

Article

Stratified Sampling Framework for Household Travel Survey: A Monte Carlo Simulation Approach for Sample Size Optimization

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Abstract

A Micro-Analysis Zone (MAZ) for localized transport planning creates challenges in cost and logistics from large sample sizes, delaying household travel surveys. Thus, this study developed a stratified sampling framework with a lower sampling rate for MAZ based on household size as a demographic stratum. Using census data from a barangay in Davao City, various sampling rates from 20% to 1% were examined using Monte Carlo simulation with one million iterations across two stratification approaches: proportional and Neyman's allocation. The simulations revealed that a sampling rate as low as 8% can estimate trip frequencies within 10% error ($MAPE \leq 10\%$) at around 95% probability. Nevertheless, there is a trade-off between these metrics, with the probability dropping to 68% to maintain an error within 5% ($MAPE \leq 5\%$) under both stratification approaches. Furthermore, trip generation modeling revealed that R-squared values for estimating the trip frequency have a 95% probability of being 0.7 or higher. Despite this, caution is warranted, as some secondary predictors lost statistical significance at lower sampling rates. Ultimately, this study recognizes the performance of lower sampling for a small urban barangay, relieving transport planners from challenges in conducting household travel surveys.

Keywords: household travel survey; trip generation model; Monte Carlo simulation; stratified sampling; Neyman's allocation; proportional allocation; Micro-analysis Zone



Academic Editor: Tianwen Zhang

Received: 22 June 2026

Revised: 22 July 2026

Accepted: 23 July 2026

Published: 28 July 2026

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1. Introduction

In the hierarchy of transportation modeling, transportation studies often require a significant shift in spatial resolution of the study area. While city-wide planning typically uses Traffic Analysis Zones (TAZs), localized planning requires moving toward Micro-Analysis Zones (MAZs) to reduce aggregation bias and increase sensitivity to transportation system effects. Standard TAZs often aggregate data to a level that blurs critical local-level interactions [1]. In the Philippine context, the barangay serves as the primary MAZ where first- and last-mile trip dynamics occur and are often facilitated by localized paratransit modes, which are overlooked in macro-scale models [2]. However, the transition to MAZ remains difficult due to the socio-spatial heterogeneity across urban communities, where population densities and trip characteristics vary significantly, requiring rigorous transport

surveys and posing significant methodological and financial challenges. Ultimately, resolving these micro-scale planning challenges depends on the precision of the baseline travel data collected directly from households in these communities.

The quality of the travel demand survey data affects the overall accuracy of the transport demand model. Data gathered from travel surveys plays an important role in the modeling process because it reflects current traffic behavior, helping analysts identify problems in transport systems [3]. Among the various procedures for data gathering, the household travel survey remains the preferred method for transport demand modeling despite the recognized advantages of other modern techniques, such as telephone interviews and the application of Geographic Information Systems (GISs) [4]. Interestingly, manual surveys are more able to provide basic information on household and individual-level characteristics and on the activity-travel behavior of household members, which is essential for the formulation of any comprehensive travel demand model [5]. The use of GPS, smartphones, panel surveys, continuous surveys, and other innovative approaches is recommended with caution. In other words, household travel surveys offer no alternative and would continue to be the only reliable data for urban planning of transport in the foreseeable future [6].

To comply with statistical requirements, large sample sizes are recommended in household travel surveys, leaving local planners constrained by cost and political considerations [7]. One study emphasized the budgetary constraints that may result from the large sample sizes required for data collection [6]. Acquiring good travel data has always been a challenge for metropolitan planning organizations, partly because of the expense of the data collection. This could be the main reason there has been no consensus on sample sizes for travel surveys in practice. Moreover, there are no straightforward, objective answers to the computation of sample size in every situation, even though it is based on a statistical concept [3]. It was further noted that some of the inputs used in the statistical process are relatively subjective and uncertain.

