FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 24, December, 2026, pp 155 – 160
DOI: https://doi.org/10.33003/fjs-2026-1024-6368

Demographic and Socioeconomic Determinants of Transport Mode Choice among Commuters in Kano Metropolis

***[1]Musa Yahaya and [2]Razaq Bayo Afolayan**

[1]Department of Physical Sciences, Al-Hikmah University, Ilorin, Kwara State, Nigeria.
[2]Department of Statistics, University of Ilorin, Ilorin, Kwara State, Nigeria.

*Corresponding authors' email: Musayahaya4185@gmail.com
ORCID iD: https://orcid.org/0009-0004-6261-2202

Received: 15 Oct. 2026
Accepted: 10 Nov. 2026
Published: 12 Nov. 2026

ABSTRACT

This study examined demographic and socioeconomic associations with transport mode choice in Kano metropolis, Nigeria. A cross-sectional survey provided 1,183 observations across Zoo Road, Hadejia Road, and Katsina Road. Multinomial logistic regression compared Public Bus, Private Motorcycle, Taxi, and Private Car with Keke Napep while adjusting for trip and spatial characteristics. Keke Napep was the most frequently used mode for 48.7% of respondents, followed by Private Car (25.3%), Private Motorcycle (18.5%), Public Bus (3.9%), and Taxi (3.6%). Omnibus likelihood-ratio tests identified gender, age group, education, and monthly household income as significant predictors; occupation ($p = .061$) and household size ($p = .179$) were not significant overall. Women had a lower relative risk of Private Motorcycle use (RRR = 0.172, $p < .001$) and a higher relative risk of Public Bus use (RRR = 6.723, $p = .020$) than men, relative to Keke Napep. Each increase in household-income category was positively associated with Private Motorcycle (RRR = 1.534, $p = .002$) and Private Car use (RRR = 3.909, $p < .001$). McFadden pseudo-R^2 was 0.7143, and in-sample classification accuracy was 85.55%. The findings support attention to commuter characteristics in transport planning. Sparse mode–predictor combinations and an inconclusive independence-of-irrelevant-alternatives assessment limit interpretation of some estimates. The findings represent adjusted associations rather than causal effects.

Keywords: Transport Mode Choice, Multinomial Logistic Regression, Demographic Characteristics, Socioeconomic Characteristics, Kano

INTRODUCTION

Transport planning depends on knowing which commuters use each mode and which characteristics are associated with their choices. Research on emerging economies places urban transport within wider socioeconomic and planning conditions (Pojani & Stead, 2017). UN-Habitat (2022) emphasises inclusive planning in response to urban growth, while the World Bank (2022) describes pressure on African transport systems from rapid urbanisation and limited mass-transit alternatives.

Kano metropolis is one of northern Nigeria's major commercial centres. Its road-based transport system includes Keke Napep, motorcycles, taxis, buses, and private cars. Abdullahi et al. (2024) examined tricycle operations and use in Kano through questionnaires and interviews, highlighting their role in everyday mobility and limitations in other public transport options. At the national level, Lenshie et al. (2022) examined the transition from commercial motorcycles to tricycles following motorcycle bans in Nigerian cities.

Previous studies provide reasons to examine commuter characteristics alongside transport conditions. Paulley et al. (2006) reviewed public-transport demand in relation to fares, service quality, income, and car ownership, principally in Great Britain with international evidence. In Nairobi, Salon and Gulyani (2010) identified affordability barriers and distinct access constraints for women, men, and children. These studies motivate attention to household resources and gender, but their findings cannot establish the direction or magnitude of associations in Kano.

The Kano tricycle study used descriptive analysis and qualitative interviews rather than a multivariable comparison across the five modes considered here (Abdullahi et al., 2024). The present study addresses this specific gap by estimating demographic and socioeconomic associations across competing modes while adjusting for measured trip and spatial characteristics. Such adjustment matters because, for example, an occupational difference may overlap with income or education. The cross-sectional design supports adjusted associations rather than causal conclusions.

