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Article

Influence of public transportation on urban mobility in Celaya: a GIS case study

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A B S T R A C T

Sustainable urban mobility represents one of the greatest challenges for medium-sized Latin American cities, where public transport plays a fundamental role in reducing air pollution and traffic congestion and improving access to basic services. This paper examines the impact of public transportation on urban mobility in Celaya, Guanajuato, using Geographic Information Systems (GIS) to study the public transportation network in terms of coverage, accessibility, and efficiency. By compiling georeferenced data on public transport routes, such as departure frequencies and passenger flows, together with details on road infrastructure and sociodemographic data from open sources. Geographic information systems were used to construct thematic maps and spatial accessibility models, which made it possible to identify areas with poor coverage, long travel times, and disparities in urban connectivity. The findings show that, although public transport covers most of the urban areas, there are peripheral areas with poor accessibility and high dependence on private transport, which negatively affects sustainable mobility in developing industrial cities. Likewise, strategic corridors were identified where improving frequencies and modal integration would significantly increase the efficiency of the system. Finally, it is essential to include spatial analysis through GIS in the design of public transport, as this enables fairer and more sustainable mobility policies to be implemented, helping to reduce congestion and improve the quality of life in cities.

1. Introduction

The rapid expansion of medium-sized cities located in industrial regions presents unique challenges for urban mobility planning: these urban centers bring together production hubs, logistics corridors, and peripheral areas whose connectivity requires public transportation solutions that go beyond simply providing vehicles and routes [1-3]. In contexts where intensive commutes to industrial areas coexist with scattered residential travel, route configuration, spatial coverage of services, and operational capacity directly determine the equity of access, system efficiency, and the city's environmental sustainability [4-6]. Transitions in urban mobility are strongly influenced by socioeconomic factors [7], necessitating adaptations in transport policies, particularly in medium-sized cities, rather than simply replicating large-scale models [8]. In Bangalore (India) [9], they found a direct relationship between coverage and accessibility, thereby improving urban inclusion and sustainability. Khan et al. used logistic regression models with data from US national surveys to show that vulnerable user groups have limited access to essential destinations via public transport [10]. In this regard, public transportation (PT) is a key tool for advancing toward sustainable urban mobility. Strengthening PT has the potential to lower the modal cost of private vehicles, reduce pollutant emissions, and increase access to services and employment, provided that planning accounts for coverage, frequency, and connectivity via modal transfer hubs [11]. Public transportation plays a crucial role in the planning of industrial cities with rapidly growing populations, since improving access to industrial areas and services reduces vehicle congestion and, in turn, environmental pollution [12]. However, the impact varies depending on the urban context: in most cases, transport investments are concentrated in the center, accentuating territorial disparities with other regions within the urban sprawl [13]. In Latin American regions, according to Ref. [14], systematic analyses of methods for assessing transportation sustainability indicate the need for tools that integrate social, environmental, and operational indicators to inform effective policies [15, 16]. Some authors, such as Miller [17] and Lovelace [18], have demonstrated that Geographic Information Systems (GIS) and geospatial tools are particularly effective in diagnosing actual public transport coverage and developing alternatives to improve network design. This establishes that network-based methods, gravity models, and generalized cost assessments have been used to measure door-to-door accessibility, identify areas with insufficient service, and analyze the impact of changes in service frequencies or routes on travel times and emissions from public transportation services. For this reason, GIS tools also enable the identification of spatial gaps and the prioritization of actions, making spatial analysis an essential input for operational planning of public transport in cities of different sizes [19]. In densely populated cities such as Mexico City, benefits have been noted in terms of mobility provision; however, if the service does not properly reach peripheral areas, there are also risks of gentrification or social inequalities [20]. In recent years, Finck [13] has noted that economic investments are concentrated in central areas, leaving peripheral areas with limited coverage and accentuating territorial disparities. On the other hand, in border cities with industrial characteristics, such as Mexicali, residents of distant peripheral areas must make long and costly commutes to work due to the absence of a coherent network, which perpetuates socio-spatial exclusion [16].

Likewise, there is a need for an assessment that integrates a detailed spatial analysis of routes, measurements of effective coverage, and demand projections in light of the introduction of new modes of transport such as passenger trains in medium-sized industrial cities in Mexico, with the aim of generating greater connectivity and facilitating daily travel in various areas of great importance in Mexico [8]. This research analyzes the need for a case study in Celaya (Guanajuato), given that it currently faces challenges related to public transportation and intermodally with the existing rail passenger transportation system, which in turn must provide greater connectivity and coverage. The research first examines the current spatial coverage of public passenger transportation routes. It then proposes a survey of the urban and interurban route network in relation to the spatial distribution of demand and, finally, the requirements in terms of capacity and route adjustment in situations where there is an increase in users due to other means of transport, with the aim of mapping accessibility and generalized travel costs based on the city's current coverage. This was carried out using georeferenced data on routes, road networks, and passenger flows, along with a method for estimating accessibility indicators and analysing scenarios. Finally, strategic recommendations are proposed to adapt the network in line with the criteria of spatial equity and sustainability, aiming to translate technical efficiency into tangible improvements in citizens' access to urban opportunities. This document proposes, unlike the conventional methods of the gravitation model of accessibility proposed by Hansen, the integration of an analysis of the Gravitation of Accessibility from the geospatial and statistical integration. 3 important pillars are established, which are described: 1. Calibration of the impedance parameter (β), which consists of implementing the calibration from the distribution of trips observed in the geographical areas within the city of Celaya, Guanajuato, allowing to reduce the risk of overestimation of accessibility in urban peripheries. Unlike using arbitrary distance friction values [20, 21]. 2. Multimodal and systemic integration (GTFS), which allows accessibility to be modelled from the perspective of service frequency and wait times, which is essential to capture transport dynamics in environments with a volume of unstructured data [22]. Finally, in the third pillar, a spatial-statistical heterogeneity analysis was carried out, which consists of applying spatial autocorrelation. This integration allows the detection of statistically significant exclusion clusters, giving a more accurate diagnosis than traditional gravitational frames.

2. Materials and methods

A geospatial and quantitative method was used in this study to analyse the effects on urban mobility in Celaya, Mexico. To this end, Geographic Information Systems (GIS) and sophisticated methods were used to examine accessibility. The methodology incorporates data collection, cleaning, and modelling procedures, as well as methods for analysing data at spatial and statistical levels. This perspective follows the methodological guidelines suggested by the specialized literature on specific topics in urban geography and transportation [23-28]. To understand the influence of public transport on mobility in the city of Celaya, Guanajuato, the study has been designed under two approaches. The first (H1) states that the city has grown much faster than the public transport network, resulting in a coverage deficit of more than 40% in peripheral areas. The second (H2) suggests that the population living on the periphery of the city not only faces a greater distance but also longer travel times between areas of greatest influence due to inefficient infrastructure. The assessment of accessibility is carried out using isochrones, which represent the maximum distance a person can walk in 5, 10, or 15 minutes from any point to public transport stops. By overlapping these ranges with the demographic distribution, it is possible to accurately locate the gaps in public transport. This data analysis is crucial for testing H1 by revealing where population density does not match service supply and highlighting key areas of the city where service or public transport coverage is unequal.

2.1 Data collection and sources

The initial stage of the study consists of data collection, which includes the identification and systematic recording of socioeconomic, spatial, and operational information. Using open data and verified sources promotes reproducibility, an essential criterion for high-impact research, as suggested by Singleton [29]. The geospatial data were derived by integrating origin-destination surveys conducted in the field with open-access, population-based statistical data from the National Institute of Geography and Statistics (INEGI) [30], which maintains a high level of detail on transport networks, infrastructure, and urban elements. Its continuous updating by INEGI provides recent data with high spatial resolution. On the other hand, in cases where data is not available, it is useful to use data from platforms such as OSM, where a higher quality of official data is required, especially in terms of road geometry, connectivity, and topological attributes of the network, as mentioned by Girres [31] and Grinberger [32]. Regarding the spatial delimitation of the study, the official administrative boundaries published by the National Institute of Statistics and Geography [30] were used. This information includes digital cartography aligned with the national geostatistical framework, which integrates the municipal outline, urban Basic Geostatistical Areas (AGEB), and block-level disaggregation. Urban AGEBs capture intermediate-scale socio-spatial patterns relevant to the analysis of urban accessibility and mobility, while block mapping enables greater detail. In addition, the use of recent official sources ensures that territorial boundaries are up to date and valid, avoids inconsistencies in georeferencing, and improves comparability with other urban studies or national databases.

