



Examining the relationship between socioeconomic structure and urban transport network efficiency: a circuitry and spatial statistics based approach

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Received: 8 October 2022 / Revised: 26 February 2023 / Accepted: 27 February 2023 / Published online: 17 March 2023
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Abstract

Access to urban public transportation services is crucial for all city residents. Undoubtedly, more efficient public transportation services should be provided for the needy ones. The study aims to develop a simple yet efficient analytical approach to spatially determine the urban areas that receive inefficient public transportation services. In this study, the spatial distribution of the efficiency of public transportation and its relation to socioeconomic variables (per capita income level and population density) are examined at the neighborhood in Izmir, Turkey, level using circuitry. The results from univariate and bivariate Global and Local Moran's I analyses reveal that the high-efficiency levels are spatially clustered, Higher-income neighborhoods have better public transportation systems compared to lower-income ones. According to Bivariate Local Moran's I analyses, among the 348 neighborhoods at least 31 and at most 81 neighborhoods are either in a High-High or Low-Low cluster for the four time periods considered. As for the relationship between circuitry and density, at least 21 and at most 75 neighborhoods are a part of a cluster. The fact that there is a significant relationship between the efficiency of public transportation and socioeconomic variables calls for alteration in the planning policies regarding urban public transportation supply. Although the variation in public transport efficiency levels across the neighborhoods can partly be attributed to physical conditions, the city should provide equal accessibility and efficiency regardless of the socio-economic status of the neighborhoods. The findings can well be generalized for cities of similar sizes in developing countries.

Keywords Circuitry · Network efficiency · Public transportation · Socioeconomic structure · Spatial distribution · Spatial autocorrelation

1 Introduction

A city is a large-sized, dense, and heterogenous social entity. Network structures shape cities, orientate the development processes, and provide mobility which shapes the lives of inhabitants. Thus, accessing adequate public transportation, which is one of the basic and most crucial public services,

is crucial for all city residents to meet their daily mobility needs.

Urban public transportation networks have been long considered in the literature with various approaches in terms of efficiency. The internal network structure of a city is characterized by its topography, design standards, and population density [1]. Since the roads are the main elements of the transportation network, urban public transportation systems are dependent on the network design. Euclidean distance and network distance were widely investigated as distance measures for efficiency and accessibility purposes starting with the earliest studies of Haggett and Chorley [2], and Barbour [3]. The search for efficiency has been an initiator in the development of the degree of circuitry. Circuitry is calculated by dividing the shortest path distance between two points by the Euclidean distance.

As a measure of network efficiency [4], circuitry is used for explaining pedestrian behavior [5, 6], assessing and

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public transportation network performance [7, 8]. Barthélemy [9] states that the characteristics of neighborhoods such as population, density, and street network structure affect accessibility and the average travel time, and thus network efficiency. To measure the public transport efficiency of a neighborhood, circuitry can be defined as the ratio of the minimum travel time by public transportation to the minimum travel time by private car for any given pair of origin and destination.

Many studies have investigated the relationship between the socioeconomic structure and public transportation in cities [10, 11]. Socio-economic characteristics are important variables in urban planning and must be well analyzed in the planning processes of public transportation systems. Stead [12] claims that the travel behavior of households is often influenced by socioeconomic characteristics. Krizek [10] shows that socio-demographic conditions affect travel behavior significantly. Furthermore, Renne and Bennet [11] state that daily mode choice decisions are related to household economics, demographic characteristics, and the overall system design. Rosenblatt and DeLuca [13] report that public transportation existence is a significant factor for households, especially those living in low-income urban neighborhoods [14, 15]. Dong [16] states that lower-income areas with lower car ownership in the city tend to use public transportation services more intensively. In addition to the per capita income levels, population density is another socioeconomic factor that differentiates spatially among the neighborhoods. Many studies report a positive relationship between public transportation usage and population density [17–20]. Néchet [21] studies the spatial correlation between

urban spatial structure and daily mobility and concludes that the population density and income levels of the inhabitants are highly correlated with daily mobility. In urban metropolitan areas, dense urban residential neighborhoods together with mixed land use have higher levels of public transportation accessibility than other parts of the city [22, 23].

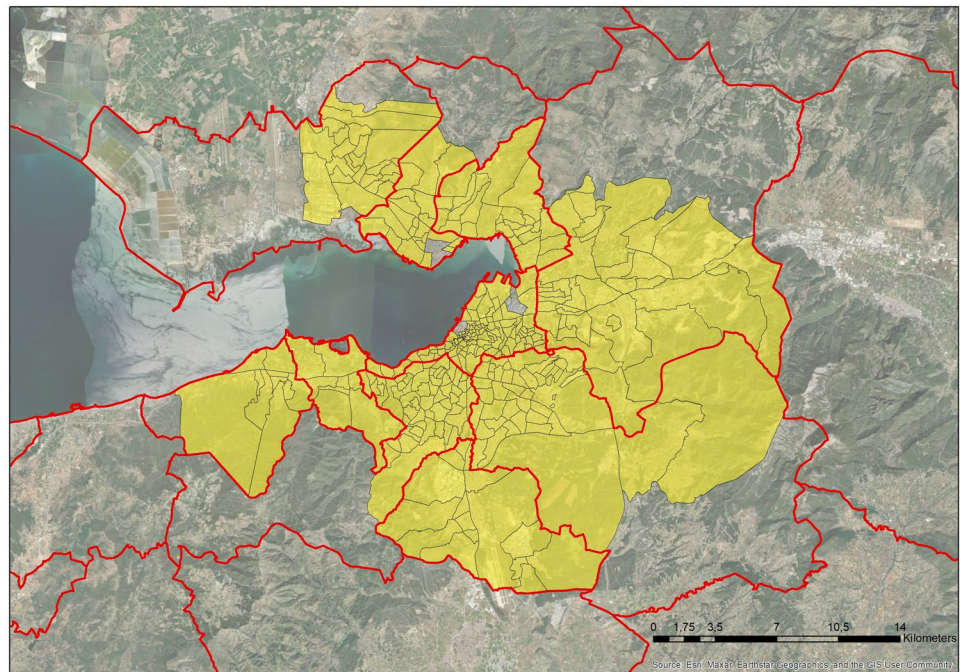
In order to examine the relationship between public transportation efficiency and socio-economic characteristics, techniques developed within the spatial statistics framework can be applied. Spatial statistics contains classical methods, and it is unique in processing multiple data and assessing spatial distribution and autocorrelation [24]. In this study, the spatial distribution and the socio-economic relations of the efficiency in public transportation (circuitry index as the determiner of the efficiency) are considered simultaneously at the neighborhood level. The city of Izmir, Türkiye, is chosen for a case study. Variation in the circuitry levels as the determiner of public transportation efficiency was calculated as the first step. Two variables were used to assess the socioeconomic structure: per capita income level and population density. Spatial autocorrelation techniques such as *univariate and bivariate Global and Local Moran's I* are used to reveal whether there is a relationship between public transportation efficiency and socioeconomic variables.

