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Original Article

Mapping Public Transportation Accessibility Inequality in DKI Jakarta Using Moran's I and LISA Analysis

Fazel Karly[1*], Silmi Afina Aliyan [1], Irene Rwabudandi [2]
[1]Universitas Pendidikan Indonesia, Bandung, Indonesia; [2]University of Rwanda, Kigali, Rwanda
*Corresponding E-mail: fazelkarly@upi.edu

ABSTRACT
Public transportation plays a central role in supporting community mobility, especially in megacities such as DKI Jakarta, which is experiencing high pressure due to population growth and urbanization. In recent years, the public transportation system in Jakarta has undergone rapid development through the introduction of modes such as TransJakarta, KRL, LRT, and MRT. However, this development has not been fully accompanied by equitable access, particularly in outlying areas that remain underserved. Therefore, this study aims to analyze spatial disparities in public transportation accessibility in Jakarta using geospatial and spatial statistical approaches. The methods used include mapping the distribution, density, and accessibility of the main public transportation modes (TransJakarta, KRL, LRT, MRT) as well as spatial autocorrelation tests using Moran's I index and LISA with inverse distance and contiguity edges and corners approaches. The analysis results show a clustered spatial pattern, with the central city area classified as a High-High cluster (high accessibility), while peripheral areas such as East Jakarta and parts of North Jakarta are classified as Low-Low and Low-High clusters (low accessibility). These findings indicate significant disparities in the distribution of public transportation services. Therefore, this study recommends that public transportation planning in Jakarta be focused on areas with service deficits to achieve a more equitable, inclusive, and sustainable mobility system.

KEYWORDS
Public transport;
Accessibility;
Spatial inequality;
Moran's I;
LISA

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INTRODUCTION

Public transport is a mass mobility system serving community movement such as buses and rail-based modes (Kuo et al., 2023) and plays a crucial role in supporting social–economic activities in dense urban areas (Ceder, 2021). Efficient public transport reduces congestion and pollution while improving mobility equity (Faghihinejad et al., 2023). Jakarta, as Indonesia's administrative and economic centre, has very high population density and complex daily mobility flows driven by concentrated economic, educational, and governmental activities (Hidayati, 2021), making public transport quality essential for sustaining urban mobility.

Jakarta's public transport system has expanded significantly in recent years due to rising mobility needs driven by population growth and traffic congestion (Muttaqin et al., 2021). TransJakarta increased from around 600,000 daily passengers in 2022 to more than 1 million in 2024 (PT Transportasi Jakarta, 2025). MRT Jakarta, operating since 2019, reached more than 3.5 million monthly passengers in 2024 with routes expanding from 15.7 km to more than 30 km (MRT Jakarta, 2019). The Jabodebek LRT, operating since 2023, serves over 100,000 passengers per month along its 41.2 km corridor (Ministry of Transportation, 2025). Meanwhile, KRL Jabodetabek ridership rose by 35% in January–May 2025, reaching nearly 180 million passengers (KAI Commuter Public Relations Manager, 2025).

Despite these improvements, service equity remains a challenge, with peripheral areas still underserved (Hafiudzan et al., 2024). This inequality increases reliance on private vehicles (Purwoko & Yola, 2022), which worsens pollution (Novelia et al., 2025) and affects access to educational (Utami & Afrilia, 2025) and health facilities (Susana et al., 2024). Service quality is also uneven, with several modes lacking standardization and reliability (Andoko et al., 2021). When public transport is inconsistent, users tend to revert to private vehicles Soza-Parra et al. (2022), indicating potential spatial inequality in accessibility. Previous studies have discussed public facility and transport inequality in Jakarta, including facility inequality using Moran's I (Indriyani & Widaningrum, 2021), KRL spatial patterns (Wijayanto et al., 2022), pedestrian accessibility in Central Jakarta (A'rachman et al., 2022), TransJakarta coverage (Hardi & Murad 2023), and demand-based performance assessment (Muttaqin et al., 2021). However, these studies generally focus on single modes and do not integrate density, accessibility, and autocorrelation using multiple spatial-weight conceptualizations such as inverse distance and contiguity edges-corners.

This study complements prior work by integrating density analysis, accessibility, and Moran's I/LISA using both inverse distance and contiguity edges-corners. Its main objective is to analyze the spatial distribution, density, accessibility, and inequality of major public transport modes in DKI Jakarta, and to formulate development recommendations based on population needs. The novelty lies in combining spatial statistical analysis with socio-economic and demographic determinants at the sub-district level, offering a new perspective for identifying service deficits and supporting transport equity policies.

METHOD

Study Area

This study was conducted in the Province of DKI Jakarta, which administratively consists of five cities and one administrative district, namely the Thousand Islands District. However, in this study, the Thousand Islands District was excluded from the analysis. This exclusion was made because the characteristics of the Thousand Islands region are very different from those of other cities in DKI Jakarta.

Geographically, the Thousand Islands are a group of islands that are relatively isolated from the main land area of Jakarta, thus having unique patterns of mobility and accessibility that cannot be directly compared with urban areas (Jambak et al., 2025). In addition, the population density in the Thousand Islands is also very low (when compared to the area of water between the islands) and scattered, making it irrelevant to analyze in the context of the distribution and equity of land-based public transport such as TransJakarta, KRL Commuter Line, MRT Jakarta, and LRT Jabodebek. Therefore, to maintain the consistency and relevance of the analysis results, this study focuses on the main land area of DKI Jakarta, which has an interconnected public transport system and network that can be analyzed spatially.

Research Data

Tabel 1. Research variables and data

Type of Variable	Data Type	Source
Administrative Boundary of Subdistricts (Kecamatan)	Spatial – Vector Polygon	(BIG, 2024)
Population per Subdistrict	Tabular	(Badan Pusat Statistik Provinsi DKI Jakarta, 2025)
TransJakarta Bus Stops & Terminals	Spatial – Vector Point	PT Transportasi Jakarta
KRL Commuter Line Stations	Spatial – Vector Point	OpenStreetMap & PT Kereta Commuter Indonesia
LRT Jabodebek Stations	Spatial – Vector Point	OpenStreetMap & PT LRT Jakarta
MRT Jakarta Stations	Spatial – Vector Point	OpenStreetMap & PT MRT Jakarta
Number of Schools per Subdistrict	Tabular	(Badan Pusat Statistik Provinsi DKI Jakarta, 2025)

Type of Variable	Data Type	Source
Built-Up Land Cover of DKI Jakarta	Spatial – Vector Polygon	(BIG, 2024)

Sources: BIG, 2024; Badan Pusat Statistik Provinsi DKI Jakarta, 2025; PT Transportasi Jakarta; OpenStreetMap; PT Kereta Commuter Indonesia; PT LRT Jakarta

Transportation data was combined using the *Summarise Within* tool to obtain the total number of public transport modes per subdistrict. This data was used as the main public transport variable. It is considered the main variable because the modes of transport included in this variable are mass public transport networks that have wide coverage, high capacity, and are officially managed by the government or integrated operators, such as TransJakarta, KRL Commuter Line, MRT Jakarta, and LRT Jabodebek.

These modes serve as the backbone of the urban transport system in Jakarta and its surrounding areas, unlike small or informal transport, which tends to be non-standardized and local in nature (Syafruddin, 2024). Thus, an analysis of the distribution of these main modes can provide a more representative picture of the disparities in public transport accessibility between sub-districts in DKI Jakarta.

