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Case Report

Developing a Home-based Trip Generation Model for a Suburb Area of a City: Case of Furi Sub-city, Sheger City

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Abstract

Rapid urbanization in Furi Sub-city has increased travel demand, placing considerable pressure on the existing transportation system. Developing locally calibrated trip generation models is therefore essential for reliable travel demand forecasting and effective transportation planning. This study develops and compares household-level home-based trip generation models using Multiple Linear Regression (MLR) and Multiple Classification Analysis (MCA). Household travel survey data were collected from 383 randomly selected households to examine the influence of socioeconomic and demographic characteristics on home-based trip production. MLR was employed to estimate continuous trip generation models, whereas MCA was used to derive category-based trip rates, and model performance was evaluated using goodness-of-fit statistics and prediction accuracy measures. The results indicate that household size, number of students, vehicle ownership, and the numbers of employed and unemployed household members are the principal determinants of home-based trip generation in Furi Sub-city. Although both MLR and MCA adequately captured household travel behavior, MLR generally demonstrated higher explanatory power and lower prediction errors for most trip purposes; whereas MCA showed better performance for total home-based trip generation based on validation error measures. Overall, the findings suggest that MLR provides a more reliable approach for household trip generation modeling in the study area, while MCA offers an interpretable alternative for estimating category-based trip rates. The locally calibrated models developed in this study provide valuable inputs for travel demand forecasting, transportation planning, and evidence-based policy development in Furi Sub-city and other rapidly urbanizing areas with similar socioeconomic characteristics.

Keywords

Household Travel Survey, Home-based Trip Generation, Multiple Linear Regression, Multiple Classification Analysis, Travel Demand Forecasting, Transportation Planning

1. Introduction

Rapid urbanization has significantly increased travel demand in many developing cities, creating growing pressure on transportation infrastructure and services. Reliable travel demand forecasting is therefore essential for planning efficient transport systems, supporting sustainable urban development, and improving mobility. Trip generation, the first stage of the conventional four-step travel demand modeling process, estimates the number of trips produced and attracted within a study area and provides the basis for subsequent transportation planning analyses. Consequently, the development of accurate

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trip generation models is fundamental to effective transport planning.

Household trip generation is influenced by various socioeconomic and demographic characteristics, including household size, employment status, income, vehicle ownership, and the number of students. Previous studies have widely applied Multiple Linear Regression (MLR) to model the relationship between these variables and trip production, while others have employed Multiple Classification Analysis (MCA) to estimate category-based trip rates. Although both approaches have demonstrated satisfactory performance in different contexts, trip generation models are highly location-specific because travel behavior varies with socioeconomic conditions, urban form, and travel patterns. Therefore, locally calibrated models are required to produce reliable travel demand forecasts.

Despite the growing body of research on trip generation modeling, several important gaps remain. First, most previous studies have applied either MLR or MCA independently, with relatively few directly comparing the two methods using the same household travel survey dataset. Second, in Ethiopia, trip generation studies have been conducted in only a few cities, limiting the applicability of their findings to other urban areas with different socioeconomic and travel characteristics. Third, many studies have relied primarily on goodness-of-fit statistics, while independent model validation using prediction error measures has received comparatively little attention. These limitations highlight the need for context-specific studies that evaluate both modeling approaches using consistent data and comprehensive performance measures.

Furi Sub-city, one of the rapidly expanding sub-cities of Sheger City surrounding Addis Ababa, has experienced substantial population growth and increasing travel demand in recent years. However, no locally calibrated household trip generation model has been developed for the area. This lack of empirical evidence limits the ability of transportation planners to accurately forecast travel demand and develop effective transport policies and infrastructure plans.

To address these gaps, this study develops and compares household-level home-based trip generation models using Multiple Linear Regression (MLR) and Multiple Classification Analysis (MCA) based on household travel survey data collected in Furi Sub-city. The study identifies the key household socioeconomic and demographic factors influencing different home-based trip purposes and evaluates the predictive performance of both modeling techniques using goodness-of-fit statistics and prediction accuracy measures. The findings provide locally calibrated trip generation models and empirical evidence to support travel demand forecasting and transportation planning in Furi Sub-city and other rapidly urbanizing urban areas with similar characteristics.