The results of this study can help the overall improvement of the public transportation systems and it can be beneficial for the decision-makers and practitioners of the city in providing more inclusive decisions and enhancing the public interest. The study aims to develop a simple yet efficient analytical approach to spatially determine the urban areas

Fig. 1 Borders of İzmir city (green), its location in Türkiye (red) and the study area (yellow)



Fig. 2 The study area (yellow) covers 348 neighborhoods (black) in 10 central districts (red)



that receive inefficient public transportation services. The overall paper was organized as follows: the data and methodology examined under Sect. 2 presents, Sect. 3 presents the analysis and results, and Sect. 4 presents the discussion and conclusions of this research.

2 Data

2.1 Study area

The city of Izmir, which is one of the most populated and largest cities in Western Anatolia, is selected as the study area. There are several reasons for doing so. First, the city offers the maximum number of public transportation modes including bus, metro, train, tramway, taxi, dolmus (public shuttle), and ferry. Second, travel time data is available for public and private transportation modes. Third, with over 4 million population, the city of Izmir provides a significant variety of socioeconomic characteristics across its neighborhoods. Forth, the city is highly representative in terms of the growth patterns observed in many of the developing country metropolises. Thus results from this research may be generalized for many cities similar in size (Fig. 1).

As Tekeli [25] states, the rapid industrialization process continued to grow faster in the 50 s and triggered rapid urbanization in the cities of Türkiye, as in other developing countries. Migration to urban areas from the rural villages caused the emergence of squatter settlements, and thus the working class settled in the city centers. Izmir city also has experienced different urbanization processes which led to a mixture of

organic and planned built environments with varying network structures. The city has a highly dynamic center in terms of commerce and tourist activities. On the other hand, mobility diminishes towards the periphery characterized by lower population density. Şenbil, Yetişkul and Gökçe [26] note that the population increase rates in neighborhoods have been different in the metropolitan area of Izmir. Besides these physical and social characteristics, public transportation is not equally available and inclusive, which creates an urge to analyze the efficiency of public transportation systems and see if any relation with social characteristics. The study covers 348 neighborhoods in 10 central districts in the metropolitan area of Izmir city (Fig. 2). The population for the districts included in the study for the year 2022 are shown in Table 1. The spatial data includes travel times for four time-off-day variations, per capita income, and population density at the neighborhood level.

Table 1 Population values of the neighborhoods in the study area (2021). *Source:* Turkish Statistical Institute

District	Population (2021)
Balcova	80,513
Bayrakli	296,839
Bornova	452,867
Buca	517,963
Cigli	209,951
Gaziemir	137,856
Karabaglar	478,788
Karsiyaka	347,023
Konak	336,545
Narlidere	63,438

2.2 Circuity data

Circuity is the ratio of the shortest path distance over the Euclidean distance, and it can be used in investigating the performance and efficiency of public transportation systems [24, 27]. Circuity (C_{ij}) is calculated as:

$$C_{ij} = \frac{D_{ij}^n}{D_{ij}^e} \quad (1)$$

where D_{ij}^n is the network distance; D_{ij}^e the Euclidean distance; i the origin; j the destination [9].

Following Nagne and Gawali [7], and Cubukcu [28], the circuity index is utilized to measure the efficiency of public transportation systems in this study. As Parthasarathi et al. [4] and Huang and Levinson [19] state circuity can also be assessed by using travel time. Huang and Levinson [29] use unweighted travel times as the shortest route in the calculation of the degree of circuity to comprehend the performance of urban public transportation systems. Owen and Levinson [8] calculate circuity by using travel times by transit and auto and compare the accessibility of transit and auto mode shares.

The following formula is used to derive the circuity to measure the efficiency of the public transportation system from points i to point j (C_{ij}^p):

$$C_{ij}^p = \frac{T_{ij}^t}{T_{ij}^a} \quad (2)$$

T_{ij}^t represents the travel time from point i to point j by public transit transportation and T_{ij}^a the travel time by private car. That is to say the lower the circuity value, the more efficient the public transportation system between the points in question.

In this research, the origin locations for the circuity index are obtained as the geographic centers of the built-up areas ($n=348$). A Transverse Mercator ITRF96 projected coordinate system is used with WGS 1984 datum. For the selection procedure of the destination points ($n=348$), the study by Boscoe, Henry and Zdeb [25] is followed. They state that physical structures that cannot be passed over like rivers, mountains, and rural areas can cause errors in the calculation of the circuity. The characteristics of the destinations were selected regarding being a multimodal public transportation hub, having the characteristics of a transfer location, accessible by pedestrians. In this case, since the structure of Izmir Gulf is a massive restriction, four destination locations ($d=4$) are assigned regarding the specific characteristics indicated earlier.

As a result, each neighborhood ($n=348$) is allocated to the closest hub ($d=4$) over the network. Thus, each origin location (n) is connected to a destination point (d). Following Huang and Levinson [29] and Owen and Levinson [8] the

Table 2 Descriptive statistics of the circuity index values by the time of day ($n=348$)

Time of Day	Minimum	Maximum	Mean	Median	Std. Deviation
06:00 AM	1.200	4.330	2.332	2.333	0.587
09:00 AM	1.200	3.930	2.411	2.444	0.576
11:30 AM	1.200	3.780	2.304	2.300	0.552
07:00 PM	1.070	4.500	2.257	2.278	0.589

circuity levels for $n-d$ pair are calculated by using travel times in Eq. (2).