Standard statistical formulae for determining sample size, intended to ensure a specific confidence level (e.g., 95%) and a narrow margin of error (e.g., 5%), often account for a large percentage of the total population in an MAZ. In a city-wide TAZ of millions, a sample of 4% to 5% is manageable, but in a study area with fewer than 50,000 households, that same statistical requirement demands surveying nearly 20% of the entire population [8,9]. This creates an unsustainable burden on local government resources, especially with smaller populations, which can entail a data collection and analysis process that is too expensive, given the study objective and the required degree of accuracy [3].

Unfortunately, having a large sample size does not necessarily equate to a representative survey. Despite a large number of surveys conducted, not every survey was thoroughly analyzed by survey contractors for the accuracy of the results. One study underlined the fact that some survey contractors are public bodies, not research institutions, and that these bodies pay less attention to the survey results' accuracy and make little to no effort in publishing survey results [10]. There is even an account of one study with 150,000 households (5% sampling rate) revealing errors of over 15% in the basic population attributes [11]. This discrepancy highlights how sample size alone is insufficient without careful consideration of how those samples are selected.

The sampling method adopted in a household travel survey plays a major role in determining the sample size. Almost all surveys are random sampling investigations, and the sampling rate is relatively large, generally in the range of 2–4% [12]. However, many experts are in doubt about the scientific quality of such sampling rates. It is also noted that certain sociodemographic groups are under-represented when this sampling method is used. People's travel situations are highly dependent on specific characteristics, such as

economic level and development phase. Thus, stratified random sampling may provide a good representation of the population, as it allocates a certain percentage to each level or classification in the sample size estimation [13].

The methodological complexities of household travel surveys directly translate into practical implementation barriers when local agencies are mandated to conduct transport planning. With the prevalence of the Public Utility Vehicle Modernization Program (PU-VMR) in the Philippines, the obligation to formulate Local Public Transport Route Planning (LPTRP) is assigned to the local government unit (LGU) as a prerequisite for the issuance of a franchising permit. However, in 2021, only 20.65% (325 out of 1575) of LGUs submitted their respective LPTRPs, and only six were issued a Notice of Compliance [14]. One study stated that the low submission rate is partly due to a lack of motivation, stemming from LGU funding shortages for conducting surveys [15]. This indicates that data collection has posed a significant challenge for metropolitan planning organizations in conducting transportation studies, partly because of the lack of a standardized, clear survey design instruction for transport planners.

There have been no universal methods for determining the appropriate survey design for a household travel survey. Sources offering practical guidelines for survey design are highly limited, and transport planners still encounter questions when choosing both the survey method and population coverage [10]. A scoping review of household travel surveys worldwide found that most surveys employ random sampling or geographic stratified sampling in large population settings [16]. No studies were found that employed household sizes as strata, nor studies that used Monte Carlo simulations to test reduced sampling rates. The gap in transportation research underscores the need for a survey sampling framework that optimizes sample sizes at a localized MAZ resolution, given that low baseline populations demand disproportionately high sampling rates.

To bridge this gap, this study integrates a stratified sampling approach to effectively reduce aggregation bias, using household size as the stratum characteristic, which is known to be strongly correlated with travel decisions [17], thereby reducing intra-stratum variance and minimizing sampling requirements. Furthermore, this study uses a high-iteration Monte Carlo simulation to model one million stratified random sampling allocations across strata using Neyman's allocation and proportional allocation, and to identify the optimum sample size that maintains acceptable estimation error thresholds for trip frequency. The simulation was also used to validate the sampling rate, specifically in the multiple linear regression trip-generation modeling. Through this comprehensive approach to sample size optimization, this study aimed to develop a Monte Carlo-based stratified sampling framework for probabilistic-accuracy analysis across different sampling rates, providing support for transport planners in conducting household surveys in MAZ. Specifically, this study aimed to

- Develop a stratification approach that integrates proportional allocation and Neyman's allocation, with varying sampling rates based on household size.
- Determine the optimal sampling rate using a Monte Carlo simulation by comparing the statistical parameters of trip frequency relative to the baseline population's trip frequency.
- Validate the performance of the identified optimum sampling rates through a comparative analysis of the trip generation model relative to the baseline population.