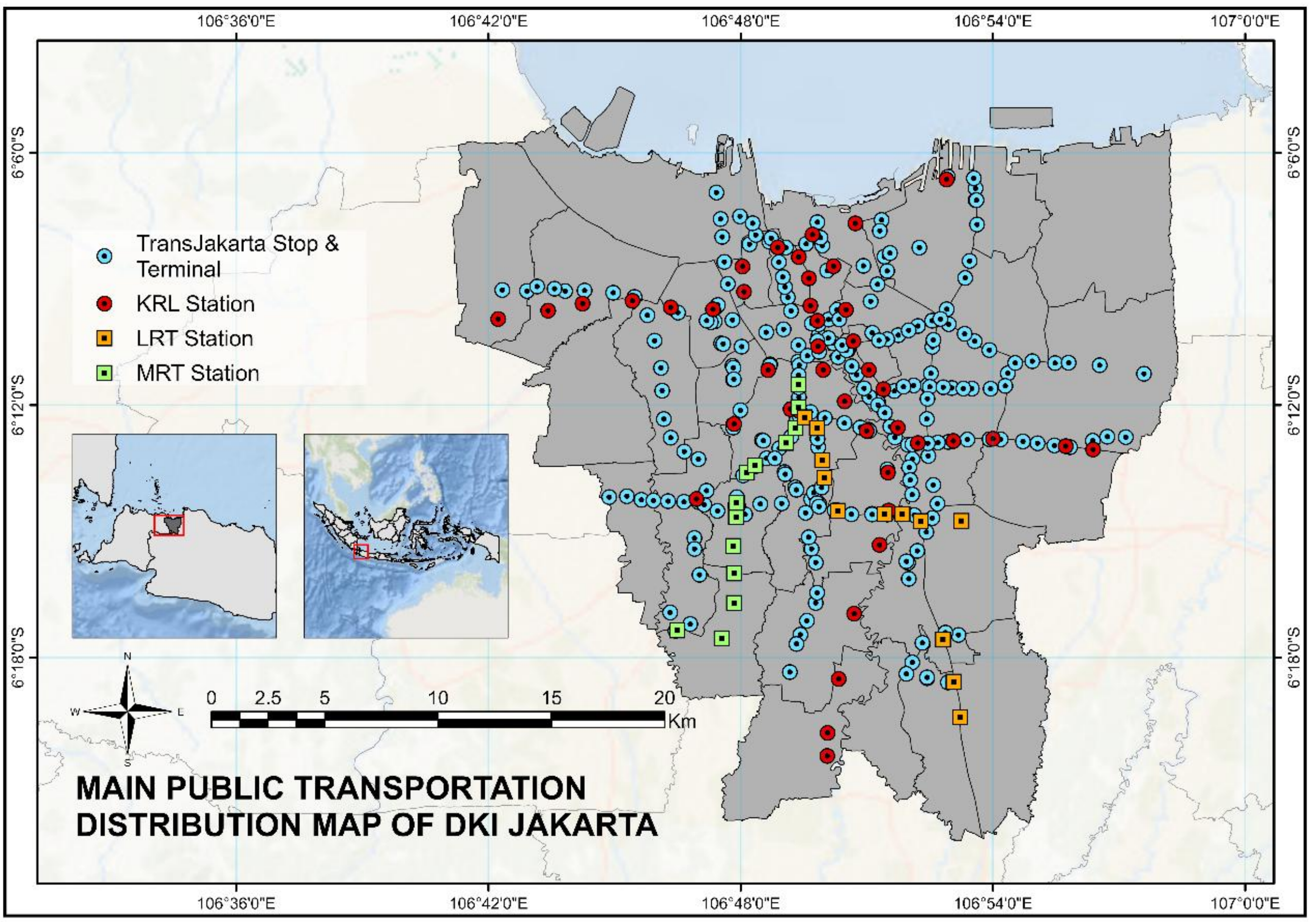

Figure 1. Map of the distribution of major public transport modes in DKI Jakarta
Source: BIG, 2024; Badan Pusat Statistik Provinsi DKI Jakarta, 2025; PT Transportasi Jakarta; OpenStreetMap; PT Kereta Commuter Indonesia; PT LRT Jakarta

Figure 1 is a visualization map of the spatial data that has been collected. This map shows the distribution of main public transport points in the study area, namely DKI Jakarta Province, which consists of TransJakarta bus stops and terminals, KRL Commuter Line stations, Jabodebek LRT stations, and Jakarta MRT stations. These points are distributed in a linear pattern that reflects the route of each mode of transport. This map is used as a basis for calculating the density and accessibility of major public transport and for further spatial analysis, taking into account the location of each major public transport facility in relation to the administrative sub-district.

Research Design

This study applies a spatial quantitative approach supported by GIS to analyze public transport accessibility inequality in DKI Jakarta (Figure 2). The workflow includes data collection and integration, thematic map generation, spatial statistical analysis, and identification of priority areas for public transport improvement. The dataset consists of population per sub-district and spatial layers of TransJakarta stops and terminals, KRL Commuter Line stations, Jabodebek LRT stations, and Jakarta MRT stations.

Two primary thematic maps were produced. The first is a transport density map derived using Kernel Density Estimation (KDE), illustrating the physical concentration of major public transport modes without accounting for population size. The second is an accessibility map, calculated as the ratio of transport nodes to sub-district population density and normalized into an accessibility index for regional comparison.

To examine spatial disparity, the study employed Global Moran's I and LISA (Local Indicator of Spatial Association) using two spatial-weight conceptualizations: Inverse Distance and Contiguity Edges Corners. Global Moran's I assessed whether high or low accessibility values tend to cluster spatially, while LISA identified local clusters, High–High hot spots and Low–Low cold spots, under both spatial-weight approaches to ensure robust results.

A comparative assessment of the two spatial conceptualizations was then conducted to evaluate differences in emerging spatial patterns and test the sensitivity of the results to each weighting method. Based on LISA clusters and the accessibility index, sub-districts classified as Low–Low with low accessibility and minimal transport density were identified as priority areas for public transport provision. These findings support more equitable transport planning aligned with actual population needs. The following section provides a detailed explanation of the technical methods applied in this research.