This study used multinomial logistic regression to examine the associations of gender, age group, educational attainment, occupation, monthly household income, and household size with five transport modes among 1,183 commuters surveyed on Zoo Road, Hadejia Road, and Katsina Road. Keke Napep was the reference category. The study provides context-specific evidence on adjusted demographic and socioeconomic associations to inform transport planning in Kano metropolis.

MATERIALS AND METHODS

Study Area and Sample

A cross-sectional survey was conducted among commuters aged 18 years and above on Zoo Road, Hadejia Road, and Katsina Road. A total of 1,251 questionnaires were administered, with 417 allocated to each corridor. Within each corridor, the planned allocation across high-, medium-, and low-density zones was 50:30:20. Following data screening, 68 cases with incomplete information in model variables were excluded, leaving 1,183 respondents (94.6%)

for the full-sample analysis. Waiting time referred to the respondent's reported mode and was retained as a control variable.

Research assistants administered the questionnaire in English or Hausa at selected survey locations over ten working days, covering morning, midday, and evening periods. Every tenth eligible commuter was approached at boarding locations; private car and private motorcycle users were approached when parked at the main boarding locations. Respondents reported their most frequently used mode for regular journeys in Kano metropolis. The recorded options included both shared and private motorised modes, and each respondent contributed one observation.

Variables

The outcome comprised five unordered categories: Keke Napep, Public Bus, Private Motorcycle, Taxi, and Private Car. Keke Napep was the reference category. The focal predictors were gender (male as reference), age group (18–24 as reference; 25–34; 35–44; 45–54; 55–64), educational attainment (no formal education as reference; primary; secondary; NCE/ND; HND/Bachelor's; postgraduate), occupation (student as reference; unemployed; self-employed; government employee; private-sector employee), monthly household income, and household size. Although the questionnaire labelled its youngest age category 15–24, eligibility was restricted to adults aged at least 18; the eligible category is therefore reported here as 18–24. Household income was recorded in five ordered brackets and entered as a single numeric term. The ten additional predictors were trip purpose, corridor, residential density zone, and distance to a transport stop, a combined traffic-congestion/road-quality rating, travel time, fare, waiting time, perceived safety, and perceived comfort. The model therefore contained 16 predictors. The congestion/road-quality rating was entered as one numeric term. Reported mode and service attributes describe respondents' regular travel and are interpreted as associations with the chosen mode.

Model Specification

Multinomial logistic regression estimates, for each non-reference mode j, the log-odds of choosing mode j rather than Keke Napep as a linear function of the predictor set (Agresti, 2013; Hosmer et al., 2013):

$$ln(\frac{P(Y_i = j)}{P(Y_i = 0)}) = \beta_{0j} + \sum_{r=1}^{k} \beta_{rj} X_{ri} \quad (1)$$

Where P(Y = j) is the probability of choosing mode j, P(Y = 0) is the probability of choosing Keke Napep, β_{0j} is the mode-specific intercept, and β_{rj} is the coefficient for predictor X_r. The model was estimated by maximum likelihood. Exponentiating a coefficient gives the relative risk ratio:

$$RRR_{rj} = exp(\beta_{rj}) \quad (2)$$

For a one-unit increase in X_r, $exp(\beta_{rj})$ multiplies the relative risk of choosing mode j rather than Keke Napep, holding the remaining predictors constant. For household income, one unit denotes an increase of one recorded bracket rather than a fixed naira increment. Model fit was assessed using the likelihood-ratio chi-square statistic, Akaike information criterion (AIC), Bayesian information criterion (BIC), and McFadden pseudo-R^2:

$$R^2_{McFadden} = 1 - \frac{\ell_1}{\ell_0} \quad (3)$$

Here ℓ_1 denotes the fitted-model log-likelihood and ℓ_0 denotes the intercept-only log-likelihood. Omnibus Type II likelihood-ratio tests evaluated each predictor across the four mode comparisons. Multicollinearity was assessed using generalized variance inflation factors, adjusted for predictor degrees of freedom as GVIF^(1/(2df)) (Fox & Monette, 1992; Hair et al., 2018). Adjusted values ranged from 1.081 to 1.623. The Hausman–McFadden assessment excluded each non-reference mode in turn. In every comparison, the variance-difference matrix was not positive-definite and a valid test statistic could not be obtained; the IIA assessment was therefore inconclusive. Classification accuracy was calculated on the same 1,183 observations used to fit the inferential model and is reported as in-sample performance. Analyses were conducted in R (R Core Team, 2023).

Statistical Equations and Estimation

In the equations, i indexes respondents, j indexes one of the four non-reference modes, r indexes the k predictors, and mode 0 denotes Keke Napep. The symbols ℓ_0 and ℓ_1 denote the intercept-only and fitted-model log-likelihoods, respectively.

The probability of choosing non-reference mode j was obtained from:

$$P(Y_i = j) = \frac{exp(\beta_{0j} + \sum_{r=1}^{k} \beta_{rj} X_{ri})}{1 + \sum_{h=1}^{4} exp(\beta_{0h} + \sum_{r=1}^{k} \beta_{rh} X_{ri})} \quad (4)$$

The corresponding probability for the reference mode, Keke Napep, was:

$$P(Y_i = 0) = \frac{1}{1 + \sum_{h=1}^{4} exp(\beta_{0h} + \sum_{r=1}^{k} \beta_{rh} X_{ri})} \quad (5)$$

Overall model improvement was evaluated with the likelihood-ratio statistic:

$$LR\ \chi^2 = -2(\ell_0 - \ell_1) \quad (6)$$

Parameters were estimated by maximum likelihood. Statistical significance was assessed at the 5% level, and interpretation emphasized the direction, magnitude and uncertainty of adjusted associations rather than causal effects.

RESULTS AND DISCUSSION

Keke Napep was the most frequently used mode for 48.7% of respondents (n = 576), followed by Private Car (25.3%, n = 299), Private Motorcycle (18.5%, n = 219), Public Bus (3.9%, n = 46), and Taxi (3.6%, n = 43). The small Bus and Taxi groups warrant caution when interpreting their mode-specific regression estimates.

Figure 1 shows that the ₦101,000–₦200,000 household-income bracket contained the largest share of respondents (30.6%, n = 362), followed by ₦51,000–₦100,000 (29.8%, n = 352). Together, the two lowest recorded brackets accounted for 50.3% of respondents; 6.0% (n = 71) reported more than ₦500,000. Income-bracket labels follow the recorded questionnaire categories.

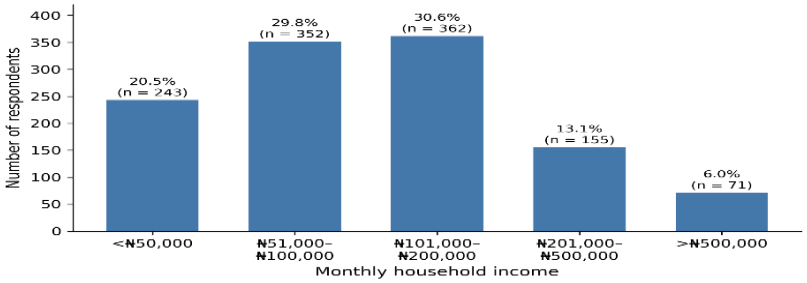


Figure 1: Distribution of respondents by monthly household-income bracket (N = 1,183)
Source: Kano Metropolis commuter survey dataset

Table 1: Bivariate Associations between Transport Mode and Selected Demographic and Socioeconomic Predictors

Predictor	χ^2	df	p
Gender	90.20	4	<.001
Household income	410.14	16	<.001
Educational Attainment	275.08	20	<.001
Occupation	115.32	16	<.001

Table 1 shows statistically significant bivariate associations between transport mode and gender, income, educational attainment, and occupation (all $p < .001$). These tests assess unadjusted relationships. In particular, the bivariate association for occupation should not be interpreted as evidence of an independent association after adjustment; the corresponding omnibus model test was not significant at the 5% level.

