INTERCITY MODE CHOICE STUDY IN AKURE, NIGERIA: BINOMIAL LOGISTIC REGRESSION AND ARTIFICIAL NEURAL NETWORK APPROACH

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ABSTRACT

This study examines the factors influencing intercity mode choice behavior among travelers in Akure, Nigeria, with the aim of identifying key determinants, developing predictive models, and providing policy recommendations for improved transportation systems. Using both the Binomial Logistic Regression (BNL) model and the Radial Basis Function (RBF) neural network, data were obtained through a structured questionnaire survey targeting travelers along Akure's three main intercity corridors—Akure-Owo, Akure-Ondo, and Akure-Osun. The survey captured trip characteristics, personal socio-demographics, and transport facility attributes from a stratified random sample of 1,360 respondents. Analysis revealed that income, cost of transportation, gender, duration of stay, purpose of trip, trip destination, age, and travel distance significantly influenced mode choice. The RBF neural network model achieved higher predictive accuracy ($R^2 = 0.991$, MAPE < 0.05) compared to the BNL model ($R^2 = 0.669$, MAPE < 0.08). Findings indicate that private transportation dominates (54.7%) due to comfort and flexibility, while public transport is preferred by lower-income groups due to affordability. It is recommended that policymakers invest in efficient, affordable, and reliable public transport to reduce private vehicle dependency, congestion, and associated environmental impacts. This research contributes by providing empirical evidence on intercity travel behavior in Akure, validating the superiority of neural network approaches in travel demand modeling, and offering practical strategies for sustainable mobility planning.

Keywords: Mode-Choice, Intercity, Predictive Modelling, Binomial logistic Model, Radial Basis Function Neural Network.

1.0 INTRODUCTION

Mode choice, a crucial stage in the transportation planning process, significantly impacts policy decisions due to the substantial costs associated with transportation systems. Minal and Ravi (2014) describe mode choice modeling as closely tied to human decision-making behavior, which continues to captivate researchers seeking to better understand commuter choices. Historically, mode choice modeling has utilized methods such as linear regression and the logit model. However, this study introduces a novel approach using artificial neural networks (ANN), also known as "Universal Approximators," to model mode choice. ANN functions similarly to the human brain, with signals transmitted through neurons before the brain interprets them (Edara, 2003).

According to Osita *et al*. (2003), mode choice and urban transportation modeling play a pivotal role in facilitating the movement of people and goods while considering cost, comfort, and traveler safety, along with various other influencing factors. Osita also notes that Nigeria has yet to fully achieve these objectives, as traveler convenience and comfort remain challenging. This has led to increased mobility demand, resulting in more private cars on the road, congestion, pollution, and transport-related health issues.

Addressing these worsening transportation problems requires a comprehensive mobility plan that prioritizes people's mobility over vehicular mobility.

Previous researchers have applied various methods and probabilistic models to estimate intercity travel demand, often focusing solely on travel time and travel cost as variables. A study by Oyedepo and Makinde (2010) used multiple linear regression (MLR) analysis to identify travel cost and travel time as the most influential factors in intercity trips. Their analysis, with travel time as the dependent variable and travel cost and distance as independent variables, resulted in an average coefficient of correlation (R) of 93.1% and a coefficient of determination (R^2) of 86.6%. Another study by Fajugbagbe *et al*. (2012) examined intercity travel characteristics in Akure—such as trip destination, travel mode, vehicle capacity, vehicle count, frequency, travel time, and cost—using regression analysis. Their findings showed that the majority of trips were made to Lagos, with 77.54% of trips by bus and 22.46% by car. Additionally, the study revealed that individuals with an average income between ₦20,000 and ₦30,000 most frequently opted for public transportation.

A study on para-transit mode choice by Owolabi (2009) in Akure, utilizing a behavioral model, highlighted that mode choice is significantly influenced by transport service quality and individual factors. The model's evaluation indicated that taxis and motorcycles hold considerable advantages over other modes, with in-tim

3.0 METHODOLOGY

3.1 Study Area Description

Akure, the capital of Ondo State in south-western Nigeria, became the state capital in April 1976 and lies between latitudes 7°05′–7°20′N and longitudes 5°05′–5°20′E. It is well connected by road to nearby towns such as Owo, Ondo, Ado-Ekiti, and Akoko, making it a key intercity transport hub. As of 2006, its population stood at 387,087 (National Population Commission, 2006) and has since grown due to urbanization and economic activities. The city's land use is predominantly residential, accounting for over 90% of developed areas, but includes mixed commercial and industrial activities (Oyedepo & Afolayan, 2016). Akure has three main intercity corridors (Akure-Owo, Akure-Ondo, and Akure-Osun) served by both formal and informal transport modes, with travel patterns influenced by its tropical climate and seasonal activities.