2. Literature Review

Household trip generation has been extensively investigated to understand the relationship between household characteristics and travel demand. Previous studies consistently identify household size, employment status, household income, vehicle ownership, and the number of students as the principal determinants of household trip production [1-5]. More recent studies have reported similar findings. [6] showed that household socioeconomic characteristics and neighborhood accessibility significantly influence both home-based commute and non-commute trip generation. Likewise, [7] identified household size, number of workers, students, income, and vehicle ownership as the most significant determinants of home-based trip production, while [8] found that household size, number of workers, licensed drivers, and educational level were the primary predictors of residential household trip generation. Similarly, [9] reported that household size, income, number of young children, and travel day significantly affect daily household trip generation. Collectively, these studies indicate that although the principal determinants of household trip production are generally consistent, their relative importance varies across cities due to differences in socioeconomic conditions, urban structure, land-use characteristics, and travel behavior. Consequently, trip generation models developed for one location cannot be directly transferred to another without local calibration and validation.

Multiple Linear Regression (MLR) has been the most widely applied technique for household trip generation modeling because it provides a simple, effect tive, and interpretable framework for quantifying the relationship between household characteristics and trip production. Several studies have successfully applied MLR to develop trip generation models and identify significant explanatory variables [2, 3, 5, 10]. More recently, [7, 8] developed MLR-based household trip generation models that demonstrated the continued effectiveness of regression techniques for urban travel demand forecasting. [11] further compared conventional linear regression with advanced machine learning algorithms, including Cat Boost and Random Forest, using National Household Travel Survey (NHTS) data. Their results showed that linear regression achieved predictive performance comparable to, and in many cases superior to, machine learning models while providing far greater model interpretability. Although MLR can adequately explain variations in household trip generation, the method relies on assumptions such as linear relationships among variables and may be less suitable when explanatory variables are categorical or when travel behavior exhibits nonlinear patterns.

To address these limitations, researchers have applied Multiple Classification Analysis (MCA) and related cross-classification techniques for trip generation modeling. [12, 13] introduced MCA as an extension of conventional cross-classification methods by incorporating analysis of variance to estimate adjusted household trip rates while reducing problems associated with sparse classification cells. Subsequently, [4, 14] compared MCA with MLR and reported that both approaches produced satisfactory household trip generation

models, although their predictive performance varied depending on study area characteristics. In addition, [15] compared MLR with an Adaptive Neuro-Fuzzy Inference System (ANFIS) for modeling home-based trips, concluding that ANFIS generally achieved higher predictive accuracy while MLR remained an effective and interpretable baseline. Similarly, [9] demonstrated the applicability of Negative Binomial regression for handling non-negative integer trip counts. Nevertheless, MCA continues to offer a practical, category-based framework that yields trip rates that are straightforward to interpret and readily applicable in transportation planning.

Despite these contributions, several research gaps remain. Most previous studies have applied a single modeling technique or compared conventional regression with machine learning methods, whereas relatively few have directly compared MLR and MCA using the same household travel survey dataset. In Ethiopia, household trip generation studies have been conducted in only a few cities, limiting the applicability of existing findings to rapidly growing urban areas with different socioeconomic and travel characteristics. Furthermore, many studies have evaluated model performance primarily using goodness-of-fit statistics, while independent model validation using prediction accuracy measures has received comparatively little attention. Addressing these gaps, the present study develops and compares MLR and MCA models for different home-based trip purposes using locally collected household travel survey data from Furi Sub-city. In addition, the predictive performance of both approaches is evaluated using goodness-of-fit statistics and prediction error measures to identify the most appropriate modeling technique for travel demand forecasting in the study area.

3. Research Methodology

3.1. Description of the Study Area

The study was conducted in Furi Sub-City, one of the twelve sub-cities administered under Sheger City, Ethiopia. Sheger City was established in 2022 through the integration of six surrounding towns, namely Sebeta, Burayu, Legatafo, Lededadi, Sululta, and Gelan, which are located around Addis Ababa. Furi Sub-City consists of three administrative districts (woredas).

According to the Furi Sub-City Administration Office (2023), the estimated population of the sub-city was 441,332 in 2023, consisting of 232,224 males (52.62%) and 209,108 females (47.38%), with an average household size of 5.8 persons per household. The sub-city covers approximately 68.09 km^2 of Sheger City, resulting in a population density of 6,481.6 persons/km^2. The rapid urban expansion and population growth in the area have increased travel demand and created additional pressure on the existing transportation system, highlighting the need for improved understanding of household trip generation characteristics.

3.2. Sample Design

A stratified random sampling approach was adopted to ensure adequate representation of households across the study area. The sampling procedure considered both the selection of representative households and the determination of an appropriate sample size. Therefore, a sample size of 383 households was considered for this study. Accordingly, a total sample of 383 households was selected for the household travel survey.

The study area was divided into three zones based on administrative boundaries. The required sample households were proportionally allocated to each zone according to population distribution. Within each zone, households were randomly selected from the identified Traffic Analysis Zones (TAZs) to conduct the household travel survey.

