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RESEARCH ARTICLE

A comparative analysis of public transport accessibility to hospitals in Córdoba (2019–2023): Where are we now?

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Abbreviations: GTFS, General Transit Feed Specification; HPA, Hospitales de Pronta Atención; IDERA, Infraestructura de Datos Espaciales de la República Argentina; INDEC, Instituto Nacional de Estadística *y* Censos; NBI, Necesidades Básicas Insatisfechas; SD, standard deviation; SISA, Sistema Integrado de Información Sanitaria Argentino

Abstract

The coronavirus disease-2019 (COVID-19) pandemic and the mobility restrictions governments imposed to prevent its spread changed the cities' ways of living. Transport systems suffered the consequences of the falling travel demand, and readjustments were made in many cities to prevent the complete shutdown of services. In Córdoba, the second largest city in Argentina, the Municipality dictated route cuts and reduced frequencies to sustain the buses and trolleys system. In 2022, Martinazzo and Falavigna assessed potential accessibility to hospitals before (2019) and during the pandemic (2021). Overall, the study indicated that average travel times increased by 20% and that the gap between less vulnerable and more vulnerable population quintiles reached almost 8 points. In this paper, potential accessibility to public hospitals in 2022 and 2023 is calculated using Martinazzo and Falavigna's (2022) work as a baseline to compare, considering that neither cutting the services during the pandemic nor recovering the service after the pandemic the Municipality performed an accessibility assessment. The main results showed that, despite the system having almost recovered its extension by 2023, it maintained the regressive tendency between less vulnerable and more vulnerable population quintiles, as the difference in average travel time between these two groups reached up to 14 min, while the cumulative opportunities measure for the high-income groups was up to 68% higher than the most vulnerable households.

Policy Significance Statement

Accessibility measures are widely used in academic works to evaluate access to urban opportunities such as jobs, education, and healthcare. In recent years, the increasing computational abilities and available databases allowed quicker and more accurate travel times and accessibility estimations. This framework provides a unique opportunity for urban and transport planners to incorporate equity issues in project management, assessing new projects and everyday transport operations. This article provides a comparative analysis of transit accessibility to public hospitals, using open code and data that allows replication and scaling. Besides, exploring the

This research article was awarded Open Data and Open Materials badges for transparent practices. See the Data Availability Statement for details.

obtained results in intersection with the distribution of groups of more and less vulnerable households can provide evidence to orient future interventions more equitably.

1. Introduction

Traditional planning models have usually been based on estimates of travel demand and its behavior from which decisions are made regarding the best transportation alternatives, a paradigm known as predict and provide. In this context, transport policies seek to enable people to move and access various destinations efficiently through measures to alleviate traffic congestion (Noland and Lem, 2002).

Accessibility has often been included in transport planning goals. However, its performance is not usually measured in practice to evaluate policies (Handy and Niemeier, 1997). Measuring accessibility patterns can help ensure that transport and land use interventions focus on spatial gaps in access to opportunities (Boisjoly and El-Geneidy, 2017b). Despite not always being considered in ex-ante evaluations of transport projects and policies, equity, related distribution effects, and social exclusion issues can be managed using accessibility measures that describe the relative access to social and economic activities of different population groups (Wee and Geurs, 2011). Lately, some efforts have been made to plan for accessibility. For example, in the UK, accessibility planning was introduced to complement policies to revitalize deprived communities, and a statistical series of accessibility indicators at the neighborhood level was also published (Geurs et al., 2012).

The main objective of this work was to show the differential impacts that changes in the public transport system have on more and less vulnerable groups of households using General Transit Feed Specification (GTFS) and other geo-referenced data to emphasize the importance of accessibility assessments in transport planning and operation. The reference is a previous work from Martinazzo and Falavigna (2022) that calculates accessibility to healthcare facilities in Córdoba (Argentina) between 2019 and 2021, used in this work as a baseline to evaluate how the modifications in the transport system in the post-pandemic years impacted population according to its social and economic vulnerability. An analysis of the impact on accessibility that the location of new hospitals has is also included. To support this research, a thorough literature review about accessibility and transport planning, assessment of access to healthcare in general and in the case of Córdoba, and new data formats as GTFS was conducted, as described in Section 2. The principal characteristics of the study area and the data and methods used are presented in Section 3, while Section 4 depicts the results and statistical analysis. Section 5 includes a brief discussion considering the previous works explored. Finally, the last section draws the central conclusions of the general context, the results obtained, and the application of the proposed methodology.

2. Literature Review

2.1. Accessibility as a measure to assess transport projects

Boisjoly and El-Geneidy (2017b) consider that accessibility is defined by a combination of factors: exogenous variables such as the distribution of activities in the territory (land use component) and the transportation network that determine the costs, time, and convenience of travel between an origin and a destination; individual characteristics such as income, education level, gender and vehicle ownership that affect the abilities and needs to access destinations; and finally time restrictions, not only imposed by the schedules and programming of the activities and the available transport but also at an individual level by personal schedules.

Thus, accessibility is determined by the spatial distribution of potential destinations, the ease of reaching each destination, and the magnitude, quality, and character of the activities found there, along with the cost, the selection of the destination, and the chosen mode of transport that also have an impact on the level of accessibility (Handy and Niemeier, 1997).

Poor transport quality can contribute to social exclusion as it restricts access to work, education, healthcare, leisure, and various activities that enhance people's life chances. Besides, deprived communities suffer disproportionately the negative impacts of insecure roads, contamination, and physical barriers that congested roads generate (Social Exclusion Unit, 2003). Accessibility analysis that focuses on the influence of transport investments on the range and number of opportunities reachable provides a holistic view that can nurture social approaches to transport planning to address social inclusion challenges (Scholl et al., 2022).

In Latin America, equity and accessibility issues have been addressed in several works that analyze accessibility to travel attracting poles (Molfino et al., 2007), accessibility levels to the labor market considering time and income constraints (Bocarejo S. and Oviedo H., 2012), public transport affordability and its differences among different household compositions by income (Falavigna and Hernandez, 2016), and accessibility for non-commuting trip purposes by income groups via private and public transport (Oviedo and Guzman, 2020), among others.

Geurs and van Wee (2004) define four classes of accessibility measures based on the perspectives from which accessibility is analyzed (infrastructure, location of activities, person-based or utility-based measures) and the accessibility components that are considered (transport, land use, temporal and individual restrains).

Infrastructure-based measures, which include travel times estimations, are direct and easy-to-communicate indicators but have the restriction that they do not consider the land use factor with its impacts on accessibility and the impact that transportation can have on the distribution of activities. Besides, some authors discussed that travel time, as an indicator of mobility, does not capture the potential of interaction for opportunities, so it does not fully reflect access to destinations (Boisjoly and El-Geneidy, 2017a).

Location-based measures are widely used in the bibliography, the simplest ones called distance or connectivity measures, both linearly and considering the road network, with indicators such as travel times or average speeds; and other contour or isochronous measures that are based on counting the number of opportunities reached in a particular time, distance or cost, named as cumulative opportunities indicator (Geurs and van Wee, 2004). Other measures based on the locations are called potential accessibility, such as the work of Hansen (1959) or Shen (1998), which improves the previous definition by including the possible competition for the available opportunities considering the demand.

On the contrary, people-based indicators measure accessibility at the individual level, tracking personal times and modes of travel to different activities, along with people's temporal and spatial restrictions, as shown in the work of Kwan (2010) carried out through travel diaries.

Finally, the indicators based on the utility theory consider that people decide on one option over others based on its ability to satisfy their needs and the utility (or not) it generates. The Multinomial Logit model (logsum) or the doubly constrained entropy model (Geurs and van Wee, 2004) are examples of utility-based measures.

2.2. The GTFS format to describe transit

A GTFS feed is a collection of comma-delimited text files collected into a single ZIP compressed file. Each text file models a specific aspect of public transport information, such as stops, routes, or trips (Google Developers, 2022). The schedules provided by GTFS data are significant for calculating travel times by public transport. The estimation of door-to-door travel time is a challenge because of the multiple steps that can integrate an entire trip by public transport, considering the access and egress from the system, the numerous itineraries that may exist to link an origin and a destination, the possible variations in departure times and the itinerary selection since the transport system availability is not uniform throughout the day.

Public transport accessibility studies were traditionally based on average values over peak hours, such as travel speed or programmed frequencies (Polzin et al., 2002; Wu and Hine, 2003), or by the usage of average values from surveys or census data from the users (Kawabata, 2003, 2009; Kawabata and Shen, 2006, 2007). GTFS feeds are new information sources with details about public transport schedules that enhance travel time estimations. When used with computational routing algorithms, they allow the inclusion of variations in departure times, door-to-door travel times distribution, and the selection of alternative itineraries beyond the shortest route.

