Contrary to what we expected, the Fortaleza's Central region – home to higher-income population and main concentration of jobs – experienced a positive impact from transit travel time variability, exceeding 50 % in some areas. In comparison, the Northwest and Southwest regions, where most of the low-income population lives, saw decreased accessibility conditions with service variability (exceeding 60 % in some areas). On average, the cumulative indicator was impacted in 50 %, while the competition metrics were impacted by only 6 %.

These spatial disparities highlight the socio-spatial inequalities associated with transit service variability under competitive conditions for activities, where lower-income populations were the most negatively affected, while higher-income groups experienced the most positive impacts. When examining the impact across different income deciles, we confirmed that the poorest individuals were disproportionately affected across all job accessibility indicators. Using the Palma Ratio indicator to understand how the richest compare to the poor, we discovered that competition metrics were more affected by variability (a 36 % increase due to variability) compared to cumulative indicators (a 32 % increase).

We also highlight the reasons behind the varying patterns in how these measures are impacted by travel time variability. Transit service variability not only limits the number of jobs accessible within a specific time threshold but also decreases competition for those job opportunities from other areas. From an inequality's perspective, the challenge lies in the uneven distribution of these effects across the city. Fortaleza, like other Latin American metropolises, has most of its population (predominantly low-income) living on the urban periphery, while job opportunities are concentrated in the city center. Public transport is primarily aimed at connecting this vulnerable population to the city center, but the lack of adequate infrastructure results in congestion, delays, and consequently, greater travel time variability. Together, these factors cause the effects of transit service variability to differ across city regions.

In Fortaleza's city center, where most job opportunities are located, the public transport network presents high levels of service variability, impacting people's ability to reach opportunities. However, such condition does not significantly impact these groups since they live close to most of the city's jobs. On the other hand, transit variability is enough to restrict other populational segments' access to the city center, especially from the periphery, where lower-income households are mostly located. These factors reduce the competition levels for those living in the city center, offsetting the lost access to jobs. When the same analysis is made for a location in the periphery (take Fortaleza's Southwest region as an example), the residents are heavily impacted by transit travel time variability in their ability to access jobs opportunities in the city center, but less impacted by the other people competing for those same jobs.

Therefore, our findings suggest that assessment studies of access to employment in the literature are likely to produce biased accessibility estimates and underestimate inequalities by ignoring issues of day-to-day travel time variability; and that such problems are further exacerbated when jobs competition is accounted for. It would be reasonable to expect similar outcomes in other urban areas with comparable demographics, land use, and transportation patterns inherent to Latin American mestropolises – where lower-income residents live in the periphery, employment is concentrated in the city center, and commuting by public transport is lengthy. Implementing dedicated public transport infrastructure can significantly alleviate the effects of variability (Diab and El-Geneidy, 2013). In this regard, fully segregated rights-of-way like BRT and metro corridors prove more efficient than bus lanes in ensuring reliable services, as the latter are more susceptible to delays caused by factors such as traffic lights, vehicle interference, and other incidents.

Nevertheless, while our proposed methodology is particularly suited to contexts in the Global South where GTFS and GPS data may be incomplete, we recognize that many cities in the region still lack such data, either because it has not been collected or is not publicly accessible to researchers. Similarly, detailed employment data is often unavailable. In addition, some cities rely heavily on informal transit systems, which are typically absent from official demand-supply databases – though this is not a significant issue in Fortaleza. We therefore emphasize the importance of city officials investing in the collection and public dissemination of consistent transport, land use, and employment data to enable further research in this area.

It's also important to point out our study's main empirical and methodological limitations. Firstly, it relies on formal employment data, potentially overlooking informal job opportunities, which are significant in Brazilian cities. In Fortaleza, for instance, approximately 40 % of the workforce is employed in the informal sector; however, the spatial distribution of informal employment is somewhat similar to that of formal employment across the city (Pinto et al., 2023), which suggests that our findings wouldn't be as impacted. Secondly, our method to create different GTFS feeds from GPS data is based on the assumption that the entire public transport network would be performing at the 50th or 85th travel time percentile, just for the purpose of representing median and dispersion transit service scenarios. Consequently, OD travel times in the 85th-percentile scenario are likely overestimated, given that not all links would simultaneously operate at this percentile. Thirdly, the use of a binary function for travel time impedance may influence the accessibility estimates, requiring further investigation with varied impedance functions and activity types. The incorporation of gravitational travel impedance functions (such as exponential) would likely provide less pronounced results. Finally, we also assume that every individual can compete for any job within the city, without considering some form of skill or educational compatibility between residents and job opportunities. Incorporating such factors could reveal even greater inequalities in competition-based measures, as low-income populations are predominantly concentrated on the urban periphery, while most employment opportunities are in the city center.

Although various sociodemographic factors influence accessibility patterns, income stands out as the main determinant in our study area. In Brazilian cities, spatial inequalities related to income and race are particularly pronounced (Bittencourt et al., 2021). While factors such as gender and age also shape mobility and accessibility needs, their spatial patterns tend to be less pronounced. Future research could build on these insights by further examining how the impact of travel time variability interacts also with race, gender, and age.

We hope our findings inspire further research into the interplay between travel time variability and competition for activities in complex urban settings. Examining this relationship is particularly important for contexts where segregated low-income populations rely heavily on public transport to access centrally located jobs. Public policies that promote housing closer to employment centers, support job creation in peripheral areas, and invest in more reliable and frequent public transport services could help reduce the unequal impacts of travel time variability on access to opportunities. Moreover, future studies should also investigate how transport projects distribute accessibility benefits amid service variability and across different accessibility indicators, incorporating social justice frameworks such as sufficientarianism and egalitarianism.

## CRediT authorship contribution statement

**Carlos Kaue V. Braga:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Carlos Felipe Grangeiro Loureiro:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization. **Rafael H.M. Pereira:** Writing – review & editing, Supervision, Conceptualization.

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## Data availability

Data will be made available on request.

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