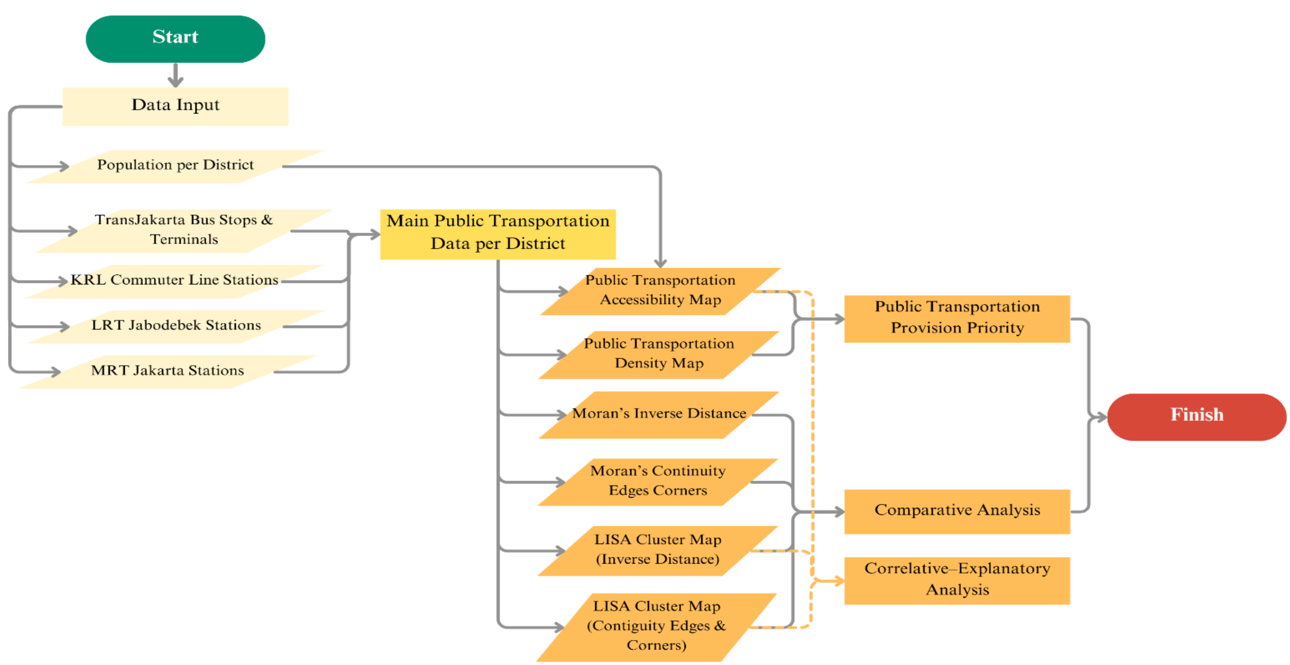

Figure 2. Research flow chart
Source: Author

Kernel Density

Kernel Density is an estimation method used to calculate the density of points in an area. This method works by calculating the number of points within a certain radius of each location on the map, then assigning a density value based on the kernel function, which will produce a map surface with a density value gradient (Khalaf et al., 2024). The Kernel Density formula can be seen in Equation 1.

$$D(x,y) = \frac{1}{(r)^2}\sum_{i=1}^{n}\left[\frac{3}{\pi}\cdot pop_i \cdot \left(1-\left(\frac{d_i}{(r)^2}\right)^2\right)^2\right] \quad (1)$$

Source: Silverman (2018)

With:

- r = bandwidth (user-defined search radius)
- n = number of input points
- pop_i = population value/weight of point i (default = 1 if there is no population field)
- d_i = distance from point i to location (x, y)

In Kernel Density Estimation (KDE) analysis, the bandwidth or search radius parameter is an important factor that determines the smoothness of the density estimation results. In this study, the bandwidth value was calculated using Silverman's Rule of Thumb (Silverman, 2018) as shown in equation 2:

$$h = 0.9 \times \min\left(SD, \frac{IQR}{1.34}\right) \times n^{-1/5} \qquad (2)$$

where SD is the standard deviation of the distance between points, IQR is the interquartile range, and n is the number of points. This value ensures a balance between local detail and pattern smoothness, so that the density map results optimally represent the spatial distribution.

In the context of this study, the kernel density method was used to describe the spatial distribution of major public transport in DKI Jakarta, such as TransJakarta bus stops, KRL stations, MRT stations, and LRT stations. The input variable in this stage was all major public transport points that had been compiled into a single layer. The result of this analysis is a public transport density map that can be used to identify areas with high and low concentrations of transport modes, which can then be used as a basis for assessing spatial accessibility.

Moran's I Spatial Autocorrelation

Moran's I spatial autocorrelation analysis is a statistical method used to measure the extent to which a variable is spatially clustered on a global scale (Mergenthaler et al., 2022). In this analysis, the Moran's I value will show whether a variable has a clustered distribution pattern, is randomly distributed, or is evenly distributed. The formula for the Moran's I value can be seen in Equation 3.

$$I = \frac{\frac{N}{W} \cdot \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\,(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \qquad (3)$$

Source: Moran (1950) in Chen (2021)
Where:

- N = number of spatial units (e.g., number of subdistricts)
- x_i = variable value at location i
- $\bar{x}$ = average variable value
- w_{ij} = spatial weight between locations i and j
- W = $\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}$ = total spatial weight

This analysis is used in research to evaluate whether there is a tendency for clustering of areas with high or low levels of public transport accessibility throughout DKI Jakarta. This method is considered appropriate because it can provide an overview of the spatial distribution of transport and reveal systematic patterns in its provision (Zhang et al., 2022).

LISA

LISA cluster and outlier analysis is a local spatial analysis method, unlike Moran's I, which is global (Huda & Imro'ah, 2023). LISA is used to identify specific locations that are clusters with high (High-High), low (Low-Low), or spatial outlier values such as High-Low or Low-High. The LISA formula can be seen in Equation 4.

$$I_i = \frac{(x_i - \bar{x})}{m_2} \sum_{j=1}^{N} w_{ij}\,(x_i - \bar{x}) \qquad (4)$$

Source: Anselin (1995) dalam Huda & Imro'ah (2023)
Where:

- x_i = variable value at location i
- $\bar{x}$ = average variable value
- x_j = variable value at location j
- w_{ij} = spatial weight between locations i and j
- m_2 = $\frac{\sum_{k=1}^{N}(x_i - \bar{x})^2}{N}$ = mean variance

In this study, LISA was used to detect subdistricts that significantly had high or low accessibility concentrations compared to surrounding areas. This method is suitable because it allows researchers to identify areas that require further public transport development policy intervention (Marada, 2010). LISA analysis was conducted alongside Moran's I because the two complement each other: Moran's I provides global patterns, while LISA provides detailed information at the local level.

Spatial Relation Conceptualisation

In Moran's I and LISA analyses, the selection of spatial relation schemes between objects (spatial conceptualisation) greatly influences the analysis results. There are several methods of spatial relation conceptualisation that can be used, as described by Tola et al., (2021) and ESRI:

- Contiguity Edges Corners (Queen's case): Two areas are considered neighbours if they share a side or corner point.
- Inverse Distance: Spatial relationships are determined based on the inverse distance between centroids, where closer locations have greater weight.
- Inverse Distance Squared: Similar to inverse distance, but the distance is weighted by the square so that the decrease in influence is more pronounced.
- Fixed Distance Band: Sets a fixed distance within which all neighbours within that radius are considered to have the same weight.
- Zone of Indifference: Combines fixed distance and inverse distance; within a fixed radius the weight is the same, outside the radius the weight decreases with distance.
- Contiguity Edges Only (Rook's case): Only considers areas that share a side as neighbours.

In this study, two spatial relationship conceptualizations were applied: Contiguity Edges-Corners and Inverse Distance. These approaches were selected to compare how inter-regional relationships are represented in spatial analysis. The Inverse Distance method is more aligned with the spatial reality of urban transport, where mobility and accessibility are influenced by actual geographic distance rather than administrative boundaries. Thus, it is considered more representative for capturing accessibility patterns based on proximity between locations (Marques & Pitombo, 2021).

In contrast, the Contiguity Edges-Corners (Queen's case) approach assumes that areas sharing borders or corners exert spatial influence on one another, making it relevant for analyses grounded in administrative units such as sub-districts. By employing both approaches, the study evaluates spatial patterns from both administrative and physical–distance perspectives, providing a more comprehensive foundation for assessing public transport accessibility inequality in DKI Jakarta.

Validation and Quantitative-Explanatory Analysis

Validation and quantitative–explanatory analyses were conducted to confirm the spatial patterns identified through Moran's I and LISA cluster maps, as well as to provide a quantitative explanation of the factors potentially influencing public transport accessibility inequality in DKI Jakarta. Spatial validation compared two spatial weighting schemes, Contiguity Edges-Corners (CEC) and Inverse Distance (ID), to ensure the consistency of the detected autocorrelation patterns. Differences in Moran's I values, z-scores, and p-values between the two approaches were used to assess the stability and significance of the resulting clusters and to verify that the findings were not dependent on a single spatial relationship configuration.