2. Materials and Methods

This study employed a quantitative cross-sectional analytic research design confined to four phases: Phase 1 focusing on the drafting of the Household Travel Survey Questionnaire (HTSQ); Phase 2 concentrating on the survey process using the developed HTSQ;

Phase 3 addressing the sample size reduction by applying different sample rates using a stratification process; and finally, Phase 4 focusing on the comparison of these sampling rates according to the different statistical parameters.

2.1. Construction of the Household Travel Survey Questionnaire (HTSQ)

The Household Travel Survey Questionnaire (HTSQ) was developed by primarily identifying potential factors that may directly influence household trip characteristics. The literature review noted that most travel surveys incorporate sociodemographic and economic factors for trip generation modeling, such as income, car ownership, household structure, and family size, as trip-influencing factors [18]. Moreover, additional detailed information, such as house ownership status, educational attainment, and household internet accessibility, was included. The HTSQ was organized into two parts: the first part consists of questions about the general household composition, while the second part comprises specific questions about the individual personal information of household members aged 7 and above. The second part is further divided into two subparts: (1) household members' demographic and economic information; (2) household members' trip information. The HTSQ is attached in Appendix A.

2.2. Survey Implementation in Davao City Using HTSQ

The finalized HTSQ was employed to execute a face-to-face survey in Davao City. A barangay is the smallest administrative division in the Philippines, serving as the primary local government unit. The barangay selected in this study was based on specific criteria. The comprehensive zoning ordinance of Davao City has set specific qualities of urban areas such as the following: if a barangay has a population size of 5000 or more; if a barangay has at least one establishment with a minimum of 100 employees; or if a barangay has five or more establishments with a minimum of ten employees and five or more facilities within the two-kilometer radius from the barangay hall [19].

Barangay 15-B of the Poblacion district was the urban study area. As shown in Figure 1, the barangay is within the Poblacion district, the most urbanized district in Davao City. The barangay has a population of 2,603 based on the 2020 census. The barangay is within the center of trade and commerce in the city and thus displays unique attributes that measure trip characteristics in an urban setting. It has a total of 153 small to large commercial and industrial establishments with an average of 42 employees, registered within the barangay administrative boundary [20].

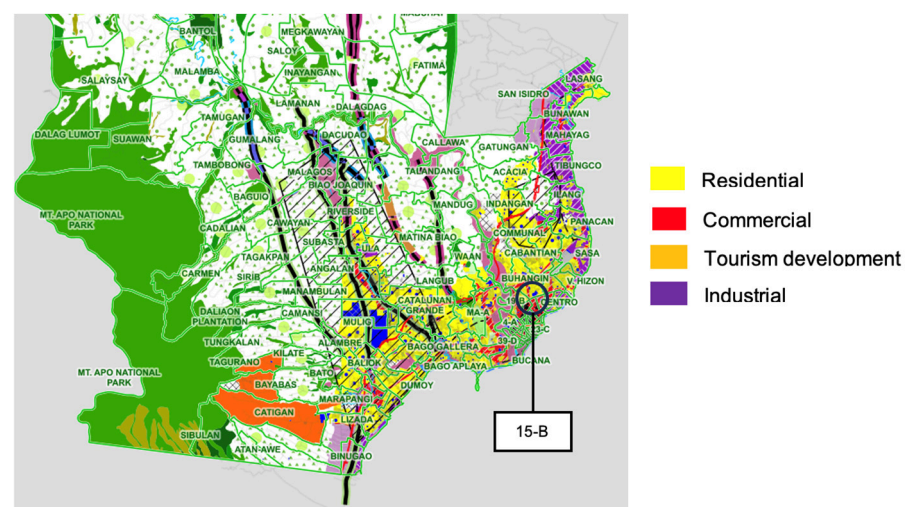


Figure 1. Davao City Zoning Map [19].

