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Regression Model for Forecasting the Vehicular Trip Generation Rate of Higher Institutions in Kebbi State Nigeria

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Abstract

Trip generation rates offer crucial data for the transport planning process, particularly for the models of the interactions between land use and transportation. Students at universities belong to a certain demography within the broader populace that is distinguished by higher rates of mobility. This study examined the AM peak hour, PM peak hour and daily trips generated by three higher institutions in Kebbi State, Nigeria. It found that the number of staff is correlated to the AM peak hour trips, PM peak hour trips and daily trips generated by higher institutions studied. These findings will improve transportation planning and allow for early identification of pressing transportation-related problems.

Keywords: *Travel Demand Forecasting, Traffic Count, Trip Generation Rate, Higher Education Institutions.*

Introduction

The foundation of a town's growth lies in its transportation system. No town can thrive without the movement of people and goods, and communities naturally develop around transportation hubs. It is widely understood that these hubs dictate the flow of traffic and, in turn, shape the form and structure of each settlement. Transportation, in its ideal form, is the movement of people, goods, and services between locations. Transportation planning, on the other hand, is the process of creating strategies that consider the social, economic, and environmental impacts on the public to achieve positive objectives. The primary goal of transportation planning is to ensure efficient access to a variety of activities that fulfill human needs and cater to the requirement for mobility. It operates on the assumption that traffic needs are influenced by land use, travel patterns, and human behavior.

In addition to planning the creation, distribution, mode of transportation, and route assignment, transportation planning also addresses travel demand and specific trips. Each journey is undertaken for a specific purpose and influenced by various factors, including personal wealth, the availability of vehicles, age, distance, and more (Panackel & Padmini, 2013).

Different types of activities, such as work, leisure, shopping, and education, are facilitated by various land uses within a region. These activities both generate and attract travelers, leading to a demand for travel to and from these areas. This, in turn, affects the transportation system. To anticipate future travel demand, trip generation models are often employed, using demographic characteristics such as income and vehicle ownership. These models play a key role in understanding the intricate relationship between land use and transportation (Basbas et al., 2019). Transportation planning remains incomplete without the incorporation of travel demand modeling. The initial phase of this four-part process, known as trip generation, serves as the foundation for estimating the number of individual journeys between Traffic Analysis Zones (TAZs) for various purposes. To capture the relationships among variables known to influence trip generation, mathematical models are frequently employed (Akinfala et al., 2022).

The creation of precise and reliable mathematical models for trip generation is crucial, as it constitutes the starting point and the cornerstone for subsequent stages of travel demand modeling. Any errors or inaccuracies at this stage can propagate and potentially compound in later phases. Furthermore, the development of dependable mathematical models allows for future planning, especially when the correlation between explanatory factors and the number of trips generated remains consistent between the base year and the forecasted year (Akinfala et al., 2022).

A trip is commonly defined as a one-way journey undertaken by an individual between two locations, utilizing a specific mode of transportation or a combination of modes, for a specific purpose (Ben-Edigbe & Rahman, 2010). Trip generation links the quantity of trips generated by a facility or land use with other significant factors. Several studies and publications from around the world, particularly in industrialized nations, have been conducted to establish trip generation rates or equations. How-ever, these findings predominantly reflect the travel characteristics of the regions where the surveys were conducted. Similar efforts have been made in underdeveloped nations, especially in African countries, albeit to a lesser extent. Notably, there has been limited research on trip generation related to land use in Nigeria (Al-Sahili et al., 2018).

The forecasting of travel demand often relies on trip generation, which predicts the number of journeys originating from or directed to specific traffic analysis zones for specific applications. Trip generation analysis focuses particularly on signi-ficant land uses, encompassing residential, commercial, industrial areas, as well as schools, hospitals, and hotels (Al-Sahili et al., 2018).

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Higher education institutions in Nigeria, such as universities and polytechnic campuses, form a distinct community with unique transportation requirements. Students in higher education typically have different travel patterns and distinctive socio-demographic characteristics compared to the general population (Ben-Edigbe, 2010; Khattak et al., 2011). Furthermore, research in this field explores the relationship between the campus environment and the travel habits of university students.