For the explanatory component, correlation tests were conducted between three sub-district–level structural variables, number of schools (educational activity), population density (mobility pressure), and built-up area (development intensity), and the LISA index values from both CEC and ID. These variables reflect Jakarta's role as an educational, economic, and administrative hub, where the distribution of services, population concentration, and physical development are expected to shape variations in public transport access. Pearson's correlation was applied to assess linear relationships because all variables met the assumptions of normality and interval/ratio measurement, following guidelines outlined by Weisburd et al. (2020).

The Pearson formula used follows the general equation with r as the correlation coefficient, n as the sample size, and x_i and y_i as the data values, as shown in Equation 5. The interpretation of the correlation strength follows the categories of Roflin and Zulvia (2021), namely 0 (no correlation), 0–0.20 (very weak), 0.21–0.40 (weak), 0.41–0.60 (moderate), 0.61–0.80 (strong), 0.81–0.99 (very strong), and 1 (perfect).

$$r = \frac{\Sigma x\, y_i - \frac{(\Sigma x_i\, \Sigma y_i)}{n}}{\sqrt{\left(\Sigma x_i{}^2 - \frac{(\Sigma x_i)^2}{n}\right) - \left(\Sigma y_i{}^2 - \frac{(\Sigma y_i)^2}{n}\right)}} \quad (5)$$

Through the integration of socio-demographic indicators, educational activities, and physical conditions of the region with LISA values, this analysis not only maps the patterns of public transport access inequality descriptively, but also explains the determining factors that potentially shape these spatial patterns.

Starting from the validation of spatial patterns using Moran's I and LISA as well as correlation analysis to identify structural factors that could potentially be related to accessibility inequality, the quantitative analysis stage in this study was limited to an explanatory-descriptive level. Given that the main objective of the study is to map and identify spatial inequality clusters, advanced methods such as spatial regression or GWR are not applied in this study.

RESULTS AND DISCUSSION

The analysis conducted in this study provides an overview of the spatial conditions of public transport in DKI Jakarta. In general, the results show that transport services are concentrated in the city centre, while suburban areas are relatively underserved. These findings are reinforced by density and accessibility analyses, as well as spatial autocorrelation testing using Moran's I and LISA. The discussion will be conducted in stages, starting with the distribution of public transport density, followed by community accessibility, then global and local spatial pattern analyses, and finally the practical implications for determining public transport development priorities.

Public Transport Density

The map in Figure 3 shows that public transport density in DKI Jakarta is highly concentrated in the central area, particularly in Central Jakarta and parts of South Jakarta and West Jakarta.

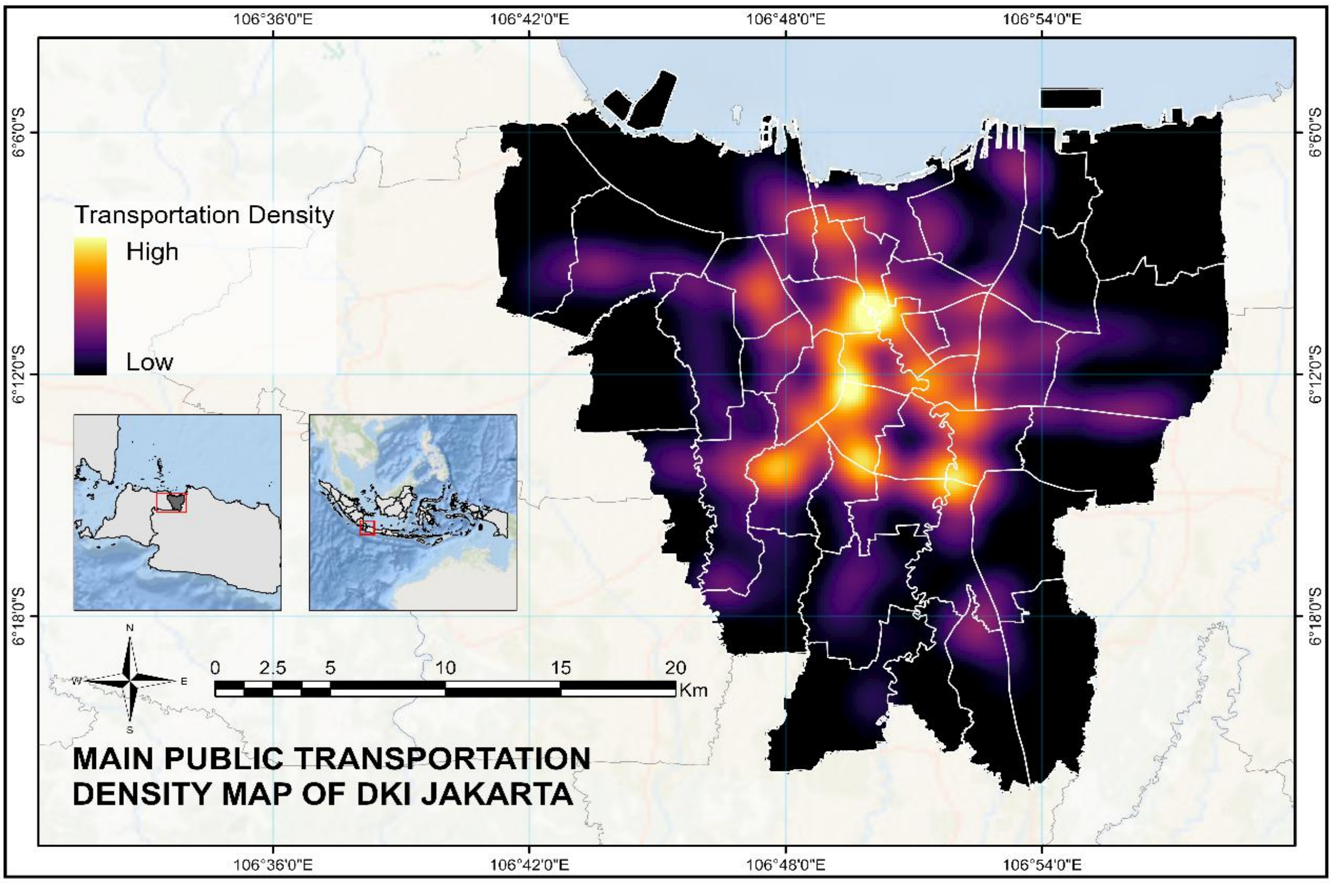

Figure 3. Map of main public transport density in DKI Jakarta
Source: Analysis Results

These areas are centres of economic and social activity, resulting in high demand and supply for public transport services. Meanwhile, peripheral areas such as East Jakarta and North Jakarta show much lower density, indicating an imbalance in the distribution of transport services. This imbalance has implications for the limited mobility of people in suburban areas, which has the potential to increase dependence on private vehicles or informal transport, as found in research (Dülmen et al., 2022).

Transport Accessibility

The map in Figure 4 shows a picture that further reinforces the spatial imbalance in public transport services. High accessibility is only concentrated in several sub-districts in the central area and part of South Jakarta, while most other areas, especially in East Jakarta, North Jakarta, and West Jakarta, show low accessibility. This condition indicates that residents in these areas must travel longer distances or face limited modes of transportation to reach public transportation facilities. This inequality has a direct impact on the cost and time burden of travel for the community, especially those with low incomes, thereby widening the social and economic gap between regions in Jakarta (Lunke, 2022). Not only that, facilities that improve accessibility also affect the pace of development in an area, so this phenomenon can cause disparities in the pace of development (Rizki Maulana et al., 2025).

