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# DEVELOPMENT OF TRIP ATTRACTION MODELS USING GENERALIZED LINEAR MODELING FOR SHOPPING CENTERS IN CHITTAGONG CITY

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**Abstract:** In developing nations, one of the most essential aspects of travel demand management (TDM) is the analysis of trip attraction in shopping malls. Shopping malls are major trip generators, as a large number of people visit these centers daily. A trip to the shopping center is usually seen as an essential travel due of its aim. As a result of its essential aspect, trip attraction plays a critical role in resolving and improving traffic problems through the development of road networks. Rapid urbanization and expansion have been noted in Chittagong city, one of Bangladesh's major cities, in recent decades due to enticing employment possibilities and the provision of social services. This additional traffic might exacerbate the current congested situation. This resulted in an extra journey to Chittagong City's shopping center. In this study, an effort has been made to determine the trip attraction rates of shopping malls in Chittagong city. The trip attraction rate is determined by physical features such as floor area (ft2), parking space, number of stores, and number of staff (per shop). This study also develops trip attraction models using Generalized Linear Modeling (GLM) with respect to physical features and Socio-demographic variables. The number of vehicles and people entering the shopping mall during peak hours on weekends and weekdays is counted every 15 minutes for first attempt. Questionnaire as technique used for data collection for second attempt. Highest trip attraction rate at weekend and weekday is Sanmer Ocean City with 286.8 PCU/hr. and 211.1 PCU/hr. In every case, the weekend trip rate is higher than the weekday travel rate. To estimate the trip attractions of shopping centers, four regression models were developed with respect to physical features and Socio-demographic variables. Floor area, number of shops, number of employees from physical characteristics have a strong correlation with number of trips. Job, income and shopping expense from socio-demographic features have a strong correlation with number of trips. This trip attraction rate can be used to estimate traffic flow and assess traffic impacts in the surroundings of a new shopping mall. The model assists in the understanding of tripping chains in the Shopping Center. The frequency of activity in the shopping center can be estimated using the model.

***Keywords: Trip Attraction, Generalized Linear Model, Chittagong City***

## 1. INTRODUCTION

Since the world's population is expanding quickly, new development has grown to a big issue in recent years. These changes are increasing and decreasing new travel demand. This traffic is degrading the road network's performance due to an unplanned existing road network [1]. Forecasting travel demand is significant for road system and service design, as well as planning, investing, and policy creation. The standard four-step travel demand forecasting procedure begins with trip generation. This stage must generate a definite value because these certain values serve as foundation for succeeding processes, and error in this step might spread throughout the method for estimating [2]. When evaluating the effectiveness of new development, such as activity centers and residential development, transport engineers and designers must include trip generation [3].

Chittagong, Bangladesh's principal commercial hub, is the center of employment possibilities and other necessary services, including health, education, etc. [4]. Yet, population growth, migration of people, and urbanization have resulted in a massive expansion in internal mobility of people, which the transportation sector is still struggling to handle. Considering the present situation on roads and highways especially the traffic related problems need to be solved first. Time is more important in every aspect of life, so some study has been made based on transport sector [1]. The study usually based on Traffic Impact Assessment (TIA) which is greatly required for making changes and approve for any type of growth purposes such as office complex, residential development and several other purpose. The usual method for performing TIA is to use trip attraction rates [5]. Trip attraction is defined as the quantity of trips drawn by various activity centers in any zones. The trip attraction is undoubtedly the most suitable in terms of traffic at particular land use activity. Additionally, it is involved in numerous stages of activities connected to traffic engineering and transportation planning [6].

Recently, shopping tours make up an increasingly big share of urban travel, especially during peak travel times. Additionally, shopping trips offer greater personal flexibility in terms of timing than do work trips [7]. Therefore, knowing trip attraction rates of shopping centers is very important. We conducted a survey to evaluate the Trip Attraction rates of six Chittagong shopping areas. The key rationale for choosing Chittagong as the location for our survey is that it has the busiest streets. It has taken steps to increase its transportation capability. Furthermore, because shopping is such a vital part of our daily lives, significant steps are being done to improve traffic facilities on congested roadways. It is yet another excellent opportunity to support of Chittagong's new future growth.