University campuses often serve as major sources of regional traffic and significantly impact nearby towns in various ways, including parking availability, traffic flow, and accessibility to services (Wang et al., 2010). With the increasing problem of traffic congestion and the scarcity of parking space resulting from rising traffic demands, several academics emphasize the promotion of sustainable mobility initiatives for university campuses.

The transportation needs of university students have garnered increased attention in recent years, with numerous studies from various countries delving into various aspects of their travel habits. Collins & Chambers (2005) argued that public policy measures should focus on individuals' attitudes and environmental conditions related to transport to facilitate a shift towards public transport, based on a sample of 205 Australian university students.

Meanwhile, Shannon et al. (2006) found that the biggest hindrance to students transitioning from driving to cycling or walking for their university commutes in Australia was journey time. Klöckner & Friedrichsmeier (2011) demonstrated that students' mode choice decisions were jointly influenced by situational factors like infrastructure availability, transit accessibility, trip characteristics, and cost, as well as psychological factors encompassing individual intentions, beliefs, norms, and attributes among students at Ruhr-University Bochum.

An analysis of data from a commuter survey of students and staff at the University of North Carolina at Chapel Hill revealed that local topography and sidewalk availability significantly influenced the attractiveness of non-motorized modes. Additionally, a separate study found that the availability of lower-cost parking permits encouraged shorter car commutes, particularly during the winter months. Students residing on or near campus were significantly more inclined to walk and bicycle and less likely to use automobiles (Khattak et al., 2011).

Taking McMaster University in Canada as a case study, researchers found that personal preferences, transportation costs, and external factors like street and sidewalk density impacted students' mode choices. Various individual elements, including socioeconomic, demographic, and psychological factors, have been extensively examined to understand their influence on travel behavior (Khattak et al., 2011; Wang et al., 2010).

Current research on the travel habits of university students increasingly emphasizes individual factors. Moreover, undergra-duate students and on-campus residents exhibited higher travel activity compared to graduate students and off-campus students (Delmelle & Delmelle, 2012). Furthermore, graduate students were more inclined to walk or cycle than undergraduate students, with male students showing a greater propensity for non-motorized travel compared to their female counterparts (Zhan et al., 2016).

Methodology

Study Location and Data Collection

The study was conducted in Kebbi State, Nigeria, where there are two universities: the Federal University Birnin Kebbi (owned by the Federal Government) and the Kebbi State University of Science and Technology, Aliero (owned by the Kebbi State Government). Additionally, Waziri Umaru Federal Polytechnic is also located in Kebbi State. The approach used in this study is based on the manual provided by the Institution of Transport Engineers (ITE).

The core of the study involved fieldwork, which required visits to various locations influenced by specific land uses (Hooper, 2017). The study primarily relies on linear regression analysis, a widely employed method for estimating trip generation rates globally. Linear models are preferred due to their simplicity in fitting unknown variables compared to non-linear models, and their statistical properties are easier to ascertain (Ahmed et al., 2014).

Initially, information about the surveyed locations was gathered through direct measurements and interviews with institution administrations. Data on the number of students and employees at the institutions studied were collected through interviews. The study involved manual traffic volume counts on weekdays from 6 a.m. to 6 p.m. over three consecutive days, from Monday to Wednesday. To identify the morning (AM) and evening (PM) peak hours, a graph of daily traffic volume variance versus time of day was created. The peak hours represent the periods with the highest traffic flow entering and leaving the universities or the polytechnic.

To estimate the trip generation rate, multiple linear regression analysis was performed using Origin Software and Microsoft Excel. Relevant statistical tests were conducted to assess the quality of the model fit. The study considered independent variables such as the number of staff, students, faculties, and departments. The data collected revealed that the AM peak hour occurred between 8:45 AM and 9:45 AM, while the PM peak hour fell between 1:15 PM and 2:15 PM.

Regression Analysis

Due to its simplicity and proven effectiveness compared to more complex count models and, in certain scenarios, soft computing models, linear regression has become a common choice for trip forecasting. While artificial neural networks (ANN) and fuzzy expert systems (FES) represent sophisticated models for predicting typical travel patterns (Akinfala et al., 2022), the margin of improvement they offer over linear regression is often negligible, prompting the question of whether the added complexity of soft computing models is necessary.