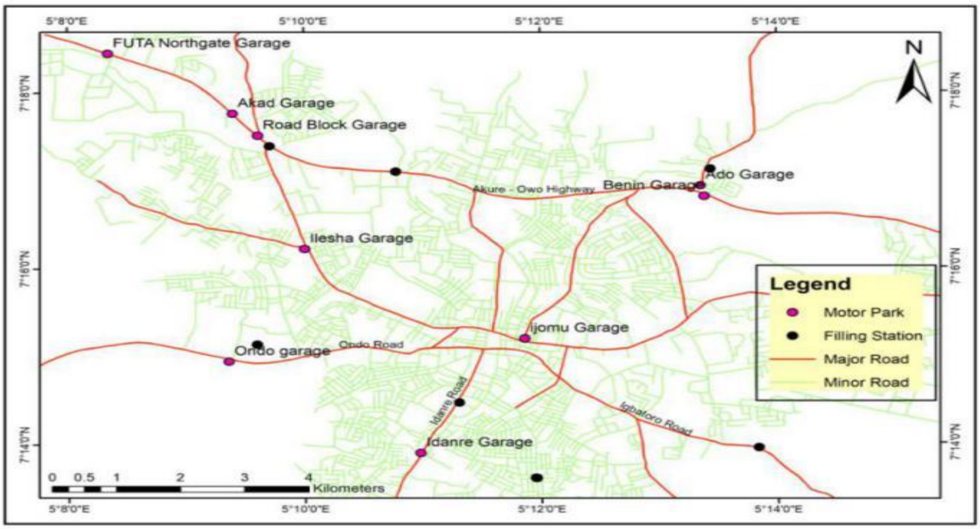

Plate 1: Road network map of Akure showing the sampling units

3.2 Apparatus and Equipment Setup

Data collection for this study relied on a structured questionnaire survey, conducted at various points along Akure's main intercity corridors and at approved motor parks. Key equipment included the questionnaires for recording responses and a laptop installed with Statistical Package for Social Sciences (SPSS) Version 29 for data input, statistical analysis, and model development. The orthogonal least squares algorithm was employed in SPSS 29 to train the Radial Basis Function (RBF) neural network model.

3.3 Data Collection and Survey Design

The survey targeted travelers along the Akure-Owo, Akure-Ondo, and Akure-Osun axes to capture a comprehensive overview of intercity travel patterns. Using a stratified sampling approach, respondents were randomly selected at filling stations and motor parks along these routes. The questionnaire captured three main data categories:

Data for this study were collected between March and May 2023 through a structured questionnaire administered to travelers at major intercity terminals, approved motor parks, and high-traffic roadside pick-up points along the Akure-Owo, Akure-Ondo, and Akure-Osun corridors. The survey instrument consisted of 32 questions divided into three main sections:

i. Trip Characteristics – travel mode, trip purpose, origin and destination, travel time, travel cost, trip frequency, and duration of stay.

ii. Personal Characteristics – age, gender, income level, educational attainment, household size, and car ownership.

iii. Transport Facility Attributes – waiting time, comfort, service quality, and safety perceptions.

A combination of multiple-choice, Likert scale (1–5 rating), and open-ended questions was used to capture both quantitative and qualitative data. The questionnaire was pre-tested with 25 respondents to ensure clarity, reliability, and validity, after which minor adjustments were made. A stratified random sampling technique was employed to ensure representation across different income groups, genders, and trip purposes. Stratification was based on observed passenger flow data from the Ondo State Ministry of Transport.

Survey administration was conducted by a team of four trained enumerators who approached travelers at designated points. Verbal informed consent was obtained from all participants, and responses were recorded anonymously. Out of 1,500 distributed questionnaires, 1,360 were completed and valid, representing a response rate of 90.67%. Data entry and cleaning were performed in SPSS version 29, with incomplete or inconsistent responses removed prior to analysis. The cleaned dataset was split into training and validation subsets for model calibration and testing.

3.4 Questionnaire Design and Distribution

The questionnaire was designed to obtain both categorical and continuous data on travel and demographic characteristics, ensuring comprehensive coverage of factors relevant to mode choice modeling. Distribution took place at designated high-traffic locations to ensure a representative sample of Akure's intercity travelers.

3.5 Sampling Approach

A stratified random sampling method was selected to capture diverse traveler profiles across various income levels, trip purposes, and family sizes. This approach helped minimize sampling bias and ensured that the collected data were reflective of the broader population in Akure.