Despite the growing expansion of commercial shopping facilities in rapidly urbanizing cities, empirical studies on trip attraction rates for such land uses remain limited, particularly in developing countries. Existing trip generation manuals mostly rely on rates derived from Western contexts, which often do not reflect the socio-demographic conditions, travel behavior, or built-environment characteristics of cities like Chittagong. As a result, planners face difficulties in accurately estimating trip ends for commercial areas, leading to inefficient transportation planning and congestion management. This gap in localized trip attraction models serves as the primary motivation for the present study.

This study contributes to the literature by developing context-specific trip attraction models for major shopping centers in Chittagong City using both physical features of commercial facilities and socio-demographic attributes of visitors. Unlike previous studies, this research separately analyzes weekend and weekday conditions, reflecting differences in travel behavior. The study incorporates updated variables and employs Generalized Linear Modeling (GLM) to account for the count-based nature of trip data and potential deviations from normality, providing robust and interpretable estimates for trip attraction. These findings support more accurate travel demand forecasting and offer planners evidence-based insights for commercial area development.

## 2. LITERATURE REVIEW

Travel forecasting models are used to foresee changes in traffic conditions and the use of the transit system in response to changes in regional growth and the accessibility of road networks. Although it is a difficult task, travel demand modeling is necessary for meaningful design and analysis of transportation networks. An essential step in the long-term transportation planning process is forecasting future travel demand because it allows planners to devise strategies for meeting future demands. Travel Demand forecasting is constantly evolving as a predictive science. Because of the multiple stages that are interconnected, the travel demand forecasting process can be completed [8].

Trip generation is the first stage of the conventional four-step modeling process. It predicts how many trips will begin or conclude in a particular traffic analysis zone. Trip generation modeling is divided into two categories: trip production and trip attraction [9][10]. A trip is when a person travel from one location (origin) to another (destination). Because a trip is deemed "made" at a person's house, trip production indicates a journey that begins or ends in a residential location [11]. Each journey has an origin and a destination, or two trip-end. A trip attraction (TA) is a journey that begins or ends in a non-residential region. A trip end is where a trip begins or terminates; a trip might have two trip ends. The number of trip endpoints per unit of independent variables per unit of time is known as the TA, or trip production "rate." (Per employee, per square feet of floor area, etc.) [12].

The trip distribution processes specify where each zone's travels will develop and how they are distributed among the research area's other zones. The outcome is a set of tables showing the traffic flow between every pair of zones One of the most important steps in the travel demand modeling process is mode selection. It is the stage at which trips between a specific origin and destination are separated into trips made by automobile drivers, trips made in a carpool, and trips made by public transportation [13]. Trip assignment use to determines the shortest way in relation to generalized travel time from each link to each other link [14].

Virakvichetra, Higashi and Pheng [17] studied traveling style in the Sydney Metropolitan Area, Australia, was investigated, and it was discovered that a variety of socio-demographic characteristics influenced traveling style. Women generally stayed nearer to residence than males do, especially if They were not native English speakers.

Recent studies after 2020 have further expanded trip generation and attraction research with more detailed socio-demographic and built-environment variables. For example, shopping-related trip attraction patterns during weekends and weekdays using large-scale activity datasets show that land-use intensity and retail floor area remain dominant predictors of trip ends (Alotaibi & Mostafa, 2021). Similarly, trip attraction to commercial centers in developing countries is strongly influenced by walkability, accessibility to public transport, and household travel characteristics (Patel & Khan, 2022). Other recent works highlight the role of machine-learning and big-data-based approaches, such as the use of ensemble regression and mobility datasets, in improving prediction accuracy for trip attraction rates (Liu et al., 2023; Wang & Li, 2021; Lee & Kim, 2024).

In addition, updated trip generation rates for commercial land uses in developing urban areas have been proposed, reflecting evolving travel behavior and land-use patterns (Al-Saadi & Hamed, 2020). Socio-demographic factors have also been found to significantly influence shopping travel in rapidly growing cities, particularly in African and South Asian urban contexts (Olawole & Adeniran, 2022; Mohamed & Rahman, 2023). Collectively, these recent findings reinforce the continued relevance of socio-economic, spatial, and behavioral factors in explaining trip generation and attraction.