Regression analysis, a specific predictive modeling approach, explores the relationship between a dependent variable (the target) and a set of independent variables (predictors). In the context of modeling the connection between travel and household factors, Ortuzar and Willumsen's Ordinary Least Square (OLS) regression modeling is employed. The least squares method is used to fit the data, including the observed dependent and independent variables, to a best-fit straight line known as the regression line. This method establishes a relationship between one or more independent variables (X) and a dependent variable (Y), as represented in Equation 1.

For all the regression analyses conducted, the significance threshold was set at 0.05 (Akinfala et al., 2022; Eromietse & Joseph, 2019).

$$YYii = \beta\beta 0 + \beta\beta ii\ XXnn + \varepsilon\varepsilon nn, \ nn = 1,2,3,4 \ldots NN \qquad (1)$$

Where $YYii$ is the estimated trips made by household *i*,
β0 the constant, $\beta\beta ii$ a vector of parameters to be estimated from the data,
$XXnn$ a vector of explanatory variables and $\varepsilon\varepsilon nn$ is the error term.
The MLR model was validated using the R^2 and Relative Error.

Results and Discusssion

AM Peak Hour Trip Generation Analysis

The initial step in the regression analysis involves assessing the nature of the relationship between the dependent variable and each of the independent variables to identify any nonlinearity. This can be accomplished by creating a scatterplot that depicts the relationship between the independent variable and the dependent variable. In this plot, we aim to fit either a straight line with a reasonable statistical fit or a curve, as illustrated in Figure 1.

Upon examining the nature of the relationship between the plots of AM peak hour trips generated and each of the independent variables mentioned above, it is evident that a linear relationship exists. This determination is made because a linear trendline adequately fits the scattered plot. However, if nonlinea-rities are detected in the relationship, the next step would involve linearizing the relationship by transforming either the dependent variable, the independent variable, or both.

The second step involves constructing an intercorrelation matrix that encompasses all variables, both the dependent and independent ones. The resulting matrix is presented in Table I. This matrix provides insight into the extent of the influence of each independent variable on the dependent variable and helps identify potential collinearity between the independent variables. It assists in planning the regression analysis by aiding in the selection of relevant independent variables while eliminating any unnecessary ones. For instance, when examining the correlation matrix, we observe that the number of staff (0.9961) and the number of students (0.9804) are statistically associated with the AM peak hour trips generated. On the other hand, the number of departments shows a correlation value close to zero (0.0331), indicating its insignificance for the regression analysis.

Furthermore, in the assessment of potential collinearity between pairs of independent variables, it's evident that two of these variables are highly correlated: the number of students and the number of staff, with a correlation of 0.9939. This suggests that these independent variables share similar characteristics and cannot both be included in the regression analysis simultaneously. Thus, one of them must be eliminated.

In this case, the number of students should be eliminated, as its correlation value (0.9804) is lower than that of the number of staff (0.9961). Therefore, the chosen independent variable for the regression analysis is the number of staff. This choice is supported by the logical assumption that car ownership among staff is likely higher than among students in the study area (Ahmed et al., 2014).