3.6 Data Analysis and Model Formulation

For modeling mode choice, two predictive models were developed: the Binomial Logistic (BNL) model and the Radial Basis Function (RBF) neural network. The following steps were taken to set up and analyze the models:

(a) **BNL Model Development** – The BNL model was formulated using SPSS 29, which analyzed how trip and personal characteristics influence the likelihood of choosing specific travel modes.

(b) **RBF Neural Network Model Development** – The orthogonal least square algorithm served as the training mechanism in SPSS 29 for the RBF neural network. This model, based on artificial neural networks (ANN), processed inputs such as income, travel cost, age, and travel distance to predict mode choice behavior, offering an innovative approach to transport demand modeling.

3.7 Model Accuracy Metrics and Model Validation

Model performance was assessed using two key metrics: the coefficient of determination (R^2) and the mean absolute percentage error (MAPE). These measures were instrumental in comparing the predictive accuracy of the BNL and RBF models.

To validate the models, the collected data were divided into training and testing sets, ensuring that both models could reliably predict mode choice behavior. The findings were used to identify key factors impacting intercity travel preferences, which inform policy recommendations for improving transportation in Akure.

4.0 ANALYSIS AND DISCUSSION OF RESULTS

4.1 Trips by Mode Choice

Survey results from 1,360 respondents (See Plate 2) showed that 54.7% preferred private transport (personal cars), while 45.3% used public transport (buses, shared taxis, minibuses). Private transport was mainly chosen for comfort, reliability, and flexible scheduling, particularly for short-distance trips, whereas public transport users which are predominantly low-income earners cited affordability as the main reason.

A Chi-square test ($\chi^2 = 92.41$, $p < 0.001$) confirmed a significant association between income and mode choice: 61.3% of high-income earners favored private transport, while 58.4% of public transport users were low-income. Gender patterns were also observed, with males showing a higher preference for private vehicles and females leaning toward public transport, often for safety and reduced driving stress.

Trip purpose influenced choice such that business travelers tended toward private transport for time efficiency, while leisure travelers opted more for public options. Short-distance trips dominated both categories, exceeding 70% of journeys, suggesting potential congestion risks along major corridors. These findings align with Fajugbagbe et al. (2016), reinforcing the role of income and trip purpose in determining mode choice in Akure.

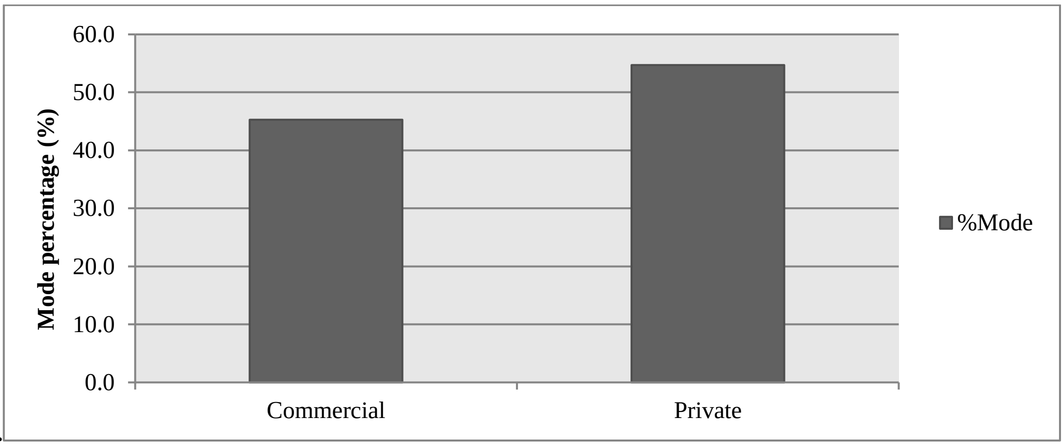

Plate 2: Mode split

4.2 Gender-wise Mode Selection

According to Plate 3, females largely preferred commercial to private means of transport. This may be due to stress and risk involved in the use of private mode of transport for intercity travels. Males preferred the use of private to commercial mode of transport in ratio of passenger per vehicles.