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2.3. Accessibility to healthcare facilities

The World Health Organization (Evans et al., 2013) sustains that universal access is needed to achieve the goal of universal health coverage, meaning that people obtain the health services they need without excessive financial risk. The availability of good health services within reasonable reach of those who need them, called physical accessibility, is one of the main elements to address this issue (Evans et al., 2013).

Access to healthcare, as defined by Penchansky and Thomas (1981), is a general concept to evaluate the degree of fit between the population needs and the services provided in five specific areas or dimensions of access, namely: (i) availability in volume and type of the required service; (ii) geographic or physical accessibility, regarding the location of the population and the location of the healthcare services; (iii) accommodation in terms of attention times and general quality of the service, and how the population can accommodate to these service characteristics; (iv) affordability, meaning the cost of the service related to the patient's income; and (v) acceptability, including health service compliance and satisfaction. Analyzing these dimensions through surveys, the authors conclude that access variations may influence patient satisfaction and healthcare services utilization.

There is evidence in the literature that relates geographic accessibility to the quality of healthcare the population receives. Wang and Luo (2005) identified spatial (geographic barriers) and nonspatial factors (socioeconomic and demographic characteristics such as social class, income, ethnicity, age, sex, etc.) that influence the variation in access to healthcare across space. Considering nonspatial factors, socio-economic disadvantages, including female-headed households, percentage of the population in poverty, nonwhite minorities, households without vehicles, home ownership, and housing units' lack of basic amenities were the most influential factors that explained the variance.

In rural areas of Malawi, Varela et al. (2019) determined that the main barriers to timely access to healthcare were the lack of suitable transport, finances, and prolonged travel times and that inadequate road infrastructure, unavailability of public transport and expensive private transport play an important part in access to healthcare centers. Douthit et al. (2015) conclude that there are significant differences in healthcare access between rural and urban areas and that some transportation difficulties, such as having (or not) a driver's license or increased travel times, are prohibitive.

Other studies conducted in urban areas showed that accessibility decreases significantly from the city center outwards, related to the concentrated distribution of hospitals and the better road and public transport conditions in the central area (Tao and Cheng, 2019; Chen et al., 2021). Previous works also showed significant disparities in access to healthcare facilities by private and public transport, in which trips by individual vehicles have lower travel times and consequently higher levels of accessibility (Peipins et al., 2013; Langford et al., 2016; Tao et al., 2018; Ermagun and Tilahun, 2020). Additionally, some authors discussed that the differentiation of healthcare facilities according to levels of attention and medical and surgical capabilities is substantial to appropriately address the gap between the population's primary needs and the quality of healthcare received (Zheng et al., 2019; Zhao et al., 2020).

This unequal geographical distribution in the intersection with nonspatial factors shown in several works that it has more impact on vulnerable population groups such as the elderly (Tao and Cheng, 2019; Ermagun and Tilahun, 2020; Chen et al., 2021), people coming from low-income neighborhoods (Ermagun and Tilahun, 2020; Zhao et al., 2020), families with children (Ermagun and Tilahun, 2020) and racialized groups (Peipins et al., 2013; Kim et al., 2021). For instance, Peipins et al. (2013) found that majority-black census tracts had longer public transportation travel times than white tracts, while Ermagun and Tilahun (2020) concluded that areas of low accessibility have a higher percentage of African-Americans, Hispanics, Asians, low-income workers, low-educated citizens, and elderly people.

Travel time or distance as a primary constraint in urban areas was reflected in several previous works, and travel time values differ among them. Peipins et al. (2013) calculated a median travel time to the nearest radiation facility of 56 min by public transport and 8 min by private. Tao et al. (2018) set a maximum travel time threshold of 124 min to ensure that the elderly could access at least one hospital within the catchment area using a previous survey as a reference, while Chen et al. (2021) threshold travel time used was 30 min, as the most of the minimum travel times modeled were under that value. However, Cao et al. (2022) discussed that the gravity-based models or floating catchment (FCA) methods that researchers usually

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adopt use the same inaccessible time of 60 or 120 min across different areas, while a more accurate approach would be to use an acceptable travel time. Cao et al. (2022) also obtained that more than 90% of the residents in Inner Mongolia accepted travel times lower than 30 min to a primary healthcare institution and that women tend to accept higher travel times while the elderly accepted shorter travel times than the youngest due to physical limitations such as deteriorating health conditions and reduced travel ability.

2.4. Accessibility to public hospitals in Córdoba

Mobility patterns to public hospitals in Córdoba have been characterized in Albrieu et al. (2011) work, where through surveys, censuses, and vehicle counts, the authors performed a comparative analysis of trips to 7 locations of public and private hospitals. The main results showed that 95% of the patients in private hospitals came from the areas with the best socioeconomic background. On the contrary, the most vulnerable sectors do not use private hospitals. Also, 59% of the people who went to the public hospital did so by public transport, and only 24% used a private car. In opposition, 61% of people attended a private hospital using a private car, compared to only 29% of public transport usage.

Martinazzo and Falavigna (2022) evaluated the potential accessibility to public hospitals between 2019 and 2021 by public transport in Córdoba to analyze and compare pre-COVID and during-COVID geographical accessibility to healthcare centers. The comparative analysis was made using the *r5r* package in *R* with the GTFS provided by the municipality, and the travel times were calculated with programmed schedules and frequencies and fixed values of maximum travel time and maximum walking distance.

The principal findings showed that for the three hospital categories evaluated, travel times increased around 20% in the study period, and the most vulnerable quintiles of the population increased their travel times 8 points above the less vulnerable quintiles. Overall, measures of central tendency and dispersion indicated significant differences between quintiles per percentage of households with unsatisfied needs (%NBI), where in general, zones with the highest proportions of households with unsatisfied needs suffered more the impact of the cuts in services during the pandemic, as shown in Figure 1.

The authors conclude that the differences in travel times for 2019 and 2021 among the least and most vulnerable groups show a higher detriment in potential accessibility for more deprived households, which illustrates part of the inequity they are subjected to.

3. Methodology

To evaluate potential accessibility to healthcare facilities in Córdoba and to compare the 2022–2023 results with Martinazzo and Falavigna's work (2022), average travel time was the selected indicator. The routing *R* package *r5r* (Pereira et al., 2021) was used to compute the travel time matrix between census zones and hospitals. This process is described in Section 3.3.

The population was characterized using information from the 2010 INDEC population census, including census zones and socioeconomic characteristics described by the percentage of households with unsatisfied basic needs per census zone (%NBI indicator). The public transport routes were obtained from the Municipality of Cordoba's open data webpage in the GTFS schedule-based format. This information is presented in Sections 3.1 and 3.2.

3.1. General characteristics of the study area

Córdoba is the capital city and head of the Capital Department of the Province of Córdoba, in the central region of Argentina, with a territory of 573.2 km^2. According to the 2010 census, the Capital Department had 1,329,604 inhabitants and 414,237 households (INDEC, 2015). In contrast, preliminary results from the 2022 census indicate that the city population is 1,565,112 (INDEC, 2023), resulting in the second-largest city in Argentina. The city is also the reference for the province and the central region, as the consolidated area of Córdoba city concentrates the employment and service

