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# Evaluating Built Environment Factors as Determinants of Public Transport Mode Share in Uyo Urban Area, Nigeria

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**Abstract**
This study investigates the key factors influencing public transport mode shares in Uyo Urban area, Akwa Ibom State, Nigeria, with a focus on understanding the role of the built environment factors on public transport mode shares. The study employed a mixed-method approach, utilizing a structured survey for data collection, capturing key variables such as population density, transit supply, road network density, and commuter preferences. Data were analyzed using Principal Component Analysis (PCA), Multiple Linear Regression, and Geographically Weighted Regression (GWR) to explore spatial and non-spatial relationships between the identified factors and public transport usage. The PCA revealed three key components influencing public transport mode share: accessibility and infrastructure quality (39.36%), environmental constraints (15.15%), and mobility and Travel behaviour (13.15%). Regression analysis indicated that environmental constraints were the most significant predictor, followed by mobility and travel behaviour and accessibility and infrastructure quality. The GWR analysis highlighted spatial heterogeneity, showing that the impact of these factors varied across different neighbourhoods within Uyo urban. The findings suggest that improving infrastructure, addressing environmental constraints, and aligning public transport systems with commuter behaviours are crucial for increasing public transport usage. Policy recommendations include enhancing transit supply, improving road connectivity, mitigating environmental challenges, and tailoring services to commuter needs. The study underscores the importance of a multi-faceted approach to public transport planning that considers both infrastructure and socio-environmental factors to improve public transport adoption and sustainability in Uyo Urban and similar urban contexts.

**Key Words:** Public Transport Mode Share, Built Environment, Uyo Urban Area, Spatial Analysis and Principal Component Analysis (PCA)

## 1 Background to the Study

The rapid growth of urban populations is one of the most significant trends of the 21st century. Projections suggest that by 2050, over two-thirds of the global population will live in urban areas (UN, 2022). This demographic shift places enormous pressure on cities to efficiently manage resources while addressing critical transportation and urban mobility challenges. One of the most pressing environmental and social challenges today is managing the mobility of people and goods. By 2030, passenger traffic is expected to exceed 80,000 billion passenger-kilometresa fifty percent increase while freight volume is projected to grow by 70 percent globally. Additionally, the number of vehicles on the road is forecasted to double by 2050, increasing the urgency for sustainable and integrated transportation solutions (Mohieldin and Vandycke, 2017). Regions such as India, China, sub-Saharan Africa, and South-east Asia are experiencing rapid urban expansion, accompanied by increasing mobility aspirations. This intensifies the demand for transportation systems (Mohieldinand and Vandycke, 2017). Failure to address these mobility challenges can result in worsening traffic congestion, environmental degradation, and socio-economic disparities. The transportation sector significantly contributes to urban air pollution and greenhouse gas emissions, underscoring the necessity of sustainable mobility solutions that promote public transit, reduce commute times, and minimize private vehicle dependence.

Urban mass transit systems play a crucial role in achieving sustainable, accessible, and equitable transportation, aligning with the United Nations Sustainable Development Goals (SDGs). These systems help reduce transport inequalities, improve road safety, and enhance energy efficiency—critical components of sustainable urbanization (World Bank, 2024). However, many cities in developing countries, including Nigeria, face significant barriers to implementing efficient transit networks, such as inadequate infrastructure, rising car ownership, and persistent congestion.

While extensive research on travel behaviour has been conducted in developed countries, including Europe and the United States, there is limited empirical evidence on transit mode choices in African cities. Studies by Boarnet

(2011) and Stevens (2016) explore the relationships between urban form and transport choices, with findings suggesting that compact urban designs encourage transit use (Ewing and Cervero, 2010; Bento *et al.*, 2005). In Latin America, Guerra *et al.* (2018) found that well-integrated transit systems in densely populated urban areas significantly reduced private vehicle dependency.

In Africa, studies on transport behaviour remain scarce but reveal important trends. Research on transport mode choices in Lagos by Olatoye and Oyelana (2019) shows that affordability drives public transport reliance, despite service limitations. Similarly, Fasina *et al.* (2020) found that travel time, safety, and comfort significantly influence mode choice decisions. These studies emphasize the need for targeted investments to enhance transit infrastructure and improve commuter satisfaction.

To address these challenges, researchers are increasingly applying advanced spatial modeling techniques such as geographically weighted regression (GWR). Unlike conventional regression methods, GWR captures spatial variations in transport behaviours, offering localized insights. Cardozo *et al.* (2012) used GWR to predict passenger demand at Madrid metro stations, while Blainey (2010) employed it to forecast rail trips in the UK. Liu and Niu (2023) similarly analyzed inter-city population movements in China using the Multiscale Geographically Weighted Regression (MGWR) model, demonstrating the importance of regional spatial linkages. However, despite its proven utility, GWR remains underutilized in African transport research. Applying GWR to study urban mobility in Uyo can provide more accurate insights into spatial variations in transit use, aiding policy formulation and infrastructure planning.

## 2 Theoretical Underpinning

Public transport mode share in urban areas is shaped by intra-city mobility, which encompasses both physical movement and spatial interactions. Intra-city mobility involves the movement of people and goods within an urban environment, facilitating daily commuting and economic activities. Such movement is not random but is influenced by specific forces (Lloyd and Dicken, 1972).

Ullman (1956) identified three fundamental principles governing urban mobility: complementarity, transferability, and intervening opportunity. Complementarity and transferability determine the feasibility of movement between two locations, while intervening opportunity affects travel volume and direction. These principles influence the efficiency of public transit systems in accommodating commuter flows. Public transport mode choice in Uyo Urban Area is largely determined by the relative accessibility of destinations, the quality of transport infrastructure, and the availability of alternative transit options (Abler *et al.*, 1972).

Urban land use patterns significantly impact intra-city mobility. Ogunbodede (2002) observed that urban mobility serves to bridge spatial gaps between residential areas and key activity centres such as workplaces, schools, and commercial hubs. The frequency of trips taken by urban residents is influenced by the concepts of range and threshold. Ayeni (1975) defined range as the maximum distance individuals are willing to travel to access services, while threshold refers to the minimum population needed to sustain a particular transport service.

In Uyo, land use characteristics including residential, commercial, institutional, and industrial zones generate movement patterns that influence public transport demand. The built environment factors that shape transit use, such as road network density, transit stop accessibility, land use diversity, and urban connectivity, play a crucial role in determining the efficiency of mass transit systems. Although emerging mobility solutions, such as ridesharing and non-motorized transport, are modifying travel patterns, public transit remains the dominant mode of commuting for most residents in Uyo. Understanding these relationships is essential for designing effective transit policies and infrastructure improvements.

This theoretical framework underscores the interconnections between urban land use, built environment factors, and public transport mode choice. It provides a foundation for analyzing determinants of public transit use and evaluating the spatial variations in transport behaviours within Uyo Urban Area.

## 3 Objectives of the Study

The main objectives of the study include the following:-

- To identify key built environment determinants that significantly influences public transport use in Uyo Urban
- To examine the relationship between built environment characteristics and public transport mode shares in Uyo Urban.
- To evaluate the spatial variations in the influence of built environment factors on public transport mode choice in Uyo Urban using GWR.