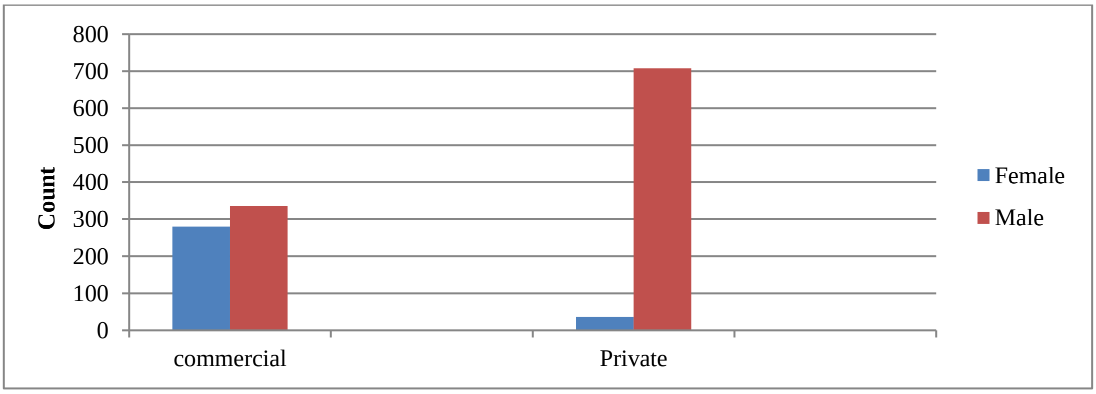

Plate 3: Mode selection by gender

4.3 Income-wise Mode Selection

Intercity travelers were divided into three groups based on their level of income as shown in Plate 4. 58.4% of commercial mode users were low-income earners, 31.5% were medium income earners and 6.5% were high income earners. 61.3% of private mode users were high income earners, 36.3% were medium income earners and 2.4% were low-income earners. Deductively, this relatively implies that people with high incomes preferred the use of private to commercial mode for their intercity travels, while people with low incomes preferred otherwise. This also corresponds with the results from the research by Fajugbage *et al.*, (2016), where he assessed intercity travel characteristics in Akure and discovered that people with an average income ranging between #20000 and #30000 travel most with public vehicles.

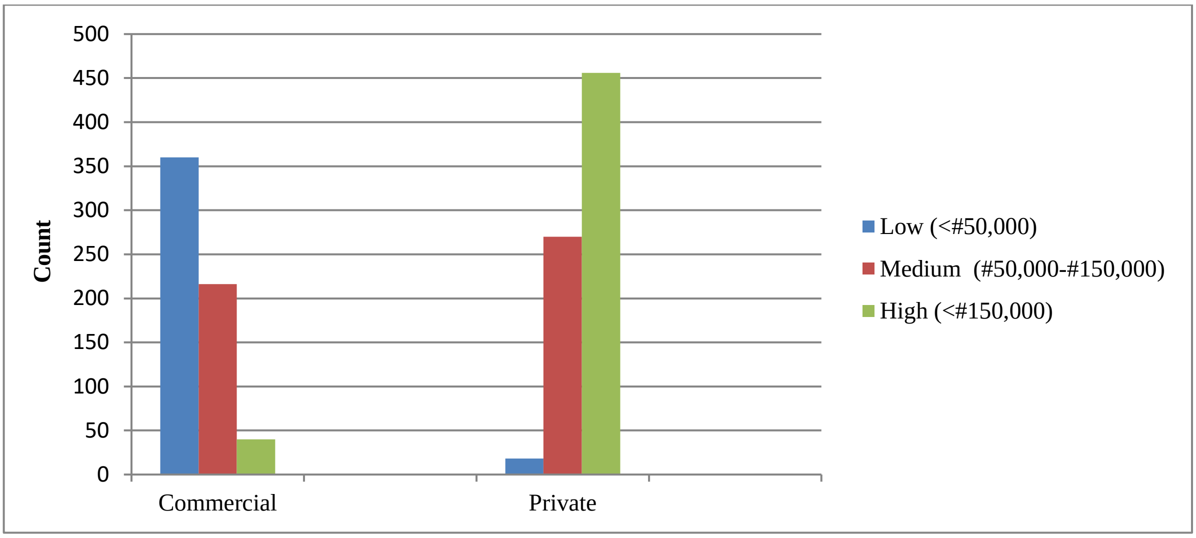

Plate 4: Mode selection by income

4.4 Mode Selection by Duration of Stay

The duration of stay of intercity travelers at their destination points were grouped into four as shown in Plate 5. 42.9% of commercial mode users stayed at their place of destination for (8-30) days, 27.3% stayed for (4-7) days, 22.1% stayed for more than 30days and 7.8% stayed for (1-3) days. For users of private mode of transport, 31.5% which is the highest on its list stayed for (1-3) days. This high percentage is due to ease of accessibility associated with the private mode of travel, where travelers can choose to travel at any point in time. The least percentage for private mode users was days exceeding 30days as most of its users preferred lesser days of stays.