3.3. Data Collection Method

A household interview survey was employed as the primary data collection method. This approach allowed the collection of detailed household socioeconomic characteristics and travel behavior information required for developing home-based trip generation models.

A structured questionnaire was prepared to collect information related to household size, number of students, household income, employment status, vehicle ownership, and daily trips by purpose. Household interviews were conducted during weekends to improve respondent availability and enhance the completeness of the collected information.

3.4. Model Specification and Estimation Techniques

The objective of model specification was to establish the relationship between household socioeconomic characteristics and home-based trip production. Two modeling approaches, Multiple Linear Regression (MLR) and Multiple Classification Analysis (MCA), were applied to develop and compare household trip generation models.

The collected survey data were coded, entered, and analyzed using the Statistical Package for the Social Sciences (SPSS). Prior to model estimation, data screening was conducted to identify missing values, inconsistencies, and potential outliers to ensure the reliability of the dataset.

3.4.1. Multiple Linear Regression Model

Multiple Linear Regression (MLR) was used to estimate the relationship between household characteristics and the number of trips generated by households. The general form of the household trip generation model was expressed as:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3. + \beta_i X_i + U \quad (1)$$

Where: Y = number of trips generated by household
α = constant term

Xi = the independent variables
βi = the partial slope coefficients
U = an error term assumed to be a random variable

The dependent variables considered in the analysis were home-based total trips, home-based work trips, home-based school trips, home-based shopping trips, and home-based other trips. The explanatory variables included household size, number of employed members, number of unemployed members, number of students, household income, age of household head, number of males in the household, number of females in the household, number of licensed driver household members and vehicle ownership.

The performance of the regression models was evaluated using the coefficient of determination (R^2), adjusted R^2, F-statistics, t-statistics, significance levels, and standard error of estimation. Model assumptions, including linearity, normality of residuals, homoscedasticity, independence of errors, and absence of multicollinearity, were examined before final model selection. Correlation analysis and Variance Inflation Factor (VIF) values were used to identify multicollinearity among independent variables.

3.4.2. Multiple Classification Analysis Model

Multiple Classification Analysis (MCA) was applied to estimate trip generation rates for different household categories. Unlike MLR, which estimates continuous relationships between variables, MCA evaluates the influence of categorical household characteristics by comparing category mean trip rates and adjusted mean trip rates.

The MCA model can be expressed as:

$$Y = \bar{Y} + \alpha_1 + \alpha_2 + \alpha_{3\ldots} + e \quad (2)$$

Where: Y = predicted trip generation
$\bar{Y}$ = grand mean of trips made by the households
α = Category effect (Household size effect, Household income effect….)
e = error

Households were classified into categories based on selected socioeconomic characteristics, including household size, employment status, student population, income level, and vehicle ownership. The significance of categorical variables was evaluated using analysis of variance (ANOVA), F-statistics, significance levels, and explanatory power measures.

The final MLR and MCA models were selected based on statistical significance, theoretical relevance of explanatory variables, model performance, and validation results. The developed models were subsequently compared to identify the most appropriate approach for predicting household-based trip generation in Furi Sub-City.

4. Result and Discussion

The household travel survey data were analyzed to identify the major determinants of home-based trip generation and to develop predictive models for Furi Sub-City. Multiple Linear Regression (MLR) and Multiple Classification Analysis (MCA) were applied to estimate total household trips and purpose-specific home-based trips, including work, school, shopping, and other trips. The developed models were evaluated using statistical goodness-of-fit measures and independent validation data to determine their predictive performance.

4.1. Descriptive Analysis and Variable Selection

The descriptive analysis was conducted to summarize the socioeconomic characteristics of surveyed households and their travel behavior. The analysis considered household size, employment status, student population, income level, vehicle ownership, and other demographic characteristics as potential determinants of household trip generation.

The results indicate that household travel behavior varies according to household composition and socioeconomic conditions. Households with higher numbers of employed members, students, and private vehicles generally generate higher trip rates because these characteristics represent increased activity participation and improved mobility opportunities.

Before model development, a variable selection procedure was conducted to identify significant explanatory variables. For MLR, candidate variables were evaluated using correlation analysis, multicollinearity diagnostics, and significance testing. Variables with statistically significant relationships and acceptable multicollinearity levels were retained.

For MCA, household characteristics were classified into different categories, and variables were selected based on category mean analysis, one-way ANOVA, and significance testing. The selected variables represent the major household factors affecting travel demand, including household activity participation, socioeconomic characteristics, and transportation accessibility.

4.2. Multiple Linear Regression (MLR) Models

The MLR models were developed to estimate household trip generation based on socioeconomic and demographic characteristics. The final selected variables and model equations are presented below.