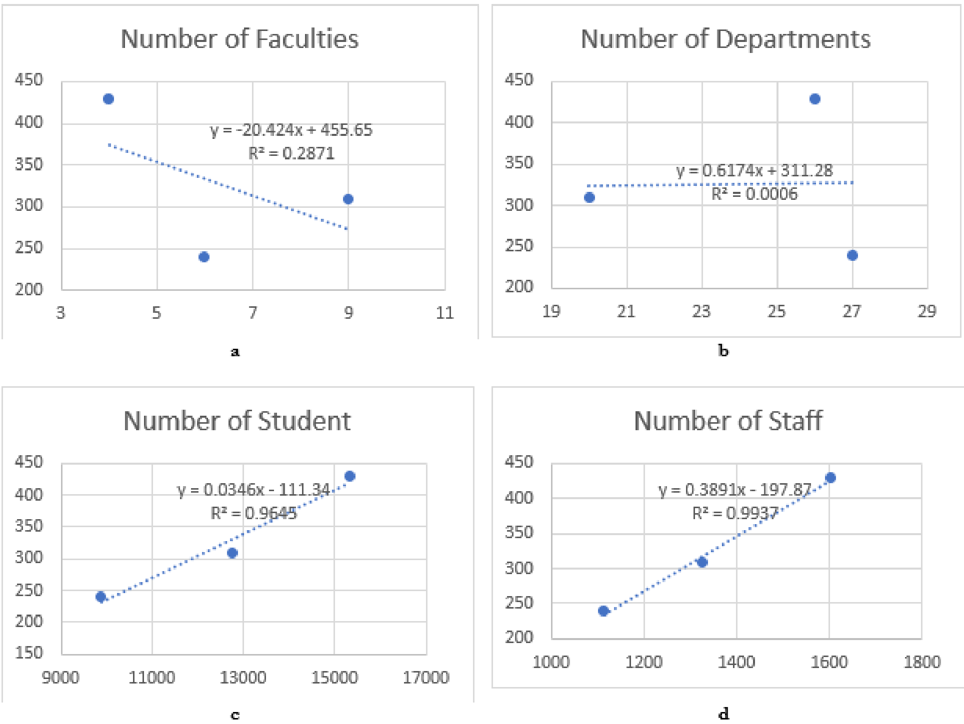

Figure 1. Developed Models for the AM Peak Hour Trips Generation.

Table 1. Intercorrelation Matrix of the Independent and Dependent Variables used for AM Peak Hour Trips

	Number of Department	*Number of Student*	*Number of Staff*	*Number of Faculties*	*Trip Generated*
No. of Depart.	1.0000				
No. of Student	-0.1645	1.0000			
No. of Staff	-0.0548	0.9939	1.0000		
No. of Faculty	-0.8571	-0.3671	-0.4673	1.0000	
Trips Generated	0.0331	0.9804	0.9961	-0.5432	1.0000

Table 2: Summary Output

Regression Statistics	
Multiple R	1.00
R Square	0.99
Adjusted R Square	0.98
Standard Error	11.75
Observations	3.00

Table 3. ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1.00	17757.74	17757.74	128.64	0.06
Residual	1.00	138.04	138.04		
Total	2.00	17895.78			

Table 4. Regression

	Coefficients	*SE*	*t-Stat*	*p-Value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-192.00	46.04	-4.17	0.15	-777.01	393.01	-777.01	393.01
Number of Staff	0.38	0.03	11.34	0.06	-0.05	0.81	-0.05	0.81

Table 2 demonstrates an exceptionally strong and highly predictive relationship between AM peak hour trips generated (*y*) and the number of staff (*x*). The multiple R value, representing the correlation, is a perfect 1.00, indicating a perfect positive linear relationship, suggesting that as the number of staff increases, so do the AM peak hour trips generated. The R-squared value is 0.99, implying that about 99% of the variation in AM peak hour trips can be attributed to the number of staff, making it an excellent predictor. The adjusted R-squared remains high at 0.98, confirming the model's strong explanatory power. The standard error of 11.75 suggests that the model's predictions are generally accurate. Despite only three observations, the model appears reliable, but causal implications should be considered.

Moving to Table 3, the ANOVA results assess the statistical significance of the regression model. The "Regression" section explains a substantial amount of variance with an F-statistic of 128.64, indicating that the number of staff significantly influences AM peak hour trips. The "Residual" section represents unexplained variance, while the "Total" section provides an overview of the total variance in the data. The significance F value of 0.06 depends on the chosen alpha level, signifying whether the relationship is statistically significant. Interpretation should align with the study's objectives and alpha level.

In Table 4, the regression results indicate a significant positive relationship between AM peak hour trips generated and the Number of Staff. The intercept is not statistically significant, suggesting unreliability. However, the Number of Staff coefficient is statistically significant, signifying its role as a predictor. The confidence interval, though wide, suggests a positive impact. In summary, Number of Staff is a statistically significant predictor of AM peak hour trips generated, while the intercept lacks significance.

PM Peak Hour Trip Generation Analysis

Figure 2 depicts a scatter diagram illustrating the relationship between the independent variable and the dependent variables. The linear trend-line within the plot suggests a linear relationship between these variables, reinforcing the analysis. Also, Table 5 provides the correlation matrix for PM peak hour trips generated. It reveals that the number of staff (0.9997) and the number of students (0.9964) are statistically associated with PM peak hour trips generated. However, the remaining independent variables exhibit negative correlations with the dependent variable, making them unsuitable for regression analysis. Additionally, a check for potential sources of colinearity highlights a strong correlation between two independent variables: Number of students and Number of Staff (correlation of 0.9939). To ensure model integrity, one of these variables must be excluded. The choice is based on their correlation with the dependent variable, and since the Number of students has a lower correlation (0.9964) compared to Number of staff (0.9997), it is selected as the independent variable for regression analysis.