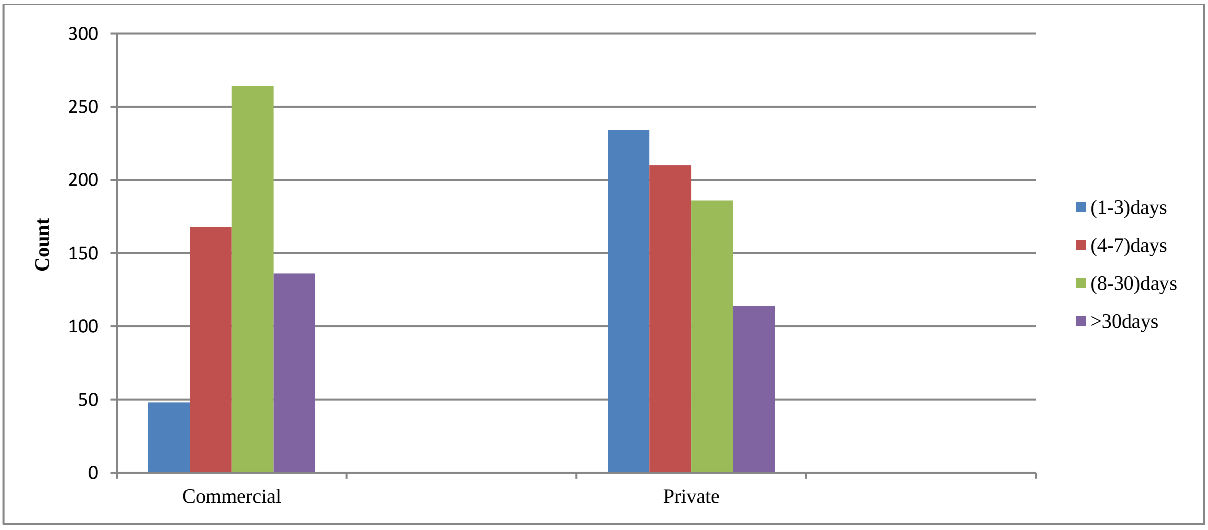

Plate 5: Mode selection by duration of stay

4.5 Mode Selection by Travel Distance

Travel distance was grouped into two; short distance and long distance. Plate 6 shows the relationship between mode of travel and each distance group. 71.4% of commercial mode travels were short distance trips and 28.6% were long distance trips, while 69.4% of private mode travels were short distance trip and 30.6% were long distance. The high percentage of short distance trip makers for private transport is an indication of why there may be the occurrence of traffic congestion at intercity routes corridors

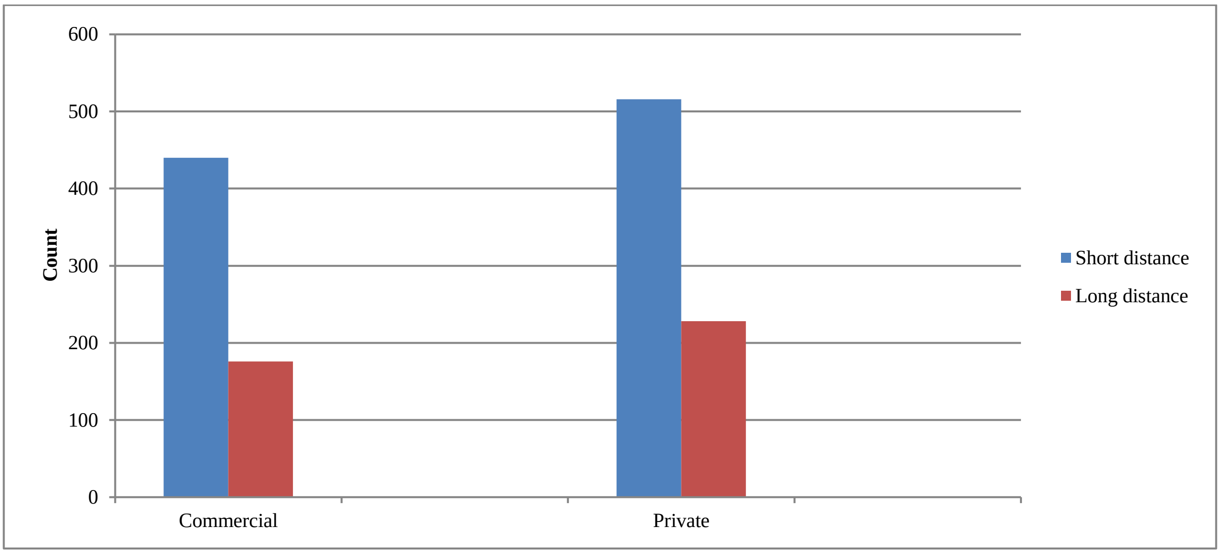

Plate 6: Mode selection by travel distance

4.6 Binomial Logistic (BNL) Model and Radial Basis Function (RBF) Neural Network Variables Relative Importance

The variables relative importance to the model is shown in Plate 7. It reveals that income had the most significant influence, followed by cost of transportation, gender and duration of stay, with respective values of 100%, 61.6%, 45.7% and 22%.