The operational data for the public transport system, defined as routes, stops, schedules, and frequencies, were initially obtained from official municipal records and the operators' technical documentation. Given that, in many cities, information is not always published in standardized formats, this procedure reduces georeferencing errors and discrepancies in frequencies often found between theoretical schedules and actual operations (Mahajan et al. [33]). A GTFS dataset was constructed from official schedules and maps following a reproducible sequence as recommended by Wu et al. [34]. The reproducible steps are shown in Table 1 composed of necessary files such as: agency.txt, stops.txt, routes.txt, trips.txt, stos_times.txt, Shapes.txt, the latter was taken as a reference for the new stroke using GIS.

Finally, the limitations of the source were considered and documented: lack of information on occupancy per trip (load), uncertainty about temporary service modifications (events, construction), and the possible discrepancy between theoretical routes and operational deviations. To mitigate this, spot observations were made (counts and actual travel times on critical segments), and this data was used to calibrate the time estimates in accessibility models, as recommended by recent reviews on the use of public and private data in transportation models, as suggested by Mahajan [33]. The process for analysing the supply of urban destinations and land use in Celaya was based on integrating geographic data from official sources (INEGI and municipal).

The objective was to create a homogeneous destination base for accessibility analysis as suggested Kocur-Bera [35]. The criteria used to define the layers are shown in Table 2. The processing of these layers followed a reproducible protocol: (1) normalization of land use codes and taxonomies between sources, (2) reprojection to a single metric system (UTM) and topological verification of polygons, (3) cleaning and geocoding of specific facilities, and (4) spatial aggregation to AGEB. The stages of the method used are shown in Figure 1.

2.2 Accessibility model

The gravitational method is one of the most influential approaches for modeling spatial interaction between origins and destinations, as it reflects how the availability of opportunities and the cost of travel influence the level of effective access within a territory. Its structure is based on Newton's law of gravity, adapted to a socio-spatial context where urban units represent origins and opportunities of interest represent destinations. The development of this stage was chosen for the application of the Hansen [36] type gravitational method due to measures of accumulated opportunity, which allow observing the interaction among citizens of the city of Celaya based on their probabilistic behavior within the network.

Table 1. File structure GTFS

Archive GTFS	Entity / Fields	Operators (Agency) Included	Detailed Primary Data Source	Structuring and Cleaning Process
agency.txt	agency_name, agency_phone, agency_timezone	Concessionaires: Verdes de Guanajuato, Saetas, STDA, Supacel, Atucsa, Puerta de Oro, Tamayo, USB, Enrique Velasco Ibarra, Omnibus, Autobuses de Celaya.	Administrative records of the General Directorate of Mobility and Transport of Celaya.	Unification of trade names and company names in an indexed digital catalogue.
stops.txt	stop_id, stop_laT stop_long stop_name	Field survey and location confirmation using GPS	In-Situ Survey (Fieldwork): Use of GPS receivers and validation using satellite images.	Identification of unofficial stops vs. official stops by means of observed ascent/descent densities. Data correction
routes.txt	route_short_nameroute_long_name route_type	Direct link by concession number and unit chromatics.	Municipal Route Plans: Technical documentation in public format and maps obtained from open access municipal portals.	Digitization and coding of urban (trunk and feeder) and suburban routes under standard route_type=3.
trips.txt	trip_id, service_id, direction_id	Operating hours by company.	Dispatch Logs: Direct interviews with checkers at terminals and route bases to obtain actual frequencies.	Modeling round-trip trips to avoid topological overlaps in the network graph.
stop_times.txt	arrival_time departure_time stop_sequence	Cycle times per operator.	Sampling Run Times: Tracking during peak (7:00-9:00 Valley (12:00–14:00), and Afternoon Peak (18:00–20:00).	Interpolation of times between stops considering traffic lights and congestion due to cycle time in vehicles.
shapes.txt	shape_pt_lat shape_pt_lon shape_dist_traveled	Geographical layout.	Urban layout through digitization in GIS following the real road network of Celaya.	Generation of accurate geometries to ensure that the distance traveled matches the value documented in the units.

Table 2. Characteristics for layer creation

Data Source	Type of Information Obtained	Purpose
INEGI	Geo-statistical Marco (AGEB, block), land use and vegetation maps, and directories of facilities (health, education, commerce, public spaces).	Establish the geostatistical base and thematic coverage at the national level.
Municipal Databases	Complementary inventories (polygons and points of parks, hospitals, schools, workplaces, and markets).	Improve thematic coverage, update records not included in the national data, and validate the information.

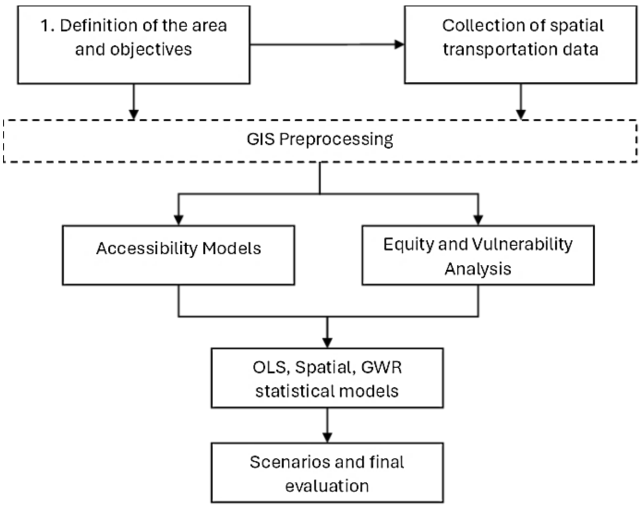

Figure 1. Research methodology

On the other hand, by not using traditional binary metrics, a continuous and probabilistic representation of human behavior in the urban environment of Celaya is sought. In concrete terms, the choice of the gravitation model is based on the attraction of a destination which decreases as the cost involved in reaching it increases, that is; the cost that I immerse in mobility, which can be the time, distance or economic expense that the network user invests. In other words, the more difficult or expensive the journey, the less likely people are to choose that destination. According to Geurs and van Wee [37], this type of model offers a more complete way of analysing accessibility, since it considers at the same time the characteristics of the transport system and the distribution of activities in the territory. In addition, unlike methods that use rigid travel time limits, the gravitational model represents accessibility gradually, avoiding excluding opportunities that are outside those established thresholds.

Stage 1: Definition and operationalization of origins and destinations: This first stage involves determining which urban areas function as origins and which as destinations. Origins are represented by an area's population, while destinations may correspond to business areas, school zones, hospitals, administrative centers, or other services of interest to users. The variables are shown below.

Oi→Population of origin

Dj→Attractiveness of the destination (jobs, services, capacity)

This phase is crucial because the gravitational method depends on the accuracy and quality of the attributes assigned to it. Recent research, including studies by Klar et al. [38] and Wang [39] on urban multimodal analysis, has shown that the lack of a precise definition of origin-destination masses can lead to biases in the spatial representation of accessibility.

Stage 2: Construction of the generalized travel cost c_{ij}: The interaction between origin i and destination j is mainly based on the cost of travel, which includes not only transit time but also all elements of the journey. This perspective is based on research findings showing that actual accessibility is influenced by real-time service quality and the system's physical structure [39-42]. The impedance of the trip between the origin (i) and the destination (j) was modeled using a generalized unified cost function, as expressed in equation (1). The generalized cost is expressed as:

$$C_{ij} = t^{walk}_{i\to stop} + t^{Wait}_{i} + t^{inVeh}_{ij} + t^{transfer} + t^{walk}_{stop\to j} + \gamma \cdot N_{transfers} + \lambda \cdot C_{ij} \quad (1)$$

Where:

$t^{walk}_{i\to stop}$: Walking time from the origin to the nearest stop.