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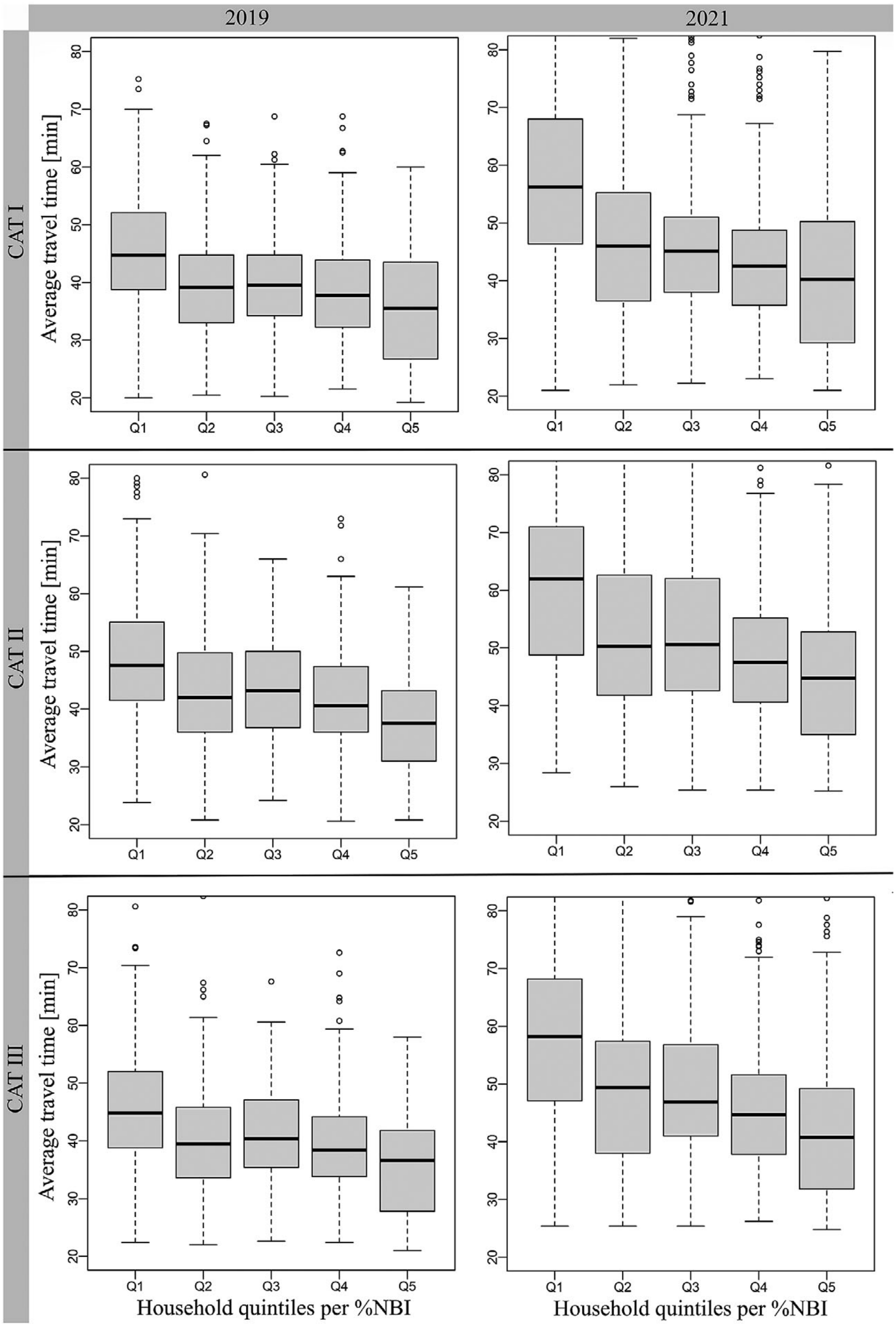

Figure 1. *Average travel times box plots per %NBI quintiles (Martinazzo and Falavigna, 2022).*

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provider centers as well as the most significant number of educational establishments, almost all of the state hospital establishments, and essential and dynamic commercial, cultural, recreational and tourist attractions (Molfino et al., 2007).

The percentage of households with unsatisfied basic needs (%NBI) measures socioeconomic status and structural poverty considering several elements apart from monetary income. In Córdoba, by 2010, 5.82% of the households showed at least one of the indicators included in the %NBI measure. To be a household with unsatisfied basic needs, at least one of the following deprivation conditions must be present: households that live in houses with more than three people per room (critical overcrowding), households that live in houses of an inconvenient type such as tenancy rooms or precarious residences, households that live in houses without flushing toilets, households with school-age children not attending school, a four (or more) member family group where only one of them is working and where the head of household attended two or less than two years to primary school (INDEC, 2000). The main deprivation conditions in Córdoba are overcrowding (3%), sanitary conditions (1.2%), and type of dwelling (1.1%) (Dirección General de Estadística y Censos de la Provincia de Córdoba, 2021).

As part of the 2010 population census, a broader survey was also conducted on a sample of households to address dwelling conditions, migration, healthcare services, social security, and employment. The results showed that, at the departmental level, 32.4% of Córdoba's population depends exclusively on the public healthcare system, which includes state plans and people without any other type of assistance. Nearly 70% of people in this situation are between 15 and 64 years old.

The public healthcare system in Córdoba has municipal, provincial, and national institutions. In Figure 2, the territorial distribution of 14 of these institutions is shown with the 2010 census zones classified in quintiles per the percentage of households with unsatisfied basic needs (%NBI). The first quintile (Q1) groups the most vulnerable households, with the highest percentage of households with NBI, and the last quintile (Q5) corresponds to the less vulnerable households, with the lowest percentage of households with NBI.

3.2. *Transport and mobility system characteristics in the study area*

The public transport system in Córdoba includes bus lines and trolley lines. The original network, licensed for 10 years in 2014, was structured with core and secondary lines. It also had six neighborhood lines, which connect areas of the city without entering the center; ring lines, which circulate clockwise and

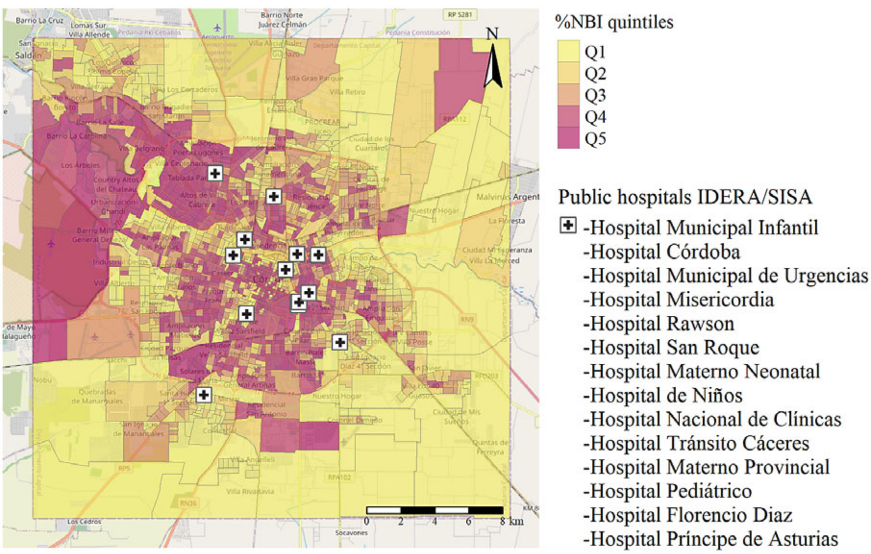

Figure 2. *Population census zoning by %NBI quintiles and public hospitals in Córdoba.*

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counterclockwise without going through the downtown area; and differential lines, which had air-conditioned buses. The system covers the extent of the city as it is an urban, not a metropolitan service, except for one line that goes to Bower on the southern periphery. Since 2021, an urban rail service is also provided but is not part of the urban transport system.

In 2019, three companies owned the concession of the 69 bus lines: Autobuses Córdoba (5/69), Coniferal (21/69), and ERSA (43/69). The municipal company Tamse provided the trolley service, consisting of three lines supplied by electric energy. During the 2021 first semester, the concession contract was still in force, but because of the decrease in demand due to the mobility restrictions for the COVID-19 pandemic, some bus lines stopped operating, and the distribution among the concession companies changed: Autobuses Córdoba (5/60), Coniferal (21/60), and ERSA (34/60). The trolley service provided by Tamse doubled the number of lines, but the power supply changed to a mixed scheme with part of the fleet using diesel engines, a system currently in force. By the end of 2021, Tamse took control of corridors 3, 8, and the neighborhood line B80, and by the end of 2022 also had lines 600, 601, 53, and 54, and the special Aerobus service that travels to and from the Airport. In the same period, Autobuses Córdoba stopped being a service provider. Tamse has 26/79 lines, Coniferal 22/79 lines, and Ersa 31/79 lines. These changes in the public transport system are described through its leading indicators in Table 1. In Figure 3, the public transport system routes were mapped using GTFS GO, a QGIS plugin to extract GTFS data to show routes and stops (MIERUNE Inc., 2023), where it can be seen how the lines cover more of the city center and less the periphery, and that almost all routes begin and end within the cities' boundaries marked with the black line.

3.3. Materials and methods

As proposed by Martinazzo and Falavigna (2022), the *r5r* package in *R* (Pereira et al., 2021) was used to calculate travel times between the centroids of the 2010 census zones (origins) and public hospitals from the IDERA-SISA database (destinations). Thereby, the travel time matrix obtained had 1,503 origins and 14 destinations. It was excluded from the analysis the mental health hospital of the city Hospital Neuropsiquiátrico, considering it is a facility that has a particular type of attention dedicated to hospitalizations and outpatient follow-up and in several of the hospitals analyzed there is a mental health service.

Besides the origin and destination information, the data requirements of *r5r* are an OpenStreetMap road network in *.pbf* format (obtained from Protomaps for this work) and a public transport feed in GTFS. zip format, using for this work the 2022 and 2023 GTFS published by the Municipality of Córdoba. The databases were initially obtained from the published 2010 INDEC population census, the IDERA

Table 1. *2019–2023 public transport system characteristics in Córdoba*

	2019	2021	2022	2023
Total extension (km)	3,471*	2,698*	2,942*	3,378*
Stops	5876	4961	5195	5553
Scheduled services per hour (veh/h)	2.70*	2.60*	3.08*	2.65*
Average daily passengers	447,693	216,550	**	**
Average daily kilometers travelled	154,344	104,340	**	**
Lines	72	66	68	79
Core lines	59	55	61	71
Ring lines	2	2	2	2
Neighborhood lines	7	2	1	2
Trolley lines	3	6	3	3
Special lines	1	1	1	1

*Data obtained through tidytransit on R using published GTFS, services from 6 a.m. to 8 p.m.
**Information not published.