2.2.1 Time-of-day variations

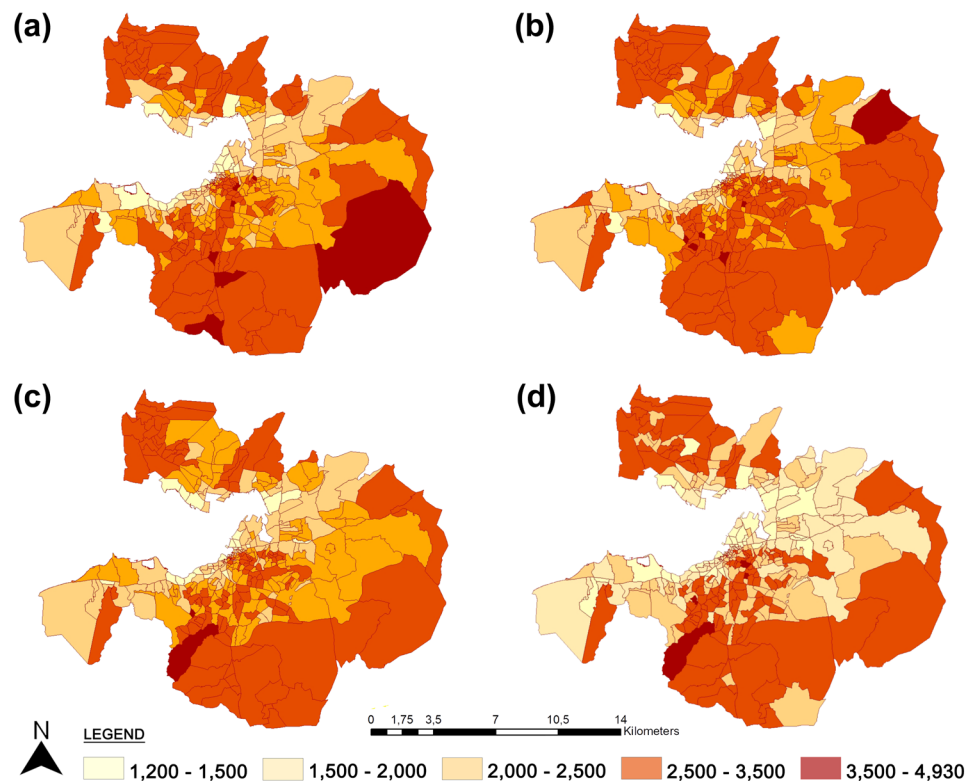
As Polzin et al. [30] point out time-of-day distribution has substantial effects on public transportation services in specifying the travel demand and travel times within a day. Based on this statement, the circuity data between the determined origin–destination ($n-d$) locations were collected at four different time-of-day periods. These time-of-day variations can be differentiated among urban areas regarding their specific internal dynamics.

For this study, Izmir city's traffic conditions are considered along with the related literature. For the city of Izmir, Elbir et al. [31] report that the AM peak is between 08:00 and 09:00 and the PM peak is between 18:00 and 19:00 in winter and summer. Considering the studies of Bowman [32] and Elbir et al. [31] as a basis, the real-time data comparisons were conducted by examining the peak and off-peak hours from IZUM (Izmir Transportation Center), Google Maps, and Yandex Maps.

2.2.2 Travel times

Online mapping technologies have been widely used increasingly in GIS-based analyzes and research. Google Maps services were introduced in 2005 and provide a free-to-use online mapping service [33], and it provides extra services such as route planners for several modes of transportation regarding departure or arrival time options. Hadas [34] used Google Transit data and examined PT networks to provide a method for the analysis of PT. Since Google Transit services are locally differentiated, there is no complete public transportation data for the city of Izmir. In this research, Google Maps services are used in deriving the “shortest travel time by car” by using the “directions” option. The travel times for the public transportation routes are acquired from a different service. “Mobility as a Service (MaaS) is the integration of various forms of transport services into a single mobility service accessible on-demand” [35] and Moovit [36] defines itself as a “Mobility as a Service (MaaS) solutions

Fig. 3 Spatial distribution of the circuitry values (T_{ij}^i/T_{ij}^a) of the neighborhoods. **a** At 06:00 AM, **b** At 09:00 AM, **c** At 11:30 AM, **d** At 07:00 PM



provider and creator of the #1 urban mobility app”. Moovit app was used for acquiring public transportation travel times of the routes from the origins (n) to destinations (d).

The travel time data are obtained in minutes simultaneously from these two online services Google Maps and Moovit and stored in a database for all the selected neighborhoods at 06:00 AM, 09:00 AM, 11.30 AM, and 07:00 PM in January 2021. The circuitry levels for different periods are shown in Fig. 3 and the descriptive statistics are presented in Table 2. Remark that the lowest average circuitry is observed at 07:00 PM accompanied by the highest variation (standard deviation). That is to say the travel times by public transportation and by private car are the closest at this period, but the variation among the neighborhoods is high. The highest average circuitry level is observed at 09:00 AM which is a crucial time for work and education trips. That is to say, public transportation is the least efficient when it is needed the most.

Table 3 Descriptive statistics for socioeconomic variables ($n=348$)

Variable	Minimum	Maximum	Mean	Median	SD
Per capita income (Turkish Liras)	2858	6499	3962.6	3862	703.3
Population density (people/km sq.)	440.6	77,704	21.6	20,765.6	11,583.5

2.3 Socioeconomic data

This research focuses on two socio-economic variables: (1) population density and (2) per capita income. The main concern here is whether there is a spatially statistically significant relationship between public transportation efficiency and the two socio-economic variables. Per capita income data is acquired from Endeksa, which formats and redistributes the data from The Turkish Statistical Institute (TUIK). Following Landcom [37], the population density of the neighborhoods is calculated by GIS software using Formula 3.

$$\text{Population Density} = \frac{\text{Number of Individuals in a Neighborhood}}{\text{Residential Land Area (km}^2\text{)}} \quad (3)$$

The distribution of the population density and per capita income values are shown in Fig. 4. The descriptive statistics for these two socioeconomic variables are shown in Table 3.