## 4 Geographical Setting of the Study Area

Uyo metropolis is located within longitude 7° 541 and 8° 001 east of the Greenwich and 4° 591 and 5° 141 north of the Equator (Figure 1). The study covers an area of 15 kilometres radius and is bounded by Nsit Ibom, Etinan, and Ibesikpo Asutan local government areas on the South, Uruan and Nsit Atai on the East, Itu, and Ibiono on the north and, Abak and Ibiono Ibom to the west. The Town is centrally located as the administrative center of Akwa

Ibom State, which cuts across eight other Local Government Areas of Etinan, Uruan, Itu, Ibiono, NsitIbom, NsitAtai, Nsit Ubium and Ibesikpo Asutan. It is easily accessible from other cities like Abak, Itu, Ikot Ekpene, Oron, Eket, and Etinan by road. The city can be reached under one hour driving from any part of the city and with improve roads, the time will considerably be reduced. The road from Aba to Calabar on the north-western flank of the capital city further promotes the accessibility of the city.

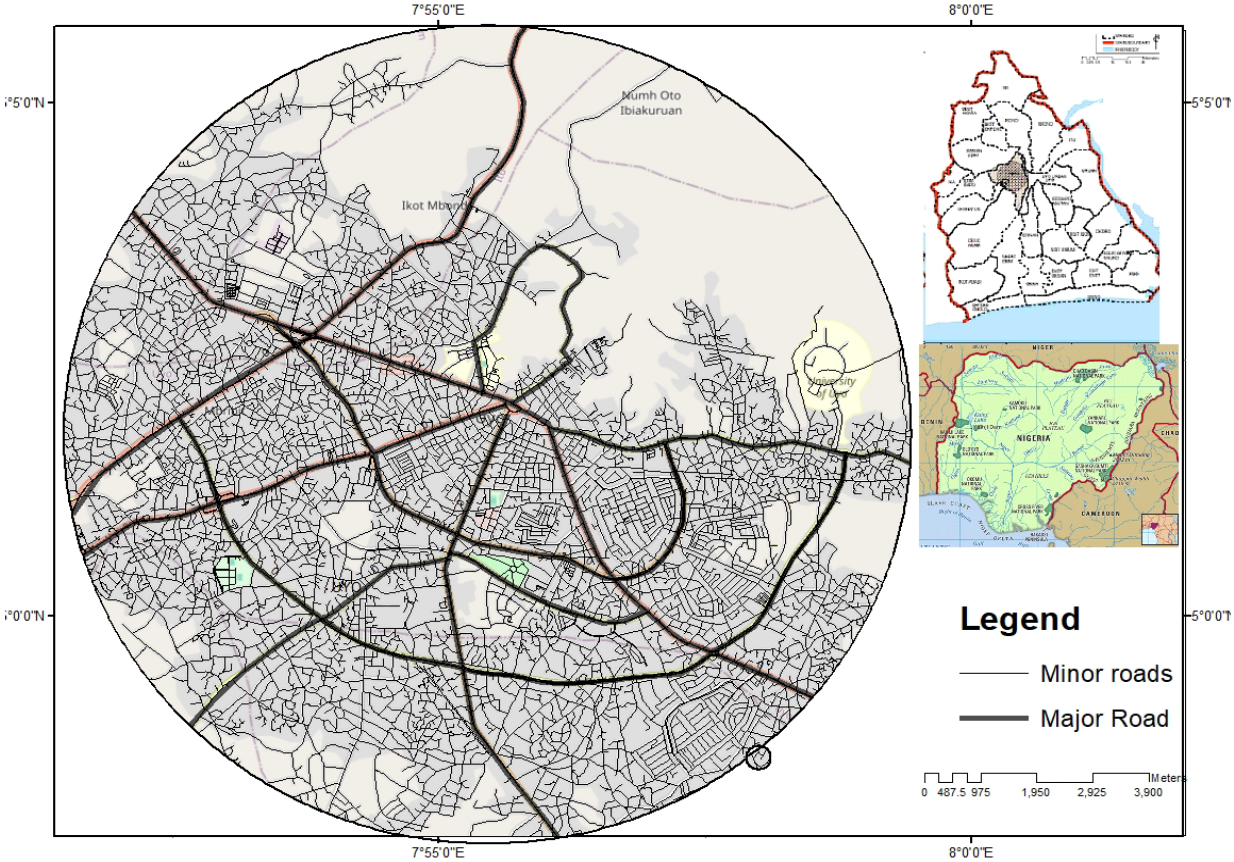


**Figure 1: Uyo Urban area showing the study Location**

## 5 Data and Software Availability

The data sources employed in this study are publicly available and are detailed in Table 2. The primary dataset was derived from OpenStreetMap (OSM, 2023), which provided comprehensive geographic data on the road network, public transport stops, and related infrastructure within the study area. To analyze and process the data, a range of software tools were utilized to ensure methodological robustness and spatial accuracy. SPSS (Version 2021) was employed for statistical procedures, particularly Principal Component Analysis (PCA), which enabled the identification of latent components influencing public transport mode choice.

**ArcGIS** served as the primary platform for spatial analysis and mapping, allowing for the generation of standardized residual maps, zonal computations, and integration of GWR results. Microsoft Excel was used for organizing raw datasets, conducting preliminary statistical summaries, and formatting data for import into other analytical platforms. Furthermore, Google Earth provided an open-access environment for geospatial visualization and verification of physical features on the ground, supporting ground-truthing and visual interpretation of spatial patterns. Collectively, these tools facilitated a seamless workflow from data acquisition through analysis to visualization, ensuring that the findings of the study are replicable and grounded in accessible, open-source, and standard analytical environments.

## 6 Materials and Method

This study utilized a survey-based research design, incorporating both primary and secondary data collection methods. It focused on examining macro- and micro-level factors of the urban built environment within the study area. A multi-stage sampling strategy was employed; combining purposive and simple random sampling techniques to ensure the dataset was both comprehensive and representative.

### 6.1 Data Types and Collection

Keymass transit indicators were derived from and calculated with the use of publicly available open datasets. These variables cover different aspects of both macro and micro urban built environment related to mass transit indicators. According to the literature, these include those variables as detailed in table 1. Some of these data were extracted from free Google earth source, online Population data. Some of the secondary data were updated and reformatted to yield new data used in the current analysis. The mass transit survey was conducted to capture mass transit behaviours within urban environments by using the manual traffic counter. The survey was taken place between the hours of 7.30 am and 7.30 pm during weekdays at each selected point, whereas the interview survey was formulated by using a specific guideline.

On the other hand, the inventory of macro built environment factors were outlined by a guideline adapted from the best practice of mass transit studies according to the identified elements, criteria and measures of the existing mass transit infrastructure. Spatial data were obtained from multiple sources, including GIS databases, open-access repositories, and field surveys. The main elements focused in both interview and inventory surveys are as shown in Table 1.

**6.2 Sampling Techniques and Data Collection** The sampling and data collection process are as follows:

**Stage 1:** Selection of Study Area and Delineation of traffic Analysis Zones
The Uyo Urban Area in Akwa Ibom State was purposively selected as the study area due to its relevance to the research objectives and its representativeness of urban transport patterns in the region. The study area was stratified into three distinct zones urban core, middle core, and outer corerepresenting varying levels of urbanization and transport dynamics.To facilitate detailed analysis, these zones were further subdivided into 33 Traffic Analysis Zones (TAZs), which served as the primary data collection units as shown in the figure 2 below:
The delineation of TAZs followed the "Network Bands" concept of neighbourhood as used by James and Ndehedehe (2014), which defines area units based on proximity along street networks. This approach considers natural and physical barriers to establish precise boundary definitions.