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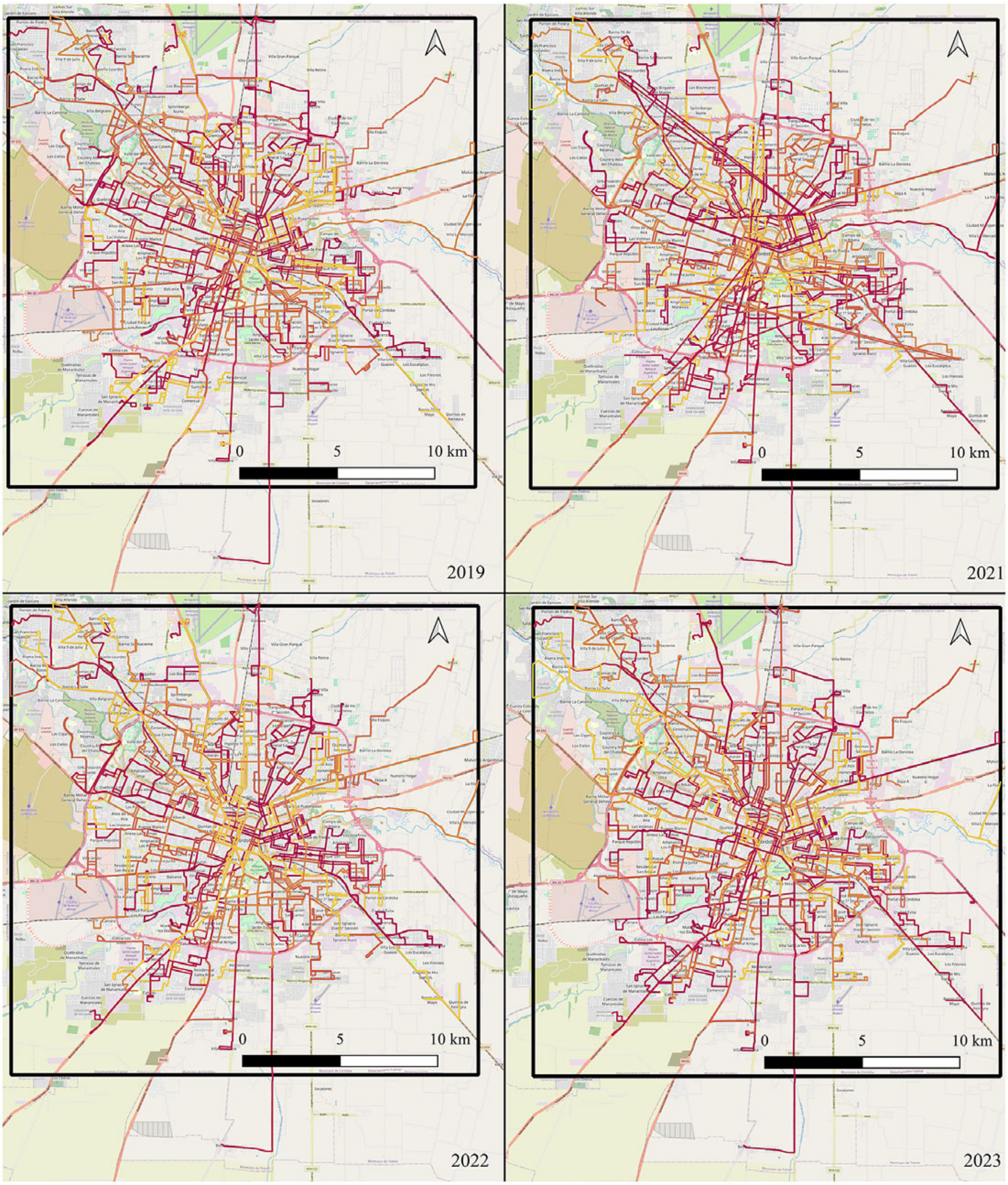

Figure 3. *Routes of the public transport system in Córdoba 2019–2023.*

database, where the hospitals' information was obtained in a *.kml* format, and the open data webpage Gobierno Abierto from the Municipality of Córdoba, where GTFS for 2022 and 2023 were published.

The centroids of the census zones used as origins were formerly obtained using QGIS, and the *.csv* database is published on an open repository on GitHub. The destinations selected were the 14 public hospitals from IDERA's database, grouped into categories to analyze the results: five hospitals belonging to CAT I (high-risk healthcare centers with specialized intensive therapy), five hospitals to CAT II (high-risk healthcare centers with intensive therapy) and four hospitals to CAT III (low-risk healthcare centers with simple hospitalization). This categorization was available on the original database according to different levels of attention and services provided. The grouping of results was made considering that patients can choose to travel to any of the hospitals in every category to receive the same healthcare attention, as hospitals in the same category have similar services and equipment.

The function *travel_time_matrix()* is one of the six fundamental functions in the *r5r* package and was used to obtain a data table with the travel times estimates between census zones and hospitals. The package uses a specific extension of the routing algorithm RAPTOR that computes all Pareto-optimal journeys between each origin–destination pair, minimizing the arrival time and the number of transfers made between them (Delling et al., 2015). The estimation is made by the schedules provided in the GTFS or by modeled schedules with a departure per minute during a time window if the GTFS is frequency-based. In both cases, a set of optimal paths is obtained in each round of the algorithm, with the difference that in the frequency-based GTFS, the schedules are randomly generated (Conway and Byrd, 2017).

The function also has arguments that can be set by the user, such as modes, departure date and time, time window, percentiles, maximum walking, biking, or by car time, maximum trip duration, fare structure, and max fare to consider monetary constraints, average walking or biking speed, among others. As selected in the previous Martinazzo and Falavigna's (2022) work, the analyzed time window was between 9 and 11 in the morning, and the departure date was set on an April Wednesday in 2022 and 2023. The maximum walking time was 10 min, equivalent to the 833 m walk used in the cited work, the maximum trip duration was 120 min, and the percentile selected was 85, meaning 85% of trips between every origin and destination pair are shorter than the obtained result.

The parameters were set to replicate an average day in an off-peak hour during the morning, as most of the facilities' attention concentrates during the morning and weekdays. Both GTFS used had different services for weekdays, Saturdays and Sundays, so the date selected is an average weekday to represent more accurately an average trip. According to the last mobility survey, 54.6% of health-related trips had departure time before 11 a.m., more than 85% of health-related trips had a perceived travel time lower than an hour, and almost all of them were less than 90 min long (De Beláustegui, 2011). A sensibility analysis of the departure time was performed to evaluate the selected time, and the results are shown in the next section. The maximum trip duration of 120 min was set to contain all trips beyond the average value of the mobility survey. The maximum walking time selected, which includes the time to access and egress public transport, is consistent with previous work in Córdoba about access to mobility services, which considers a 5-min walk appropriate to access a bus or tram stop (Martinazzo, 2022).

The resultant travel time matrix was processed to calculate an average per hospital category per zone. This way, in the grouped per category data frames obtained, each row corresponds to only one census zone with a single travel time value identified by its code, with additional information about the number of total households and the number of households with NBI. The percentage of households with NBI (%NBI) was calculated and used to classify the households into weighted quintiles per number of households so that the zones were classified accounting for 20% of households each.

The cumulative opportunities indicator was also calculated using *r5r* (Pereira et al., 2021) for a maximum travel time of 60 min to complement the analysis of travel times from Martinazzo and Falavigna's (2022) work. The time frame was selected considering that, in Córdoba, over 95% of the trips last less than an hour (De Beláustegui, 2011). The *accessibility()* function was used, setting the step decay function, a maximum walking time of 10 min, a maximum trip duration of 120 min, and the percentile selected was 85, as it was set for the travel time matrix.

To complete the analysis of travel times and evaluate how changes in the location of facilities during 2023 impacted the accessibility to healthcare, the minimum travel time per hospital category per zone was also obtained from the original 2023 travel time matrix. *r5r* (Pereira et al., 2021) was also used to obtain a new travel time matrix considering the locations of three new facilities called "Hospitales de Pronta Atención" that were projected by the Municipality, which information was retrieved from the open data Municipality webpage Gobierno Abierto (Municipalidad de Córdoba, 2023a).

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4. Results

Average travel times for the three hospital categories were graphed in Figure 4 as box plots by quintiles in proportion to the percentage of households with unsatisfied basic needs (%NBI). There is a clear trend of lower travel times for the less vulnerable households (Q5) and higher travel times for the quintiles that group most households with unsatisfied basic needs (Q1), with a decreasing Q1-Q5 tendency. The first quintile has the higher average travel time in all cases and the most spread distribution for both years, showing more distance between minimum and maximum values in the box plots. If the comparison is made between both study years, the mean value indicated in the boxplots of Figure 4 shows lower travel times for 2023 than for 2022, and the spread of the estimations also seems smaller for 2023.