$t^{Wait}_{i} \approx \frac{h_r}{2}$: Estimated wait time, dependent on Route R headway.

t^{inVeh}_{ij}: Time spent in the vehicle.

$t^{transfer}$: Penalty for transfers, adding walking times, and additional waits.

$$t^{transfer} = \sum_{k=1}^{n_{Trans}} \left(t_k^{transfer\_walk} + \frac{h_{r_k}}{2} \right) + P_k \quad (2)$$

Where:

$t_{k=1}^{transfer\_walk}$: Travel time between the platform and the transfer node or public transport stop.

$\frac{h_{r_k}}{2}$: Estimated waiting time for the vehicle on the public transport route.

P_k: Penalty for transfer (minutes)

When the monetary cost is included, consider the following equation

$t^{Walk}_{Stop} \rightarrow$ Hike from the last public transport stop to the destination (Dj)

γ: It is a fixed penalty coefficient for transshipment.

$$C_{ij} = \lambda_t \cdot minutes + \lambda_m \cdot monetary\_cost \quad (3)$$

$N_{transfers}$= Number of transfers, consider modal transfer centers.

$\lambda \cdot Cost_{ij}$= Cost generated for the trip (tariff cost)

λ : Time Value Conversion Factor

Substituting Eq. (2) in Eq. (1), the value of the generalized cost is calculated from Eq. (4):

$$C_{ij} = t^{walk}_{i\to stop} + t^{Wait}_{i} + t^{inVeh}_{ij} + \sum_{k=1}^{n_{Trans}} \left(t^{transfer\_walk}_{k} + \frac{h_{r_k}}{2} \right) + P_k + t^{walk}_{stop\to j} + \gamma \cdot N_{transfers} + \lambda \cdot C_{ij} \quad (4)$$

Stage 3: selection of the impedance function: The impedance, or decay, function models how travel cost reduces interaction between points. In contemporary accessibility studies, Panagiotopoulos [43] and Sharma [44] have used the exponential functions and power functions, which are described below.

- **Negative exponential.** To quantify the relationship between elements i and j, an exponential decay function based on the cost or distance c_{ij} was initially used, expressed in equation 5.

$$f(C_{ij}) = e^{-\beta C_{ij}} \quad (5)$$

Consider the following: when the parameter beta is greater than 0; higher values cause the influence to decline rapidly over time. This function assumes that marginal increases in travel times reduce the likelihood of moving between nodes, which is consistent with empirical evidence from recent urban studies. Its beta parameter modulates sensitivity to time: higher values imply a steeper decline [44] state that the impedance function $f(C_{ij})$ for accumulated accessibility equals zero when the travel time exceeds the threshold t and takes the value of one otherwise (see Eq. (6)).

$$f(C_{ij}) = 1 \; if \; f(C_{ij}) \leq t \;\; Otherwise \quad f(C_{ij}) = 0 \quad (6)$$

- **Power function.** Used when it is desired to model opportunity hierarchies where cost acts as a more gradual moderator. In recent literature Wang et al. [39] Chen et al. [45] and Raggiani [46] suggest that the exponential function provides a better fit in dense urban contexts and structured transportation systems (see E1. (7)).

$$f(c_{ij}) = c_{ij}^{-\alpha} \quad (7)$$

Stage 4: Calculation of gravitational accessibility: Once the mass values and costs are established, the accessibility of each origin is calculated as the weighted sum of the attractiveness of all destinations adjusted by impedance [36]:

$$A_{ij} = \sum D_j f(c_{ij}) \quad (8)$$

Where:
A_i= source accessibility i.
D_j= attractiveness of the destination j.
c_{ij}= travel cost between i y j.
$f(c_{ij})$= Impedance function, which indicates how the interaction decreases as the travel cost increases. Replacing the expression of c_{ij} (Eq.(7)) of the negative exponential function, this relation is expressed as:

$$A_{ij} = \sum D_j \, e^{-\beta C_{ij}} \quad (9)$$

The gravitational accessibility index expresses, in a single quantitative measure, how much actual access a point in the territory has to the opportunities available in the city. These opportunities can be jobs, healthcare services, schools, commerce, or other relevant urban facilities. The value of the index depends not only on the number of existing opportunities but also on how difficult it is to reach them, incorporating the perspectives of the user and the mobility system. In other words, this index simultaneously reflects:

- The magnitude of the opportunities (D_j)
- The friction or impedance of the trip $f(c_{ij})$

The values obtained using the exponential function demonstrated that zonal accessibility is highly sensitive to network configuration. The observed disparity between gross supply and individual experience, as travel time increases, will, in turn, affect the destination contribution index. These delays can be due to various factors, such as long walks, long waits due to infrequent service, multiple transfers, congestion, and other factors. When a relative measure per inhabitant at the origin is desired, the following equation can be used (see Eq. (10)):

$$A_i^{pc} = \frac{1}{P_i} \sum D_j f(c_{ij}) \quad (10)$$

Where: P_i= population at the origin i.

Stage 5: Flow modeling through spatial interaction: In urban and transportation analysis, it is not only used to measure accessibility but also to estimate potential mobility flows between pairs of zones. This approach is based on the principle of spatial interaction, according to which the intensity of movements between two places depends simultaneously on:

- The magnitude of the activity at the source.
- The scale or attractiveness of the destination.
- Travel friction or the overall cost between the two points.

The estimated flow model is calculated from Eq. (11).

$$T_{ij} = K \cdot O_i^{\alpha} \cdot D_{J\;j}^{\gamma} \cdot f\; C_{ij} \quad (11)$$

Where:
T_{ij} = Estimated flow from the origin i to destination j.
O_i = Demand at the origin (population, households, students, etc.).
D_j = Destination attractors (jobs, facilities, travel attractions)
C_{ij}= Generalized travel cost between i and j, measured in travel time using public transportation.
α, γ = Parameters that control the relative influence of sources and destinations
$f\; C_{ij}$ = spatial decay function (describes how interaction decreases as cost increases)

In traditional models, estimated flows between zones may not exactly match the totals observed at origins or destinations. This is a relevant issue when it is required to:

- the total number of trips departing from each zone (generators), or
- the total number of trips arriving in each zone (attracted)

In contexts where you want to preserve the sum of flows observed at sources or destinations, you use versions with constraints (singly or doubly constrained). For example, to maintain the sum of outputs from each source (see Eq. (12)):

$$T_{ij} = O_i^{Out} \cdot \frac{D_j f(c_{ij})}{\sum_k D_k \, f(c_{ik})} \quad (12)$$

The usefulness of this approach has been demonstrated in studies that integrate intra-urban transportation data, particularly those derived from sensors or vehicle tracking [39].

Stage 6: Decay parameter calibration: The β parameter needs to be adjusted so that it can accurately show users' sensitivity to travel time. Calibration can be achieved through comparison with observed flows, error reduction, or statistical models. Typical calibration is based on reducing the mean square error between observed flows and data obtained from the model:

$$\hat{\beta} = \arg\min_{\beta} \sum_{i,j} \left(T_{ij}^{obs} - T_{ij}(\beta)\right)^2 \quad (13)$$

3. Results

The public transport system in the municipality of Celaya has a hierarchical spatial structure. There is a significant concentration of routes, stops, and services in consolidated urban and suburban areas, especially in the historic center and the most important industrial areas within the logistics corridor of the Laja Bajío region. Figure 2 illustrates this characterization of the system. A network was constructed consisting of 79 active routes (considering round-trip) and 1,443 (fixed) stops, operating according to variable frequency schedules based on geographical location and time, using public transport data (GTFS) created specifically for this research. To describe mobility in cities in a functional way, it is essential to consider the spatial disparity in the population density of public transport stops. To capture the complexity of mobility in Celaya without falling into statistical distortions, a spatial disaggregation approach was adopted. Although the population data originally came from the AGEB (Basic Statistical Geographic Area) for its census detail, it was decided to transfer the information to a 500 x 500-meter grid. The objective was to standardize the territory into uniform cells, eliminating the geometric biases of irregular polygons and reducing area errors, with the aim of estimating the habitability of each area in a way that is equitable to people who live far from access to public transport. On the other hand, the incorporation of postal code centroids fulfills a strictly logistical role. Centroids were used as aggregation nodes to model micromobility flows. This allows us to understand large-scale displacements through the city without overloading the model with microscopic details that would not alter the overall trend.