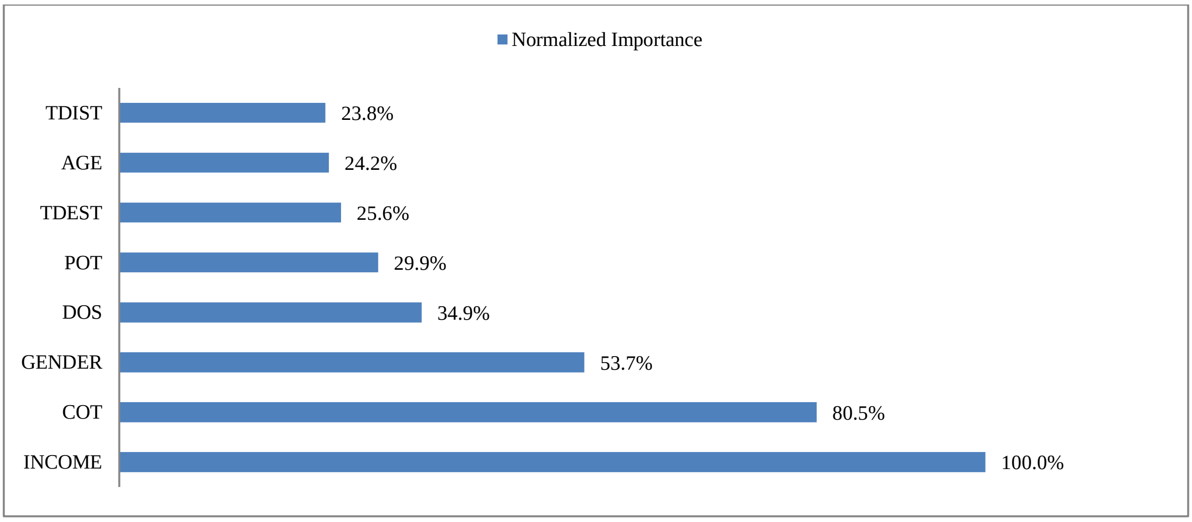

Plate 7: Normalized Independent Variable Importance

4.7 Binomial Logistic Model Parameter Estimates

The parameter estimates of the model showed in Table 1 were used computing the utilities for each mode of transport. All the variables presented in the table have significant parameter estimates and logical signs. The logistic regression coefficient for each independent in the table is identified as B. The values of B for TDEST, DOS and TDIST were negative, which implies that an increase in these variables would increase private transportation usage. While reduction in the positive values of B would increase the usage of commercial means of transportation.

Table 1: Parameter Estimates for Mode Choice Model

Independent variables	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Constant	-15.006	1.328	127.590	1	0.000	0.000	-	-
GENDER	3.782	0.477	62.747	1	0.000	43.893	17.219	111.885
AGE	0.352	0.194	3.287	1	0.070	1.422	.972	2.082
INC	4.731	0.374	159.790	1	0.000	113.352	54.436	236.032
POT	0.111	0.077	2.087	1	0.149	1.117	0.961	1.299
TDEST	-0.257	0.048	28.126	1	0.000	0.774	0.704	0.851
COT	4.323	0.388	124.278	1	0.000	75.448	35.280	161.348
DOS	-0.423	0.155	7.445	1	0.006	0.655	.484	0.888
TDIST	-14.380	1.426	101.739	1	0.000	0.000	0.000	0.000

The empirical utility function equation (1) for each mode of travel is given as;

$$U_{comm} = Bconst + B_{GEN}GEN + B_{AGE}AGE + B_{INC}INC + B_{POT}POT + B_{TDEST}TDEST + B_{COT}COT + B_{DOS}DOS + B_{TDIST}TDIST \quad (1)$$

Where,

U_{comm} is Utility of Commercial Transport.

$$U_{comm} = -15.006 + 3.782GEN + 0.552AGE + 4.731INC + 0.111POT \; -0..254TDEST + 4.323COT - 0.423DOS - 14.380TDIST \quad (2)$$

The utility of commercial transport was worked by substituting the mean values (see Table 1) of the respective variables into equation (2)

4.8 Binomial Logistic Model Validation

Likelihood ratio test (Table 2) indicates the contribution of the variable to the overall relationship between the dependent and individual independent variable in differentiating between the groups specified by the dependent variable (Boateng and Abaye, 2019). The likelihood ratio test is a hypothesis test that the variable contributes to the reduction in error measured by the -2 log likelihood statistic.