These general tendencies were also observed in the work of Martinazzo and Falavigna (2022), as described in Section 2.4, and are confirmed by the principal statistics in Table 2. The difference in average travel times between Q1 and Q5 is around 15 min for 2022 and 14 min for 2023. Despite that, the improvement between 2022 and 2023 in quality and extension of services (see Table 1) further affected the most vulnerable households, as travel times decreased between 5 to 7 min for Q1, around 1 min more than Q5 for the three hospital categories. Besides, the average reduction for the two most vulnerable quintiles, Q1 and Q2, is 6.88% higher than for Q4 and Q5, but only in the order of seconds of difference. Overall, the total average travel time was reduced by 12.32%, 14.16%, and 11.73% for CATI, CATII, and CATIII. The spread in the distribution seen in Figure 4, analyzed through the minimum and maximum, is consistent with the standard deviation (SD) in Table 2.

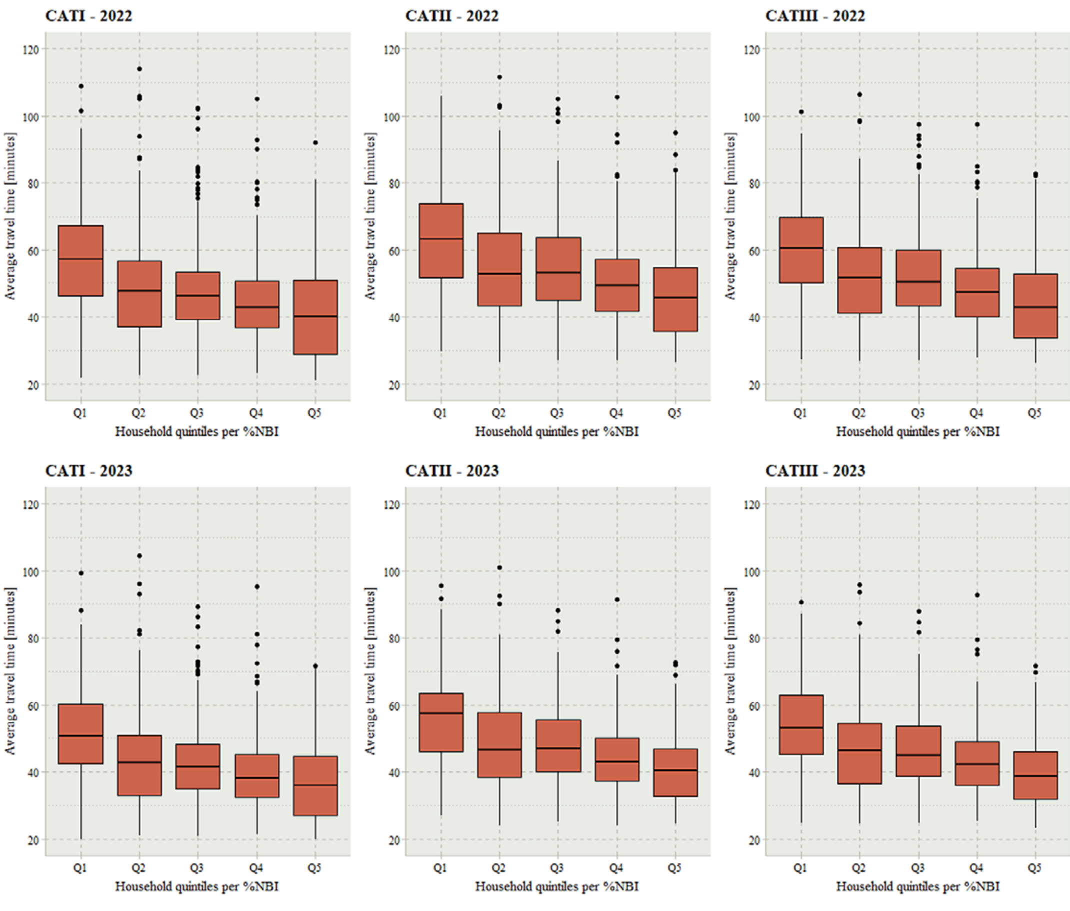

Figure 4. *Average travel times box plots per %NBI quintiles.*

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Table 2. *2022–2023 descriptive statistics per hospital category per %NBI household quintiles*

		2019[a]			2022			2023		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
CAT I	Q1	45.50	44.80	13.40	56.45	57.25	16.90	50.67	50.75	15.22
	Q2	39.70	39.10	10.30	48.35	47.75	15.25	43.44	42.75	13.43
	Q3	39.80	39.50	8.74	47.94	46.25	14.02	42.48	41.50	11.70
	Q4	38.50	37.80	8.57	44.57	42.75	12.62	39.41	38.25	10.42
	Q5	35.50	35.50	9.24	41.32	40.00	14.06	36.53	35.75	11.21
	Total	39.62	39.25	10.62	47.41	46.00	15.37	42.21	41.50	13.24
CAT II	Q1	48.80	47.60	13.20	62.35	63.20	16.46	55.05	57.40	14.22
	Q2	43.40	42.00	11.20	54.19	52.80	14.78	47.93	46.60	12.48
	Q3	43.60	43.20	10.10	54.68	53.00	13.78	47.77	46.80	11.07
	Q4	41.50	40.60	9.10	50.78	49.20	12.27	44.29	43.00	9.81
	Q5	37.50	37.60	8.03	46.91	45.70	12.57	40.62	40.20	9.32
	Total	42.77	41.80	11.00	53.46	52.40	14.82	46.83	45.60	12.33
CAT III	Q1	45.70	44.80	12.80	59.17	60.40	16.06	53.39	53.00	14.61
	Q2	40.30	39.50	10.50	51.42	51.80	14.36	46.35	46.20	12.44
	Q3	41.10	40.40	9.20	51.84	50.40	12.93	46.12	45.00	10.82
	Q4	39.20	38.40	8.51	48.16	47.40	11.60	42.94	42.20	9.63
	Q5	35.60	36.60	8.31	44.15	42.80	12.59	39.27	38.80	9.66
	Total	40.21	39.60	10.43	50.64	50.00	14.35	45.32	44.60	12.34

[a]Data from Martinazzo and Falavigna (2022).

Despite the improvements in the average travel times between 2022 and 2023, once compared with the pre-pandemic results that Martinazzo and Falavigna (2022) obtained, the post-pandemic travel times of 2023 are higher (see 2019 values in Table 2). The travel times for 2023 are up to 7 min higher, with remarkable differences of around 4 min between Q1 and Q5, as described in the previous analysis. Overall, the 2023 total average travel time is 6.53%, 9.50%, and 12.71% higher for CATI, CATII, and CATIII. This trend can be seen graphically in Figure 5, which shows the average travel time per %NBI quintiles for the three hospital categories between 2019 and 2023. The figure also reveals that the higher travel time values were during 2021–2022, as expected for the cuts in routes and services described in Section 3.2. The modifications the transport system suffered in the study period did not impact the tendency where the more vulnerable households have higher average travel times, and the gap between Q1 and Q5 during and after the pandemic is more extensive than in 2019.

The results obtained were also analyzed geographically, as can be seen in Figure 6, where the areas in grey have no travel time data because of the parameters maximum travel and walking time set in *r5r*; that is to say, that does not include the zones which have travel times higher than 2 h or the nearest stop is further than a 10-min walk. For 2022, travel time values were obtained in 1,422 zones over 1,503 for the three hospital categories, while for 2023, results in 1,425 zones were obtained in the three categories.

The maps show that in 2023 there are more zones with lower travel times, painted in yellow tones, than in 2022, where there are more zones with violet tones, indicating higher travel times. Also, the zones with higher average travel times groups in the city's periphery, especially in the western and northwestern areas. This trend is observed for the three hospital categories, similar to the territorial pattern observed in Martinazzo and Falavigna's work (2022).