Household face-to-face interviews were conducted with at least 90% of the household population within the barangay. This study gathered data from 741 households in the barangay, out of the 820 actual number of households according to the barangay office, which were subsequently tallied, cleaned, processed, and stratified, as discussed in the succeeding phase. This study failed to achieve a 100% census due to unreachable households, because of either gated physical barriers or outright household refusals.

2.3. Allocation of Samples Through Stratification Methods

The census conducted in the preceding phase yielded a dataset of population size N , involving household and household characteristics in the barangay, which were subsequently employed in the current phase. Initially, the dataset was stratified into sub-populations or strata, N_h , based on household size categories, as shown in Table 1. This stratification boundary was established using Dalenius–Hodges Rule [21] as discussed in the succeeding section.

Table 1. Population dataset strata of household sizes.

Stratum (N_h)	Household Size (HS)
1	1–2
2	3–4
3	5–6
4	7 and above

2.3.1. Strata Boundaries Approximation

The Dalenius–Hodges Rule [21] was employed to determine the optimal stratification boundaries for household sizes. The procedure is shown in Figure 2 below:

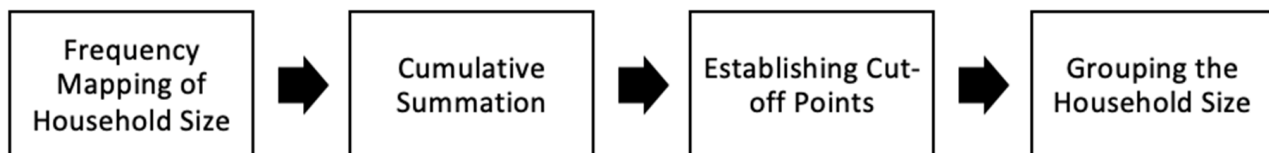


Figure 2. Dalenius–Hodges Rule Process.

The process begins by generating the frequency distribution of the population, where the total number of households f_x was recorded for each distinct household size ($x = 1, 2, \dots, 20$), with 20 being the maximum recorded HS in this study. The raw frequencies were stabilized by taking their square roots $\sqrt{f_x}$ to minimize variance within the strata. A running total of these transformed values was then computed sequentially from size 1 through 20 to establish a cumulative square root frequency C_x (see Equation (1)). Next, the total cumulative sum was divided by the desired number of strata ($k = 4$) (see Equation (2)) to determine a standardized target interval size $\bar{F}$. This interval size was used to establish equidistant theoretical boundaries at increments of $\bar{F}$, $2\bar{F}$, $3\bar{F}$, and $4\bar{F}$. Finally, adjacent household sizes were systematically grouped into the same stratum by mapping these theoretical boundaries back to the cumulative square root frequency of each HS and identifying the corresponding cut-off points while maintaining a similar interval across strata. Because household size is a discrete grouped variable, the upper household-size boundary corresponding to each theoretical cut-off was selected to define the operational strata [22]. Once these optimal boundaries were fixed, the original frequencies f_x within the grouped sizes were summed to yield the final subpopulation size N_h for each completed stratum.

$$C_x = \sum_{x=1}^{20} \sqrt{f_x} \quad (1)$$

$$\text{Target Interval} = \frac{C_x}{k} \quad (2)$$

2.3.2. Allocation Methods

The allocation of samples into the four (4) strata was implemented in two ways: proportional allocation (PA) and Neyman's allocation (NA).