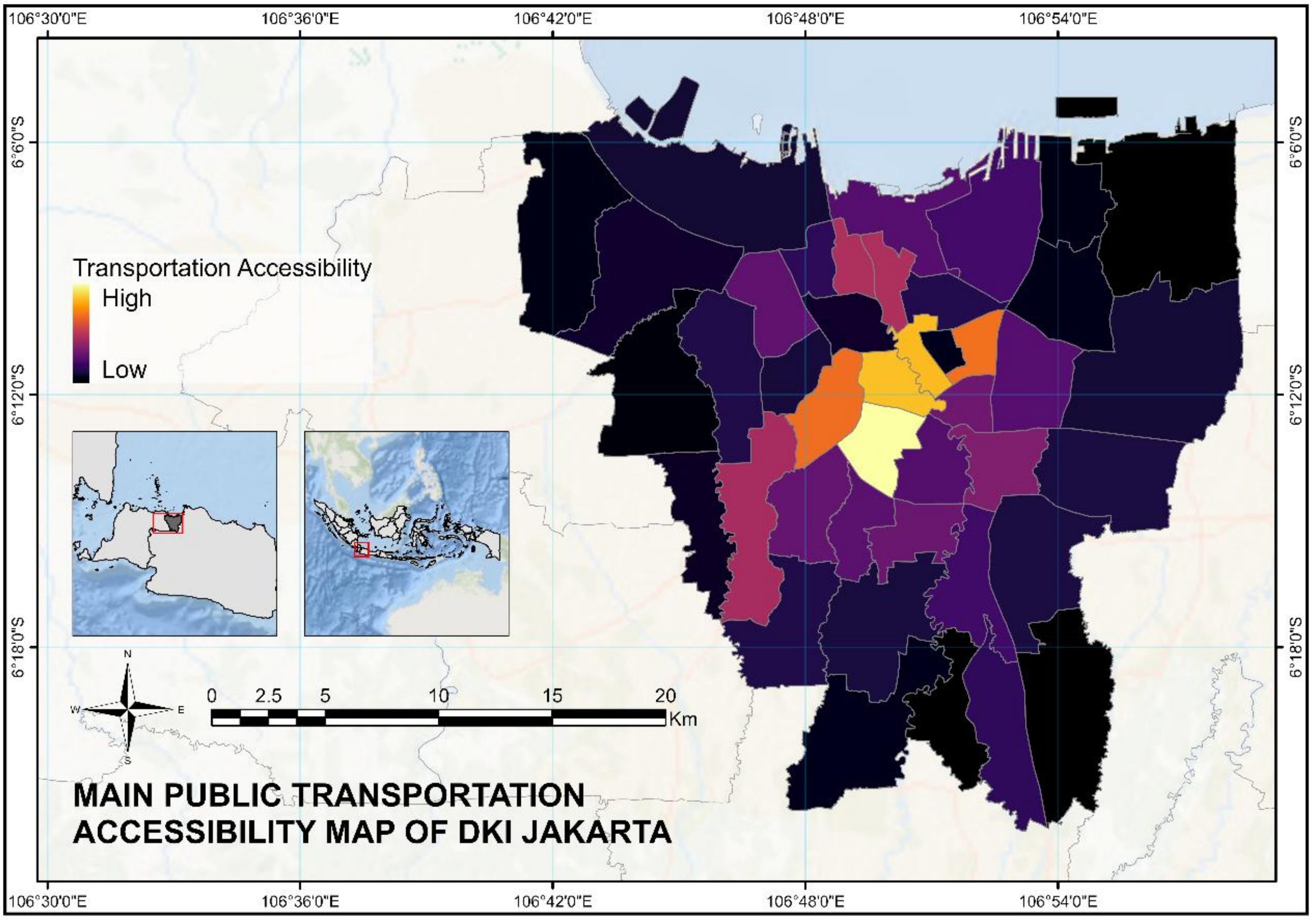

Figure 4. Map of main public transport accessibility in DKI Jakarta
Source: Analysis Results

Moran's I Approach

The results of spatial statistical analysis using Moran's I index show a value of 0.352584 with a z-score of 4.259236 and a p-value of 0.000021. This positive and fairly high index value indicates the presence of positive spatial autocorrelation, which means that areas with similar values (high with high or low with low) tend to be close to each other. The z-score, which is well above the critical value of 1.96 (even exceeding 2.58), reinforces that this pattern is statistically significant and does not occur randomly. In other words, the spatial distribution of the main public transport accessibility variable shows a clustered pattern rather than a random or dispersed one.

Tabel 2. Moran's I spatial autocorrelation table using the inverse distance approach

Parameters	Value
Moran's Index	0,352584
Expected Index	-0,024390
Variance	0,007834
z-score	4,259236
p-value	0,000021
Conceptualization	INVERSE_DISTANCE
Distance Method	EUCLIDEAN

Source: Analysis Results

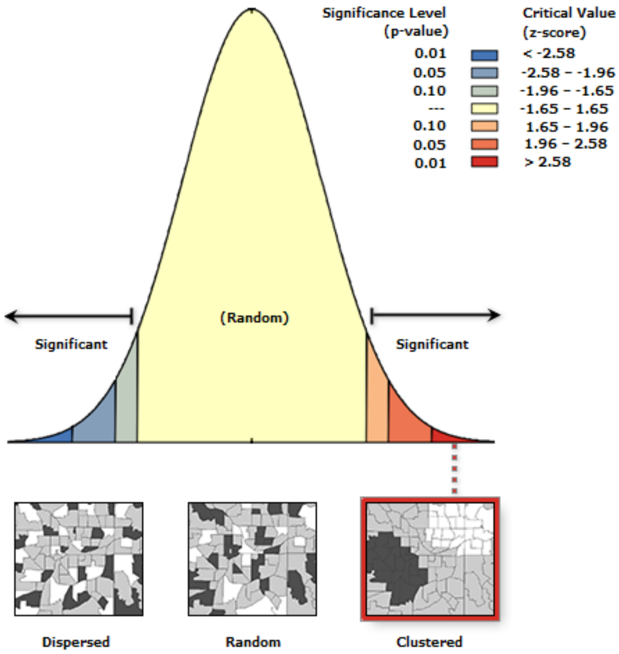

Figure 5. Results of Moran's I spatial autocorrelation analysis using the inverse distance approach
Source: Analysis Results

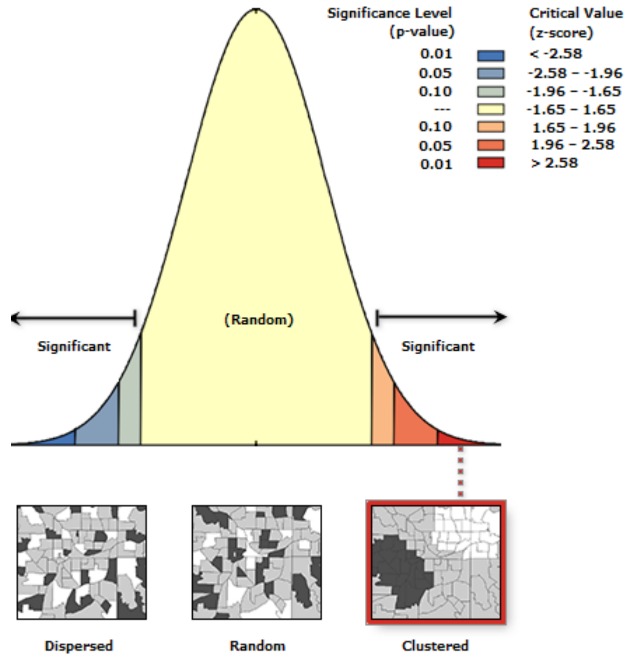

Figure 6. Results of Moran's I spatial autocorrelation analysis using the continuity edges corners approach
Source: Analysis Results

This is also consistent with the normal distribution graph, which shows the z-score falling on the extreme right of the curve, in the red zone (high significance). Based on this, it can be concluded that there is a clear spatial concentration: some areas significantly form good transport clusters, while other areas consistently lag behind. These findings provide empirical evidence of spatial inequality in the distribution of public transport services in DKI Jakarta.