The zones with no travel data are in the periphery of the city, and the areas are more extensive than other zones near the city center. This situation could influence the final result because centroids were used as the origins of the trips, and in larger areas, this point could not be representative of an average walking distance to transit stops. Overall, zones with no data are coincident among all the categories and in both

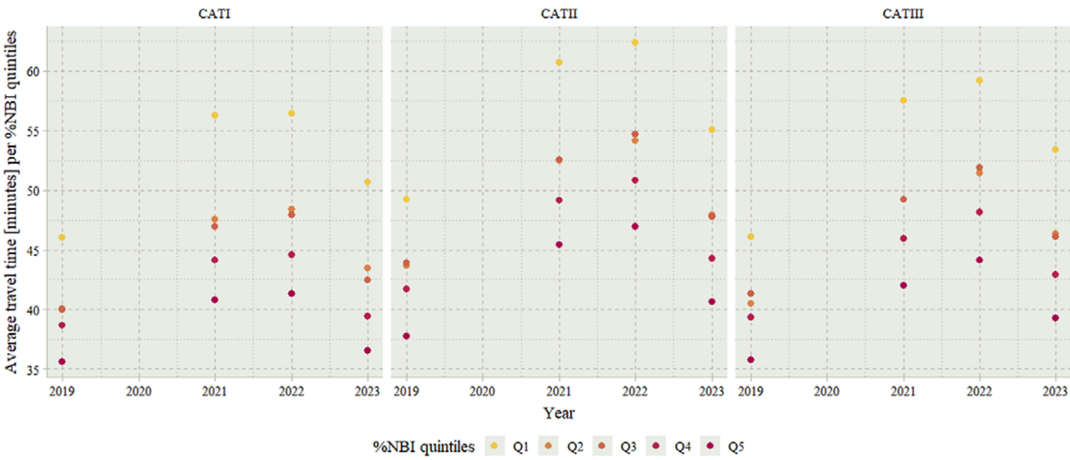

Figure 5. *Average travel times means 2019–2023.*

years studied. This pattern was also observed in the work of Martinazzo and Falavigna (2022) used as a baseline.

Figure 7 shows that when we intersect the travel time data with the percentage of households with NBI per census zone, the characteristics of the periphery zones with the highest travel times are dissimilar. In the categorization presented in the bivariate maps, most of the northwestern zones with high travel times correspond with the lowest percentages of households with NBI. On the contrary, the zones with high travel times in the western and southwestern parts of the city periphery are also zones with a high percentage of vulnerable households. Other areas allocated in the boundaries with high travel times have, in general, high rates of households with NBI.

This analysis is significant considering that the value "high" in the percentage NBI scale is higher than the city average percentage of households with NBI (see Section 3.1). Additionally, the geographical distribution of the higher travel times and its coincidence with the zones with greater vulnerability is similar to the previous assessment about the differences between the extreme quintiles of households Q1–Q5.

As explained in Section 3.3, this analysis includes the cumulative opportunities to complement the previous travel times estimations. The calculated indicator represents the number of opportunities, in this case, public hospitals, that people can reach in a maximum of 60 min using public transport, with access and exit from the stops in walking mode. Table 3 exhibits average values by quintiles in proportion to the percentage of households with unsatisfied basic needs (%NBI). Similar to the distribution of average travel times, the less vulnerable quintiles have higher levels of access for both years, and 2023 has higher mean values for all the quintiles, adding almost two opportunities in total. The gap between Q1 and Q5 is significant, with around five opportunities for both years.

Regarding the geographical distribution, it can be seen in Figure 8 that for 2022 and 2023, the sectors with the worst access conditions are in the peripheries. There is also a marked difference between the 2 years of study in the number of census radios that reach the highest number of opportunities, with 2023 generally showing the best access conditions.

To assess the departure time during the morning, as presented in the previous section, the average travel time was obtained for departures at 7 a.m., 8 a.m., 9 a.m., and 10 a.m. For 2022, the lowest average travel time is achieved with the 7 a.m. departure, and the travel time increases every hour, as seen in Table 4. A departure at 8 or 9 a.m. has similar travel times, while a departure at 10 a.m. has, on average, 1 min more than a departure at 7 am. This same pattern repeats if the analysis is done by quintiles in proportion to the percentage of households with unsatisfied basic needs (%NBI). In the 2023 schedule, this tendency changes, as the highest average travel times are with a 7 a.m. departure, while the lowest travel times are with a 9 a.m.

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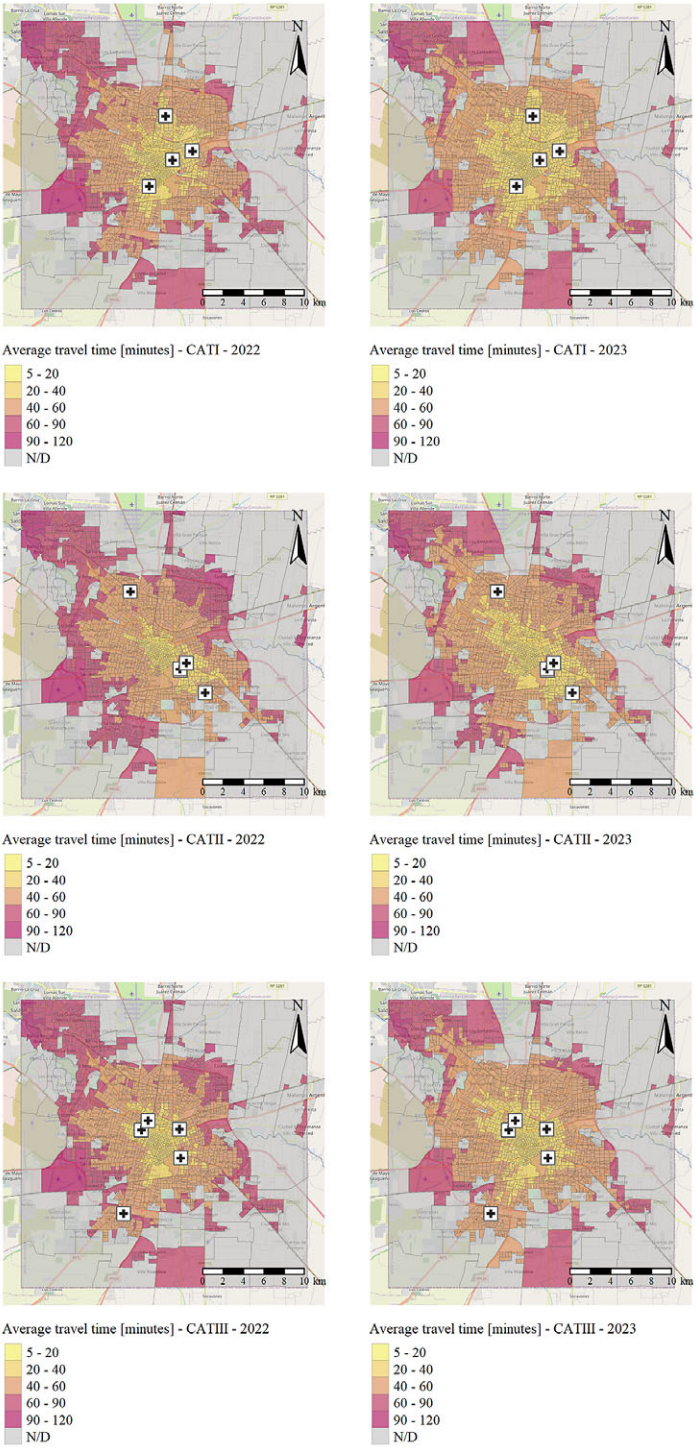

Figure 6. *Spatial distribution of travel times.*

departure. Overall, the differences in average travel times for the different departure times are around a minute for both years. Therefore, any of the chosen departure times over the morning are equally representative, considering the mobility survey data presented in Section 3.3.