Samples of size n were randomly drawn from the dataset according to the required sampling rate as full sample sizes. The succeeding procedure involved the stratification process, by which a specific sampling rate, such as 20%, 15%, 10%, 8%, 5%, 4%, 3%, 2% and 1%, was used to allocate sample size n_h into four strata. Twenty percent was used as the ceiling sampling rate in this study in reference to the recommended sampling rate for a low population area [8,9]. Further, regions across the world use sampling rates from 5% to as low as 1% [11] of the total households for large areas, where the complexity of the studied question influences the variation in the sampling rate, the desired accuracy, the population size, the cost of the survey, and the applied sampling methods. As such, this study examined sampling rates of 20%, 15%, 10%, 8%, 5%, 4%, 3%, 2% and 1%, as these have appeared in numerous household transport surveys. In addition, this study aimed to capture the behavior of trip parameters as the sample size decreased to as low as 1%.

In PA, the ratio of the sample size of the strata n_h to the total sample size n must be equal to the ratio of the subpopulation size N_h to the population size N (see Equation (3)). Hence, the population was divided into subpopulation strata based on four household sizes, and the strata were reduced proportionally using the above-mentioned sampling rates.

$$\frac{n_h}{n} = \frac{N_h}{N} \quad (3)$$

In NA, optimal allocation was implemented using Neyman's optimal allocation, which n_h is computed using Equation (4).

$$n_h = n \frac{N_h \sigma_h}{\sum_{h=1}^H N_h \sigma_h} \quad (4)$$

where σ_h is the population standard deviation of the parameter of interest, which, in this study, is the daily average frequency of trips per household.

2.3.3. Stratification Process

To evaluate the efficiency of allocation methods, the process begins with the population dataset, which serves as the initial sampling frame, as shown in Figure 3. This dataset was stratified using PA and NA. To evaluate the efficiency of these allocation methods, a Monte Carlo simulation was performed across a range of sampling rates from 20% to 1%. For each combination of allocation method and sampling rate, the sample allocation across the four strata was iterated one (1) million times to ensure statistical stability and minimize sampling bias [23]. The output of this process was a one-million-sample dataset, which was then subjected to a validation step to assess the accuracy and reliability of the sampling and allocation methods used.

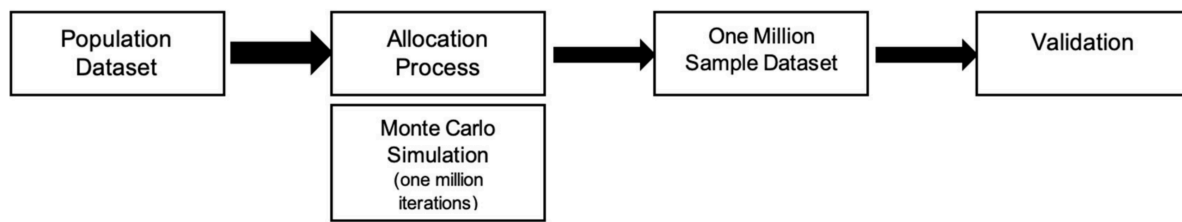


Figure 3. Stratification Process.

The resulting dataset was then aggregated to produce a probabilistic estimate of each of the sampling method's performance, providing a statistical representation of risk that includes the Mean Absolute Percentage Error (MAPE). Through Monte Carlo Simulations, the expected behavior of PA and NA can be estimated close to their true value. This is due to the fact that the large sample data obtained through repeated samplings follows the law of large numbers and the Central Limit Theorem [24]. The number of iterations was empirically determined based on the computational speed and consistency of the values of the resulting MAPE. It was found that one million iterations were computationally feasible on a modern general-purpose computer using MATLAB R2024b with 5–10 min per run on average, depending on the specified sampling rate. This number of iterations is also commonly used in both scientific and financial simulations, making it possible to assess potential errors and low-probability risks that are unnoticeable at lower sampling iterations [25,26]. Random sampling in the Monte Carlo Simulation was performed using random permutations (without repeating any samples) of sample indices per iteration through the *randperm* function in MATLAB. Throughout the pre-trial and proper experimentation phases, random seeding was left to the default current state of the *randperm* function and did not specify a constant value. This is to confirm the consistency of the selected one million iterations converging close to the true value with a precision of 2 significant figures across multiple experimental runs. With these experimental conditions established, the consistency of each simulation was ensured to reliably approximate the target distribution and the expected precision range.