Within household-income brackets, Private Car use increased from 6.2% in the lowest group to 81.7% in the highest, while Keke Napep use declined from 67.9% to 9.9% (Table 2). Private Motorcycle users were predominantly male: 190 of the 219 users were men. Educational attainment also differed by mode. These are unadjusted comparisons and do not establish independent effects. Table 2 presents percentages within each household-income bracket. Figure 2 summarises the overall mode shares.

Table 2: Transport Mode by Monthly Household-Income Bracket (Column Percentages)

Mode	<₦50k	₦51–100k	₦101–200k	₦201–500k	>₦500k
Keke Napep	67.9%	64.8%	41.4%	16.8%	9.9%
Public Bus	4.5%	4.3%	3.6%	3.9%	1.4%
Private Motorcycle	12.8%	18.5%	27.3%	12.3%	7.0%
Taxi	8.6%	2.3%	3.6%	0.6%	0.0%
Private Car	6.2%	10.2%	24.0%	66.5%	81.7%

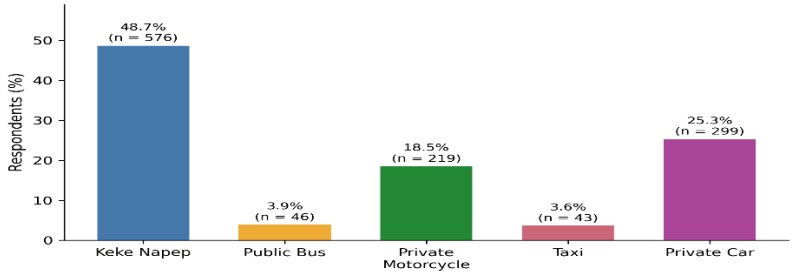


Figure 2: Most frequently used transport mode among respondents (N = 1,183).
Source: Kano Metropolis commuter survey dataset.

Table 3: Multinomial Logistic Regression Model Fit

Statistic	Value
-2 Log-Likelihood (intercept only)	2,974.15
-2 Log-Likelihood (final model)	849.72
Likelihood-ratio χ^2 (df = 128)	2,124.43, $p < .001$
McFadden Pseudo R^2	0.7143
Akaike information criterion (AIC)	1,113.72
Bayesian information criterion (BIC)	1,783.73
Classification accuracy (in-sample)	85.55%

Table 3 shows that the full model improved on the intercept-only model (LR $\chi^2 = 2,124.43$, df = 128, $p < .001$). McFadden pseudo-R^2 was 0.7143; this likelihood-based measure is not the proportion of outcome variance explained. AIC and BIC

were 1,113.72 and 1,783.73, respectively. In-sample classification accuracy was 85.55%. Because this accuracy was calculated using the estimation observations, it describes fit to the observed sample rather than predictive performance on new respondents.

Table 4: Omnibus Likelihood Ratio Tests for the Focal Predictors

Predictor	LR chi-square	df	p	Decision
Gender	53.69	4	< .001	Significant
Age group	66.95	16	< .001	Significant
Educational attainment	38.66	20	.007	Significant
Occupation	25.50	16	.061	Not significant
Household income	22.41	4	< .001	Significant
Household size	6.29	4	.179	Not significant