Tabel 3. Moran's I spatial autocorrelation table using the continuity edges corners approach

Parameters	Value
Moran's Index	0,303579
Expected Index	-0,024390
Variance	0,007520
z-score	3,782133
p-value	0,000155
Conceptualization	CONTIGUITY_EDGES_CORNERS
Distance Method	EUCLIDEAN

Source: Analysis Results

The results of Moran's I analysis using the contiguity edges corners approach show an index value of 0.303579, with a z-score of 3.782133 and a p-value of 0.000155. This positive and significant index value indicates the presence of positive spatial autocorrelation, meaning that areas with similar characteristics (high or low) tend to cluster geographically. The z-score, which is well above the significance threshold of 1.96 and even exceeds 2.58, indicates that the detected cluster pattern is not random but statistically significant. This is reinforced by a very small p-value (less than 0.01), allowing us to reject the null hypothesis that there is no spatial autocorrelation. The p-value is generated through a permutation approach, which is a built-in procedure in calculating Moran's I in most spatial data processing applications.

From the accompanying normal distribution graph, the z-score position is on the extreme right (red zone), which describes a clustered distribution pattern. This means that the distribution of public transport in DKI Jakarta shows a tendency to cluster in certain areas, with high service clusters concentrated in the central area and parts of the west or south. Conversely, areas with low access or service are also concentrated, particularly in the northern and eastern regions. This contiguity approach considers spatial relationships based on similarities in administrative boundaries, reinforcing the interpretation that inequality in public transport access occurs not only because of physical distance, but also because of structural administrative restrictions between regions, similar to the findings of Anastasiadou et al. (2021) in their study on barriers to population mobility.

Thus, these results consistently show that public transport planning and development in DKI Jakarta is still uneven, and there is an urgent need to expand public transport coverage to spatially disadvantaged areas. This finding is also supported by Saputra (2023), who also found that rapid transport development is not supported by its own distribution.

Moran's I analysis using the inverse distance and contiguity edges-corners approaches both show significant positive spatial autocorrelation in the distribution of public transport in DKI Jakarta. The Moran's I value is higher in the inverse distance approach (0.352584) than in contiguity (0.303579), indicating that spatial relationships based on geographical proximity are stronger in explaining transportation distribution patterns than proximity based on administrative boundaries, in line with the findings of García-Palomares et al. (2018). A comparison of z-scores also shows a similar difference, namely 4.259236 for inverse distance versus 3.782133 for contiguity, indicating that the detected cluster patterns are more statistically significant when proximity is measured based on the physical distance between regions.

The difference in index values (≈0.049) and z-scores (≈0.48) is substantial enough to indicate a difference in sensitivity between the two methods. This difference shows that the inverse distance approach is more responsive in detecting spatial clustering of public transport, while contiguity tends to abstract regional relationships based on administrative boundaries. Thus, the choice of spatial weight conceptualization has been shown to affect the strength of the resulting autocorrelation, and this difference has important implications for the interpretation of public transport access inequality in Jakarta.

LISA Approach

The map in Figure 7 shows spatial clusters based on the proximity of distances between regions.

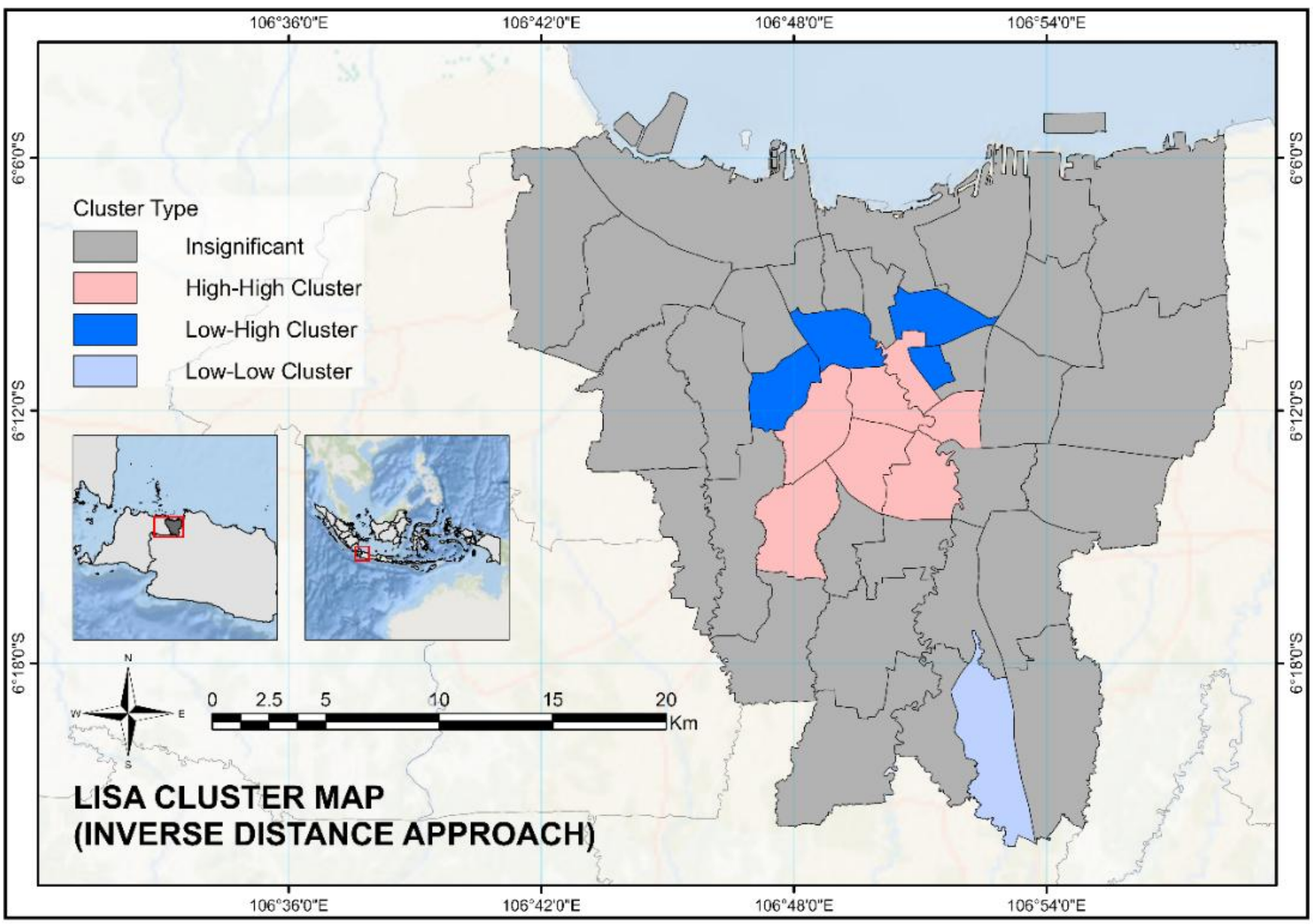

Figure 7. LISA inverse distance approach cluster map
Source: Analysis Results

A High-High cluster (pink) was identified in central Jakarta, indicating that these areas (Tanah Abang, Menteng, Senen, Kebayoran Baru, Setiabudi, Tebet, and Matraman) have high public transport values (e.g., density or accessibility) and are surrounded by areas with similar values. This reinforces previous findings and is also in line with research conducted by Gao & Zhu (2022), which found that city centres are the dominant hubs for public transport services.