Overall, this multiscale model ensures that each stage of the analysis employs the unit of measurement most relevant to its objective, striking a balance between local sociodemographic accuracy and the operational effectiveness of the transport system throughout the urban area. The analysis is based on widely recognized urban density and spatial statistics models, such as those used in urban transport research, which integrate statistical and GIS analyses [47].

3.1 Model calibration

To ensure that the GTFS dataset reflected the operational reality of Celaya and not an ideal scenario, a calibration phase based on empirical observations was implemented. This adjustment is essential in situations where actual operations differ significantly from theoretical plans due to traffic and typical city conditions. The biggest demands were the focal point of the exhibition design. A total of n = 45 complete trips covering 20 of the active urban routes were monitored. Data collection was done over 15 typical days, Monday through Wednesday. To capture the variability of the network, the observations were divided into three time windows: Morning Peak (07:00–09:00), Valley (12:00–14:00), and Afternoon Peak (18:00–20:00). The calibration focused on adjusting travel times (stop_times.txt). A travel time adjustment factor (β) was calculated for each segment i of the route, based on the relationship between the observed time (T_obs) and the initial theoretical time (T_teo); the values are shown in Table 3. This factor allowed us to quantitatively adjust the average speeds in the model, reflecting the impact of local congestion and delay times in high-density stops. To measure the overall fit of the model, two robust statistical metrics were used: the Mean Absolute Percentage Error (MAPE) β (Eq. (14, 15)) for travel times, and the Root Mean Square Error (RMSE) for frequencies.

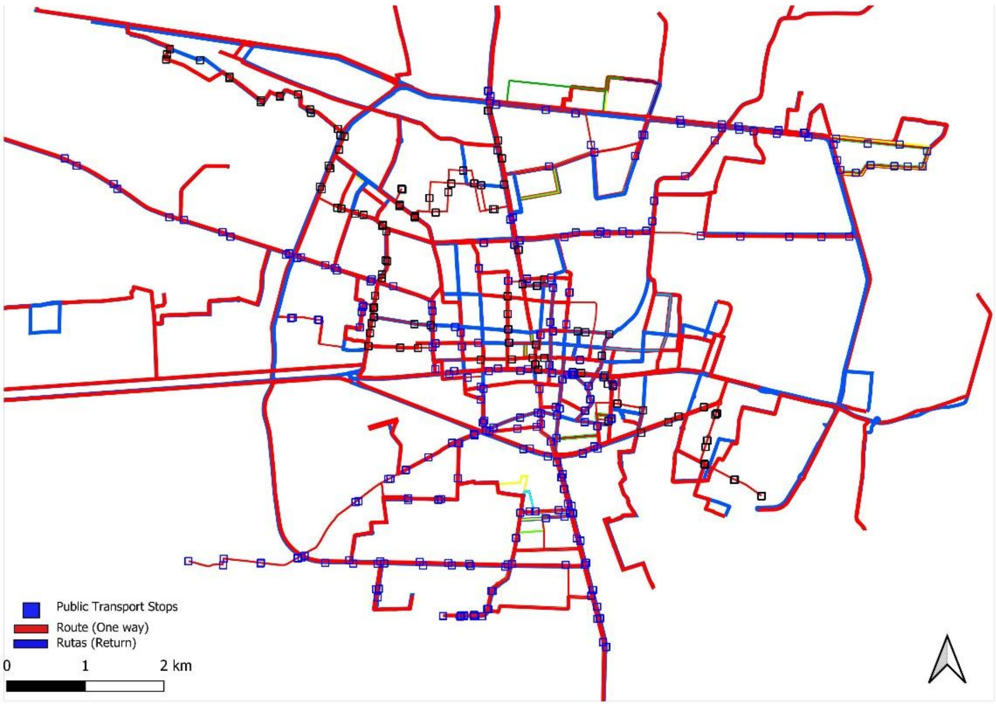

Figure 2. Location of routes and public transportation stops
Note: Location of urban and suburban routes

Table 3. Travel times factors

Segment / Section	Geographic description (Celaya, Gto.)	βiMorning Peak (07-09h)	βiOff-peak (12-14h)	βiAfternoon peak (18-20h)	Typical Error (σ)
Central Trunk Line	Bulevar Adolfo López Mateos (Central section)	1.38	1.15	1.42	± 0.08
Collector Ring	Av. 2 de Abril / Constituyentes	1.22	1.08	1.25	± 0.05
Peripherical Radials	Salvatierra Exit / Av. Tecnológico	1.12	1.02	1.15	± 0.04
Low-Density Areas	Access to communities (ej. Tamayo / San Miguel Octopan)	1.05	1.00	1.07	± 0.02
Transfer nodes	Immediacies wholesale market / Central	1.45	1.20	1.50	± 0.12

Table 4. Validation statistics results

Operating Parameter	Average Observed Value (μobs)	Modeled Mean Value (μmod)	Error Metric (MAPE/RMSE)	Validation Approval Value	Confidence Level Z 1-α /2
Travel Time (Route)	52.40 min	53.80 min	**2.67 % (MAPE)**	< 10.0%	95%
Frequency	12.50 min	12.10 min	**0.58 min (RMSE)**	< 1.5 min	95%
Trading Speed	16.20 km/hr	15.80 km/hr	**0.40 km/hr (RMSE)**	± 2.0 km/hr	90%
Delay Time (Stop)	22.00 sec	24.50 sec	**11.3 % (MAPE)**	< 15.0 %	95%

The equations applied are:

$$MAPE = \frac{100\ \%}{n} \sum_{t=1}^{n} \left| \frac{T_{obs} - T_{mod}}{T_{obs}} \right| \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (T_{obs} - T_{mod})^2} \tag{15}$$

Where T_{obs} and T_{mod} are the values modeled in the final GTFS. The results of the calibration are presented in Table 4, which shows margins of error that comply with accepted standards for urban public transport models. The graphical results are shown in Figure 3.

3.2 Stop density calculation

The density of stops per unit space is defined as (see Eq. (16):

$$D_i = \frac{N_i^{Stops}}{Area_i} \tag{16}$$

Where:

D_i= density of stops (D_i= μ, stops/km^2).

N_i^{Stops} = are the counted number of stops within the study area

This formula constitutes a standard measure of spatial density, comparable to other urban transportation studies in which infrastructure supply is related to land coverage. Based on the total distribution of 1,443 stops over a total area of 274.60 km^2, an overall average density is obtained (see Eq. (17)):

$$D_i = \frac{1443\ Stops}{274.60\ km^2} = 5.25\ {}^{stops}/_{km^2} \tag{17}$$

To evaluate the variability of the stop density, robust statistical measures were used. The standard deviation (sigma) of the density describes the dispersion around the mean, and the coefficient of variation (CV) (See Eq.(18)) is calculated as:

$$CV = \frac{\sigma}{\mu} \tag{18}$$

According to Taylor [48], a coefficient of variation greater than 1 is interpreted as high heterogeneity in urban and transportation analysis literature, indicating that relative variability exceeds the mean (in accessibility and urban density studies, this is a common criterion for characterizing spatial inequality) [49]. From field data collection and geospatial analysis of the network, an observed standard deviation of 6.4 stops/km^2 was obtained. This value reflects the public transport stops per square kilometres in the study area (see Eq. (19)). The resulting coefficient of variation is shown in the following equation:

$$CV = \frac{6.4\ {}^{Stops}/_{km^2}}{5.25\ {}^{Stops}/_{km^2}} = 1.22\ {}^{Stops}/_{km^2} \tag{19}$$