**Table 1:Public transport related variables**

| S/N | Variables | Definition of Variables | Unit of Measurement |
|---|---|---|---|
| 1 | Average Distance to Transit Stops | Measures how far people must travel to access transit | meters |
| 2 | Household size | The number of people living in a single household. | Number |
| 3 | Population density | Total number of people/ per $km^2$ | Pop/sq.m |
| 4 | Mean Household income | the average income of all households in a particular area | Naira |
| 5 | Mean Road width | The mean road width/ per $km^2$ | meters |
| 6 | Transit Supply | Measures availability of public transport services | Number |
| 7 | Educational level | Percentage of certain level of education | Percentage |
| 8 | Street density | Total number of street divided by the area of TAZ. | sq.m |
| 9 | Public Transport Stop Density | Number of transit stops per TAZ. | Number |
| 10 | Intersection density | the number of intersections TAZ. | Number |
| 11 | Public transport mode shares | public transport mode users | Number |

Author's field work, 2024

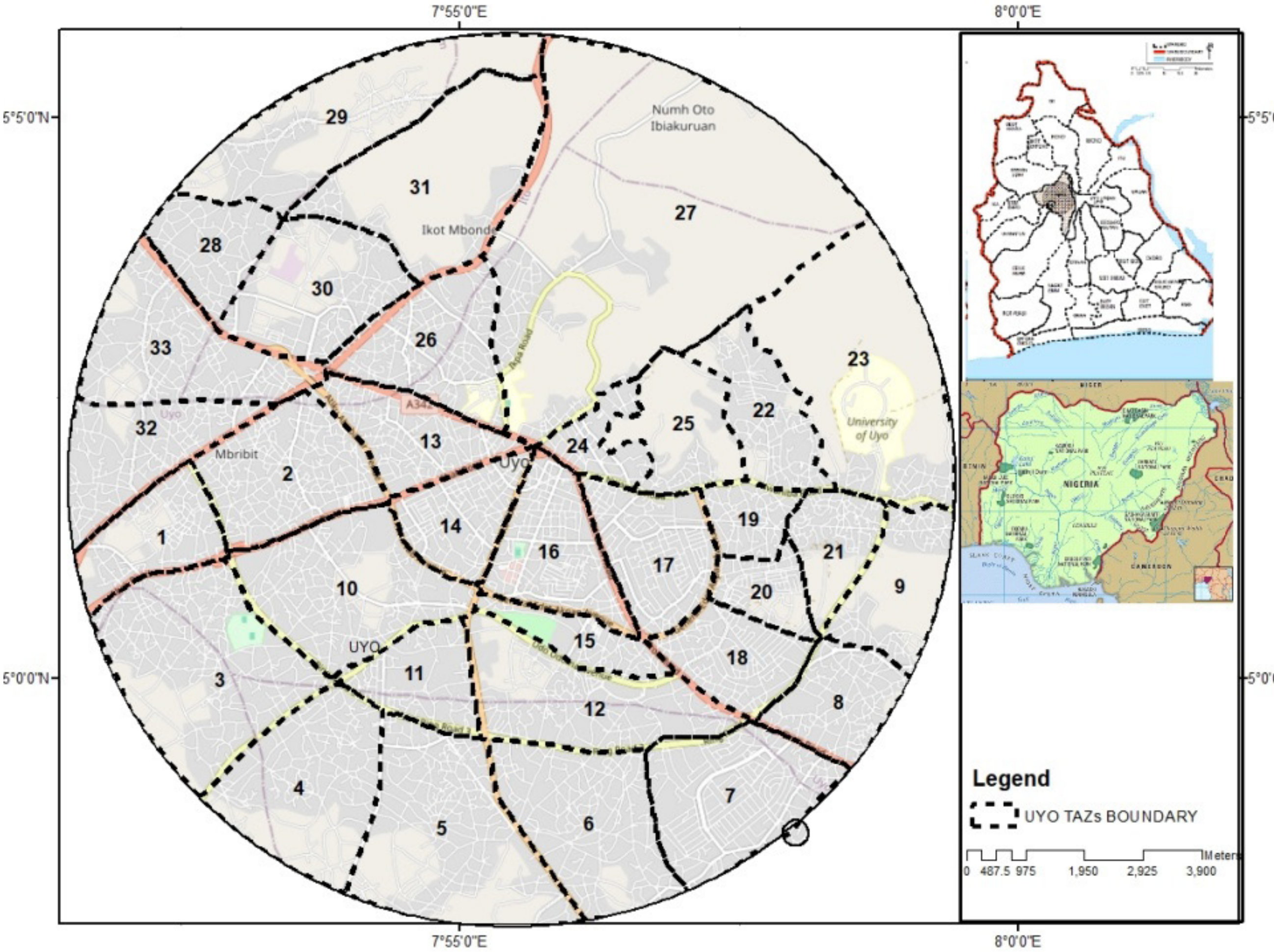


**Figure 2: Uyo Urban area showing the TAZs**

**Stage 2: Selection of Communities**

From the defined TAZs, 33 communitieswere purposively selected based on their socio-demographic characteristics, ensuring a comprehensive representation of factors influencing transport behaviour across the study area.

**Stage 3: Household Sampling and Questionnaire Administration**

Within each community, households were randomly selected to participate in the study. The sample size for each community was proportionally determined based on projected population figures. Population estimates were derived from the 2006 census and arithmetically projected to the end of 2023, applying a 2.5% annual growth rate as recommended by National Population Commission NPC (2006).

The total number of households in each community was used to calculate a representative sample size, employing a modified version of the Tarro Yamane formula. The final sample size was set at 575 households**.** However,580 questionnaires was correctly administered and returned valid, representing over 95% of the total questionnaires distributed, ensuring a robust response rate.

## 7 Methods of Data Analysis

This study employed a combination of analytical techniques, including PCA, MLR, and Geostatistics, with all statistical procedures conducted using the Statistical Package for the Social Sciences (SPSS). PCA was used to identify the key determinants influencing public transport mode choice among respondents within the study area. By reducing the dimensionality of the dataset, PCA extracted the most significant variables, thereby simplifying the dataset and highlighting the core factors driving variations in mode choice behaviour.

### 7.1 Factor Analysis

In this study, ten key variables identified as determinants of public transport mode choice were analyzed using Principal Component Analysis (PCA), a multivariate technique for dimensionality reduction. The analysis yielded three principal factors, which were subsequently used to compute factor scores. These scores served as input variables in the subsequent Multiple Linear Regression (MLR) analysis.

The Kaiser criterion guided the selection of the optimal number of factors to retain. According to this rule, only factors with eigenvalues greater than one should be extracted from the correlation matrix (DeCoster, 1998).

The extraction of factors was carried out using the principal components method. To enhance the interpretability of the resulting factors, a varimax orthogonal rotation was applied. This rotation technique maximizes the loading of each variable on a single factor, ensuring that each factor is strongly associated with a specific subset of variables.

### 7.2 Factors Influencing public Mode share in Uyo Urban

To identify the most significant factors influencing public Mode share, a PCA with varimax rotation was performed, considering ten variables such as estimated population, intersection density, transit supply, distance to transit stops, population density, household size, public transport stop density. Mean road width. Street density and mean household income. The results showed that three factors explained 80.032% of the variance in public Mode share (see Table 5). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0. 664, and Bartlett's test of sphericity was significant (Chi-Square = 472.228, p = 0.000), indicating that the data was suitable for factor analysis.