Meanwhile, the Low-High clusters (dark blue) in several areas such as Palmerah, Gambir, Johar Baru, and Kemayoran subdistricts indicate areas with low values but surrounded by high-value areas, indicating the potential for sharp spatial inequality. The Low-Low cluster (light blue) in Ciracas Subdistrict indicates that this area has low access to or density of transportation and is also surrounded by areas with similar characteristics, highlighting the existence of areas that are structurally disadvantaged in terms of public transportation services.

Using the continuity edges corners approach, the map in Figure 8 reveals a slightly different cluster pattern. The High-High cluster remains concentrated in the central area (Tanah Abang, Menteng, Kebayoran Baru, Setiabudi, Tebet, and Matraman), but a High-Low cluster (dark red) appears in western Jakarta (Grogol Petamburan), indicating an area with high transport value but bordering on low-value areas. This finding reflects the potential for spatial isolation, where areas with good access are surrounded by disadvantaged areas.

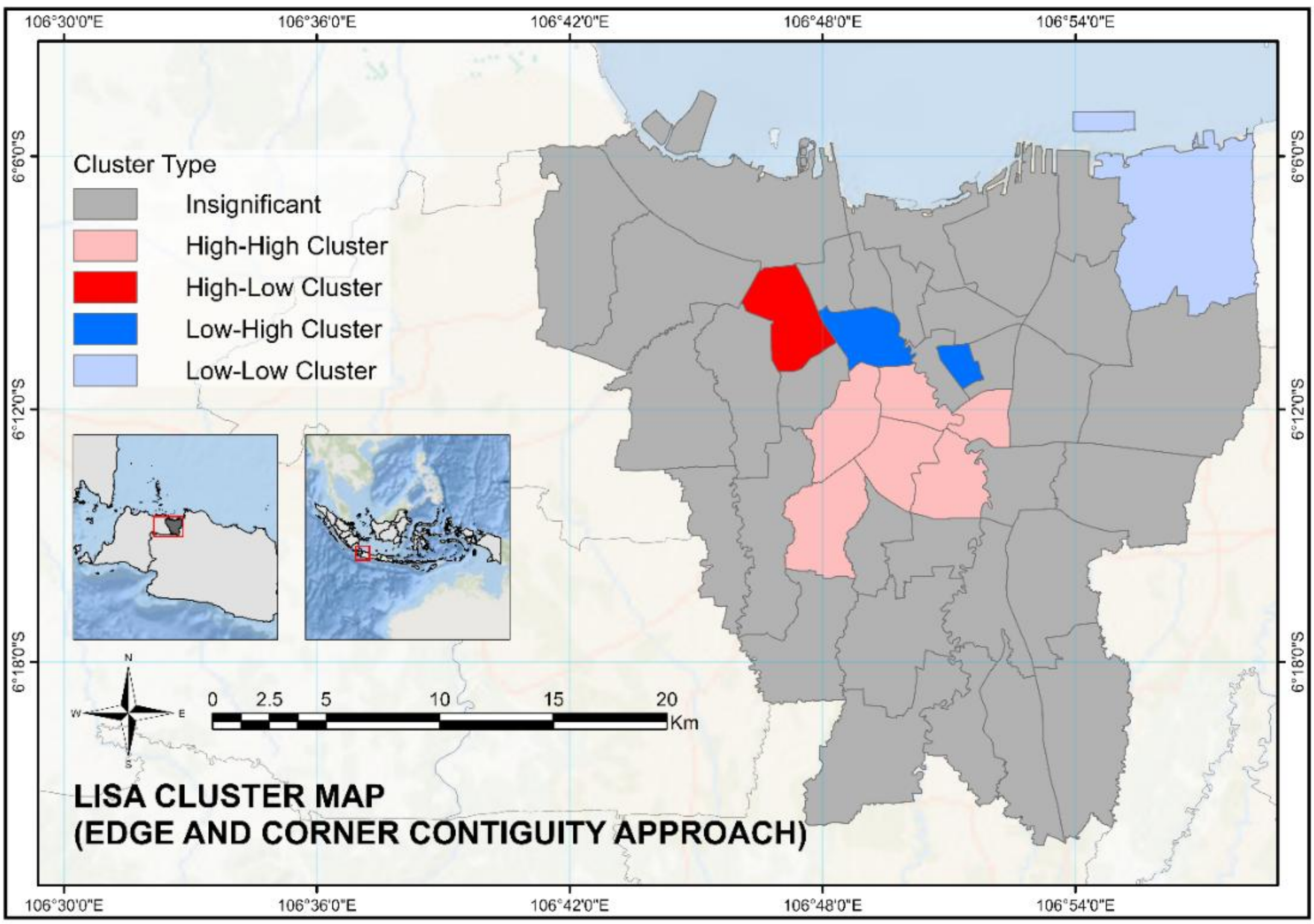

Figure 8. LISA continuity edges corners cluster map
Source: Analysis results

Meanwhile, Low-High (dark blue) and Low-Low (purple) clusters also appear in the north and east (Gambir and Johar Baru Low-High, Cilincing Low-Low), consistent with the pattern of inequality in transport infrastructure distribution. This approach provides a more contextual picture of the relationship between administrative regions, confirming that inequality is not only physical but also structural in nature based on regional boundaries.

The LISA map using the inverse distance and contiguity edges corners approaches shows different but complementary cluster patterns. In the inverse distance approach, the High-High cluster appears concentrated in central Jakarta, while the Low-Low cluster is scattered in the east and south. Conversely, in the contiguity approach, the High-High cluster remains centred in the same area, but the patterns of the Low-High and High-Low clusters become more apparent, indicating the existence of areas with conditions that differ from their neighbours. This indicates that the contiguity approach is more sensitive in capturing local spatial anomalies, while the inverse distance approach better describes macro spatial patterns. In general, both approaches show that public transport inequality in DKI Jakarta has complex spatial dimensions, both on a local and global scale.

Furthermore, Figure 9 is a graph showing a comparison of the significance of Local Moran's I (LMiP) between the spatial conceptualisation of Inverse Distance (ID) and Contiguity Edges-Corners (CEC). In general, most subdistricts in DKI Jakarta have a significance value below 0.5, indicating weak spatial clustering. However, there are variations between regions; for example, Kelapa Gading, Kemayoran, and Pancoran show higher CEC values than ID, indicating that topology-based methods are more sensitive in detecting local clusters. Conversely, Taman Sari and Kembangan have higher ID values, indicating stronger spatial patterns based on physical distance. These differences confirm that the choice of spatial conceptualisation affects the results of LISA analysis and needs to be adjusted to the geographical characteristics of the study area.

Moran's I results serve as a global indicator that generally states that there is spatial autocorrelation in transportation data, and both approaches used produce statistically significant values. These findings are consistent with the LISA map, which identifies specific (local) clusters, both High-High and Low-Low, in certain areas. Thus, the Moran's I results and the LISA map complement each other: Moran's I confirms that the distribution pattern of transport is not random and forms clusters, while the LISA map shows in detail where these clusters are located. This provides a strong basis for stating that the inequality of access to and distribution of public transport in Jakarta is not only real but also localized in certain areas that can be prioritized for public transport development policies.