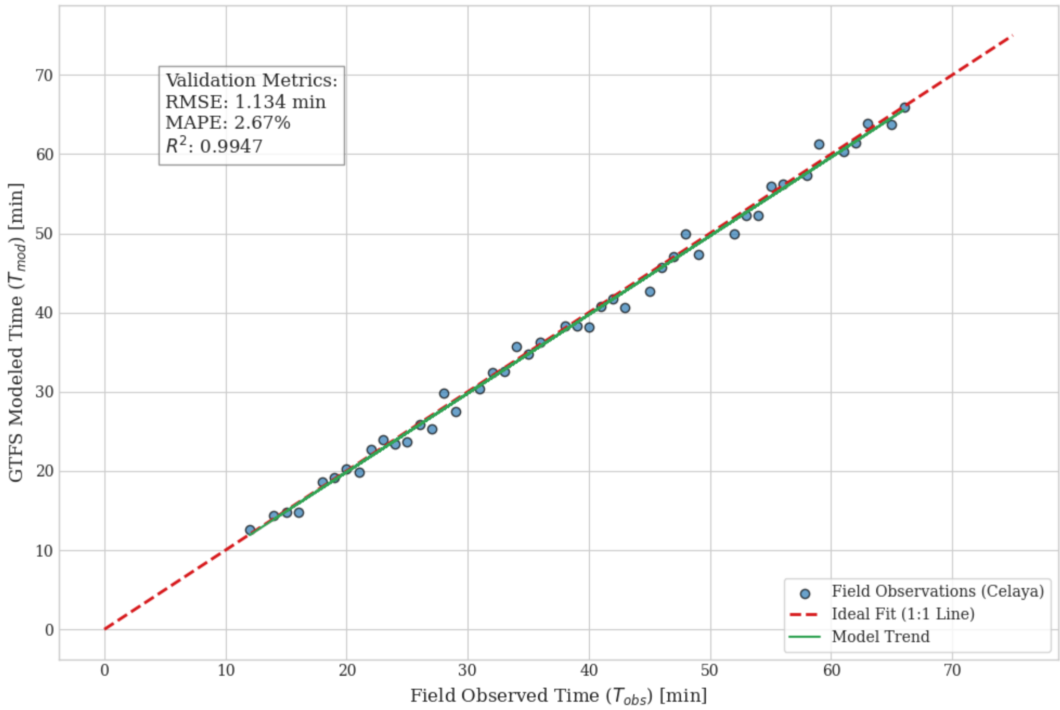

Figure 3. Validation of the GTFS transit model for public transport

This value confirms a highly heterogeneous distribution of stops across the territory, with a significant difference between densely served areas and those with limited coverage.

3.3 Percentiles and spatial contrast

To characterize inequality at the extremes of spatial distribution, representative percentiles were estimated:
P10 ≈ 1.1 stops/km²
P50 (median) ≈ 4.3 stops/km²
P90 ≈ 14.8 stops/km²
The comparison between the extremes is expressed as a ratio (see Eq. (20)):

$$R = \frac{P_{90}}{P_{10}} = \frac{14.8}{1.1} \approx 13.45 \text{ stops/km}^2 \tag{20}$$

This indicates that areas with high stop availability have stop densities more than 13 times higher than those in areas with lower coverage. The differences between quantiles reflect the presence of urban service clusters and gaps (Figure 4).
The results from the Lorenz curve and the Gini Coefficient show that accessibility in Celaya is not only reflected at the extremes but also reveals a structural imbalance across the entire public transport network. The values obtained P90/P10 (see Eq. (20)) suggest a wide gap, so the calculated Gini coefficient is 0.532, as shown in the figure, which reveals a proportion of the trips that are centered in the central core and at the ends with the main corridors. This causes isolation in the system's functionality. On the other hand, the Theil index (0.545) confirms that the current route design favors areas with a high density of stops, in contrast to coverage areas, where it can be assumed that the population's income is medium or low (Figure 5). Therefore, the approach in Celaya of adding more public transport routes will not be enough to mitigate the effects; it is important for decision-makers to consider redistributing network density and optimizing frequencies in areas with less access to transport.

3.4 Spatial autocorrelation of stop density

Beyond global metrics, to determine whether densities not only differ but also exhibit an organized spatial pattern (clustering), the global spatial autocorrelation index, Moran's [50,51], is estimated. This statistic has been widely used in mobility studies to identify spatial dependence and clustering in variables such as transport density, travel, or urban infrastructure [52]. The general form of Moran's l [44] is Eq. (21):

$$I = \frac{n}{W} \cdot \frac{\sum i \sum j w_{ij}(x_i - \bar{x})(x_j - x)}{\sum i (x_i - \bar{x})^2} \tag{21}$$

where:
n it is the total number of spatial units (cells)
w_{ij} It is a spatial weight between the cells i and j.
x_i, x_j they are the values of stop density.
$\bar{x}$ it is the average of the variable,
W it is the sum of all the spatial weights.
This statistic assesses whether similar values are spatially clustered (Moran's I > 0) or dispersed (Moran's I < 0) with statistical significance. In this case, the total value of Moran's I, assuming a Zone radius of 300 meters. According to Ortuzar [53] it justifies the use of fixed radii, which is why the radius of 300 meters is considered based on the distance that a pedestrian is willing to walk based on the comments of pedestrians. The estimated value is due to the high heterogeneity of the data (CV > 1). Therefore, the assumption of statistical normality was discarded, generating a robust approach of 999 random permutations. This procedure allowed the generation of an empirical reference distribution, guaranteeing that the probability that the observed patterns are the product of chance is less than 1 in 1000 (p < 0.001).

$I \approx 0.41, p < 0.001$

This finding indicates a significant spatial clustering of stop densities, in which high-density areas tend to be close to each other and, similarly, low-density areas. It can therefore be concluded that the statistical significance where $p < 0.001$ rules out the observed pattern being a result of spatial randomness, which is strong evidence of structured heterogeneity [46]. Recent studies show that this type of spatial dependence is common in values related to urban transportation and accessibility variables, which validates the use of Moran's *l* [54]. Figure 6 combines a density surface with individual points to highlight patterns of spatial autocorrelation.

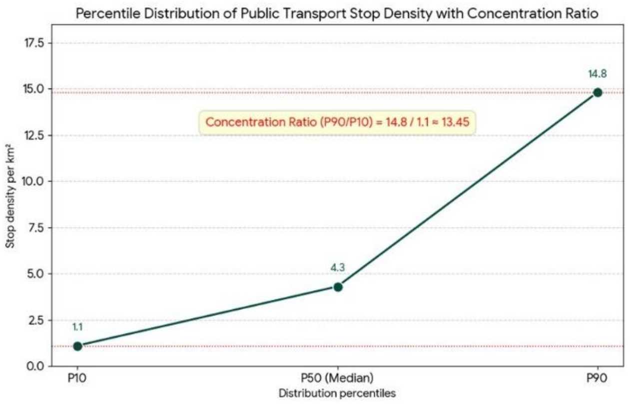

Figure 4. Percentile distribution of stop density with concentration ratio

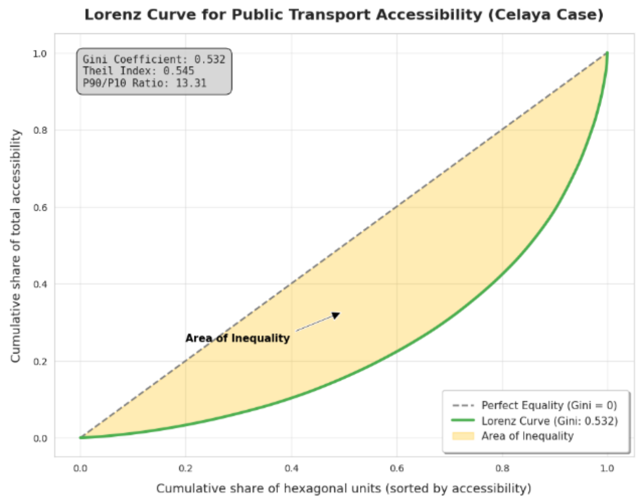

Figure 5. Lorenz curve for public transport accessibility

The generalized travel cost is a synthetic measure that combines several dimensions of travel, enabling a more accurate representation of the spatial friction that influences interactions between urban areas. Following recent literature in transportation geography, this cost is not limited to physical distance but acts as a proxy for the total effort required to make a trip, including temporal, operational, and spatial components (according to equation 1). In this study, the generalized cost (Cij) was calculated from the origin-destination matrix using the geographic centroids of the analysed zip codes. Since the main objective is to evaluate spatial patterns of accessibility and interaction, the distance between zones was used as an initial approximation of cost, if greater spatial separations generate non-linear increases in travel time, resource consumption, and users' perception of effort. Table 5 summarizes the variables used to construct the generalized cost and their roles in the model.