**Table 2: KMO and Bartlett's test for the pedestrian variables**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .638 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 472.228 |
| | Df | 55 |
| | Sig. | .000 |

Source: Author's statistical analysis (2024)

**Table 3: Components extracted**

| Components | Eigen Value | % Contribution |
|---|---|---|
| *Accessibility and Infrastructure Quality* | 3.936 | 39.355 |
| *Environmental Constraints* | 1.515 | 54.503 |
| *Mobility and Travel Behavoiur* | 1.316 | 67.658 |

Source: Author's statistical analysis (2024)

**Table 4: Components Extracted**

| Component matrix | | | | Rotated Component Matrix | | | Communalities |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 1 | 2 | 3 | .837 |
| Estimated Population | .892 | -.165 | .121 | .820 | .404 | | .523 |
| Intersection density | .626 | .206 | -.299 | .693 | -.191 | | .747 |
| Transit Supply | .579 | .496 | .407 | .566 | | .653 | .499 |
| Distance to Transit Stops(X4 | .699 | | | .690 | | .116 | .588 |
| Population density | .745 | | | .766 | | | .634 |
| Household size | .763 | | | .793 | | | .829 |
| Public Transport Stop Density | .899 | -.128 | -.128 | .348 | .348 | | .721 |
| Mean road width | .170 | -.738 | -.738 | .839 | .839 | -.132 | .896 |
| Street density | -.191 | .558 | .558 | | .691 | .916 | .491 |
| Mean Household income | .259 | -.490 | -.490 | | | | .837 |
| Total | | | | 3.936 | 39.355 | 39.355 | |
| % of Variance | | | | 1.515 | 15.148 | 54.503 | |
| Cumulative % | | | | 1.316 | 13.155 | 67.658 | |

Source: Author's statistical analysis (2024)

From Table 4 above, the data on ten determinants variables from the field however, produced three (3) components with Eigen values exceeding 1, which together accounted for a total of 67.658**% of** the variance explained. The rotated solution showed that 9 variables loaded positively and 1 negatively on the first component, 2 variables loaded positively and negatively on the second component while 2 variables loaded positively and negatively on the third component respectively. After identifying the component loadings and the variables they represent, the components were given titles that closely describe the pattern or structure of the positive loadings.PCA was conducted to identify key underlying dimensions influencing public transport mode share. Three components with eigenvalues greater than 1.0 were extracted, explaining a cumulative variance of 67.658%. The rotated component matrix and communalities are presented in Table4

Component 1: Accessibility and Infrastructure Quality explained 39.36% of the total variance. It included strong loadings from variables such as (Estimated Population (X1) Intersection density (X2,), Transit Supply(X3),Distance to Transit Stops(X4), Population density(X5),Household size(X6) Public Transport Stop Density X7 Mean road width(X8) Mean Household income (X10) and public). This factor captures features of the built environment that enhance or constrain public transport access.

Component 2: Environmental Constraints, accounting for 15.15% of the variance, had high loadings from Mean road width(**X8)** and Street density(**X9)**, which may reflect contextual variables like crime, noise, or socio-political disruptions, which can discourage public transport use.

Component 3: Mobility and Travel Behaviour, which explained 13.15%, was characterized by loadings from Mean road width(**X8)** and Street density(**X9)**, suggesting a focus on user commuting patterns, preferences, and possibly travel time or frequency.Communalities ranged from 0.491 to 0.896, indicating that the extracted components adequately represent the variance in most of the original variables.

### 7.3 Multiple Linear Regression Estimation

To investigate the influence of the key determining factors on public transport mode shares. Three main factors that emerged from the factor analysis were employed further in multiple linear regression analyses. The factor scores were saved and used as dependent variables of public transport mode shares as shown in Table 5.

Multiple linear regression analysis was conducted using the factor scores as predictor variables against public transport mode shares.The dependent variable in the regression model was public transport mode shares **(Y)**, while the independent variables are the key determinants identified. The regression model was structured as:

$$Y = \beta o + \sum \beta ini{=}1\ Xi + e \qquad (1)$$

The above equation can be further expressed as follows;

$$Y = \beta o + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5 + \beta 6X6 + \beta 7X7 + e \qquad (2)$$

where**Y** denotes Public Transport Mode Share, X is the independent variable (i.e., *accessibility and infrastructure quality, environmental constraints, mobility and travel behaviour*); $\beta o$ is the intercept constant term; $\beta$ = slopes coefficients. $e$ is the constant term, k x denote the explanatory variables, 1 tok are the coefficients associated with k explanatory variables. The regression outputs are presented in Tables 5-6 below.

**Table 5: Model Summary of Regression Analysis**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | 713[a] | . .508 | .457 | 74.40855 | .508 | 9.977 | 3 | 29 | .000 |

Source: Author's statistical analysis (2024)

**Table 6: Coefficients[a]**

| Model | Unstandardized Coefficients | | Standardized Coefficients | T | Sig. | 95% Confidence Interval for B | | Correlations | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | B | Std. Error | Beta | | | Lower Bound | Upper Bound | Zero-order | Partial | Part |
| (Constant) | 264.950 | 12.953 | | 20.455 | .000 | 238.458 | 291.441 | | | |
| Factor 1 | 35.972 | 13.154 | .356 | 2.735 | .011 | 9.070 | 62.874 | .356 | .453 | .356 |
| Factor 2 | 48.189 | 13.154 | .477 | 3.664 | .001 | 21.287 | 75.091 | .477 | .562 | .477 |
| Factor 3 | 39.528 | 13.154 | .391 | 3.005 | .005 | 12.626 | 66.431 | .391 | .487 | .391 |

a. Dependent Variable: Traffic Volume

Source: Author's statistical analysis (2024)

### 7.4 Regression Analysis Results

A multiple linear regression analysis was conducted to examine the influence of three underlying factors on public transport mode shares. The model was found to be statistically significant, $F(3, 29) = 9.977$, $p < .001$, indicating that the combination of the predictors reliably explained variation in public transport mode shares. The model produced an R value of 0.713, suggesting a strong positive relationship between the independent variables and the dependent variable. The R Square value of 0.508 implies that approximately 50.8% of the variance in public transport mode shares is accounted for by the three factors combined. After adjusting for the number of predictors, the adjusted R Square value stood at 0.457, indicating a moderately strong model fit.

Further examination of the coefficients revealed that all three factors made significant contributions to the model. Factor 1 had an unstandardized coefficient (B) of 35.972 ($p = .011$), suggesting that a one-unit increase in this factor is associated with a 35.972-unit increase in public transport mode shares, holding other variables constant. Factor 2 was the most influential predictor, with a coefficient of 48.189 ($p = .001$), while Factor 3 contributed with a coefficient of 39.528 ($p = .005$). The standardized beta coefficients for Factor 1 ($\beta = .356$), Factor 2 ($\beta = .477$), and Factor 3 ($\beta = .391$) further indicate that Factor 2 had the greatest relative effect on traffic volume, followed by Factors 3 and 1, respectively.

All predictors had statistically significant t-values, and their 95% confidence intervals did not include zero, reinforcing the reliability of their contributions to the model. The standard error of the estimate was 74.41, indicating the average deviation of observed traffic volume values from the predicted values. In summary, the regression model demonstrates that the identified factors significantly and positively influence public transport mode shares in the study area. These findings underscore the importance of the examined variables in shaping traffic conditions and provide a quantitative basis for policy and planning interventions.