Trip attraction often represents count-based data (number of trips) and may violate the assumptions of traditional multiple linear regression (MLR), such as normality and homoscedasticity. Count data are inherently non-negative and discrete, and traditional linear regression models can produce biased or inefficient estimates when applied to such distributions. Generalized Linear Models (GLMs) provide a flexible framework for modeling count outcomes by allowing non-normal response distributions and appropriate link functions (e.g., log-link) suitable for Poisson or Negative Binomial regression, which are well-established methods for count data modeling. For example, Poisson and Negative Binomial regression have been widely used in transportation and related fields to model count outcomes such as trip frequencies, traffic accident counts, and similar travel demand measures, addressing issues of overdispersion and distributional assumptions that linear models cannot handle effectively. Recent studies in trip generation and transportation count data modeling similarly recommend count-based regression frameworks to overcome the limitations of linear models for discrete trip counts (Cameron & Trivedi, 2013; Hilbe, 2011; Abdulkabir et al., 2015; Alotaibi & Mostafa, 2021; Patel & Khan, 2022).

## 3. METHODOLOGY

### *A. Trip Rate*

The fundamental goal for a trip is to see a certain location, which is why trips are made in the first place. These journeys start at the origin and travel to the creation or generator before returning to the source [18]. In common usage, trip rate refers to the number of people who enter and exit a development for a specific trip rate parameter factor. For example, trip rates are determined by Gross Floor Area, or GFA. Users can apply trip rates to anticipated developments using this component, and are advised to strike a balance between their selection criteria and the size of their selected samples in order to achieve their goals. For computing different trip attraction rates, use the following equations [5][19]:

1. Peak hour person trip attraction rate (Trips per 1000 sq. ft. per hour) = (Peak hour person trip /Gross Floor Area (GFA)) *1000.
2. Peak hour person trip attraction rate (Trips per shop per hour) = (peak hour person trip/total number of shop).
3. Peak hour vehicle trip attraction rate (Trips per 10 parking spaces per hour) = (Peak hour vehicle trip/number of parking spaces) *10.
4. Peak hour person trip attraction rate (Trips per 100 employees per hour) = (Peak hour person trip/ total no of employee of shopping centers) *100.

### *B. Generalized Linear Modeling (GLM)*

Trip attraction represents discrete count-based traffic flows observed at shopping centers during peak periods. Such data are more appropriately modeled using a Generalized Linear Modeling (GLM) framework, which allows flexible specification of response distributions and link functions. A Poisson regression model with a log-link function was employed to relate trip attraction to relevant explanatory variables, ensuring non-negative predicted values and interpretable parameter estimates. The GLM framework is widely applied in transportation studies for modeling trip counts and flow-based outcomes, particularly where traditional linear assumptions may not hold. The trip attraction count is assumed to follow a Poisson distribution:

$Y_i \sim \text{Poisson}(\mu_i)$

The systematic component of the model is expressed as:

$$\ln(\mu_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} \qquad (1)$$

where,

$Y_i$ = observed trip attraction

$\mu_i$ = expected number of trips

$\beta_0$ = intercept

$\beta_k$ = regression coefficients

$X_{ki}$ = explanatory variables

The expected trip attraction is therefore:

$$\mu_i = \exp(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki})$$

### *C. Independent Variables*

Several parameters were employed as independent variables in previous research. Some of the characteristics may not be appropriate for this study because earlier studies were centered on shopping centers. The following are the independent variables addressed in this study for physical features [1][5][3][15][24]: (a) Number of Restaurants (b) Total number of parking spaces available (c) Gross floor area of shopping center (d) Total number of shops (e) Total number employees (f) Number of Entry gate.

Socio-demographic Variables [8][17][25][26]: (a) Age (b) Gender (c) Job (d) Income (e) Number of people at home (f) Number of working people (g) Number of School going people (h) Transport mode.

(i) Transport cost (j) Driving License (k) Distance from home (l) Time needed from home (m) Shopping expense (n) Shopping Duration.

### *D. Validity and Reliability Test*

The validity and reliability of the questionnaires used during this work were tested to verify that they accurately measured the study parameters. Some equipment is regarded legitimate if this can accurately measure what it claims to determine and offer the factors' data under investigation [26].

### *E. Data Structure and Analytical Considerations*

Data Structure and Analytical Considerations

The dependent variable (trip attraction) and independent variables were collected at two distinct levels of analysis. Trip attraction counts were observed at the shopping mall level (six malls), whereas socio-demographic variables were obtained at the individual respondent level (N = 383 for weekend, N = 364 for weekday). After data cleaning and removal of incomplete responses, 309 observations were retained for GLM estimation, resulting in 308 degrees of freedom for the fitted models. Trip attraction counts were aggregated at the shopping mall level (six malls), while socio-demographic variables were collected at the individual respondent level. Only complete cases were used in the final GLM estimation. Due to the differing levels of observation, no direct one-to-one matching was performed. Physical-feature-based regression models were developed using only mall-level data, and socio-demographic models were estimated separately using respondent-level data. This approach ensures that the statistical models are appropriately applied to each dataset and maintains the integrity of the analysis.