3 Methodology

3.1 Univariate global and local spatial autocorrelation analysis

The circuitry values as the efficiency determiner for the public transportation systems are examined twofold: *spatial univariate analysis* and *spatial bivariate analysis*. As for the *spatial*

Fig. 4 Spatial distribution of the socioeconomic values of neighborhoods. **a** Spatial distribution of the per capita income, **b** Spatial distribution of the population density

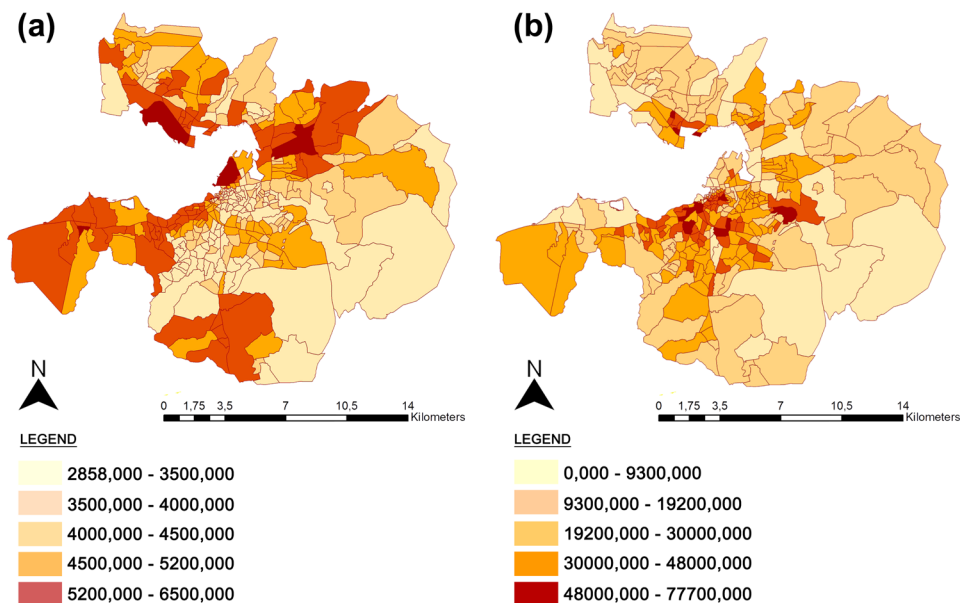


Table 4 Summary table of Univariate Global Moran’s I statistics for circuitry index

Time of day	Moran’s I index	Expected index	z-Score	p-Value	Distribution pattern
06:00 AM	0.303458	-0.002882	20.72966	<0.01	Clustered
09:00 AM	0.294273	-0.002882	20.09861	<0.01	Clustered
11:30 AM	0.308224	-0.002882	21.0398	<0.01	Clustered
07:00 PM	0.281405	-0.002882	19.23927	<0.01	Clustered

Table 5 Summary table of Anselin Local Moran’s I statistics for circuitry index (n = 348)

Time of day	HH cluster	LL cluster	HL outlier	LH outlier	Not Significant (p-Value > 0.05)
06:00 AM	41*	71*	5*	1*	230
09:00 AM	41*	68*	2*	1*	236
11:30 AM	46*	65*	4*	1*	232
07:00 PM	55*	66*	2*	1*	224

*Statistically significant at $\alpha=0.05$ level

univariate analysis Univariate Global Moran’s *I* and Local Moran’s *I* statistics are used to investigate the spatial distribution pattern of circuitry indexes. Moran’s *I* index is introduced by Moran [38, 39] and further developed and clarified by Cliff and Ord in their work in 1973 [40]. The idea behind Global Moran’s *I* is to investigate whether there is a significant pattern for the attributes in a spatial context. *Anselin Local Spatial Autocorrelation* technique was developed by Luc Anselin in 1995 based on the previous studies of Patrick A. P. Moran [38, 39] where the purpose is to describe the “clusters” and the “outliers” and assess the effects of specific spatial attributes

on global statistics [41]. All of the univariate spatial analyzes are performed on the ArcMap 10.5 software.

The idea behind *Global Moran’s I* is to investigate whether there is a significant pattern for the attributes in a spatial context. The local spatial autocorrelation techniques are differentiated from the global spatial autocorrelation techniques. *Anselin Local Spatial Autocorrelation* technique was developed by Luc Anselin in 1995 based on the previous studies of Moran [37, 38]. For all the observations that are being analyzed, a separate Anselin Moran’s *I* statistic is calculated. As an output, the Moran scatter plot has quadrants and the interpretation of the local Moran’s *I*