Table 5. Variables used in estimating the generalized travel cost

Variable	Description	Unity	Source
Origin (i) Destination (j)	Origin and destination area (postal codes)	—	INEGI
Latitude (i) Length (j)	Centroid coordinates of the area (i)	Decimal degrees	INEGI
Distance (ij)	Geodesic distance between centroids	Kilometers	Self-calculation
Cost (ij)	Overall cost of travel	Dimensionless unit	Derived
(β)	Cist sensitivity parameter	—	Calibration

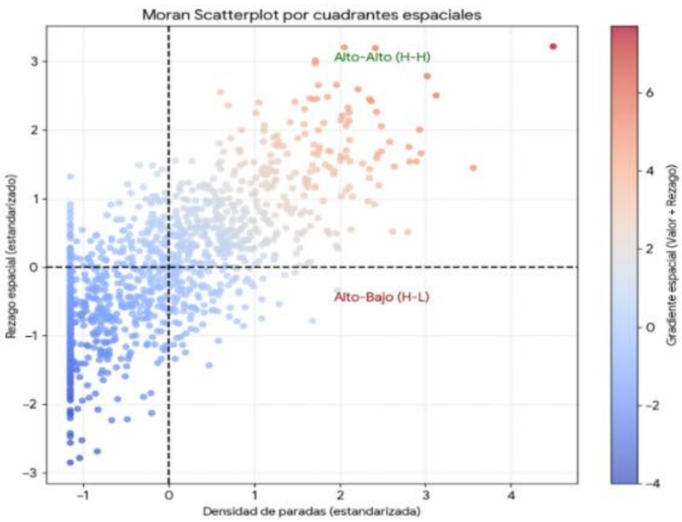

Figure 6. Moran's I spatial distribution of the stop density diagram

Figure 7 summarizes the spatial structure of the generalized travel cost and its relationship to the intensity of the modelled flows, thereby allowing us to identify patterns of territorial heterogeneity and nonlinear behavior in urban mobility. The results of the clustering analysis (k-means) were applied to the average generalized cost per zone. This procedure enabled urban zones to be classified into three clearly differentiated groups based on their relative levels of spatial friction. The groups were determined using the elbow method and the silhouette score, with the results presented in Table 6. The results from applying the elbow method indicate that the ideal inflection point is k=3, while the silhouette score reaches a maximum of 0.58. This means that there is internal cohesion as well as an effective separation between categories. This structure allows the classification of zones according to spatial friction, suggesting a pattern within the transport system for the municipality of Celaya and determining the effort in daily mobility.

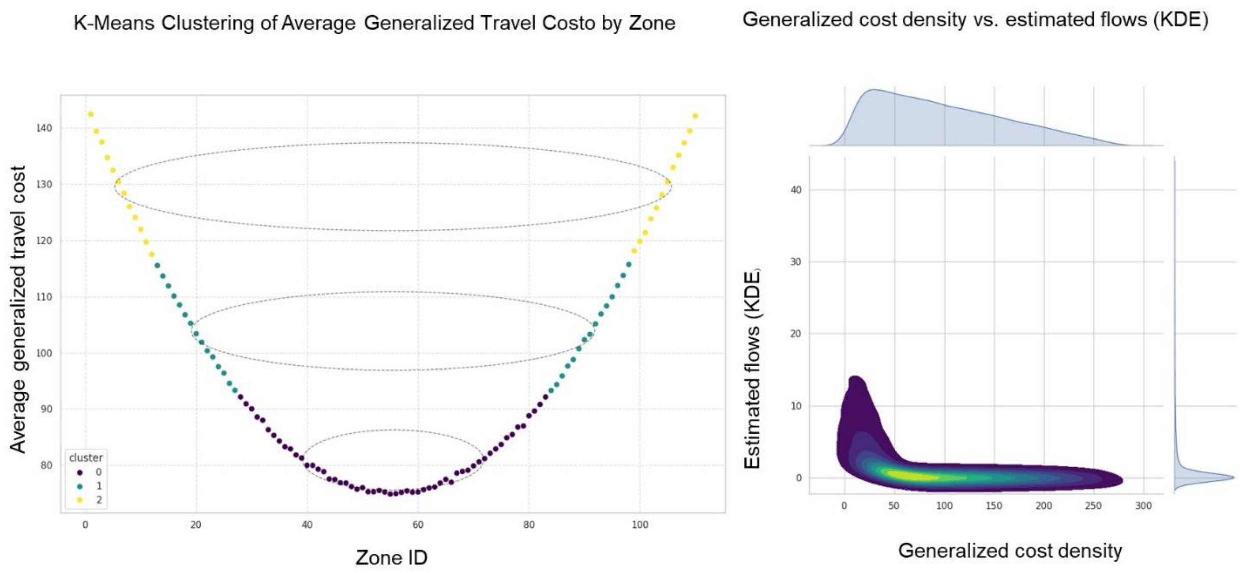

Figure 7. Generalized cost of trips by zones

Table 6. Validation metrics for the selection of the number of clusters (k)

Number of Clusters (k)	Intra-cluster Sum of Squares (WSS)	Silhouette Score (Average)	Stability Assessment
2	145.28	0.42	Underrated structure
3	88.45	0.58	Optimal Inflection Point
4	76.12	0.49	Marginal overadjustment
5	68.34	0.41	High fragmentation

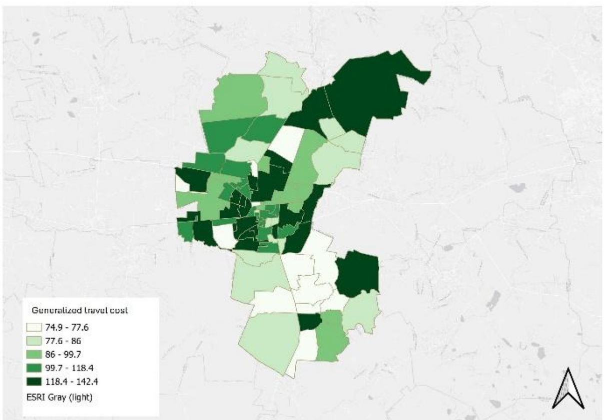

Figure 8. Generalized travel cost

Intermediate and high costs are gradually distributed toward the extremes, but the results are clustered in the center of the spectrum. This configuration suggests a coherent spatial pattern in which relative location within the urban system plays a crucial role in the effort required for daily mobility. Areas with lower costs are those closer to the public transport system than others, which means cumulative distances are shorter and, therefore, there is greater potential for access, as shown in Figure 8. On the other hand, groups with high costs tend to be in areas with greater geographical obstacles to interaction, which is commonly associated with greater territorial dispersion or a peripheral location. From a transport geography perspective, this finding supports the assumption that generalized costs are not distributed randomly but rather reflect spatial disparities and the underlying structure of the urban system. The two-dimensional study compares network capacity with service impartiality by combining per capita accessibility (PCA) and gross zonal accessibility (GZA).