## 4. RESULTS AND DISCUSSIONS

### *A. Trip Attraction Variation at Weekend and Weekday*

The trip rates are calculated during evening peak hours of six different shopping mall. The number of individuals and vehicles drawn to shopping malls for a variety of reasons such as shopping, fitness facilities, restaurant dining, and other offerings were recorded.

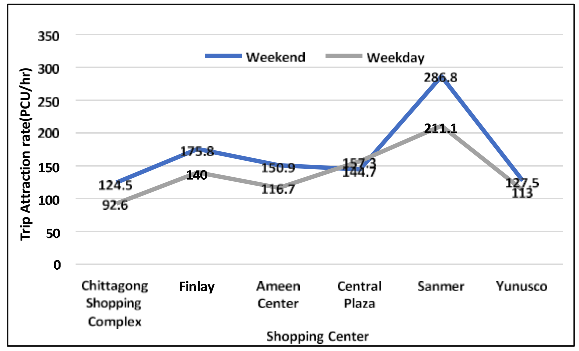


**Figure 1.** Trip Attraction Variation at Weekend and Weekday

The result shown in the above "**Fig. 1**" indicates highest trip attraction rate is 286.8 PCU/hr at weekend and 211.1 at weekday in Sanmar Ocean City. Lowest peak hour trip attraction is Chittagong Shopping Complex both weekend and weekday and they are 124.5 PCU/hr at weekend and 92.6 PCU/hr at weekday. Weekend's day trips attraction rate is higher than the weekday. Chittagong Shopping Complex, Finlay Square, Ammen center, Sanmer Ocean city and Yunusco City Center's trip attraction rate are higher in weekend day than weekday. But Central Plaza's trip attraction rate is higher in weekday than weekend. Sometimes traffic affect trip variation in weekend and weekday.

### *B. Trip Attraction Based on Physical Features*

One of the study's main goals is to see how much trip is attracted to specific qualities or how trip is connected to physical features of the shopping complex. Only the peak hour trip attraction value is used in this estimate because it is our primary focus. Both peak hour person trip attraction is related to floor space, parking area, number of shops, and number of staffs in the following figure. As the mentioned "**Fig. 2**" shown that Sanmer Ocean City, a well- known shopping center offering name-brand clothes, received the most people per floor area at peak hour. Sanmer Ocean city received 146.67~147 trips per hour as well at weekend. The peak hour person trip attraction rate for gross floor space is 150.21person trips/1000 ft2/hr, implying that for every floor area on a weekend day, a 150.21~151 trip is attracted each hour and it is 31% of total trip attraction on weekday. Central Plaza, a major market mall with branded clothing, received the most people per floor area at peak hour. The lowest peak hour trip attraction rate is 6.65person trips/1000 ft2/hour at Chittagong Shopping Complex.

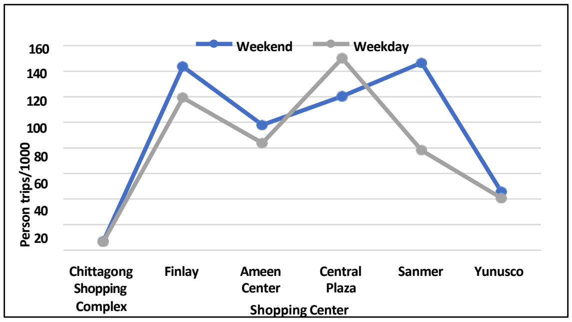


**Figure 2.** Trip Attraction Rate Variation (Respect to floor area)

Another significant conclusion from the "**Fig. 3**" is that the peak hour vehicle trip attraction rate for 10 parking spaces is 25.43 Vehicles/10parking/hr, implying that each parking attracts 25.43~26 trips each hour over the weekday. During peak hour, Central Plaza received the most vehicle per parking spots. Chittagong Shopping Complex has the lowest peak-hour visitation rate of 12.45 vehicles per 10 parking per hour.