Table 5: Selected Mode Specific Coefficients Relative to Keke Napep

Outcome	Predictor	β (SE)	RRR	p
Public Bus	Female	1.906 (0.818)	6.723	.020
Public Bus	Age 25–34	3.171 (0.706)	23.847	<.001
Public Bus	Age 55–64	-4.711 (1.339)	0.009	<.001
Private Motorcycle	Female	-1.760 (0.284)	0.172	<.001
Private Motorcycle	Household income	0.428 (0.135)	1.534	.002
Private Motorcycle	Age 25–34	0.878 (0.305)	2.406	.004
Taxi	Age 25–34	2.111 (0.541)	8.260	<.001
Taxi	Household income	-0.048 (0.343)	0.953	.889
Private Car	Household income	1.363 (0.243)	3.909	<.001
Private Car	Age 45–54	5.375 (0.780)	215.785	<.001
Private Car	Household Size	0.341 (0.132)	1.406	.010
Private Car	Occupation: Private Sector	3.018 (0.622)	20.449	<.001
Private Car	Education: Postgraduate	2.819 (0.610)	16.764	<.001

Note. Selected coefficients summarized the focal demographic and socioeconomic contrasts discussed in the text. All estimates are adjusted for the other predictors. Reference categories were male, age 18–24, no formal education, student, and Keke Napep. Income denotes a one-category increase in monthly household income. Some coefficients in the full model showed numerical instability associated with sparse mode–predictor combinations; individual RRR magnitudes should therefore be interpreted cautiously.

The omnibus likelihood-ratio tests identified four significant demographic or socioeconomic predictors: gender (LR chi-square = 53.69, df = 4, p < .001), age group (LR chi-square = 66.95, df = 16, p < .001), educational attainment (LR chi-square = 38.66, df = 20, p = .007), and monthly household income (LR chi-square = 22.41, df = 4, p < .001). Occupation was not significant at the 5% level (LR chi-square = 25.50, df = 16, p = .061), and household size was not significant overall (LR chi-square = 6.29, df = 4, p = .179).

The mode-specific coefficients show how the adjusted associations differed across alternatives (Table 5). Women had a lower relative risk of Private Motorcycle rather than Keke Napep use than men (RRR = 0.172, p < .001), but a higher relative risk of Public Bus rather than Keke Napep use (RRR = 6.723, p = .020). The gender contrasts for Taxi and Private Car were not statistically significant. Each increase of one household-income category was associated with higher relative risks of Private Motorcycle (RRR = 1.534, p = .002) and Private Car use (RRR = 3.909, p < .001), while the Bus and Taxi income contrasts were not significant. The Car contrast for ages 45–54 versus 18–24 was large (RRR = 215.785) and should be interpreted cautiously given the small numbers in some mode–predictor combinations. Household size had a significant Car-specific coefficient (RRR = 1.406, p = .010), although its omnibus test across the four alternatives was not significant. Figure 3 displays the unadjusted mode composition across household-income brackets.

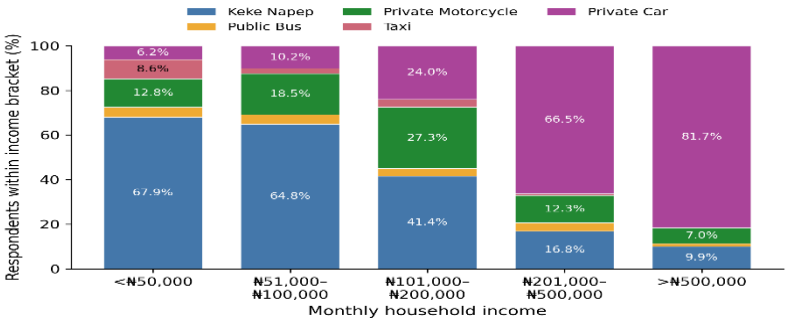


Figure 3: Transport mode composition within monthly household-income brackets (N = 1,183)
Source: Kano Metropolis commuter survey dataset

The household-income pattern was the clearest socioeconomic finding. Private Car use increased across the income brackets, and household income remained significant after adjustment for the other measured characteristics. The adjusted association was specific to Private Motorcycle and Private Car rather than a statistically significant shift for every alternative. Paulley et al. (2006) similarly identify income and car ownership as relevant to public-transport demand, although their review principally concerns Great Britain and does not establish an equivalent effect size for Kano. The present results provide local evidence of differences between household-income groups.