The PCA measures the average accessibility available to each person, manifesting the conditions of equity in the distribution of the public transport service, while the GZA represents the total volume of accessible opportunities in an area or zone, highlighting the overall capacity of the system and the spatial concentration of opportunities (work, school, among others). The GZA, which represents the total supply of opportunities, has an average value of 227.08 units, this represents the cumulative sum of opportunities that are accessible to the user (jobs, services, schools, among others); in contrast, Accessibility per Capita (APC), which is the true barometer of individual experience, has a median of only 14.86 units. This demonstrates the asymmetry inherent in the system. This demonstrates the asymmetry in the network, revealing that the real benefit to the user is very limited by the increase in travel time within the public transport system. The APC has a pronounced positive asymmetry, indicating that individual opportunity is a scarce, concentrated commodity, as seen in the histograms, where the mode is at low values. Five percent of areas have access that is nearly 3.01 times the distribution average (the median APC is 14.86 units), as indicated by the 95th-percentile APC of 44.80 units (Figures 9 and 10). This extreme degree of inequality highlights the system's inability to equalize quality of life, a finding consistent with research linking territorial socioeconomic polarization to unequal accessibility. Most areas operate in a system of relative scarcity, which increases competition for resources and opportunities. The research focuses on Critical Vulnerability Zones (CVZs), which are areas with low Accessibility by zone (ABZ) and low APC, constituting 20% of the total area. These CVZs, located in the lower left quadrant of the scatter plot, are doubly penalized: their network potential is very low (less than 172.96 ABZ units), and the APC is extremely restricted. It is crucial that investment policy focus specifically on these CVZs, prioritizing not only improving the ABZ (aiming to exceed at least the median of 208.56 units) but also increasing the APC. Intervention in these areas of dual deficit is the most essential action for reducing socio-spatial exclusion, which is the main purpose of equity-focused transportation planning.

The starting point for our accessibility analysis was the validation of the gravity model, in which the Kernel Density Estimation (KDE) diagram confirmed the existence of strong exponential friction that discourages generalized high-cost travel (CGV). However, the limitation of gravity models lies in their discrete nature, which evaluates the cost between aggregated zonal centroids. The introduction of the concept of isochrones is a necessary methodological evolution, as it converts discrete cost into a continuous spatial footprint, defined as the line connecting all points accessible from a given origin within a maximum time threshold or CGV. The shape and extent of isochronous polygons constitute a direct geometric representation of network impedance and territorial barriers, overcoming zonal simplification. By generating isochrones, the real impact of the friction detected by the KDE analysis can be visualized; that is, where and why the flow stops.

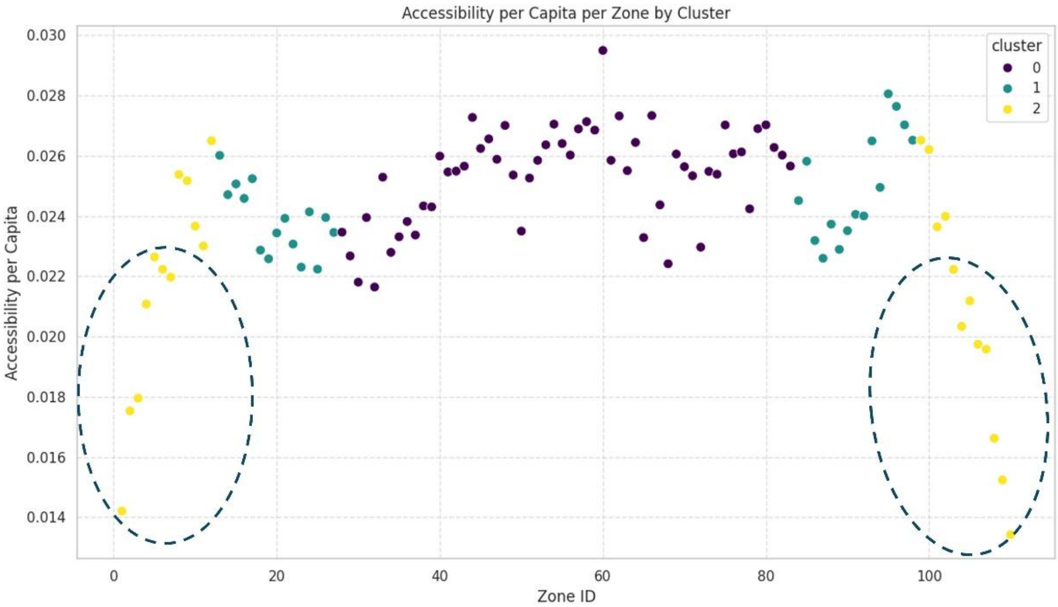

Figure 9. Per capita geographic accessibility

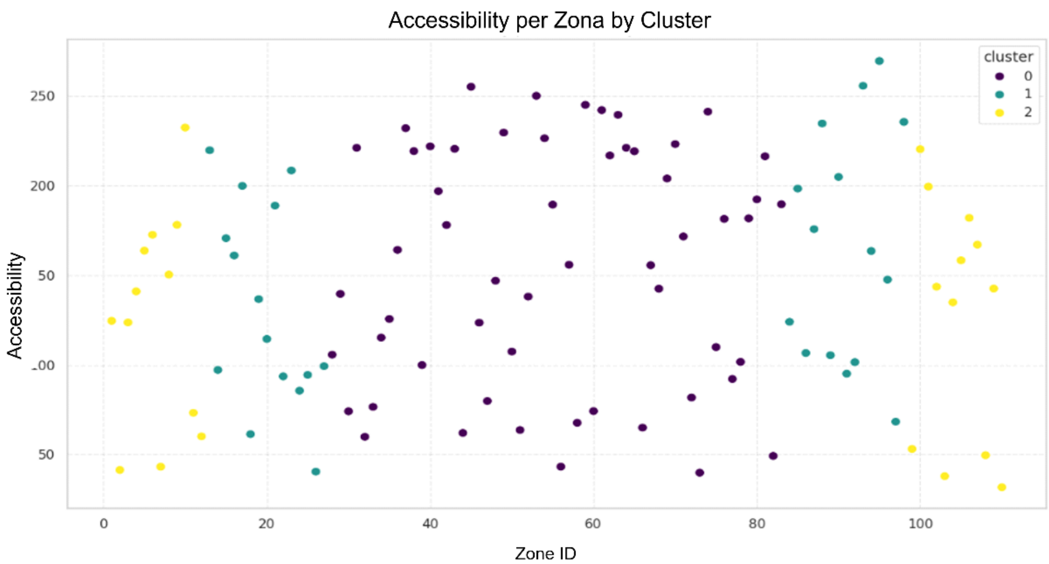

Figure 10. Accessibility by zone

The zonal matrix model is unable to capture discontinuities or barrier effects, which are evident in the irregular shape of the polygon. The use of isochrones to diagnose the disparity detected through clustering analysis between Cluster 0 (Core) and Cluster 2 (Periphery) brings the analytical sequence to an end. Inequality in the opportunity surface can be quantified both visually and spatially, thanks to the isochrone map: for a given time, a suburban route was selected along which the user would travel on foot for 3, 5, 10, and 15 minutes (Figure 11).

To achieve an equitable approach, it is essential to use isochrones when planning transportation, as they enable the objective identification of areas with low accessibility and the calculation of opportunity deprivation. For transportation planners, this allows for the establishment of territorial equity objectives, such as ensuring that the shape of Cluster 2's isochrones approaches a specific area rather than simply reducing the total cost. This visual tool serves to communicate disparity to policymakers, showing the opportunity cost faced by peripheral communities and guiding investment toward areas where expanding the isochrone is most urgently needed (Figure 12).