The regression statistics in Table 6 demonstrate an exceptionally strong and highly predictive relationship between the number of staff and PM peak hour trips generated. The multiple R value, representing the correlation, is a perfect 1.00, indicating a perfect positive linear relationship. This means that as the number of staff increases, the number of PM peak hour trips generated also increases. The R-squared value, which measures how well the independent variable explains the variation in the dependent variable, is 1.00, signifying that 100% of the variation in PM peak hour trips can be attributed to the number of staff, making it an excellent predictor. The adjusted R-squared, accounting for the number of independent variables, remains at a perfect 1.00, underlining the model's strong explanatory power. The small standard error of 3.13 suggests that the model's predictions are highly accurate, given the relatively low standard deviation. With three observations, this analysis underscores the reliability of the model in predicting PM peak hour trips based on the number of staff.

Meanwhile, the ANOVA results in Table 7 evaluate the statistical significance of the regression model. In the regression section, the model explains a substantial amount of variance, with a sum of squares (SS) of 14825.58 and one degree of freedom (df). The mean square (MS) for the regression is also 14825.58. The F-statistic, at 1513.30, measures the ratio of the variance explained by the regression model to the unexplained variance (residual). The significance F value is 0.02, indicating that the regression model is statistically significant. This suggests that the number of staff is a significant predictor of PM peak hour trips, with a p-value less than the chosen alpha level (significance threshold).

Overall, the regression coefficients from Table 8 provide insights into the relationship. The intercept is -101.28, which represents the predicted number of PM peak hour trips generated when there are zero staff members. However, the p-value of 0.08 suggests that the intercept is not statistically significant, implying it may not be a reliable estimate. On the other hand, the coefficient for the Number of Staff is 0.35, indicating that for each additional staff member, there is an estimated increase of 0.35 PM peak hour trips generated. The high t-statistic of 38.90 and a relatively low p-value of 0.02 indicate that this coefficient is statistically significant. It suggests that the Number of Staff is a meaningful predictor of PM peak hour trips generated. The confidence interval for the Number of Staff coefficient ranges from 0.24 to 0.46, implying a high level of confidence in the precise magnitude of this effect.

In summary, the analysis indicates a highly significant and positive relationship between the Number of Staff and PM peak hour trips generated. The model is highly predictive, with the Number of Staff being a meaningful and statistically significant predictor, as evidenced by the ANOVA results and regression coefficients.