4.2.1. Total Home-Based Trip Model

The total home-based trip model identified number of employed household members, students, household gender composition, licensed drivers, age of household head, and vehicle ownership as significant predictors.

$$TT = -0.776 + 1.118Nemplo + 1.579Nstudent + 0.532Nmale + 0.526Nfemale + 0.573NDlicensed + 0.056AHHhead + 1.061Nownvehicle \quad (3)$$

The results indicate that employment, education-related activities, and transportation availability are major determinants

of household trip production. Households with more employed members, students, and vehicles generate higher levels of travel demand.

4.2.2. Home-Based Work Trip Model

The work trip model identified employed household members, unemployed household members, and vehicle ownership as significant predictors.

$$HBW = -0.180 + 2.232Nemplo + 0.113Nunemplo + 0.561Nownvehicle \quad (4)$$

The number of employed members was the dominant factor influencing work trips, confirming that commuting demand is strongly associated with household employment characteristics.

4.2.3. Home-Based School Trip Model

The school trip model included number of employed members, students, age of household head, and vehicle ownership.

$$HBSCH = -0.141 - 0.089Nemplo + 2.041Nstudent + 0.008AHHhead + 0.586Nownvehicle \quad (5)$$

The number of students showed the strongest influence, indicating that school travel demand is primarily generated by households with school-age members.

4.2.4. Home-Based Shopping Trip Model

The shopping trip model identified household size, employment, unemployment, household income, and vehicle ownership as significant factors.

$$HBS = 0.446 + 0.040HHsizeUG - 0.211Nemplo + 0.302Nunemplo + 4.592*10\text{-}6HHincome + 0.164Nownvehicle \quad (6)$$

The results suggest that shopping travel is influenced by household consumption requirements and accessibility. The negative relationship with employment may indicate that employed individuals combine shopping activities with work-related travel.

4.2.5. Home-Based Other Trip Model

The other trip model included household size, employment, unemployment, age of household head, and household income.

$$HBO = -0.167 - 0.061HHsizeUG + 0.227Nemplo + 0.483Nunemplo + 0.018AHHhead + 5.992*10\text{-}6Hhincom \quad (7)$$

The findings indicate that discretionary travel is influenced by household composition and socioeconomic conditions.

4.3. Multiple Classification Analysis (MCA) Models

MCA was applied to identify differences in household trip generation rates among different socioeconomic groups. The approach provides category-based trip rates that are useful for household travel demand forecasting.

4.3.1. Total Home-Based Trip MCA Model

The significant factors were grouped employment, grouped unemployment, grouped student population, grouped income, and grouped vehicle ownership.

$$TT = \mu + \alpha(GNemplo) + \beta(GNunemplo) + \gamma(GNstudent) + \delta(GHHincome) + \phi(GNownvehicle) + \varepsilon \quad (8)$$

Where: μ: grand mean, α: : employment effect, β: unemployment effect, γ: student effect, δ: income effects, ϕ: vehicle ownership effect, ε: error term

The results show that household activity participation and mobility resources strongly affect total trip generation. Households with higher employment, student population, income, and vehicle ownership generally produce higher trip rates.

4.3.2. Home-Based Work Trip MCA Model

The significant factors were household size, grouped employment, household head education, vehicle ownership, and the interaction between household size and education.

$$HBW = \mu + \alpha(GHHsize) + \beta(GNemplo) + \gamma(HHheadedu) + \theta(GNownvehicle) + \delta(GHHsize * HHheadedu) + \varepsilon \quad (9)$$

Where: μ: grand mean, α: household size effect, β: employment effect, γ: education type effect, θ: vehicle ownership, δ: interaction effects, ε: error term

The findings indicate that work trip generation varies according to household structure, employment level, and socioeconomic characteristics.

4.3.3. Home-Based School Trip MCA Model

The significant factors were household size, student population, vehicle ownership, and their interaction effect.

$$HBSCH = \mu + \alpha(GHHsize) + \beta(GNstudent) + \gamma(GNownvehicle) + \delta(GHHsize * GNownvehicle) + \varepsilon \quad (10)$$

Where: μ: grand mean, α: household size effect, β: student effect, γ: vehicle ownership effect, δ: interaction effects, ε: error term

The results confirm that student population is the main determinant of school trip generation.

4.3.4. Home-Based Shopping Trip MCA Model

The significant factors were household size and vehicle ownership

$$HBS = \mu + \alpha(GHHsize) + \beta(GNownvehicle) + \varepsilon \quad (11)$$

Where: μ: grand mean, α: household size effect, β: vehicle ownership effect, ε: error term

The model indicates that shopping travel varies according to household requirements and transportation accessibility.