2.4. Analysis of Sample Size Reduction

There were two validation processes to determine which of the varying sampling rates can generally represent the population trip characteristics: (1) by comparing the population mean estimate of the trip frequency, and (2) by comparing trip generation models (see Figure 4). The code used for data analysis is openly available on GitHub at <https://github.com/arcangelzer0/Household-Travel-Sampling-Framework>. The analysis was performed using MATLAB R2024b.

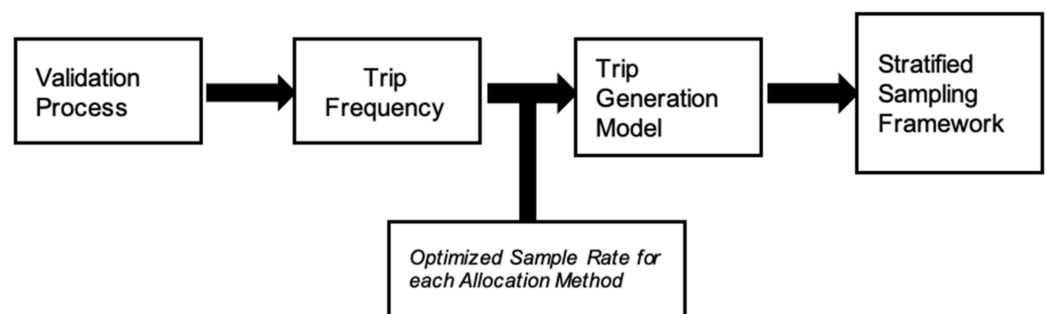


Figure 4. Validation Process.

2.4.1. Identification of Optimum Sampling Rate for Each Allocation Method

To evaluate the stability of the trip frequency estimates, a Monte Carlo simulation was integrated with the stratification process to generate one million independent stratified sample sets. For each iteration, the trip frequency was quantified using the stratified mean and the MAPE, as defined in Equations (5) and (6), respectively. These individual results were then aggregated to determine performance metrics, including the Average Stratified Mean, Average MAPE, standard error (SE), the coefficient of variation (CV), and empirical probability distribution.

$$\bar{y}_{st} = \sum_{h=1}^H W_h \bar{y}_h \quad (5)$$

$$\text{MAPE} = \left| \frac{\mu - \bar{y}_{st}}{\mu} \right| \% \quad (6)$$

where μ is the true population mean, W_h is the stratum weight, $\bar{y}_h$ is the individual stratum mean, and $\bar{y}_{st}$ is the unbiased estimate of the population mean of each one million iterations.

This study assessed varying sampling rates by balancing accuracy and precision. The SE was utilized to measure the statistical precision of the estimated trip means. It is useful to determine how an average trip rate in one iteration can vary from the mean. Though no threshold has been set for a good SE, a lower SE indicates that the sample means are more closely distributed around the population mean. Furthermore, CV was used to assess precision by measuring the dispersion of one million computed stratified trip means against the true population mean. CV uses normalization of the variance relative to the mean. A few studies prefer to measure results against a 10% error threshold, although there is no universal standard cut-off for a good CV [27,28]. Lower CV values represent tighter clustering around the mean and improved stability of estimates [29]; therefore, this study preferred to analyze its results against a CV of <5%, similar to other studies in risk analysis [30,31], to ensure that simulated sample means of trip frequency are highly stable in a small sample size. Furthermore, to directly quantify the average magnitude of the percentage difference from the baseline population's true trip frequency, the Mean Absolute Percentage Error was used to assess accuracy [32]. A 10% MAPE threshold was used as the ceiling for acceptable prediction error, as cited in the literature [33] pertaining to standard classification of forecasting accuracy; less than 10% MAPE is interpreted as "highly accurate" forecasting.