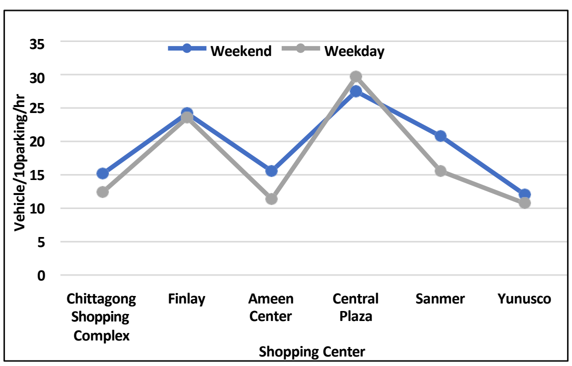


**Figure 3.** Trip Attraction Variation (Respect to Parking Spaces)

### *C. Socio-demographic Analysis*

Socio-demographics are merely a population's characteristics. The study of a population based on characteristics like age, race, and sex is known as demographic analysis. The section shown relationship between different demographic features like transport mode and gender, job level and transport mode etc. "**Fig. 4**" shown that distribution of transport mode. It can be seen that people mostly use CNG and bus. In the "**Fig. 5**" shown that nearest distance people mostly come to the shopping mall.

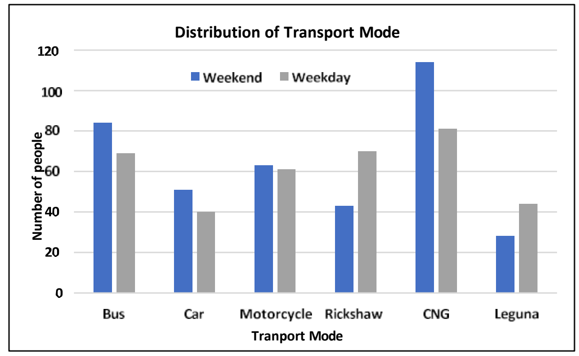


**Figure 4.** Distribution of Transport Mode

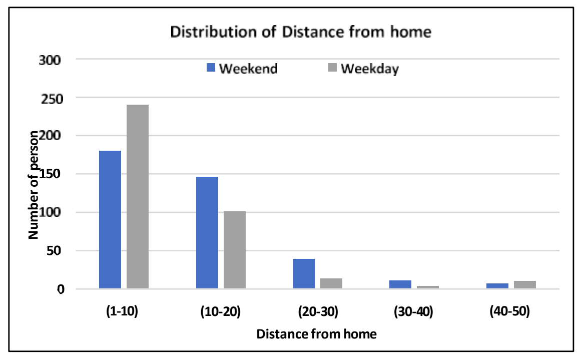


**Figure 5.** Distribution of Distance from Home

## 5. TRIP ATTRACTION MODELLING UTILIZING GENERALIZED LINEAR MODEL ANALYSIS

Generalized Linear Models (GLMs) were employed to analyze trip attraction because the dependent variable represents count data. A Poisson probability distribution with a log link function was therefore selected. Model adequacy was evaluated using goodness-of-fit statistics, likelihood-based information criteria, and Wald tests of parameters. Separate models were developed for weekend and weekday conditions to capture temporal variations in travel behavior.

### *A. Generalized Linear Model at Weekend*

The weekend GLM was estimated using valid observations after data screening. Descriptive characteristics of categorical and continuous variables are summarized in **Tables 1** and **2**, respectively. These variables represent socio-demographic attributes, travel characteristics, and shopping behavior of respondents during weekends.

Model adequacy was assessed using goodness-of-fit statistics (**Table 3**). The deviance and Pearson chi-square statistics indicate no evidence of lack of fit, suggesting that the Poisson GLM adequately represents the observed trip attraction data. Information criteria values (AIC, AICC, BIC, and CAIC) further support the suitability of the fitted model.

The overall significance of the model was examined using Wald chi-square statistics (**Table 4**). The intercept-only model was found to be statistically significant at the 1% level ($p < 0.001$), indicating a stable baseline trip attraction level during weekends. Parameter estimates for the weekend GLM are presented in **Table 5**. The intercept coefficient is statistically significant ($p < 0.001$), confirming that the expected number of trips attracted to shopping centers during weekends is significantly different from zero. The scale parameter was fixed at one, consistent with Poisson regression assumptions.