4.3.5. Home-Based Other Trip MCA Model

The significant factors were household size, unemployed household members, and household head occupation.

$$HBO = \mu + \alpha(GHHsize) + \beta(GNunemplo) + \gamma(HHheadoccup) + \varepsilon \quad (12)$$

Where: μ: grand mean, α: household size effect, β: unemployment effect, γ: occupation type effect, and ε: error term

The results indicate that discretionary travel is affected by household composition and activity availability.

4.4. Model Validation and Comparison

The developed models were validated using a 70% training dataset and 30% testing dataset. Model performance was evaluated using R^2, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and prediction accuracy.

Table 1. *Comparative Performance of MLR and MCA Models.*

Performance Measure	Trip Purpose				
	TT	**HBW**	**HBSCH**	**HBS**	**HBO**
R^2 for MLR (from the final model)	0.859	0.853	0.9652	0.440	0.307
R^2 for MCA (from the final model)	0.808	0.571	0.911	0.116	0.313
Adjusted R^2 for MLR (from the final model)	0.857	0.852	0.9649	0.432	0.297
Adjusted R^2 for MCA (from the final model)	0.802	0.549	0.909	0.107	0.299
MAE for MLR (from test model)	1.7967	0.5192	0.3338	0.3086	0.6187
MAE for MCA (from test model)	1.1911	1.1441	1.7168	0.4328	0.6391
RMSE for MLR (from test model)	2.2679	0.7458	0.5952	0.3747	0.7355
RMSE for MCA (from test model)	1.6545	1.4225	1.9377	0.4664	0.7983
MAPE for MLR (from test model)	19.40%	13.63%	6.89%	29.76%	46.59%
MAPE for MCA (from test model)	13.61%	36.54%	27.88%	31.17%	61.92%
Prediction Accuracy for MLR	80.60%	86.37%	93.11%	70.24%	53.41%
Prediction Accuracy for MCA	86.39%	63.46%	72.12%	68.83%	38.08%
Better Model	MCA	MLR	MLR	MLR	MLR

The comparison indicates that model performance varies depending on trip purpose. Although MLR generally achieved higher explanatory power, MCA provided better prediction accuracy for total household trips.

For total trips, MLR achieved a higher R^2 value (0.859) compared with MCA (0.808). However, MCA produced lower validation errors (MAE = 1.191 trips, RMSE = 1.655 trips, and MAPE = 13.61%) compared with MLR (MAE = 1.797 trips, RMSE = 2.268 trips, and MAPE = 19.40%). This indicates that MCA better captured differences among household groups for overall trip generation.

For work, school, shopping, and other trips, MLR provided better prediction performance. This is because these trip purposes showed stronger relationships with measurable household characteristics, which are effectively represented through regression analysis.

5. Conclusion and Recommendation

This study developed household-level home-based trip generation models for Furi Sub-city using Multiple Linear Regression (MLR) and Multiple Classification Analysis (MCA) based on household socioeconomic and demographic charac-

teristics. The results identified household size, number of students, number of employed household members, number of unemployed household members, and vehicle ownership as the key determinants of home-based trip generation. The analysis also showed that the relative influence of these variables differs by trip purpose, highlighting the importance of developing purpose-specific trip generation models rather than applying a single model to all trip types.

Both MLR and MCA produced statistically significant models and adequately represented household travel behavior. However, model validation showed that MLR generally achieved higher explanatory power and better prediction accuracy than MCA for most trip purposes, indicating that MLR is the more suitable approach for estimating household trip generation in the study area. The locally calibrated models developed in this study provide a reliable basis for travel demand forecasting and can support transportation planning, infrastructure investment, and public transport service planning in Furi Sub-city. Future research should incorporate additional explanatory variables, such as land-use characteristics, accessibility, and travel cost, and evaluate advanced modeling techniques to further improve prediction accuracy.

Abbreviations

ANFIS	Adaptive Neuro-Fuzzy Inference System
ANOVA	Analysis of Variance
HBO	Home Based Other Trip
HBS	Home Based Shopping Trip
HBSCH	Home Based School Trip
HBW	Home Based Work Trip
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCA	Multiple Classification Analysis
MLR	Multiple Linear Regressions
NHTS	National Household Travel Survey
RMSE	Root Mean Square Error
SPSS	Statistical Package for the Social Sciences
TAZs	Traffic Analysis Zones
TT	Total Home Based Trip
VIF	Variance Inflation Factor

Author Contributions

Hewan Nigussie Melissie: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing

Conflicts of Interest

The author declares no conflicts of interest.

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