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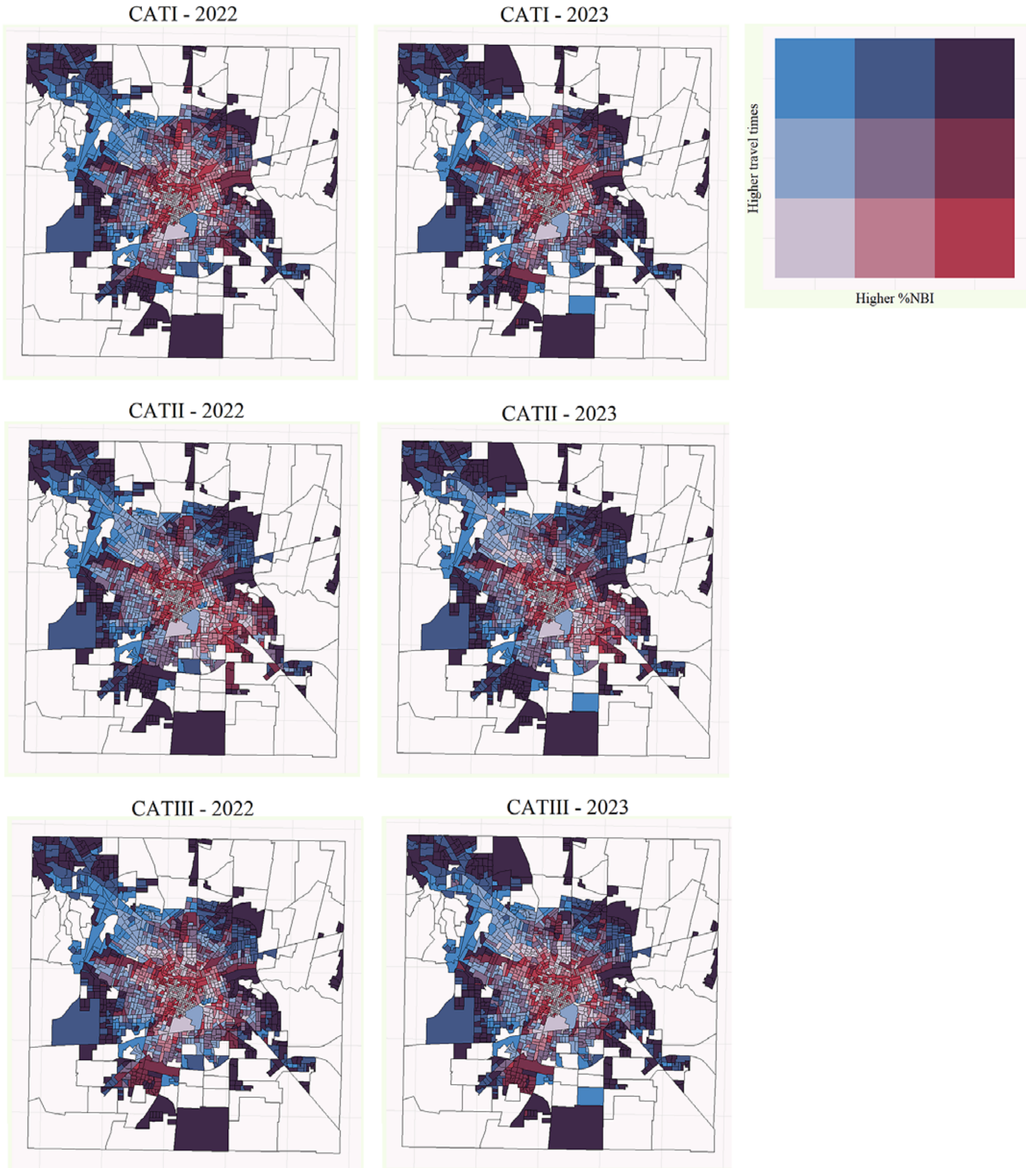

Figure 7. *Spatial distribution of travel times – Bivariate maps.*

As the location of activities is a fundamental element of accessibility, some of the changes in the healthcare system during 2023 were assessed. The Municipality is currently installing new facilities called "Hospitales de Pronta Atención" (HPA), which provide health services to the residents decompressing the demand in the other points of the healthcare network, working with all the standards for the provision of intermediate health services and in coordination with the central Municipal Hospital "Hospital Municipal de Urgencias" (Municipalidad de Córdoba, 2023b). As was presented in the previous section, the minimum travel time was used to compare accessibility in 2023 before and after these new hospitals. In Figure 9, it can be seen the differences in the minimum travel time to a CATIII facility with the addition of the HPA to the public healthcare system, especially in the northwestern part of the city, where "Hospital de Pronta Atención Cura Brochero" was installed in the Arguello neighborhood, and the west with the "Hospital de Pronta Atención Villa Adela". Looking at Figure 6, the location of the three new hospitals has

Table 3. *2022–2023 mean values of cumulative opportunities measure per %NBI household quintiles*

	2022	2023
	Mean	Mean
Q1	5.11	7.15
Q2	7.99	9.88
Q3	8.80	10.72
Q4	9.42	11.40
Q5	10.19	12.05
Total	8.40	10.33

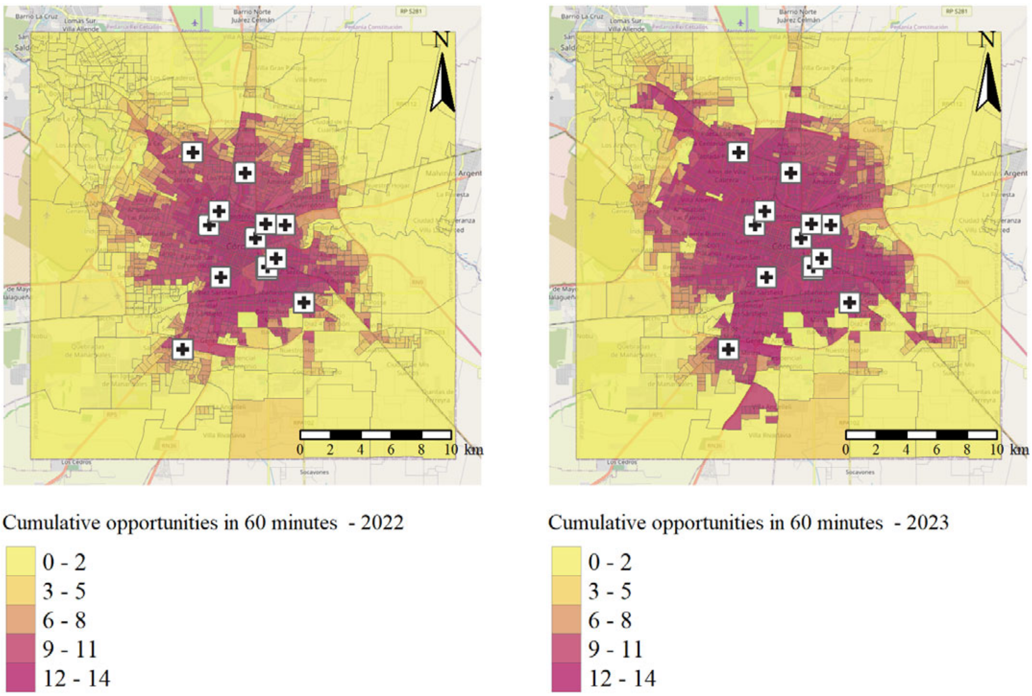

Figure 8. *Spatial distribution of cumulative opportunities measure.*

the potential to enhance accessibility as they are installed in zones or proximate to zones with an average travel time of over 40 min. However, the social impact is diverse among zones as the northwestern corresponds with zones with the lowest percentages of households with NBI while the western side of the city has much of the households in vulnerability, as was concluded previously from Figure 7. The east and southeast parts of the periphery that have high levels of households with NBI are still not covered by these changes in the healthcare system.

Table 5 shows the average minimum travel time to a CATIII hospital by quintiles in proportion to the percentage of households with unsatisfied basic needs (%NBI). The less vulnerable households have the lowest minimum travel time before and after the HPA. However, with the new hospitals, Q1 reduced their minimum travel time by nearly 4 min and Q2 by around 2 min. Additionally, the gap in percentage between Q1 and Q2 was reduced by 10% with the implementation of the HPA, and in minutes decreased from 12 to 9 min.

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Table 4. *Sensibility analysis of departure time*

		2022 - Departure time 7 am			2022 - Departure time 8 am			2022 - Departure time 9 am			2022 - Departure time 10 am		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
CAT I	Total	47.11	46.00	15.29	47.29	46.00	15.39	47.41	46.00	15.37	47.70	46.38	15.56
CAT II	Total	53.18	52.00	14.69	53.30	52.00	14.68	53.46	52.40	14.82	54.54	53.40	15.11
CAT III	Total	50.00	49.40	14.16	50.22	49.70	14.26	50.64	50.00	14.35	51.35	50.80	14.53
		2023 - Departure time7 am			2023 - Departure time 8 am			2023 - Departure time 9 am			2023 - Departure time 10 am		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
CAT I	Total	42.50	41.25	13.58	42.25	41.25	13.22	42.21	41.50	13.24	42.25	41.25	13.42
CAT II	Total	47.64	46.20	12.66	47.09	46.00	12.37	46.83	45.60	12.33	46.97	45.60	12.53
CAT III	Total	45.80	45.00	12.86	45.35	44.40	12.54	45.32	44.60	12.34	45.36	44.60	12.54

5. Discussion

In the literature review, the presented cases revealed a variety of accessibility analyses used as reliable academic sources that sometimes fail to influence transport planning and operation practices. The main barriers to actively including accessibility as a fundamental asset in transport planning are gaps in data and knowledge necessary to carry on these types of analyses (Boisjoly and El-Geneidy, 2017b). In this research, as referenced by Martinazzo and Falavigna's work (2022), a method to dynamically evaluate modifications in the transport system is presented as an alternative to complement the evaluation of urban and mobility projects. The usage of georeferenced data to allocate people and activities in the territory and the characterization of the transport system through GTFS feeds provide the necessary flexibility and accuracy to address changing urban scenarios. Besides, using the so-called simple indicators such as travel times and the number of opportunities reached, presented as location-based measures by Geurs and van Wee (2004), might be the best way to assertively communicate the impact of different public transport and land use actions on accessibility. Furthermore, the systematization of these practices over the years can be a fundamental input on which future urban plans can be based.