**Table 1.** Categorical Variable Information

| | | | Percent |
|---|---|---|---|
| Factor | Gender | 1.00 | 55.7% |
| | | 2.00 | 44.3% |
| | | Total | 100.0% |
| | Transport Mode | Bus | 20.1% |
| | | Car | 15.5% |
| | | Motorcycle | 18.4% |
| | | Rickshaw | 11.3% |
| | | CNG | 25.9% |
| | | Leguna | 8.7% |
| | | Total | 100.0% |
| | Job | Student | 28.8% |
| | | Govt. Job | 10.7% |
| | | Private Job | 24.9% |
| | | Businessmen | 6.5% |
| | | Housewife | 24.9% |
| | | others | 4.2% |
| | | Total | 100.0% |
| | Driving License | Yes | 27.8% |
| | | No | 72.2% |
| | | Total | 100.0% |
| | Shopping Center | Finlay Square | 21.7% |
| | | Sanmar Occen Center | 18.1% |
| | | Chittagong Shopping Center | 17.5% |
| | | Center Plaza | 13.3% |
| | | Yunusco City Center | 16.5% |
| | | Ameen Plaza | 12.9% |
| | | Total | 100.0% |

**Table 2.** Continuous Variable Information

| | | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Dependent Variable | Trip Attraction | 41 | 68 | 53.79 | 9.229 |
| Covariate | Age | 15 | 58 | 31.9612 | 10.31131 |
| | Income | 6000 | 350000 | 26815.53 | 22073.11386 |
| | Distance from home | 1 | 45 | 13.8382 | 8.44192 |
| | Transport Cost | 10 | 250 | 89.5858 | 65.31843 |
| | Time needed from home | 10 | 120 | 25.7184 | 13.38303 |
| | Shopping Expense | 300 | 15000 | 1449.676 | 1199.06615 |
| | Shopping Duration | 30 | 180 | 80.8414 | 39.19777 |
| | Number of People at home | 3 | 8 | 4.7929 | 1.18807 |
| | Number of Working People | 1 | 3 | 1.6926 | 0.60246 |
| | Number of People at School Age | 1 | 3 | 1.5599 | 0.57587 |

**Table 3.** Goodness of Fita

| | Value | df | Value/df |
|---|---|---|---|
| Deviance | 0 | 308 | 0 |
| Scaled Deviance | 0 | 308 | |
| Pearson Chi-Square | 0 | 308 | 0 |
| Scaled Pearson Chi-Square | 0 | 308 | |
| Log Likelihoodb | -565.067 | | |
| Akaike's Information Criterion (AIC) | 1132.133 | | |
| Finite Sample Corrected AIC (AICC) | 1132.146 | | |
| Bayesian Information Criterion (BIC) | 1135.866 | | |
| Consistent AIC (CAIC) | 1136.866 | | |

**Table 4.** Tests of Model Effects

| Source | Type III | | |
|---|---|---|---|
| | Wald Chi-Square | df | Sig. |
| (Intercept) | 5952.085 | 1 | <.001 |

**Table 5.** Parameter Estimates

| Parameter | B | Std. Error | 95% Wald Confidence Interval | | Hypothesis Test | | |
|---|---|---|---|---|---|---|---|
| | | | Lower | Upper | Wald Chi-Square | df | Sig. |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| (Intercept) | 1.792 | 0.0232 | 1.746 | 1.837 | 5952.085 | 1 | <.001 |
| (Scale) | 1[a] | | | | | | |

### B. Generalized Linear Model at Weekday

A separate GLM was developed for weekday conditions using valid weekday observations. The distribution of categorical and continuous variables is presented in **Tables 6** and **7**. Compared to weekends, weekday trip attraction exhibits greater variability, reflecting differences in work-related and routine travel behavior.

Goodness-of-fit statistics for the weekday model are shown in **Table 8**. The deviance and Pearson chi-square values divided by their degrees of freedom (≈1.58) indicate an acceptable model fit, suggesting mild dispersion but remaining within acceptable limits for Poisson GLM applications. Likelihood-based criteria (AIC, AICC, and BIC) were used for model evaluation. The Wald chi-square test results (**Table 9**) demonstrate that the intercept-only weekday model is statistically significant at the 1% level ($p < 0.001$), confirming a strong baseline trip attraction effect on weekdays.

Parameter estimates for the weekday GLM are reported in **Table 10**. The intercept coefficient is positive and statistically significant ($p < 0.001$), indicating a higher expected trip attraction level during weekdays compared to weekends. As with the weekend model, the scale parameter was fixed at one in accordance with Poisson regression assumptions.