## 7.5 Geographically Weighted Regression (GWR) Estimation

To achieve this objective, we employed GWR, a technique that allows for the exploration of spatial heterogeneity in the relationships between built environment factors and public transport mode choice across Uyo Urban. This method was chosen to examine how different urban characteristics, such as population density, road network density, and proximity to public transit, influence public transport use differently in various parts of the city.

The study area was delineated into TAZs, which served as the spatial units for the analysis. TAZs are commonly used in transportation planning studies as they aggregate travel behaviour and urban characteristics in a way that aligns with transportation and land use patterns. These zones were selected to provide a meaningful scale for analyzing public transport mode share at a localized level.

## 7.6 Data Preparation

Built environment variables as documented in table 1 were collected in each TAZ. To reduce multicollinearity and simplify the analysis, PCA was performed on the set of built environment variables. This technique helped identify underlying patterns and reduced the dimensionality of the dataset.Component scores were calculated for each TAZ, which quantified the strength of the various latent factors. These component scores were then used as independent variables in the GWR model to assess their relationship with public transport mode share.

The study applied GWR to assess the spatial variations in the relationship between the built environment factors (represented by the PCA-derived component scores) and the public transport mode share at the TAZ level. GWR allows for the estimation of separate regression coefficients for each spatial unit, offering insights into how the effect of each built environment factor varies across the urban landscape.

The public transport mode share was treated as the dependent variable, while the PCA component scores served as independent variables. The adaptive kernel method was employed to optimize the bandwidth of the GWR model, ensuring that spatial variations in the relationship were accurately captured. The bandwidth selection was guided by minimizing the Akaike Information Criterion (AICc).

## 7.7 Spatial Visualization of Results

The results from the GWR analysis were visualized through thematic maps, which displayed the local regression coefficients for each TAZ. These maps provided a clear picture of spatially varying relationships, showing areas where certain built environment factors had stronger or weaker influences on public transport mode choice as shown in Figure 3a-c below:

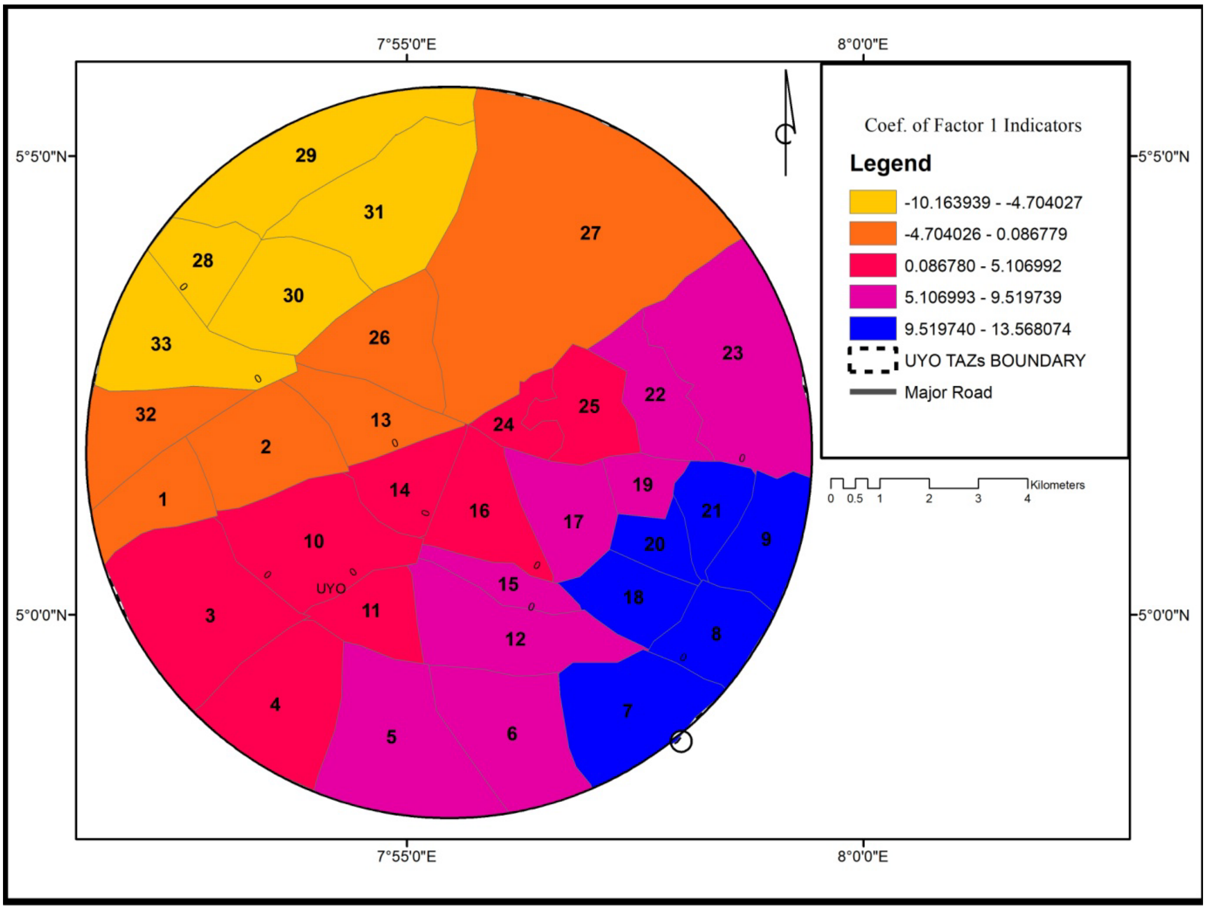


**Figure 3(a) Showing** *accessibility and infrastructure quality* **in Uyo Urban area**

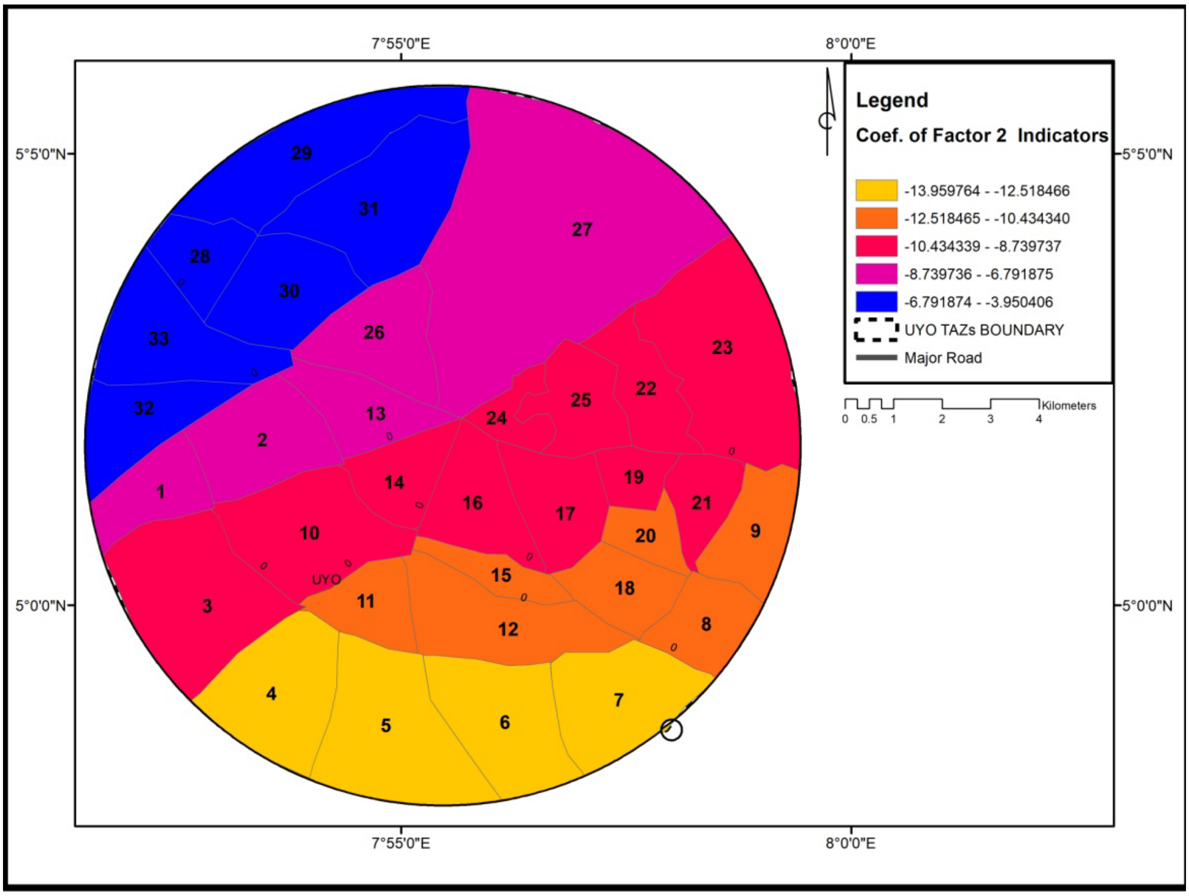


**Figure 3(b) Showing distribution of** *environmental constraints* **in Uyo Urban area**

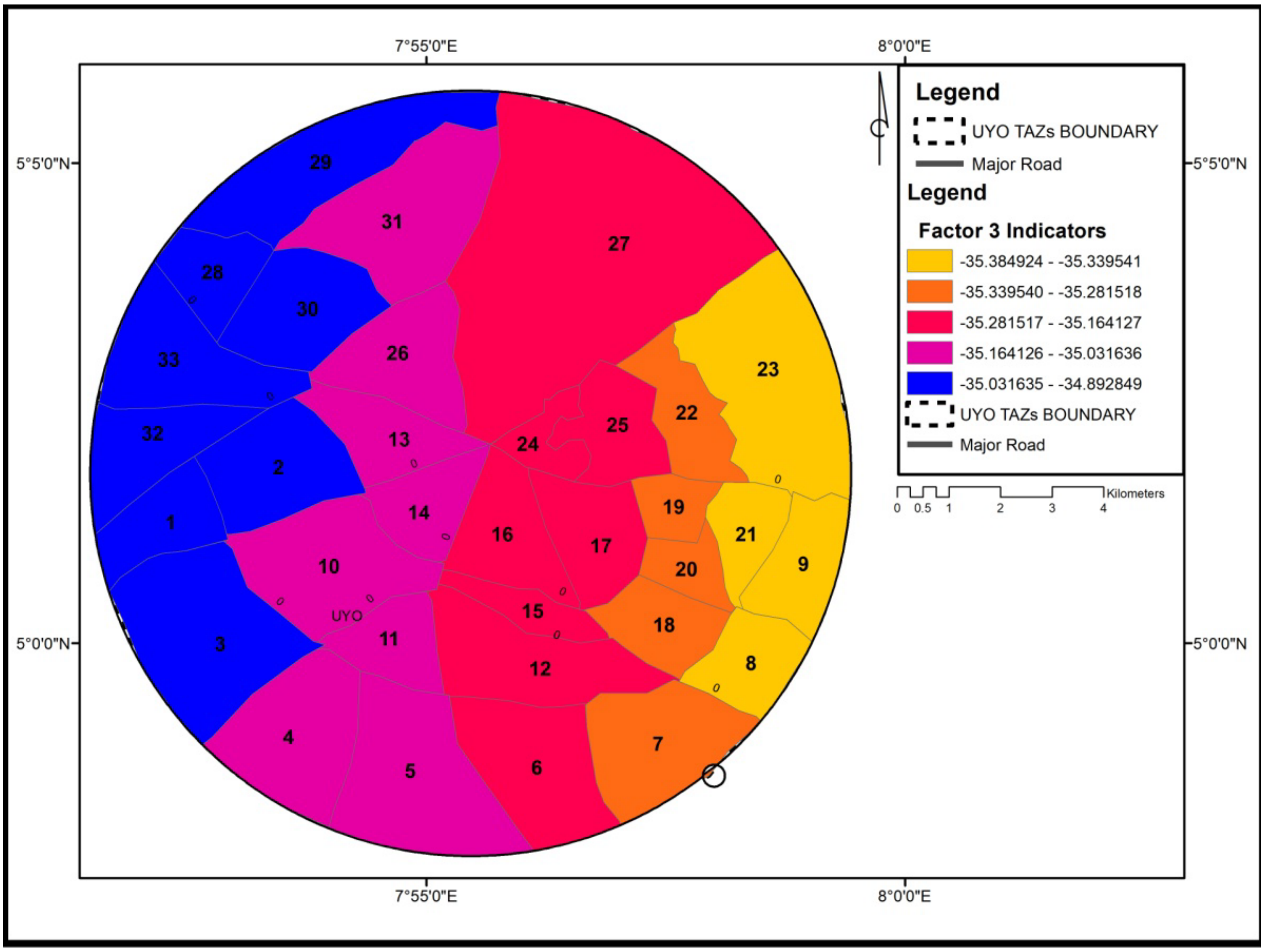


**Figure 3(c) Showing distribution of mobility behavior factors in Uyo Urban area**

The spatial variation in the influence of built environment factors on public transport mode choice in Uyo Urban was examined using GWR. The results, presented in three thematic maps (Figure 3(a-c)), reveal substantial spatial heterogeneity, indicating that the effects of built environment characteristics on public transport use differ considerably across TAZs within the study area.

Figure 3(a) illustrates the spatial distribution of the local coefficients for the first built environment factor. The map shows both positive and negative associations with public transport mode choice across the urban space, suggesting that this factor encapsulates characteristics such as road network connectivity, land use compactness, and transit accessibility. Zones located in the south-eastern and central parts of Uyo particularly Zones 7, 9, 18, and 20 exhibit high positive coefficient values. This implies that the built environment in these areas is conducive to public transport use. Conversely, the north-western zones, including Zones 28 to 33, show negative coefficient values, indicating that built environment conditions in these areas may be less favourable for public transport, potentially due to low population density, limited transit services, or car-dependent infrastructure.

Figure 3(b) presents the local coefficients for the second built environment factor, which uniformly exerts a negative influence on public transport mode choice across all TAZs. Although the direction of influence remains consistent, the strength varies spatially. The strongest negative impacts are observed in the southern zonesparticularly Zones 4, 5, 6, and 7 suggesting that these areas may be characterized by urban sprawl, poor pedestrian infrastructure or limited transit coverage. In contrast, the north-western zones, such as Zones 29, 30, and 31, still exhibit negative coefficients but with relatively weaker magnitudes, possibly are reflecting more neutral or transitional built environment conditions.