Table 2: Binomial Logistic model R Square values

-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
370.414	0.669	0.894

Cox and Snell R Square operate like the coefficient of determination 'R^2', with higher value indicating greater model fit (Piepho, 2019). Here, the Cox & Snell R Square value is 0.669 (i.e 66.9%) indicating that approximately 66.9% of the variation in the dependent variable (modal choice) can be explained by the estimated Binomial Logistic model. Cox & Snell R^2 measure is limited in that it cannot reach the maximum value of 1. Therefore, Nagelkerke proposed a modification that had the range from 0 to 1 (Pate et al., 2023). The model validation run was made with the same model specification. The model was calibrated for data of 12

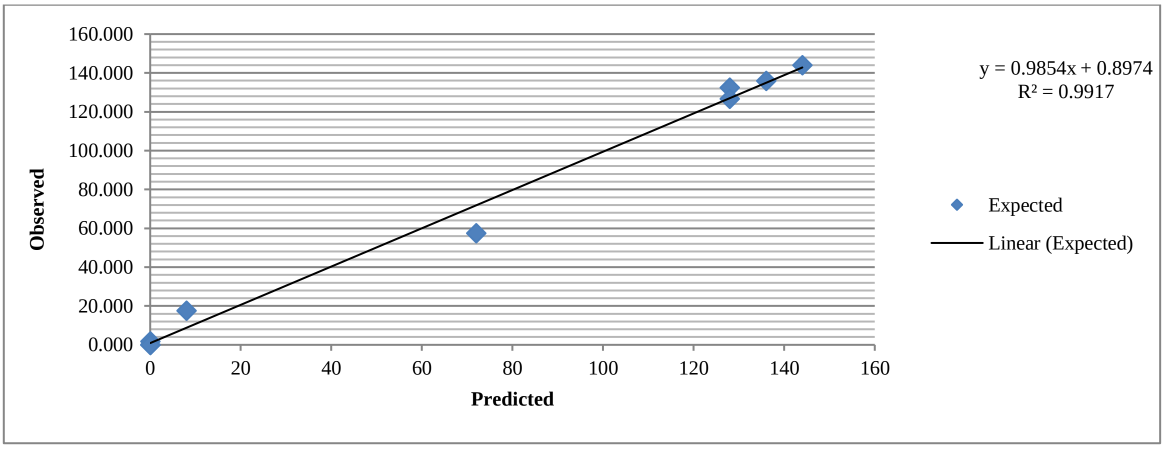

Plate 8: Observed Versus Expected (Commercial Transport Mode)

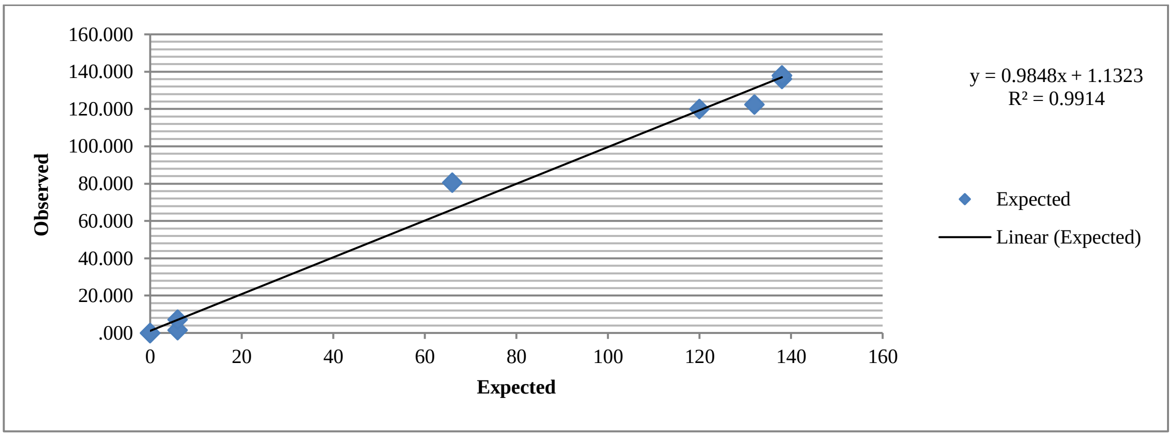

Plate 9: Observed Versus Expected (Private Transport Mode)

4.9 Radial Basis Function (RBF) Neural Network Parameter Estimates

The model estimate for all independent variables is shown in Appendix B. The prediction model gave a total of 9 hidden nodes with each node having an associated prediction for each mode of travel (as in Table 3).