Another substantial aspect of the presented methodology is the intersectional analysis between accessibility measures and the intrinsic characteristics of the population. The importance of these disaggregations of the results has been proven as the travel times and cumulative opportunities reached vary significantly among the less vulnerable and more vulnerable population groups. In addition, the implementation of new locations without considering equity issues enhanced accessibility heterogeneously in the quintiles of the population, being that previous work in Córdoba concluded that the high-income population predominantly uses private hospitals and that the low-income population that relies on public healthcare systems uses mainly public transport to travel. These differences in the impact of transport projects regarding equity correspond with previous work in Latin America (Bocarejo S. and Oviedo H., 2012; Falavigna and Hernandez, 2016; Oviedo and Guzman, 2020), as usually, the most exposed groups of people have lower levels of accessibility and considerable difficulties to reach urban opportunities.

Particularly regarding the evaluation of access to healthcare facilities, as described in Section 2.3, it is significant in terms of the capability of people to fulfil their essential care needs and the general objective of achieving universal health coverage (Evans et al., 2013). It is also vital to consider non-mandatory trips, other than work and education trips, to promote equity in access to all urban opportunities that integrally enhance the quality of life (Oviedo and Guzman, 2020). Indicators of geographic accessibility, such as the ones calculated in this research, are necessary to identify the gaps in potential access to healthcare. The center-periphery dynamic described for Córdoba is similar to the trends illustrated by previous works

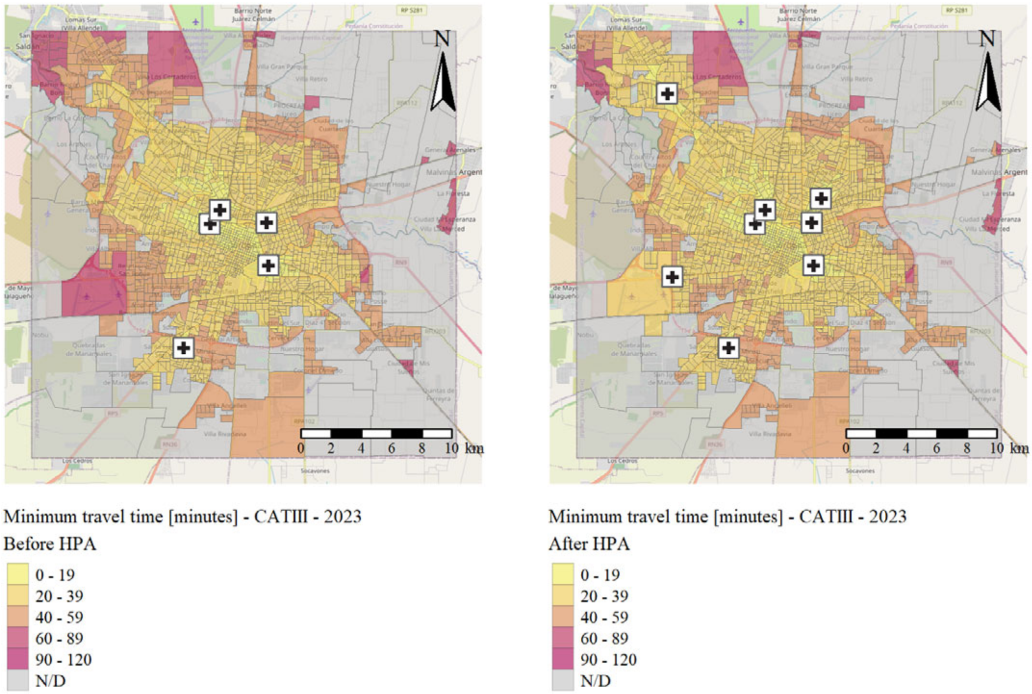

Figure 9. *Spatial distribution of travel times – Before and after HPA.*

Table 5. *2023 mean values of minimum travel time per %NBI household quintiles before and after HPA*

	2023 - Before HPA	2023 - After HPA
	Mean	Mean
Q1	38.89	35.19
Q2	31.67	29.28
Q3	31.77	29.50
Q4	29.91	28.62
Q5	27.15	26.47

(Tao and Cheng, 2019; Chen et al., 2021), as well as the differences among income groups (Ermagun and Tilahun, 2020; Zhao et al., 2020). The travel times obtained are dissimilar and, in general, lower than an hour, as was presented in previous works (Peipins et al., 2013; Tao et al., 2018; Chen et al., 2021; Cao et al., 2022), but the 30 min acceptable travel time proposed by Cao et al. (2022) it is only achievable in the city center.

6. Conclusions

Public transport is a fundamental tool to address climate change and guarantee sustainability and inclusion in urban areas that suffered the impacts of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) pandemic.

In Córdoba, during 2020 and 2021, the Municipality decided to make cuts in services to guarantee the financial sustainability of the urban transport system, whose demand plummeted, in a general context of

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high inflation rates and economic regression. These modifications were not planned considering social issues, so the system sustained, during and after the pandemic, the previous scheme of inequity where the more vulnerable households needed to travel more time than the most affluent sectors to access healthcare opportunities. During 2023, the system almost recovered its pre-pandemic extension, but travel times remain higher than in 2019. Furthermore, the gap between the quintiles with the higher and the lower percentages of households with unsatisfied basic needs grew between 2019 and 2023, reaching 14 min. When these travel time patterns are analyzed geographically, it shows that overall, the city's periphery has higher travel times and that some sectors also have high percentages of households with NBI. In terms of cumulative opportunities, the differences between extreme quintiles are also significant, as in 2022, Q5 doubled Q1 number of opportunities reached in 60 min, and in 2023, the number of opportunities of Q5 is 68.57% higher than the opportunities reached by Q1 households. To decentralize the healthcare attention, the Municipality projected three new hospitals called "Hospitales de Pronta Atención", two of them located in the periphery. The results showed that the minimum travel time lowered in the zones near the location of the hospitals, but the impact was not homogenous in social terms. Much of the benefits impacted zones in the northwestern periphery with the lowest proportion of vulnerable households and zones in the western area with high percentages of households with NBI. In contrast, vulnerable zones of the southern and eastern periphery still have a minimum travel time of over 40 min.

Despite the challenging context confronted to prevent the collapse of the public transport system, the measures the Municipality took failed to assess the social characteristics of the population. The strengthening of the public healthcare system is not sufficient by itself to improve geographic accessibility as its installation is conditioned to the availability of vacant lots, and it is not viable to enlarge the number of healthcare institutions limitlessly. The public transport system needs to have coverage and quality of service enough to guarantee travel times that are acceptable to the population. The available information and methods may serve as an instrument to analyze public transport performance with equity criteria. While the results presented are not determinant because they refer to a punctual urban opportunity, the central purpose is to emphasize the importance of the accessibility assessment in transport planning that leads to evidence-based decision-making that considers social evaluations. The accessibility measures provide strong guidance to direct projects towards a more equitable system and are fundamental to be incorporated by transport and mobility practitioners, especially given the upcoming expiration of the urban transport system concession contract in Córdoba.

The sensibility analysis performed and the revision of the mobility patterns in Córdoba make the study case representative enough of an average trip for health purposes. However, to serve as a planning tool, the research should be extended to other types of trips in modes, selected destinations, and time frames studied. Despite the travel time being an easy-to-communicate measure, some more complete accessibility indicators should be used in addition to enhance the robustness of the research, especially to consider the competence for the opportunities between population groups and the characteristics of the activities. Another limitation of the methodology proposed is that the use of schedule-based GTFS makes the results realistic only if the system works according to the programs. In the case of Córdoba, there is no GPS open database available to control if the buses comply with the scheduled services, and it is a valuable source of information to, in future works, control and correct the programming of public transport. To integrate all this information and to better represent the zones, especially those with large areas, new types of zoning, such as hexagonal grids, can also be used.

Although the accessibility indicators in this research were calculated through fixed parameters, such as maximum walking distance and maximum travel time, the method presented is flexible enough to allow changes and evaluate multiple cases. This capacity of adaptation may allow the evaluation to reproduce the quality standard that the transport system aims to reach. Additionally, using open data sources provides a replicable, simple process, and the GTFS format and packages as *r5r* to assess rapid realistic routing constitute an opportunity to model different and changing scenarios.

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Competing interest. The author declares no competing interests exist.

Author contribution. Conceptualization: L.M.; C.F. Methodology: L.M.; C.F. Data curation: L.M. Formal analysis: L.M. Investigation: L.M. Methodology: L.M. Project administration: C.F. Resources: C.F. Software: L.M. Supervision: C.F. Validation: L.M. Data visualization: L.M. Writing original draft: L.M. Writing – review & editing: L.M.; C.F. All authors approved the final submitted draft.

Data availability statement. Replication data and code can be found on GitHub: https://github.com/LucilaMartinazzo/Public-transport-accessibility-to-hospitals-Cordoba-2019-2023-. The original work and other data and code can be found in this GitHub repository: https://github.com/LucilaMartinazzo/Tesis-de-Maestria.

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