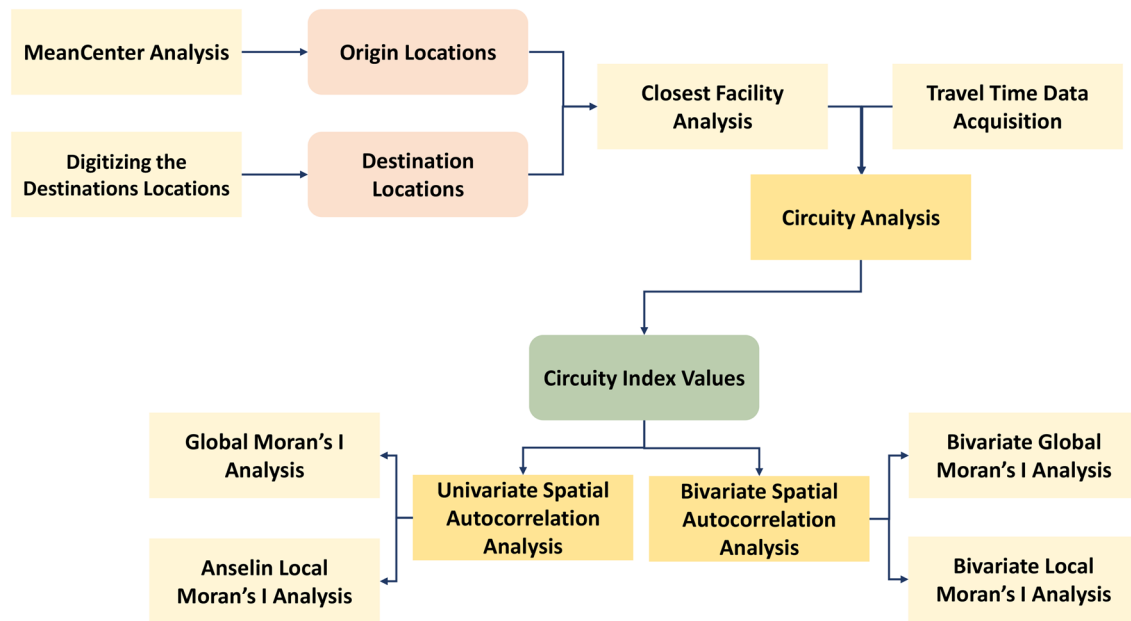


Fig. 5 Summative flow chart of the processes held

offer the spatial clusters (high-high or low-low) or the spatial outliers (high-low or low-high) where the effects of specific spatial attributes on global statistics are assessed [40, 42]. All the univariate spatial autocorrelation analysis are performed on the ArcMap 10.5 software.

3.2 Bivariate global and local spatial autocorrelation analysis

For a better understanding of the spatial relation between public efficiency and socio-economic variables in question, namely population density and income, *Bivariate Global Moran's I* and *Bivariate Local Moran's I* statistics are applied. *Bivariate Global Moran's I* is introduced by Luc Anselin, Ibnu Syabri, and Oleg Smirnov in their study in 2002 further extending the previous study of the Moran

scatter plot. Bivariate global spatial autocorrelation identifies whether there is a relation between the investigated variable and a different variable for the geographic units regarding the values for these variables [43]. The value of *I* ranges from -1 to $+1$. $I > 0$ addresses a positive spatial autocorrelation, and $I < 0$ a negative spatial autocorrelation between the variables in question.

The concept of Bivariate Local Moran's I is introduced and developed by Luc Anselin, Ibnu Syabri, and Oleg Smirnov in their above-mentioned study in 2002. They extend the earlier study of Anselin (1995), Local Indicator of Spatial Association (LISA). Bivariate Local Moran's I statistic measures the linear association, and it may be positive or negative, where high similarity and high dissimilarity values indicate a strong relationship. As in the Moran Scatter Plot, it presents quadrants and the interpretation of

Table 6 Bivariate global Moran's *I* statistics between circuitry index and socioeconomic variables in Izmir

Variable	Time of the day	Moran's I index	Expected index	z-Score	p-Value
<i>Per capita income</i>					
	06:00 AM	-0.079	-0.0029	-8.6012	≤ 0.05
	09:00 AM	-0.088	-0.0029	-9.2149	≤ 0.05
	11:30 AM	-0.075	-0.0029	-7.2068	≤ 0.05
	07:00 PM	-0.100	-0.0029	-10.5704	≤ 0.05
<i>Population density</i>					
	06:00 AM	-0.073	-0.0029	-8.7275	≤ 0.05
	09:00 AM	-0.053	-0.0029	-8.4069	≤ 0.05
	11:30 AM	-0.082	-0.0029	-11.9843	≤ 0.05
	07:00 PM	-0.014	-0.0029	-2.4276	≤ 0.05

Fig. 6 Anselin Local Moran’s I analysis clusters and outliers regarding circuitry level at four time-of-day periods. **a** At 06:00 AM, **b** At 09:00 AM, **c** At 11:30 AM, **d** At 07:00 PM

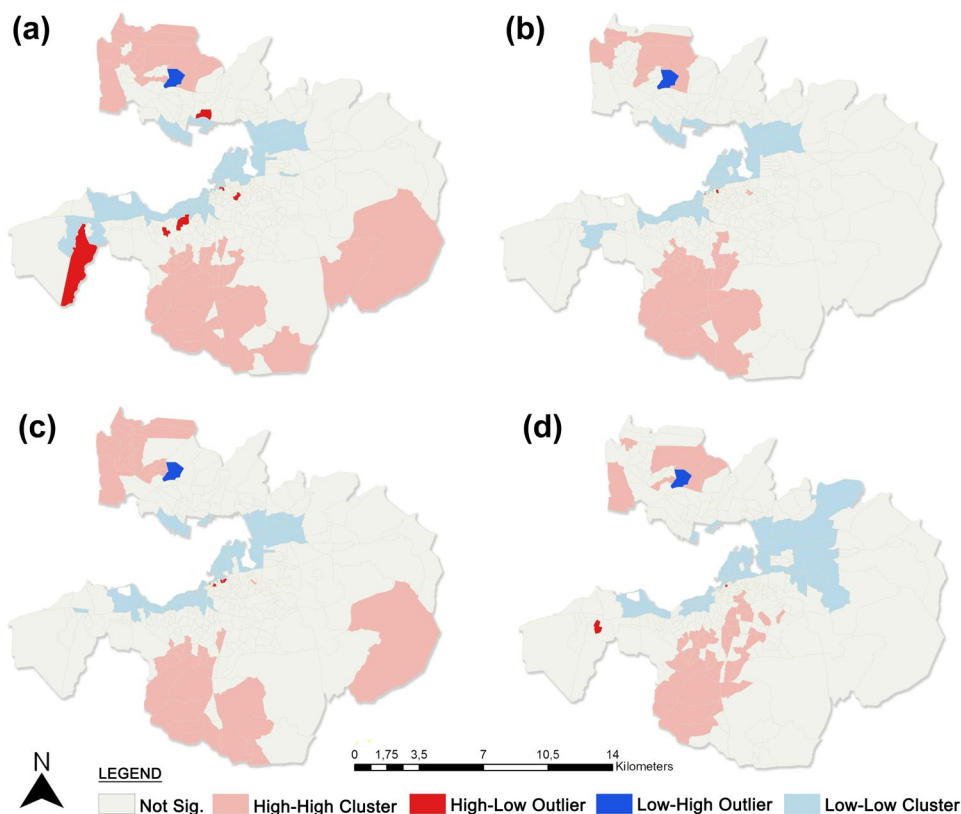


Table 7 Summary table of Bivariate Local Moran’s I statistics for circuitry index and socioeconomic variables ($n = 348$)