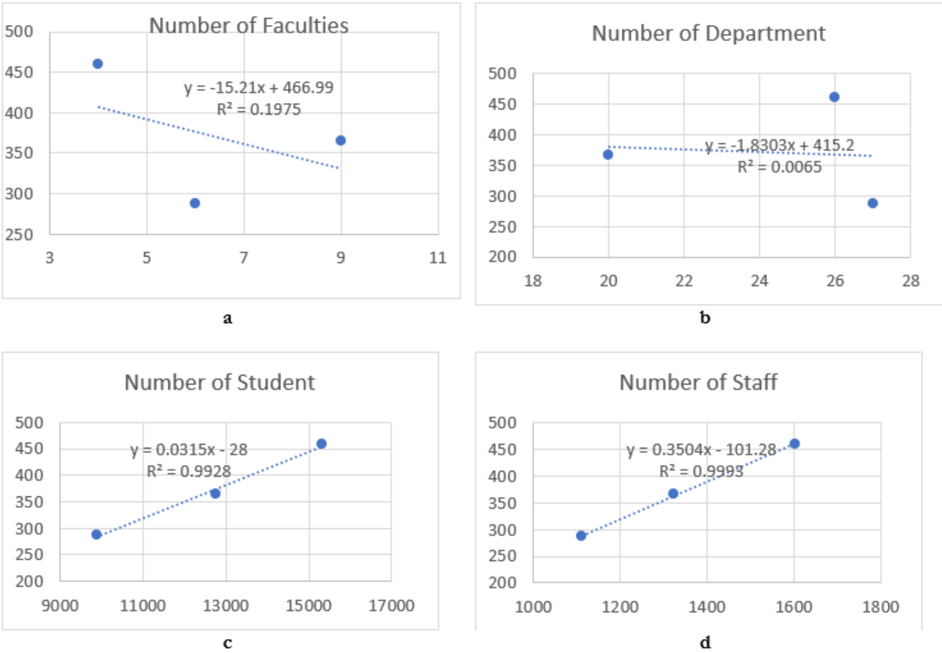

Figure 2: Developed Models for PM Peak Hour Trip Generation

Table 5: PM Peak Hour Regression Analysis Results

	Number of Department	*Number of Student*	*Number of Staff*	*Number of Faculties*	*Trip Generated*
Number of Department	1				
Number of Student	-0.1645	1			
Number of Staff	-0.0548	0.9939	1		
Number of Faculties	-0.8571	-0.3671	-0.4673	1	
Trip Generated	-0.0805	0.9964	0.9997	-0.4444	1

Table 6. Summary Output

Regression Statistics	
Multiple R	1.00
R Square	1.00
Adjusted R Square	1.00
Standard Error	3.13
Observations	3.00

Table 7. ANOVA

	df	***SS***	***MS***	***F***	***Significance F***
Regression	1.00	14825.58	14825.58	1513.30	0.02
Residual	1.00	9.80	9.80		
Total	2.00	14835.38			

Table 8. Regression Results

	Coefs.	SE	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-101.28	12.27	-8.26	0.08	-257.12	54.57	-257.12	54.57
Number of Staff	0.35	0.01	38.90	0.02	0.24	0.46	0.24	0.46

Daily Trip Generation Analysis

Scatter diagrams were used to visualize the relationship between the independent variable and the dependent variable. A straight line with a reasonable statistical fit was fitted, as illustrated in Figure 3: Upon examining the nature of the relationship between daily trips generated and each independent variable, it became evident that a linear relationship exists. This is supported by the fact that a linear trendline fits the scatter plot well.

Table 9 presents the intercorrelation matrix results for daily trip generation. Upon analyzing the correlation matrix, it is evident that the number of staff (0.9965) and the number of students (0.9812) are statistically associated with the PM peak hour trips generated. However, the remaining independent variables exhibit either a negative or weak correlation with the dependent variable. As a result, these variables are not suitable for inclusion in the regression analysis.

Additionally, during the assessment for potential sources of collinearity between pairs of independent variables, it was discovered that the number of students and the number of staff were highly correlated. Consequently, due to their similarity, only one of these independent variables can be included in the regression analysis. In this case, the number of students was eliminated due to its lower correlation value with the trips generated. Thus, the chosen independent variable for the regression analysis is the number of staff.

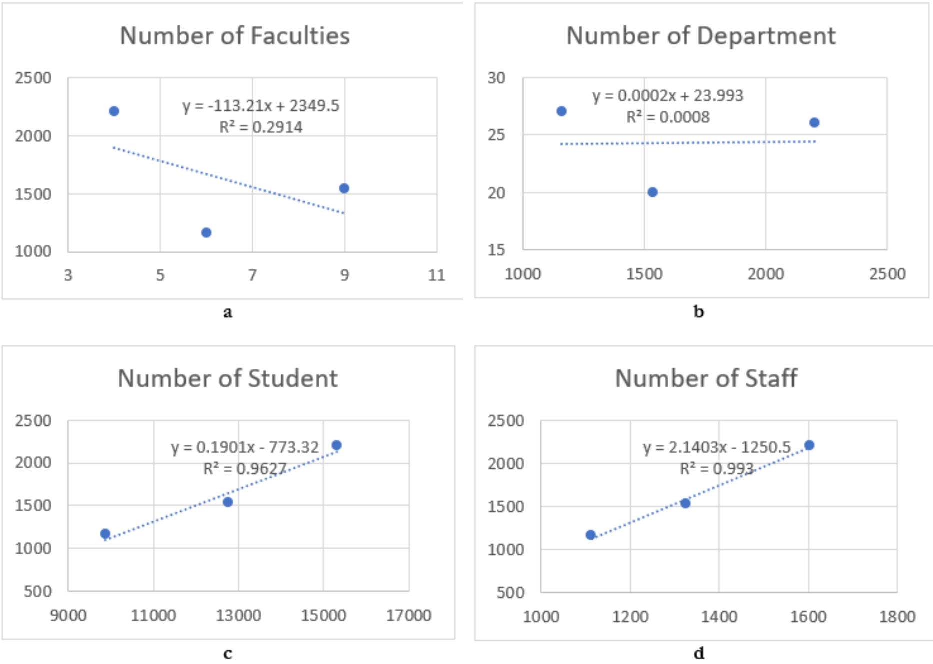

Figure 3: Developed Models for Daily Peak Hour Trip Generation.