**Table 6.** Categorical Variable Information

| | | | Percent |
|---|---|---|---|
| Factor | Gender | 1 | 55.70% |
| | | 2 | 44.30% |
| | | Total | 100.00% |
| | Transport Mode | Bus | 20.10% |
| | | Car | 15.50% |
| | | Motorcycle | 18.40% |
| | | Rickshaw | 11.30% |
| | | CNG | 25.90% |
| | | Leguna | 8.70% |
| | | Total | 100.00% |
| | Job | Student | 28.80% |
| | | Govt. Job | 10.70% |
| | | Private Job | 24.90% |
| | | Businessmen | 6.50% |
| | | Housewife | 24.90% |
| | | others | 4.20% |
| | | Total | 100.00% |
| | Driving License | Yes | 27.80% |
| | | No | 72.20% |
| | | Total | 100.00% |
| | Shopping Center | Finlay Square | 21.70% |
| | | Sanmar Occen Center | 18.10% |
| | | Chittagong Shopping Center | 17.50% |
| | | Center Plaza | 13.30% |
| | | Yunusco City Center | 16.50% |
| | | Ameen Plaza | 12.90% |
| | | Total | 100.00% |

**Table 7.** Continuous Variable Information

| | | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Dependent Variable | Trip Attraction | 41 | 68 | 53.79 | 9.229 |
| Covariate | Age | 15 | 58 | 31.9612 | 10.31131 |
| | Income | 6000 | 70000 | 25796.12 | 12135.88584 |
| | Number of People at home | 3 | 8 | 4.7929 | 1.18807 |
| | Number of Working People | 1 | 3 | 1.6926 | 0.60246 |
| | Number of People at School Age | 1 | 3 | 1.5599 | 0.57587 |
| | Distance from home | 1 | 45 | 13.8382 | 8.44192 |
| | Transport Cost | 10 | 250 | 89.5858 | 65.31843 |
| | Time needed from home | 10 | 120 | 25.7184 | 13.38303 |
| | Shopping Expense | 300 | 15000 | 1449.676 | 1199.06615 |
| | Shopping Duration | 30 | 180 | 80.8414 | 39.19777 |

**Table 8.** Goodness of Fita

| | Value | df | Value/df |
|---|---|---|---|
| Deviance | 487.85 | 308 | 1.584 |
| Scaled Deviance | 487.85 | 308 | |
| Pearson Chi-Square | 487.739 | 308 | 1.584 |
| Scaled Pearson Chi-Square | 487.739 | 308 | |
| Log Likelihoodb | -1141.774 | | |
| Akaike's Information Criterion (AIC) | 2285.549 | | |
| Finite Sample Corrected AIC (AICC) | 2285.562 | | |
| Bayesian Information Criterion (BIC) | 2289.282 | | |

**Table 9.** Tests of Model Effects

| Source | Type III | | |
|---|---|---|---|
| | Wald Chi-Square | df | Sig. |
| (Intercept) | 263955.944 | 1 | <.001 |

**Table 10.** Parameter Estimates

| Parameter | B | Std. Error | 95% Wald Confidence Interval | | Hypothesis Test | | |
|---|---|---|---|---|---|---|---|
| | | | Lower | Upper | Wald Chi-Square | df | Sig. |
| (Intercept) | 3.985 | 0.0078 | 3.97 | 4 | 263955.944 | 1 | <.001 |
| (Scale) | 1a | | | | | | |

## 6. CONCLUSION

This study focuses on determining the trip attraction rates of six shopping centers and develops trip attraction models using Generalized Linear Modeling (GLM). Trip attraction data was collected at six shopping centers in the research area and presented in this study. Planning for transportation facilities must take trip attraction rate into consideration. This trip attraction rate can be used to estimate traffic flow and assess traffic impacts in the surroundings of a new shopping mall. The study's computed trip attraction rates might be helpful for the regional transportation system or for channelizing traffic control around a mall. According to the findings, problems can be rectified by enhancing traffic facilities and expanding Chittagong's current road network. It can also aid in the identification of the trip attraction model's inputs and outputs. If for an existing shopping center an additional floor space area or a greater number of parking spaces are being planned, then the estimate for the additional trips attracted can be estimated. The model assists in the understanding of trip chaining in the shopping center. The model can be used to determine the level of activity in the shopping center.

## 7. ACKNOWLEDGMENT

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