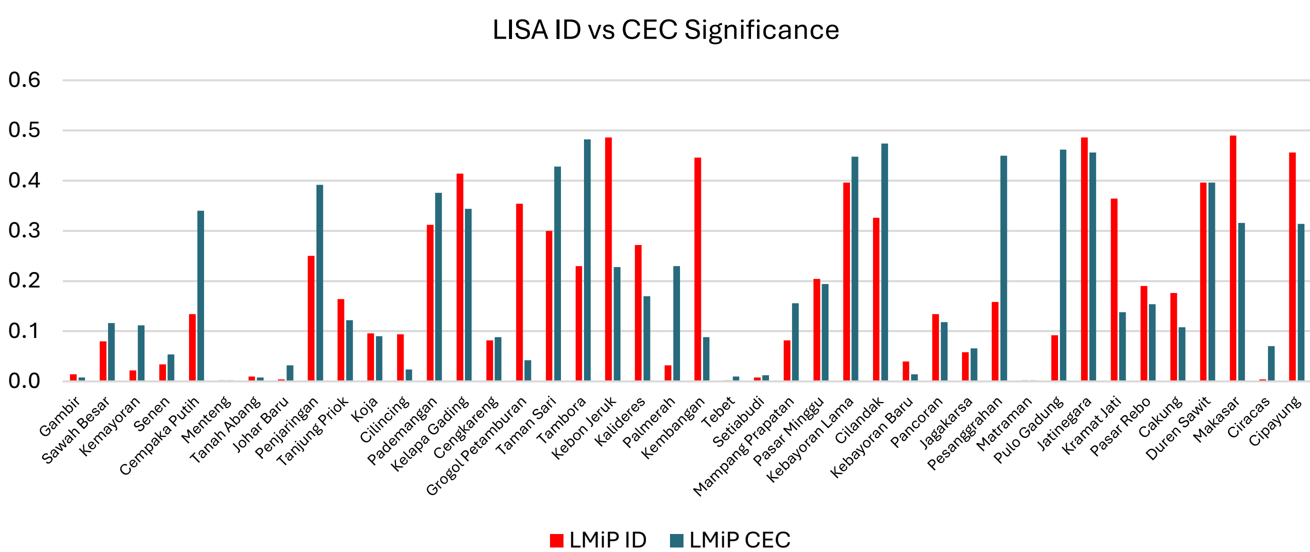

Figure 9. Graph of LISA significance values for the inverse distance and continuity edges corners approaches
Source: Analysis Results

Distribution and Inequality of Public Transport

Theoretically, built environment characteristics such as density and land use patterns, particularly built-up land, have a strong relationship with the availability and quality of public transport access (He et al., 2023). These findings are consistent with the research by An et al. (2022), which shows a significant relationship between population density, land structure, and mobility patterns with public transport use. In addition, the distribution of activities and education levels also shape the needs and availability of public transport services in a region (Hopson et al., 2024). Based on this rationale, a correlation test was used to assess the extent to which social, demographic, and physical variables per sub-district explain the patterns of distribution and spatial inequality in public transport detected by LISA.

Table 4. Correlation Table of Socio-Demographic and Physical Variables of the Region with the LISA Index of Public Transport Accessibility

Spatial Metrics	Number of Schools	Population Density	Population Density
CEC	-0.0174	-0.5226	0.0946
ID	-0.1074	-0.4353	-0.0054
Acc	-0.5123	-0.1412	-0.4631

Source: Analysis Results

The correlation results in Table 4 show that the relationship patterns between structural variables and LISA-based indices differ between spatial weighting methods. In the CEC approach, the number of schools has a very weak relationship (r = –0.0174), while population density shows a strong negative correlation (r = –0.5226) and built-up area has a very weak positive correlation (r = 0.0946). This indicates that LISA-CEC is more sensitive to physical boundary-based neighbourhood structures, making density the most dominant factor in forming spatial clusters, while the other two variables have minimal influence.

In contrast, the ID (inverse distance) method shows a weak negative relationship with the number of schools (r = –0.1074), a moderate negative relationship with density (r = –0.4353), and a relationship close to zero with built-up area (r = –0.0054). Distance-based weights cause the influence of neighbours to be more widespread and stable, so that physical variables such as built-up area no longer have a strong contribution to local autocorrelation variation.

For the accessibility variable (Acc), the correlation is strongly negative towards the number of schools (r = –0.5123) and built-up area (r = –0.4631), and weakly negative towards population density (r = –0.1412). This indicates that more built-up areas with more educational facilities tend to have lower accessibility inequality (more homogeneous structure), while less built-up areas have higher accessibility inequality.

Public Transport Development Priorities

Spatial analysis using Moran's I and LISA confirms that public transport distribution in DKI Jakarta remains highly unequal. Both inverse distance and contiguity edges-corners methods produce significantly positive Moran's I values, showing clear clustering of high-access and low-access areas, similar to patterns observed in Porto (Rocha et al., 2023). LISA maps reinforce this by identifying High–High clusters in central Jakarta (Gambir, Tanah Abang, Menteng) and Low–Low clusters in suburban areas of East, South, North, and West Jakarta, indicating structural—not random—spatial disparities.

Policy interventions should prioritize subdistricts consistently classified as Low–Low or Low–High. In East Jakarta, Cipayung and Pasar Rebo require additional TransJakarta corridors or feeder services due to expanding residential areas that remain underserved. In South Jakarta, Jagakarsa and Cilandak would benefit from MRT or LRT network extensions, supported by urban improvements such as public spaces to encourage ridership (Ceysara & Aji, 2025). In North Jakarta, Cilincing and Koja show internal spatial inequality under the contiguity approach, highlighting the need to enhance connections between commuter rail, buses, and other modes, consistent with findings by Carroll et al. (2021). In West Jakarta, Kembangan and Cengkareng exhibit low or insignificant cluster values, indicating uneven development and the need to strengthen west–east transport connectivity.

Strategic recommendations include expanding TransJakarta corridors, extending MRT and LRT lines to non-central districts, and improving feeder networks as emphasized by Vahia & Shukla (2021). Integrated routes and ticketing systems are also essential to ensure seamless multimodal travel. Additionally, incentives for private operators, according to Rodriguez-Valencia et al. (2023), can accelerate service expansion to low-access areas. Ensuring that public transport is accessible, affordable, and efficient across all regions will help reduce spatial inequality and promote inclusive, sustainable urban mobility.

CONCLUSION

Spatial analysis of public transport distribution and accessibility in DKI Jakarta demonstrates clear spatial inequality. Central Jakarta and parts of South and West Jakarta show high service density, while peripheral areas, particularly East and North Jakarta, remain underserved. Moran's I confirms statistically significant clustering, and LISA maps highlight High–High clusters in the urban core and Low–Low or Low–High clusters in suburban areas.

Comparing the two spatial-weight conceptualizations, inverse distance more accurately captures distance-based mobility realities, whereas contiguity edges-corners remains useful for identifying administrative-based spatial interactions and detecting finer local variations. The integration of both methods therefore enables a more comprehensive understanding of public transport accessibility inequality from geographical and governance perspectives.

Based on these spatial patterns, public transport development should prioritize peripheral areas with consistently low accessibility to promote mobility equity and spatial justice. Future research is encouraged to incorporate additional dimensions, such as service quality, frequency, affordability, and user satisfaction, and integrate socio-economic and time-series data for a deeper understanding of Jakarta's evolving transport accessibility.

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