Table 9: Daily Trips Intercorrelation Matrix Analysis

	Number of Department	*Number of Student*	*Number of Staff*	*Number of Faculties*	*Trip Generated*
Number of Department	1				
Number of Student	-0.1645	1			
Number of Staff	-0.0548	0.9939	1		
Number of Faculties	-0.8571	-0.3671	-0.4673	1	
Trip Generated	0.0291	0.9812	0.9965	-0.5398	1

Table 10: Daily Trips Regression Analysis.

Regression Statistics	
Multiple R	0.99648112
R Square	0.992974623
Adjusted R Square	0.985949246
Standard Error	62.56594444
Observations	3

Table 11. ANOVA

	df	SS	MS	F	Significance F
Regression	1	553279.44	553279.44	141.34	0.05
Residual	1	3914.50	3914.50		
Total	2	557193.93			

Table 12. Regression Results

	Coeffs	SE	t Stat	p-Value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-1250.51	245.18	-5.10	0.12	-4365.79	1864.76	-4365.79	1864.76
Number of Staff	2.14	0.18	11.89	0.05	-0.15	4.43	-0.15	4.43

Table 9 displays the correlation coefficients between the variables. It indicates the strength and direction of the relationships between the number of departments, number of students, number of staff, number of faculties, and daily trips generated. The significant positive correlation of 0.9965 between the number of staff and daily trips generated suggests a strong positive relationship. This correlation analysis demonstrates that daily trips generated are closely related to the number of staff.

Table 10 provides statistical measures of the regression model that assesses how well the independent variable (number of staff) explains the variation in the dependent variable (daily trips generated). The multiple R value of 0.9965 indicates a very high positive correlation between the number of staff and daily trips. The R^2 value of 0.9930 suggests that approximately 99.30% of the variation in daily trips can be explained by the number of staff, making it an excellent predictor. The adjusted R^2 of 0.9860 accounts for the number of independent variables and remains high, indicating the model's strong explanatory power. The SE represents the accuracy of the model's predictions, with a lower value suggesting greater accuracy. With an observations count of 3, this analysis reinforces the reliability of the model in predicting daily trips based on the number of staff.

Table 11 presents the results of the analysis of variance for the regression model. The regression section assesses the variance explained by the model, with a sum of squares (SS) of 553279.44 and a mean square (MS) of 553279.44. The high F-statistic of 141.34 suggests that the regression model is statistically significant, indicating that the number of staff is a significant predictor of daily trips. The residual section represents the unexplained variance, with an SS of 3914.50 and an MS of 3914.50. The total section provides the overall variance in the data, considering both the regression and residual variances. The significance F value, presented as 0.05, is the p-value associated with the F-statistic. Depending on the chosen significance level (alpha), if alpha is less than 0.05, it suggests that the regression model is statistically significant.

Table 12 displays the regression coefficients for the model. The intercept value of -1250.51 represents the predicted daily trips generated when there are zero staff members. The p-value of 0.12 suggests that the intercept may not be statistically significant. The *number of staff* coefficient of 2.14 indicates that for each additional staff member, there is an estimated increase of 2.14 daily trips generated. The high t-statistic of 11.89 and a p-value of 0.05 indicate that the coefficient for the number of staff is statistically significant, making it a meaningful predictor of daily trips. However, the wide confidence interval (-0.15 to 4.43) suggests some uncertainty about the exact magnitude of this effect.

In summary, the analysis reveals a strong positive relationship between the number of staff and daily trips generated, with the number of staff being a statistically significant predictor of daily trips. The high R^2 value and F-statistic further support the model's reliability. However, the practical implications and potential causality of this relationship should be carefully considered, and the significance level should align with the study's objectives.