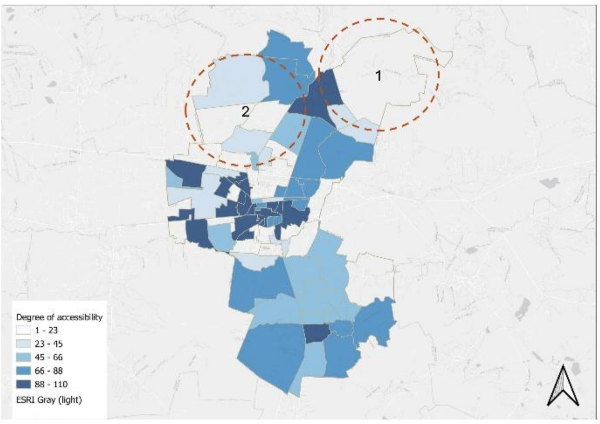

Figure 11. Per capita accessibility

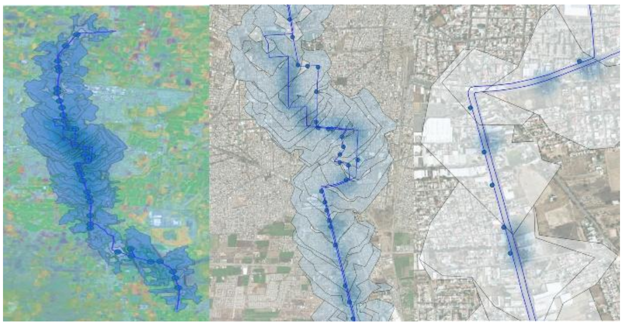

Figure 12. Isochronous analysis of the Octocpan route accessibility

3.5 Implications for smart mobility in middle-income cities

The methodology presented in this manuscript is structured around open data from public government platforms (GTFS). This offers a major applicability advantage for smart mobility in medium-sized cities or growing industrial areas. Beyond the descriptive findings shown in this research, recent literature shows that open data-based approaches have established themselves as an emerging standard for accessibility analysis and transport system planning in complex urban contexts. Several studies have shown that the use of GTFS in GIS environments allows for an accurate assessment of accessibility, identification of territorial gaps, and improvement of the operational efficiency of public transport. As demonstrated by Javanmard et al. (2025) [54] the use of GTFS can overestimate accessibility by up to 10.97%, which is why it is important to integrate real-time data to improve analytical accuracy. On the other hand, Haamer et al. [55] emphasize the incorporation of GPS data for accessibility modeling, which is based on real travel patterns, which brings a reduction in the gap between accessibility. In the context of middle-income cities in Latin America, they share very similar characteristics, such as 1. high dependence on public transport, 2. operational informality, 3. Limitations on data availability.

Table 7. Literary contribution in Latin American countries

City/Country	Open Data (GTFS/OGD)	Integration with open platforms (OSM / APIs)	Real-time data usage (AVL/GPS)	Application in accessibility policies	Source(s)
Mexico City (Mexico)	Emerging; partial development of GTFS and open data in transport	High integration in academic and collaborative projects	Limited; low adoption of GTFS-RT and AVL in analytics	Incipient; Limited use in structural planning	Barbero & Uechi (2012) [57]
Bogotá (Colombia)	Medium-high; availability of OD surveys and transport data	Integration with GIS and analytics platforms	Limited–medium; Use of data observed in studies	High orientation to equity and accessibility	Vecchio (2020) [58]; estudio de accesibilidad Bogotá
Buenos Aires (Argentina)	High; Use of open data and replicable code	High interoperability with open platforms	Medium; Progressive integration of dynamic data	High; Use in Urban Services Evaluation	Martinazzo et al. (2023) [59]
Rio de Janeiro (Brazil)	Media; Availability of urban transport data	Integration with accessibility and GIS models	Medium-high; Use of quantitative accessibility data	Medium-high; Focus on territorial inequality	Boisjoly et al. (2019) [60]
Santiago (Chile)	High; More consolidated digital ecosystem	High multimodal integration and digital platforms	High; use of GPS and real-time mobility data	High; Policies aimed at efficiency and sustainability	Opitz et al. (2024) [61]
Curitiba / Medellín (Brazil / Colombia)	Medium-high; Structured transport systems	Integration with urban planning	Medium; Less evidence of open real-time data	High; Emblematic cases of mobility policies	Vecchio (2020) [59]
Latin America (regional vision)	Nascent development of open data infrastructures	Unequal integration; Persistent digital divides	Limited in many intermediate cities	Growing; Greater emphasis on equity	Ballari et al. (2025) [62] ; UITP (2025) [63]

On the other hand, there are important differences in how government agencies generate data to regulate these systems and to adopt smart mobility technologies. For example, according to Stefanidis et al. [56], the study compares Mexico City, Lima, and Buenos Aires, finding that up to 10% of accessibility inequality is attributed to microspatial conditions. Based on the contributions of this study and comparing with the findings of other authors, the regional contributions made in other Latin American countries were analyzed. The summary is shown in Table 7, synthesizing information from empirical evidence and specialized literature, and situating the case study (in Mexico) in relation to regional trends in the development of smart mobility ecosystems. The comparison shows the degree of technological maturity, the availability of data, and the level of institutionalization of smart mobility tools. Similarly, key metrics are analyzed, such as 1. Open Data, 2. Integration with open access platforms, 3. Use of real-time data, 4. Application of public policies aimed at accessibility.

4. Discussion

Celaya exhibits a significantly more critical fragmentation of accessibility than other industrial hubs in the Bajio region of Mexico, such as Leon, Queretaro, and Guadalajara. This reflects that compact cities, or those with transit–oriented development (TOD) policies, manage to mitigate spatial friction and extensive growth with tangible benefits, as expressed by Salim [64]: low energy consumption, short travel times, and minimized resource consumption, to name a few. For this reason, the fragmentation of the city of Celaya has created a profound gap between the network's installed capacity and the actual user experience. This phenomenon also coincides with other cases of intermediate cities in Latin America. As Guzmán [65] notes, a transportation network, rather than peripheral expansion, generates social exclusion. On the other hand, in Celaya, something similar to what Lucas [66] describes occurs amid accelerated urbanization; relative location is no longer a geographical variable but has become the main predictor of inequality in daily mobility efforts. On the other hand, it is recognized that applying a gravitational model implies accepting certain assumptions that simplify human mobility. In this study, we assume that cost is the only driver of decision, omitting the diversity of individual situations that define urban transport such as income, access to a car, gender or age completely modify the travel experience, values that have been highlighted by authors such as Lucas et al. [66], Stefanidis [56] Sales et al (2019) [1]. In this paper, although spatial behaviors were identified, there are areas of opportunity for future research to detect barriers that are currently undetectable for the most vulnerable sectors of the city. This is because real accessibility is contingent on the system's operational capacity to reduce economic and time barriers. An essential contribution of the study is the distinction between absolute and per capita accessibility, which shows that high population density can diminish the apparent advantages of connectivity. The technical information obtained highlights that the success of urban planning should be evaluated not only on physical structures but also on the equity of opportunity availability for citizens. Therefore, a paradigm shift in public policymaking is suggested, aiming to reduce penalties for transfers and increase their frequency in areas with high marginal benefits. Finally, to shift municipal management towards a more transparent and effective model that responds to the population's mobility needs, it is essential to implement methodologies that leverage open data generated by public service providers for the benefit of citizens.

5. Conclusion

In this research, an exhaustive analysis of the current configuration of urban mobility in Celaya was carried out, based on the synergy between Geographic Information Systems (GIS) and gravitational modeling of total travel costs. The results show that, although the coverage of the public transport network is extensive, with a density of 5.25 stops/km2, spatial inequality reflects high heterogeneity in public transport stops (CV=1.22 Stops/km^2). On the other hand, they state that the generalized costs of trips and network configuration are closely related to the efficiency of public transport and users' accessibility to the system. This shows a notable difference in the distribution of travel costs, proven by Moran's I values ≈ 0.41, $p < 0.001$, which do not reflect random results. The findings reflect that increasing the number of routes will not be enough to improve mobility in the city. The comparison of the GZA (227.08) and APC (14.84) values reflects a gap between the availability of the various opportunities in the geographical space and the experience perceived by users with longer travel times, transfers, and high costs in areas with less connectivity, so it is necessary to generate a plan based on coverage. Finally, based on the findings found, the following recommendations are suggested:

- Generate a redistribution of public transport stops, in which areas with low accessibility are prioritized (Zone 1 and 2).
- Optimize strategic corridors of the public transport network to minimize widespread costs and waiting times.

In order to improve operational efficiency and mobility in intermediary cities, it does not depend on network expansion as mentioned above, but rather on a perspective of managing the coverage and efficiency of the infrastructure through a robust and comprehensive methodology of GIS, GTFS, and a calibrated gravitational model that contributes to public policies aimed at much more sustainable and inclusive mobility.

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Ethical issue
The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement
The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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