The prominence of Keke Napep in this sample is consistent with the importance of tricycles in everyday Kano travel described by Abdullahi et al. (2024). Their study focused on tricycle operators and users, whereas this analysis compares five reported modes; the sampling frames do not support a direct comparison of mode shares. Lenshie et al. (2022) provide broader Nigerian context for the transition from commercial motorcycles to tricycles, but that policy transition does not explain the adjusted coefficients estimated here.

Gender was associated with Public Bus and Private Motorcycle use in opposite directions. Women were less likely than men to choose Private Motorcycle rather than Keke Napep, but more likely to choose Public Bus. The survey establishes these adjusted differences but cannot determine whether they arise from safety, cultural expectations, affordability, or another unmeasured factor. Interviews or focus groups would be needed to examine those explanations. Research on mobility in Nairobi likewise identifies different access constraints for women and men and highlights affordability (Salon & Gulyani, 2010). The reasons for the Kano associations require direct investigation.

Age and education were significant in the omnibus tests, but their coefficients differed across modes and some were affected by sparse categories. The results therefore support mode-specific interpretation rather than a single general statement that older or more educated commuters prefer one type of transport. Occupation also requires caution: several category coefficients were significant for particular modes, yet the omnibus occupation test did not reach the 5% level. Household size likewise had a significant Car coefficient but was not significant overall.

Although particular occupation contrasts were significant for individual modes, the present model does not provide sufficient evidence to classify occupation as an independent overall determinant. Future work could use broader occupational groups or a larger sample of Public Bus and Taxi users to estimate these contrasts more reliably.

Trip and spatial characteristics were retained to adjust the demographic and socioeconomic comparisons. Fare, travel time, waiting time, safety, and comfort describe the reported mode and may also reflect the conditions experienced after choosing that mode. Their inclusion does not establish a causal explanation of choice. The article focuses on demographic and socioeconomic associations within this adjusted model.

The results support planning that recognizes differences between user groups without treating demographic characteristics as direct causes of behavior. The Kano State Ministry of Transport could assess whether affordable shared services meet the needs of commuters across income groups, particularly as Car use rises with income. KAROTA and other relevant agencies could examine the safety, access, and service conditions affecting women's use of Public Bus, Private Motorcycle, and Keke Napep. Because the survey did not measure the reasons for the gender differences directly, qualitative research should precede interventions designed around cultural or safety explanations. More broadly, the World Bank (2022) describes bus rapid transit as a potential response to urban growth and limited mass-transit capacity in African cities. Its suitability for Kano would require a separate assessment of demand, affordability, routes, and infrastructure. Regular collection of commuter data would also help transport authorities monitor changing mode shares and assess whether service improvements meet the needs of different income and demographic groups.

The cross-sectional design supports interpretation as association rather than causation. Entering household-income brackets as one numeric term assumes equal changes in log-relative risk between adjacent brackets, despite unequal monetary intervals. Bus and Taxi had only 46 and 43 observations, respectively, and some coefficients in the full model showed numerical signs consistent with separation. Such estimates should not be treated as precise effect sizes. The Hausman–McFadden assessment was inconclusive because the required variance-difference matrices were not positive-definite, so IIA remains unverified. Self-reported travel and service attributes may contain measurement error, and the three-corridor sample does not establish representativeness for all Kano commuters or other cities. Future analyses could assess coefficient stability using penalised estimation and alternative choice-model specifications. Related methodological work by Amalahu et al. (2025) explored Bayesian dynamic mixed logistic regression using simulated transportation data, providing an example of an alternative framework for future mode-choice research.