Beyond these point estimates, the probability distribution of the MAPE was analyzed across the full simulation. By modeling the MAPE distribution, the probabilistic risks and performance trade-offs associated with varying sampling rates are captured, allowing for a more nuanced understanding of estimator reliability. This probability distribution tallied the number of times the iteration met the MAPE thresholds ($\leq 10\%$, $\leq 8\%$, $\leq 5\%$, $\leq 2\%$). In addition to CV, SE, and MAPE, the optimum sampling rate was identified based on its empirical probability such that the MAPE thresholds were met in at least 60% of the one million iterations. While a 60% empirical probability level accepts a higher degree of residual risk than a 90% estimate, it is consistent with standard industry practice for capital projects [34]. To date, no published studies have applied Monte Carlo simulation using a comparable performance threshold in household travel surveys. Consequently, this study adopts the 60% threshold as a study-specific threshold, informed by existing use of Monte Carlo simulation in civil engineering [35]. Although this threshold represents a moderate level of confidence, it is considered appropriate for household transportation surveys, where travel behavior is inherently influenced by sociodemographic, economic, and temporal variability. As such, the 60% is a practical balance between statistical reliability and practical feasibility in evaluating sampling rates. The interpretation of the Monte Carlo simulation results based on this threshold is presented in Table 2 [35].

Table 2. Interpretation of the Monte Carlo Simulation Measured in Terms of Probability.

Probability	Interpretation
Less than 10%	Probability to occur is very low
10% to 40%	Probability to occur is relatively low
40% to 60%	Probability to occur is moderate
60% to 80%	Probability to occur is high
More than 80%	Probability to occur is certain

Overall, this study sets thresholds for MAPE (10%), CV (5%), and empirical probability (60%). Selection of these thresholds is imperative for trip frequency modeling because the low-count, integer nature of travel demand data magnifies variance into disproportionately large percentage discrepancies, especially since an accurate trip frequency estimate is necessary to influence subsequent steps in travel demand modeling.

2.4.2. Validation Through the Trip Generation Model

Multiple linear regression was used to model trip generation to quantitatively assess the influence of sociodemographic and economic factors on household trip frequency. Specifically, the regression model of this study, as shown in Equation (7), was composed of the socioeconomic and demographic factors as independent variables.

$$TF = \beta_1 V_1 + \beta_2 V_2 + \dots + \beta_i V_i + c \quad (7)$$

where TF is the household trip frequency and β_1 to β_i are regression coefficients, c is the baseline constant or intercept, and V_i represents sociodemographic and economic variables, as detailed in Table 3.

Table 3. Socioeconomic and Demographic Variables.

Code	Variables
V_1	Household Size
V_2	No. of Male Members
V_3	No. of Female Members
V_4	Children (under 7 y/o)
V_5	No. of Senior Citizens (>59 y/o)
V_6	No. of Working Members
V_7	No. of Students
V_8	No. of Motorized Vehicle
V_9	Income
V_{10}	No. of Driver's License Holders
V_{11a}	Household Ownership Status (Tenant = 1; Others = 0)
V_{11b}	Household Ownership Status (Owned = 1; Others = 0)
V_{12}	Household Structure (Nuclear-1; Extended = 0)