Variable	Time of the day	HH cluster	LL cluster	HL outlier	LH outlier	Not significant
<i>Per capita income</i>						
	06:00 AM	31*	81*	87*	45*	104
	09:00 AM	32*	72*	74*	49*	121
	11:30 AM	31*	77*	80*	44*	116
	07:00 PM	33*	48*	54*	52*	161
<i>Population density</i>						
	06:00 AM	24*	75*	93*	52*	104
	09:00 AM	28*	71*	75*	53*	121
	11:30 AM	21*	74*	83*	54*	116
	07:00 PM	34*	57*	45*	51*	161

*Statistically significant at $\alpha = 0.05$ level

the Local Moran’s I offer the spatial clusters such as HH or LL (High-High or Low-Low) or the spatial outliers such as HL or LH (High-Low or Low-High) [42]. Positive similarity exposes spatial clustering with similar values. Likewise, negative values expose spatial clustering with dissimilar values [44]. In terms of spatial associations, dissimilar neighboring values refers to spatial outliers, and they should take into account in local inconsistencies [45].

Bivariate Moran’s I and *Bivariate Local Moran’s I* analysis are performed in the GeoDa 1.18.0.0 software which is an open-source software introduced in 2003 and developed by Luc Anselin and his colleagues. As an output, the

Bivariate Moran Scatter Plot consisted of the x-axis, y-axis as its spatial lag that is a different variable and the observed Moran’s I value. The significance can be sustained by implementing the permutation approach.

As explained earlier, circuitry values are used as the efficiency determiner and the overall spatial analysis is conducted to reveal the spatial pattern associated with the selected socio-economic data. Multiple methods are combined for the spatial autocorrelation analysis. Along with the circuitry indices, socio-economic variables were used as inputs within a system such as an input-output chain with the specified analysis. The input-output chain for the

circuitry and spatial autocorrelation analysis applied in the study is shown in Fig. 5.

4 Analysis and results

4.1 Univariate global and local spatial autocorrelation analysis of the circuitry

Univariate global and local spatial autocorrelation analyses techniques are applied to examine the spatial distribution of efficient and in efficient neighborhoods in terms of public transportation. The null (H_0) and alternative hypotheses (H_A) tested are as follows:

H_0 The spatial distribution of the circuitry values is randomly distributed.

H_A The spatial distribution of the circuitry values is not randomly distributed.

The results show that the spatial distributions of the circuitry levels are not random for the four time-of-day periods and the findings are statistically significant at $\alpha=0.05$ level. The results indicate a clustered pattern for all periods rejecting the null hypothesis. This finding reveals that neighborhoods with similar circuitry indexes tend to be located at closer distances to each other. That is to say, the efficiencies or deficiencies of public transportation systems tend to cluster in Izmir (Table 4).

However, the Global Moran's I analysis does not give any spatial information about the location(s) of the cluster(s). The patterns at the local association level may differ. So, the Local Moran's I Statistic is performed to derive information on the locations of the clusters as well as the outliers. In this approach, the tested null (H_0) and alternative hypotheses (H_A) are as follows:

H_0 There is no local spatial association between the neighborhoods regarding the circuitry levels,

H_A There is a local spatial association between the neighborhoods regarding the circuitry levels.

The Anselin Local Moran's I analysis provides information on the locations of the clustered neighborhoods regarding circuitry levels. The findings show that the distribution of over 200 neighborhoods is spatially random at all time-of-day periods (Table 5). For these neighborhoods, the null hypothesis can not reject. On the other hand, the remaining neighborhoods are either a part of a cluster or an outlier.

As seen in Fig. 6, the low-low clusters, where neighborhoods with low circuitry values are surrounded by neighborhoods with low circuitry levels, are mainly concentrated along the seashore of Izmir. These are the neighborhood clusters with high public transportation efficiency. Whereas, the high-high clusters, which are the clusters of lower efficiency levels of public transportation services are located predominantly at the periphery. There is one low-high outlier neighborhood and this result is consistent at all time-of-day periods. This neighborhood is Mustafa Kemal Neighborhood in the Karsiyaka district. This neighborhood is a planned residential area highly accessible from the highway as it is situated right next to a highway exit. Thus, the buses use the highway resulting in low circuitry levels. The high-low outliers differ in number and location regarding the time-of-day periods (Fig. 6).

Regarding the results of the Global Moran's I analysis, it can be said that public transportation service efficiencies and deficiencies are clustered and concentrated in some urban areas in Izmir city. Public transportation gets more efficient as we move from the periphery to the center. As revealed by the spatial clusters and the outliers, public transportation is more efficient and easier to access in the city center and along the shoreline in Izmir city. This finding is consistent with previous research which claims central and older parts of cities have relatively more efficient and more accessible public transit [22, 27, 46].

4.2 Bivariate global and local spatial autocorrelation analyses

Bivariate global spatial autocorrelation identifies whether there is a relation between the investigated variable and a different variable [47]. Regarding the variables considered in this study, the null (H_0) and alternative (H_A) hypotheses for the *bivariate global spatial autocorrelation analyses* are as follows:

H_0 There is no spatial correlation between the circuitry level and per capita income,