Overall, the thematic maps underscore the presence of significant spatial heterogeneity in the built environment's influence on public transport mode choice. These findings point to the need for location-specific planning interventions. While transit-supportive zones may benefit from reinforcing existing infrastructure and services, zones where the built environment poses barriers to public transport use require targeted improvements. The spatial insights provided by the GWR and the accompanying maps offer a strong empirical foundation for evidence-based land use planning, infrastructure investment, and policy formulation aimed at promoting sustainable urban mobility in Uyo Urban.

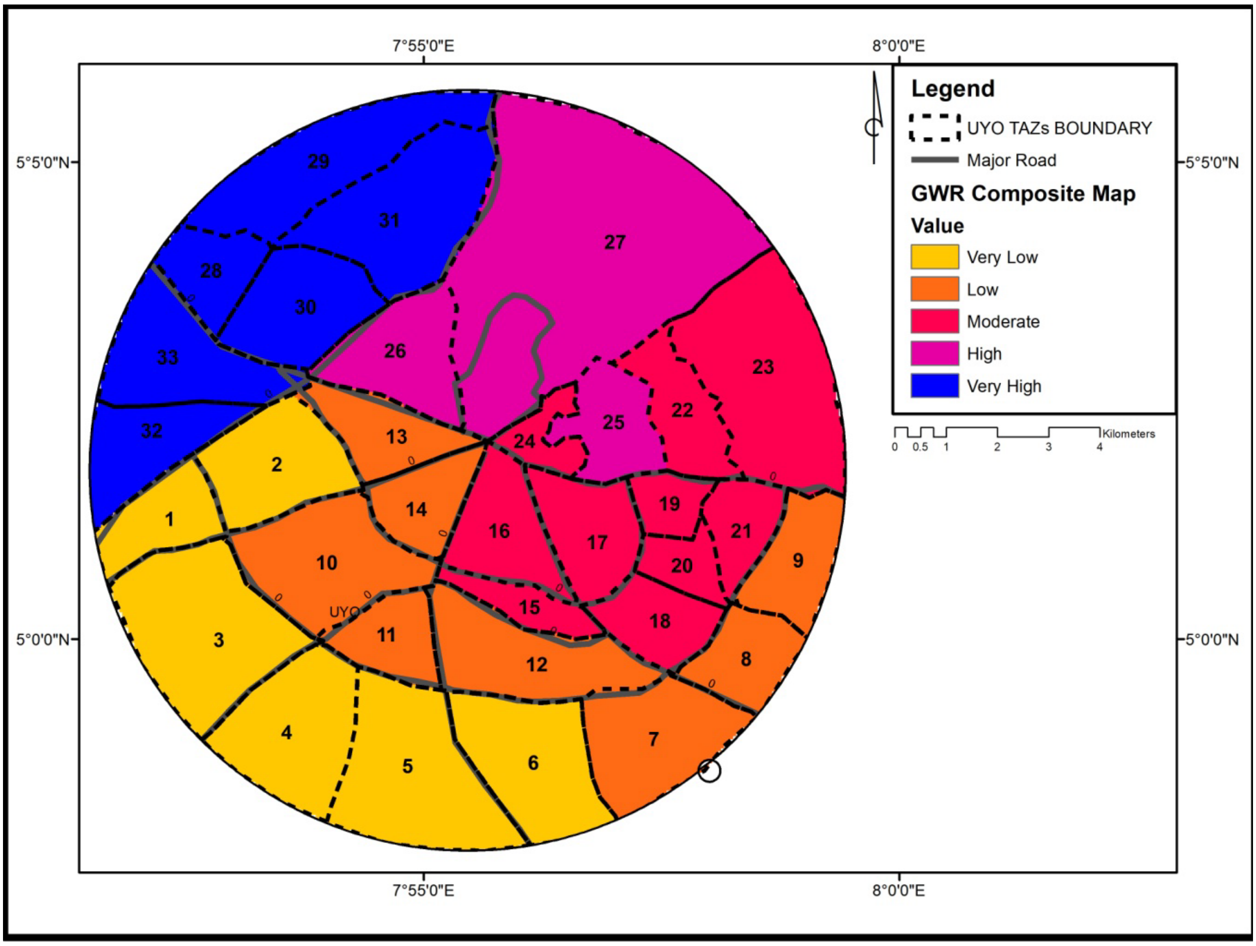


**Figure 4: The WGR composite map of public transport mode determinants inUyo Urban**

The Figure 4 above illustrates the spatial distribution of factors influencing public transport mode share across Uyo Urban Area. The composite map illustrates the spatial variation of key built environment factors across TAZs in Uyo. TAZs 9, 10 and 5 for instance, reflect higher concentrations of positive built environment attributessuch as dense road networks, mixed land use, and access to transit conditions that are likely to encourage greater public transport mode share.

Conversely, lighter zones TAZs 27, 28 and 31exhibitslower built environment scores, indicating spatial disadvantage or car-oriented environments, which may discourage public transport use and increase reliance on private vehicles or walking for longer distances.This spatial disparity confirms that public transport mode share is not evenly distributed across the urban area, and is strongly influenced by built environment characteristics. Areas with higher scores align with transit-supportive urban form, reinforcing the study's hypothesis that built environment plays a critical role in shaping transport behaviour.

The analysis reveals notable spatial disparities across the TAZs. Zones with high positive deviations (red shades) are concentrated in areas with robust infrastructure and high road network density, suggesting efficient public transport service coverage. In contrast, zones with low or negative deviations (blue shades) are predominantly located on the urban periphery or in regions with limited connectivity, highlighting the need for targeted interventions to enhance public transport accessibility and service delivery.

The WGR model underpins the spatial analysis, transforming quantitative findings into a spatially explicit representation. This approach provides a clear visualization of how determinants influence public transport mode share across the urban landscape, thereby facilitating the identification of priority intervention areas.

## 8 Discussion of Findings

**Geographically Weighted Regression (GWR) Results**

The GWR analysis provided valuable spatial insights, revealing spatial heterogeneity in the relationships between built environment factors and public transport mode choice across Uyo Urban. By utilizing TAZs, the analysis highlighted how the impact of factors like population density, road network density, and proximity to public transit varied across different areas of the city. The GWR model, optimized by minimizing the Akaike Information Criterion (AICc), captured spatial variations in how built environment factors influence public transport mode share. The thematic maps produced from the analysis showed that in some TAZs, factors such as accessibility and infrastructure qualityspecifically transit supply and proximity to transit stopshad a stronger impact on public transport use, whereas in other areas, environmental constraintslike street density and road width played a more significant role. These findings suggest that public transport policies and interventions must be tailored to the specific characteristics of each neighbourhood to address spatial disparities in public transport usage.

### 8.1 Policy Implications

The findings from this study have important implications for public transport policy and planning in Uyo Urban. First, improving accessibility and infrastructure qualityis essential for boosting public transport usage. Investments in expanding transit supply, enhancing road connectivity, and ensuring that transit stops are more accessible to residents can significantly improve public transport demand.

Second, addressing environmental constraintsespecially in areas with high road widths and street densitiescan help alleviate factors that discourage public transport use. This might involve improving urban safety, reducing noise pollution, and addressing socio-political challenges that hinder the attractiveness of public transport.

Lastly, the analysis of mobility and travel behaviouremphasizes the importance of aligning public transport systems with commuter preferences. This includes minimizing travel times and offering flexible schedules that cater to commuter needs. Understanding and adapting to commuter behaviours is key to improving public transport service delivery and making it a more appealing option.