Table 3: RBF Neural Network Hidden Layer Estimates

		Commercial	Private
Hidden Layer	H(1)	-0.115	1.115
	H(2)	-0.069	1.069
	H(3)	1.005	-0.005
	H(4)	1.105	-0.105
	H(5)	1.113	-0.113
	H(6)	1.183	-0.183
	H(7)	-0.129	1.129
	H(8)	-0.024	1.024
	H(9)	0.413	0.587
Total		4.482	4.518

The probability of choosing commercial mode of transport is given by:

$$p_{comm} = 0.498 \quad (3)$$

The probability of choosing private mode of transport is given by:

$$p_{priv} = 0.502 \quad (4)$$

4.10 Radial Basis Function (RBF) Neural Network Model Validation

Model calibration was done using 849 samples and 361 samples for model testing. The validation of this model was done using the hold out samples of 150. Each modelling stages has its associated prediction success, where later stages in the model show better prediction success than the previous (i.e., 94.6% < 94.7% < 98%).

The mean absolute percentage error for commercial and private mode of transport is 0.032 and 0.011 (i.e., 3.2% and 1.1%) which is less than 0.05, showing high prediction success. The coefficient of determination 'R2' is 0.991, indicating that approximately 99.1% of the variation in the dependent variable (modal choice) can be explained by the estimated Radial Basis Function (RBF) Neural Network.

4.11 Binomial Logistic (BNL) Model and Radial Basis Function (RBF) Neural Network Comparison

Performance comparisons were drawn between the two models using the Coefficient of Determination 'R2' and Mean Absolute Percentage Error 'MAPE'. From the performance comparison in Table 4, it shows that R2 for Radial Basis Function (RBF) Model gave better prediction success than that of Binomial Logistic (BNL) model, since R2 values closest to 1 gives a better prediction success. RBF Model also shows its high level of performance in terms of the MAPE, with its value relatively low when compared for each mode. Although, the modes probabilities were not measure to access the performance of both models, but since RBF model gives a better prediction success its becomes inevitable that the mode probabilities of RBF model overwrite that of the other model probabilities.

Table 4: BNL and RBF Model Performance Comparison

<table>
<tr><td>Criteria</td><td>Modes</td><td>BNL Model</td><td>RBF Model</td></tr>
<tr><td rowspan="2">R square</td><td>Commercial</td><td rowspan="2">0.669</td><td rowspan="2">0.991</td></tr>
<tr><td>Private</td></tr>
<tr><td rowspan="2">MAPE</td><td>Commercial</td><td>0.078</td><td>0.032</td></tr>
<tr><td>Private</td><td>0.024</td><td>0.011</td></tr>
<tr><td rowspan="2">Probability</td><td>Commercial</td><td>0.100</td><td>0.498</td></tr>
<tr><td>Private</td><td>0.900</td><td>0.502</td></tr>
</table>

5.0 CONCLUSION

Binomial Logistic correlation and Radial Basis Function (RBF) relative importance helped to identify deterministic variables that have significant influence on the mode choice of intercity travellers to be Income (INC); Cost of Transportation (COT); Gender (GEN); Duration of Stay (DOS); purpose of trip (POT); Trip Destination (TDEST); Age (AGE); and Travel Distance (TDIST).

Output of Binomial Logistic (BNL) analysis showed that the probability of intercity travellers choosing private mode of transport is 0.56 (i.e. 56%). Also, output of the Radial Basis Function (RBF) showed that the probability of intercity traveller choosing private mode of transport is 0.502 (i.e. 50.2%).

R^2 value for Binomial Logistic (BNL) model and Radial Basis Function (RBF) neural network was 0.669 and 0.991 respectively. When these values were compared, it showed that the RBF neural network gives better prediction success. The RBF also showed better performance in terms of the Mean Absolute Percentage Error 'MAPE' between the observed and predicted values. Whereas the RBF neural network for commercial and private mode had a MAPE of 0.032 and 0.011 respectively, and respective value of 0.078 and 0.024 for BNL model. Therefore, it is recommended that transport researchers should practise the use of Radial Basis Function (RBF) neural network approach for their choice models, as it has proved to produce more prediction accuracy than the Binomial Logistic (BNL) model. Subsequently, since mode choice model has identified private mode as the dominant mode of intercity travels away from the study area, it is recommended that providing an active and efficient public transportation system which is comfortable, reliable, accessible and cheap to intercity travelers will help reduce the use of private cars use, especially in cases of short distance trips.

This research contributes to knowledge by:

(a) providing data on intercity travel characteristics of intercity travelers in Akure.

(b) maximizing our conceptual and scientific understanding about the awareness and behaviour of intercity travelers towards existing intercity transportation system and services.

(c) calibrating models that can be used in predicting modal split behaviour in the study area.

(d) establishing the superiority of Radial Basis Function (RBF) neural network to the Binomial Logistic (BNL) model in predicting mode choice behaviour of intercity travelers in the study area.

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