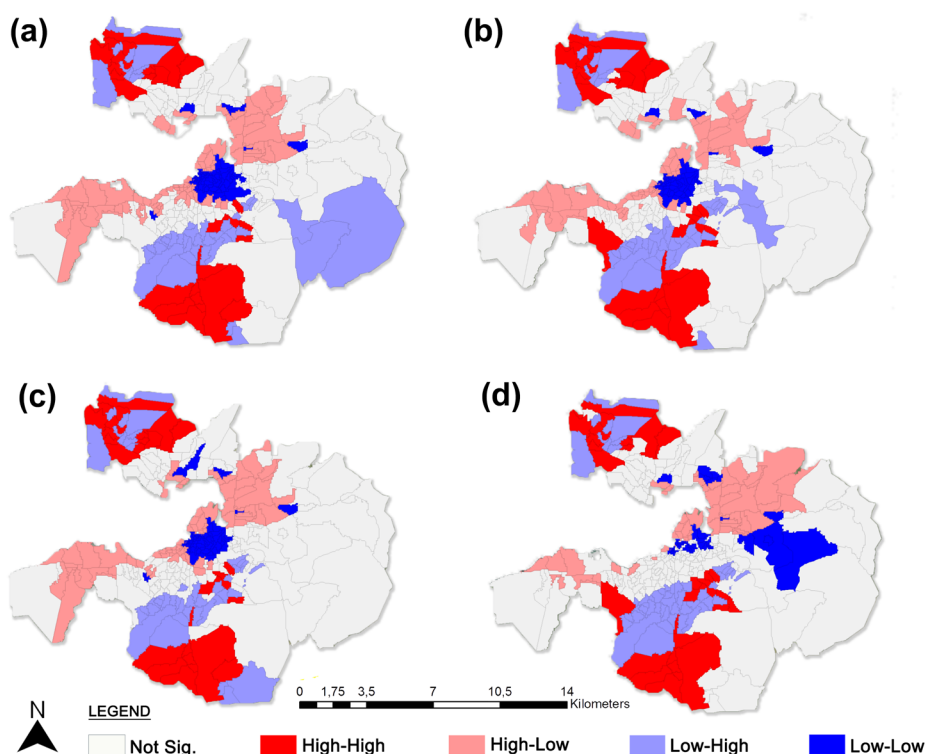
H_A There is a spatial correlation between the circuitry level and per capita income,

and,

H_0 There is no spatial correlation between the circuitry level and population density,

H_A There is a spatial correlation between the circuitry level and population density.

Fig. 7 Bivariate Local Moran cluster maps of per capita income and circuitry index as the input. **a** At 06:00 AM, **b** At 09:00 AM, **c** At 11:30 AM, **d** At 07:00 PM



As shown in Table 6, there is a negative and statistically significant ($\alpha = 0.05$) spatial relation between the circuitry levels and the two socio-economic variables at all time-of-day periods. Thus, the null hypotheses are rejected, and alternative hypotheses are accepted. These findings show that the neighborhoods with lower per capita income levels have higher circuitry values, which indicate lower public transportation efficiency, and vice-versa. This result is relatable to Galster and Killen [47], who state that higher-income households are more advantaged in getting better and adequate public services. Lower transit efficiency for lower-income groups is a clear failure in planning and public service supply. Lower-income groups have fewer resources for motorized trips and their overall mobility is limited. Thus, lower service levels and inefficient public transportation result in shorter and fewer trips per day compared to high-income households [43, 48].

According to the results, the neighborhoods with higher population density have lower circuitry which indicates higher public transportation efficiency. This result is plausible since transit transport supply is relatively less costly in highly-populated neighborhoods. As stated by Schouten [22] high-density mixed-use urban residential neighborhoods have higher levels of public transportation accessibility. Many studies found a positive relationship between public transportation usage and population density [17–20]. Levinson et al. [41] stated that there is a

strong positive correlation between public transportation system occupancy and high density.

Since there is an overall spatial correlation between the circuitry level and investigated socioeconomic variables, a spatial assessment at the local level regarding the socioeconomic variables is legitimate. The bivariate local spatial correlations are assessed by Bivariate Local Moran's I Statistics and the linear associations between the socioeconomic variables of each neighborhood and the average of its neighboring circuitry levels are examined regarding the four time-of-day periods. In this perspective, the null (H_0) and alternative (H_A) hypotheses are;

H_0 There is no local spatial association between the circuitry level and per capita income.

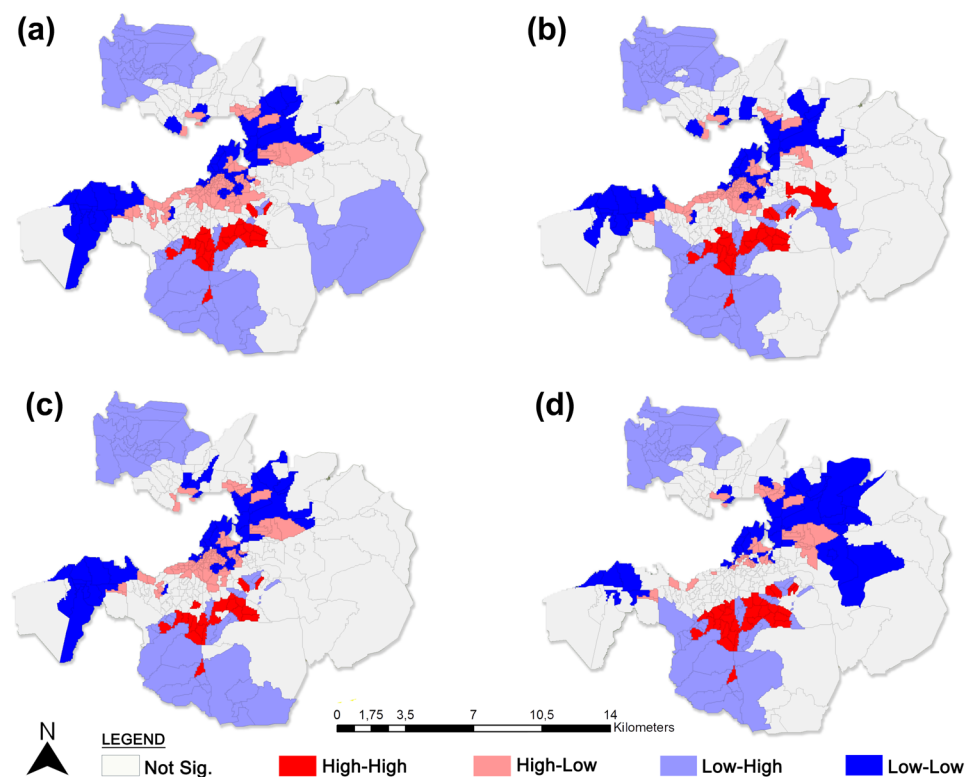
H_A There is a local spatial association between the circuitry level and per capita income.

and,

H_0 There is no local spatial association between the circuitry level and population density.

H_A There is a local spatial association between the circuitry level and population density.

Fig. 8 Bivariate Local Moran cluster maps of population density and circuitry index as the input. **a** At 06:00 AM, **b** At 09:00 AM, **c** At 11:30 AM, **d** At 07:00 PM



A bivariate LISA Cluster Map is created presenting the spatial clusters (High-High or Low-Low) or the outliers (High-Low or Low-High) on GeoDa. The numbers of significant and insignificant clusters and outliers obtained from the Bivariate Local Moran's I analyzes are presented in Table 7.