## 9 Conclusion

This study demonstrates that public transport mode share in Uyo Urban is influenced by a combination of accessibility, environmental factors, and commuter behaviours. The findings from the PCA, regression analysis, and GWR highlight the need for a multi-dimensional approach to public transport planningone that considers not only infrastructure improvements but also the social, environmental, and behavioural contexts that shape commuting patterns. Tailoring interventions to the specific needs and characteristics of different neighbourhoods is essential to fostering sustainable and efficient public transport systems in Uyo Urban and similar urban settings.

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## APPENDICES

### Appendix I

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .527 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 147.573 |
| | df | 45 |
| | Sig. | .000 |

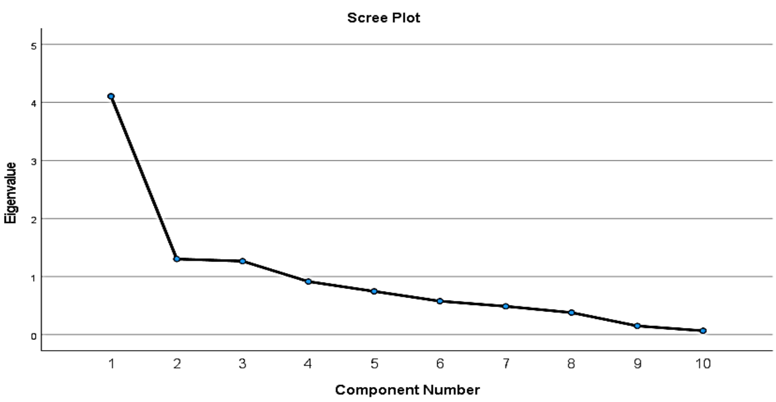
### Appendix 11

**Total Variance Explained**

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 4.107 | 41.072 | 41.072 | 4.107 | 41.072 | 41.072 | 4.101 | 41.011 | 41.011 |
| 2 | 1.303 | 13.030 | 54.102 | 1.303 | 13.030 | 54.102 | 1.304 | 13.036 | 54.047 |
| 3 | 1.266 | 12.664 | 66.766 | 1.266 | 12.664 | 66.766 | 1.272 | 12.719 | 66.766 |
| 4 | .915 | 9.149 | 75.915 | | | | | | |
| 5 | .746 | 7.461 | 83.376 | | | | | | |
| 6 | .577 | 5.771 | 89.147 | | | | | | |
| 7 | .488 | 4.882 | 94.029 | | | | | | |
| 8 | .380 | 3.800 | 97.829 | | | | | | |
| 9 | .150 | 1.501 | 99.330 | | | | | | |
| 10 | .067 | .670 | 100.000 | | | | | | |

Extraction Method: Principal Component Analysis.

### Appendix I11



**Appendix IV**

| Rotated Component Matrix[a] | | | |
|---|---|---|---|
| | Component | | |
| | 1 | 2 | 3 |
| X7 | .882 | | -.246 |
| X1 | .880 | | -.159 |
| X6 | .762 | | |
| X5 | .760 | | |
| X4 | .701 | .120 | .237 |
| X2 | .657 | -.108 | .269 |
| X9 | -.235 | .907 | |
| X3 | .554 | .666 | |
| X8 | .231 | | .782 |
| X10 | .231 | | -.658 |

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 4 iterations.

**Appendix** v

**Coefficients**[a]

| | | Unstandardized Coefficients | | Standardized Coefficients | | | 95.0% Confidence Interval for B | | Correlations | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Model | | B | Std. Error | Beta | t | Sig. | Lower Bound | Upper Bound | Zero-order | Partial | Part |
| 1 | (Constant) | 264.950 | 12.953 | | 20.455 | .000 | 238.458 | 291.441 | | | |
| | Factor Scores 1 | 35.972 | 13.154 | .356 | 2.735 | .011 | 9.070 | 62.874 | .356 | .453 | .356 |
| | Factor Scores 2 | 48.189 | 13.154 | .477 | 3.664 | .001 | 21.287 | 75.091 | .477 | .562 | .477 |
| | Factor Scores3 | 39.528 | 13.154 | .391 | 3.005 | .005 | 12.626 | 66.431 | .391 | .487 | .391 |

a. Dependent Variable: Public Transport mode Share

**Appendix** v1

**Model Summary**[b]

| | | | | | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .713[a] | .508 | .457 | 74.40855 | .508 | 9.977 | 3 | 29 | .000 |

a. Predictors: (Constant), Factor Scores3, Factor Scores 2, Factor Scores 1
b. Dependent Variable: Public Transport mode Share

**Appendix** v11

**ANOVA[a]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 165716.908 | 3 | 55238.969 | 9.977 | .000[b] |
| | Residual | 160562.348 | 29 | 5536.633 | | |
| | Total | 326279.256 | 32 | | | |

a. Dependent Variable: Public Transport mode Share
b. Predictors: (Constant), Factor Scores3, Factor Scores 2, Factor Scores 1

**Appendix** v111

| **S/N** | *Accessibility and Infrastructure Quality* | *Environmental Constraints* | *Mobility and Travel Behaviour* | **Public Transport Mode Share** |
|---|---|---|---|---|
| 1 | .00636 | .24750 | .19650 | 300.00 |
| 2 | .29243 | 1.38387 | 1.63815 | 380.00 |
| 3 | -.41524 | -1.50749 | -.83234 | 370.00 |
| 4 | .52015 | -.49448 | -1.03116 | 305.00 |
| 5 | -.56327 | -1.07070 | -1.44746 | 400.00 |
| 6 | -.29890 | -.86230 | -.68414 | 427.00 |
| 7 | .80690 | .32335 | -1.08710 | 293.00 |
| 8 | -.40940 | -1.10950 | .84872 | 200.00 |
| 9 | 2.26393 | .23200 | -1.13485 | 425.00 |
| 10 | -.78681 | .25926 | -.65997 | 385.00 |
| 11 | 3.32621 | -.47711 | .21315 | 385.00 |
| 12 | .27994 | .61411 | -.29821 | 234.00 |
| 13 | .58163 | -.63098 | -.12123 | 275.00 |
| 14 | -.33711 | 3.03058 | .45545 | 285.00 |
| 15 | -.59807 | .94566 | -.79786 | 191.00 |
| 16 | -.57092 | .27705 | .82577 | 350.00 |
| 17 | -.25916 | -.29759 | -.09828 | 356.00 |
| 18 | -.86398 | .05025 | .19717 | 358.00 |
| 19 | -1.22892 | 1.28024 | -.66704 | 373.00 |
| 20 | -1.25055 | .84348 | .25168 | 229.00 |
| 21 | -.69685 | -.69051 | -.08996 | 295.00 |
| 22 | -1.01703 | .10840 | 1.52264 | 103.00 |
| 23 | -.78372 | -.50645 | -.39568 | 457.00 |
| 24 | -1.27744 | -1.83619 | .59832 | 336.00 |
| 25 | .06921 | .95737 | -1.42007 | 320.00 |
| 26 | 1.44769 | -.24901 | 2.32035 | 242.00 |
| 27 | 1.07224 | -.08733 | .11633 | 170.00 |
| 28 | .80350 | .36712 | 1.89366 | 178.00 |
| 29 | .11391 | .32470 | -.50980 | 168.09 |
| 30 | .02377 | 1.45704 | -.76248 | 335.35 |
| 31 | -.23602 | -1.42599 | .87725 | 323.56 |
| 32 | .54278 | -.71883 | -1.30890 | 254.54 |
| 33 | -.55728 | -.73753 | 1.39140 | 184.89 |