Conclusion

Campuses of universities and polytechnics often significantly contribute to the demand for travel. Various studies have shown that user profiles, such as graduate and undergraduate students, staff, and faculty, play a substantial role in the trip rates associated with these educational facilities. This study specifically investigated the generation of trips during the AM peak hour, PM peak hour, and daily trips by three higher institutions in Kebbi State, Nigeria. The study considered four independent variables, namely the number of departments, faculties, students, and staff, in the development of a mathematical regression model that can be utilised for forecasting future travel demand in this land use context in the region. The research revealed a correlation between the number of staff and the AM peak hour trips, PM peak hour trips, and daily trips generated by the higher institutions under examination. As the first step towards creating a "Nigerian trip generation manual," this study plays a pivotal role in establishing local and reliable trip generation rates for the primary land uses in Nigerian cities and towns. Trip generation, being the initial phase of transportation planning, is essential for Nigeria to institutionalise dependable and scientifically grounded transportation planning data. The study's findings will enhance transportation planning and facilitate the early identification of significant transportation challenges arising from substantial new developments.

References

Ahmed, I., Abdulrahman, S., Hainin:, M. R., & Hassan, S. A. (2014). Trip Generations At "Polyclinic" Land Use Type In Johor Bahru, Malaysia. *Promet-Traffic&Transportation*, *26*(6), 467–473.

Akinfala, O. O., Ogunwolu, F. O., & Onyedikam, C. (2022). *A Soft Computing Approach To Trip Generation Estimation In Lagos Metropolis , Nigeria. 13*(1), 6–22. https://doi.org/10.33736/jcest.3821.2022

Al-Sahili, K., Eisheh, S. A., & Kobari, F. (2018). Estimation of new development trip impacts through trip generation rates for major land uses in Palestine. *Jordan Journal of Civil Engineering*, *12*(4), 669–682.

Basbas, S., Takatzoglou, K., Mintsis, G., Christos, T., & Ioannis, P. (2019). Trip Generation Rates for a University Campus : The Case of the Aristotle University of Thessaloniki , Greece. *Springer Nature Switzerland AG 2019*, *1*, 11–18. https://doi.org/10.1007/978-3-030-02305-8

Ben-Edigbe, J. (2010). Multivariate school travel demand regression based on trip attraction. *International Journal of Humanities and Social Sciences*, *4*(6), 1156–1160.

Ben-Edigbe, J., & Rahman, R. (2010). Multivariate school travel demand regression based on trip attraction. *World Academy of Science, Engineering and Technology*, *42*, 1169–1173.

Collins, C. M., & Chambers, S. M. (2005). Psychological and situational influences on commuter-transport-mode choice. *Environment and Behavior*, *37*(5), 640–661.

Delmelle, E. M., & Delmelle, E. C. (2012). Exploring spatio-temporal commuting patterns in a university environment. *Transport Policy*, *21*, 1–9.

Eromietse, E. T. U. J., & Joseph, O. O. (2019). *Comparative Assessment Of Radial Basis Function Neural Network And Multiple Linear Regression Application To Trip Generation Modelling In Akure , Nigeria*. *9*(2), 163–176.

Hooper, K. G. (2017). *Trip generation handbook*.

Khattak, A., Wang, X., Son, S., & Agnello, P. (2011). Travel by university students in Virginia: Is this travel different from travel by the general population? *Transportation Research Record*, *2255*(1), 137–145.

Klöckner, C. A., & Friedrichsmeier, T. (2011). A multi-level approach to travel mode choice–How person characteristics and situation specific aspects determine car use in a student sample. *Transportation Research Part F: Traffic Psychology and Behaviour*, *14*(4), 261–277.

Panackel, L. S., & Padmini, A. K. (2013). *Formulating A Trip Production Prediction Model For The Residential Land Use In Medium Sized Towns Of Kerala*. 166–174.

Wang, X., Khattak, A. J., & Son, S. (2010). *What Can Be Learned from Analyzing University Student Travel Demand ?* https://doi.org/10.3141/2322-14

Zhan, G., Yan, X., Zhu, S., & Wang, Y. (2016). Using hierarchical tree-based regression model to examine university student travel frequency and mode choice patterns in China. *Transport Policy*, *45*, 55–65. https://doi.org/10.1016/j.tranpol.2015.09.006