Bivariate Local Moran's I statistics between circuitry and socioeconomic variables reveal the clusters and the outliers as shown in Fig. 7 and Fig. 8. For the first group of local-level analyses, it is observed that the Low-Low clusters are mostly concentrated in the areas close to the traditional city center of Izmir (Fig. 7). These are the neighborhoods with low per capita income surrounded by low circuitry levels with higher transportation efficiency. The results are highly compatible with the previous literature. The lower-income groups tend to live near the city center to benefit from public transportation and have easier access to amenities and jobs [46]. The High-High clusters are mainly located at the edge of the study area. These areas are characterized by higher income groups surrounded by areas with lower public transportation efficiency. These are wealthier neighborhoods and possibly auto-dependent areas with high car ownership levels.

The High-Low outliers are mostly concentrated in areas close to the seashore along the Izmir Gulf (Fig. 7). These areas are wealthier neighborhoods getting a higher level of public transportation service. The seaside neighborhoods in Izmir consist of high-income level households and the results

are as it was expected, concurring with the statement of Galster [47] stating that higher-income households are more advantaged in getting adequate public services. The areas identified as Low-High outliers are located mostly away from the city center mainly in the North to East directions at the edge of the study area. These are low-income neighborhoods getting less efficient public transportation services. The results concur with the statements of Pucher [48] who suggests that neighborhoods with lower income have been given insufficient public transportation service with high fares contradiction to the unqualified and crowded travel supply. These neighborhoods need special attention with more efficient and enhanced public transportation services.

For the second group of local-level analyses, the neighborhoods in which the alternative hypothesis is accepted at the $\alpha = 0.05$ level indicate that there is a significant local spatial association between the circuitry level and population density as shown in Fig. 8. The areas labeled as Low-Low clusters are separately clustered, but these are generally located in the gulf and its periphery and among the shoreline to the West. These are the neighborhoods with low population density surrounded by low circuitry levels which means higher transportation efficiency. High-High clusters present the neighborhoods with high population density surrounded by high circuitry levels that indicate lower public transportation efficiency.

As Schouten [22] argues that in an urban metropolitan area, mixed-use highly dense urban residential neighborhoods are higher levels of public transportation accessibility than other parts of the city. In addition, Ewing and Cervero [17, 27] states that local urban population densities are directly related to the public transportation systems, with the second variable of mixed land use, similar to the statements of Kitamura et al. [19] arguing that high densities relate to more enhanced public transportation service levels. The policymakers should consider the service deficiencies in the neighborhoods characterized by high population density but low public transport efficiency.

The High-Low outliers are mostly concentrated in areas close to the seashore and traditional city center, indicating high population density with higher public transportation efficiency. The results are as expected and in line with Levinson et al. [41] suggesting that employment and commercial activities are located in the high-density urban central areas due to the availability of public transportation systems with less dependency on private cars. These neighborhoods are the areas where daily commercial activity and business centers are intense. Highly dense urban areas with mixed-uses have high accessibility with shorter travel times [17, 23, 27]. Schouten [22] argues that in an urban metropolitan area, mixed-use highly dense urban residential neighborhoods are higher levels of public transportation accessibility besides other parts of the city.

The areas labeled as Low-High outliers are located away from the city center mainly in the North to East directions at the edge of the study area indicating low population density with public transportation deficiencies. These areas have high circuitry values which can be due to the long network distances. However, it must be considered that in the literature the areas in the outwards with low-population density are mostly related to high-income and suburban settlements [19, 49]. On the other hand, Schouten [22] argued that there is low public transportation access in the outlying rural areas that are sparsely populated. It is crucial that the demographics and the social characteristics must be examined in detail in such areas. In public transportation system installments, the low-income households living outside the high-density inner cities should be considered [43].

5 Conclusions

This research has put forth a worthy approach to spatially determining the urban areas with adequate and inadequate efficiency levels. It is revealed that the efficiency of public transportation services in neighborhoods is significantly differentiated regarding their socioeconomic structure.

The results of the univariate spatial autocorrelation analyses show that public transportation service efficiencies and deficiencies are being clustered and concentrated in some urban areas. Higher public transportation efficiency is observed in areas close to the seashore and the traditional city center of İzmir while lower public transportation efficiency levels are often located on the periphery away from the seashore. The results are consistent with the relevant literature addressing that the neighborhoods with better socio-economic structures are getting more efficient public transportation services than other parts of the city. Levinson et al. [42] note that transportation needs must be evaluated by taking the density into the account while Kawabata [41] offers that it would be an overall advantage for all to develop more efficient and connected public transportation systems, not only for the low-income, low-skilled, and those with dependence on public transit.

The fact that there is a significant and spatially related relationship between the efficiency of public transportation and population density and income calls for alteration in the planning policies regarding urban public transportation supply. Although the variation in public transport efficiency levels across the neighborhoods can partly be attributed to physical conditions such as slope or distance, the city should provide equal accessibility and efficiency regardless of the socio-economic status of the neighborhoods.

As in almost all research, there are several limitations in this study. Travel time data acquired for public transportation systems from Moovit online services might be slightly outdated. Also, the methods used in this study would address different outcomes if the data collection and analysis were performed for a year-long period. So, the seasonal changes in public transportation efficiencies could have been assessed in a spatial context. Lastly, the presence of ferry services has a share and advantage in the general public transportation system in the city of Izmir. But methodologically, there has been a situation of immeasurability for these systems, so the effects of ferry systems have been ignored due to this study's configuration.

Despite these shortcomings, the findings of the study reveal important inefficiencies in public transportation services considering the spatial extent. This study is unique in that it measures the efficiency of public transport systems at the neighborhood level using the degree of circuitry and the findings can well be generalized for cities of similar sizes in developing countries. The methods described here can be applied in a comprehensive spatial context as a decision support system to improve urban public transport supply.

Author contributions ESK: Literature search/review, analyzing, manuscript writing, content planning; KMC: literature search/review, analyzing, manuscript writing, content planning.

Funding No funding was received for conducting this study.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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