Conclusion

Gender, age group, educational attainment, and monthly household income were significant overall among the six focal demographic and socioeconomic predictors. Occupation and household size were not significant in their omnibus tests. Relative to Keke Napep, women had a lower adjusted relative risk of Private Motorcycle use and a higher adjusted relative risk of Public Bus use than men. Higher household-income category was positively associated with Private Motorcycle and Private Car use. These mode-specific associations can inform transport planning that considers differences between commuter groups, while sparse categories, coefficient instability, and the inconclusive IIA assessment require cautious interpretation.

REFERENCES

Abdullahi, A., Abdulganiyu, I. A., Morakinyo, O. E., Abdulquadri, K., & Yusuf, R. (2024). Exploring the efficiency of tricycles as a public transportation mode in Nigeria: A case study of Kano metropolis. *Journal of Environmental Spectrum, 4*(1), 79–90. https://www.researchgate.net/publication/391326995_Exploring_The_Efficiency_of_Tricycles_as_A_Public_Transportation_Mode_in_Nigeria_A_Case_Study_of_Kano_Metropolis

Agresti, A. (2013). *Categorical data analysis* (3rd Ed.). Wiley. https://www.wiley.com/en-gb/categorical-data-analysis-3rd-edition-p-9781118710944

Amalahu, C. C., Nwabueze, J. C., Enogwe, S. U., & Ekeadinotu, C. B. (2025). Applying Bayesian dynamic mixed logistic regression to mobility networks. *FUDMA Journal of Sciences, 9*(5), 101–105. https://doi.org/10.33003/fjs-2025-0905-3654

Fox, J., & Monette, G. (1992). Generalized collinearity diagnostics. *Journal of the American Statistical Association, 87*(417), 178–183. https://doi.org/10.1080/01621459.1992.10475190

Hair, J. F., Jr., Babin, B. J., Anderson, R. E., & Black, W. C. (2018). *Multivariate data analysis* (8th Ed.). Cengage Learning. https://www.cengage.uk/c/multivariate-data-analysis-8e-hair-babin-ander-son-black/9781473756540/

Hosmer, D. W., Jr., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd Ed.). Wiley. https://doi.org/10.1002/9781118548387

Lenshie, N. E., Ezeibe, C. C., Joshua, M. M., & Nwangwu, C. (2022). From motorcycle to tricycle: Neoliberal political economy, informal transportation, and urban/peri-urban mobility in Nigerian cities. *Transportation Journal, 61*(2), 195–227. https://doi.org/10.5325/transportationj.61.2.0195

Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J. M., Wardman, M. R., Shires, J. D., & White, P. (2006). The demand for public transport: The effects of fares, quality of service, income and car ownership. *Transport Policy, 13*(4), 295–306. https://doi.org/10.1016/j.tranpol.2005.12.004

Pojani, D., & Stead, D. (Eds.). (2017). *the urban transport crisis in emerging economies*. Springer International Publishing. https://doi.org/10.1007/978-3-319-43851-1

R Core Team. (2023). *R: A language and environment for statistical computing* [Software]. R Foundation for Statistical Computing. https://www.r-project.org/

Salon, D., & Gulyani, S. (2010). Mobility, poverty, and gender: Travel 'choices' of slum residents in Nairobi, Kenya. *Transport Reviews, 30*(5), 641–657. https://doi.org/10.1080/01441640903298998

UN-Habitat. (2022). *World cities report 2022: Envisaging the future of cities*. United Nations Human Settlements Programme. https://unhabitat.org/world-cities-report-2022-envisaging-the-future-of-cities

World Bank. (2022, November 29). *With bus rapid transit, African cities are riding toward a better future*. https://www.worldbank.org/en/news/feature/2022/11/28/with-bus-rapid-transit-african-cities-are-riding-toward-a-better-future

©2026 This is an Open Access article distributed under the terms of the Creative Commons Attribution 4.0 International license viewed via https://creativecommons.org/licenses/by/4.0/ which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is cited appropriately.