The variables V_1 , V_2 , V_3 , V_4 , V_5 , V_6 , V_7 , V_{10} , and V_{12} refer to sociodemographic variables that characterize household composition, whereas V_8 , V_9 , and V_{11} refer to economic variables that reflect the household's income capacity. For categorical variables (V_{11} and V_{12}), number coding was used to run the trip generation modeling analysis. For V_{11} , the response was constrained to either "Tenant", "Owned", or "Informal Settler". Because these categories do not possess an inherent ordinal relationship, V_{11} was represented in the multiple linear regression model using dummy variable encoding to avoid imposing an artificial linear ordering among the categories. Informal Settler households were selected as the reference category, and two binary variables were created: V_{11a} (Tenant), coded as 1 for tenant households and 0 otherwise, and V_{11b} (Owned), coded as 1 for owner-occupied households and 0 otherwise. Consequently, Informal Settler households were

represented by $V_{11a} = 0$ and $V_{11b} = 0$. The estimated coefficients for V_{11a} and V_{11b} therefore represent the differences in household trip generation between “Tenant” and “Informal Settler” households and between “Owned” and “Informal Settler” households, respectively, while controlling for the remaining explanatory variables in the model. Similarly, the V_{12} response was constrained to either “Nuclear,” coded as 1, or “Extended,” being the reference, coded as 0. On the other hand, variable V_9 is in Philippine pesos.

The Monte Carlo simulation was also used to evaluate whether the candidate sampling rate is able to reliably capture the variables in the population trip-generation model. The frequency with which the variables emerged as statistically significant across all iterations was tracked. In reference to Table 2, the sampling rate’s reliability was evaluated based on the empirical probability that variables became statistically significant in one million iterations and based on whether they were found to be consistent with the population trip-generation model. For example, at a probability of less than 40%, the sampling rate was interpreted as “poorly reliable” in explaining that variable. At 40% to 60%, the sampling rate was interpreted as “moderately reliable” in explaining that variable. A high probability of 60% to 80% means the sampling rate is “reliable.” Finally, at a very high probability of more than 80%, the sampling rate is “highly reliable.” Concurrently, the stability of the coefficient of determination, R-squared, was assessed across the one million iterations to determine how well the sociodemographic and economic variables explain the variability of the household trip frequency.

3. Results

3.1. Stratification Boundary

The stratification results for household size demonstrated a practical application of the Dalenius–Hodges Rule. The goal of this method was to create strata that were internally homogeneous by ensuring that the intervals of the cumulative square root of frequencies C_x are approximately equal. Table 4 shows the cumulative frequencies for the strata.

Table 4. Household Size Frequency.

HS	f_X	$\sqrt{f_X}$	C_x
1	105	10.25	10.25
2	152	12.33	22.58
3	171	13.08	35.65
4	151	12.29	47.94
5	40	6.32	54.27
6	80	8.94	63.21
7	15	3.87	67.08
8	11	3.32	70.40
9	9	3.00	73.40
11	6	2.45	75.85
20	1	1.00	76.85

Table 4 displays the HS frequencies and the computed cumulative square-root frequency of each HS; the survey recorded a maximum of 20 household sizes in the barangay. HS 3 had the highest frequency, followed by HS 2 and HS 4. The total cumulative square root frequency for the entire population was 76.85, yielding an optimal target interval size $\bar{F}$ of approximately 19.21 per stratum, which yielded a theoretical cut-off stratum boundaries ($\bar{F} = 19.21$, $2\bar{F} = 38.42$, $3\bar{F} = 57.64$, and $4\bar{F} = 76.85$).

Table 5 below shows that the stratum boundaries were depicted in HS 2, HS 4, and HS 6. Boundaries were identified by choosing the cumulative square-root frequency C_x values corresponding to theoretical cut-off stratum boundaries. Stratum 1 is composed

of small households of sizes 1 to 2, ending at a cumulative square root frequency C_x of 22.58. Stratum 2 captures medium-sized households (sizes 3 to 4), bringing the C_x to 47.94. Stratum 3 narrows to households of sizes 5 to 6 (63.21). Finally, Stratum 4 consolidates all remaining large households of sizes 7 and above, completing the distribution at a total cumulative metric of 76.85. The increments C_x showed decreasing density with increasing size: the Stratum 1 interval is 22.58; the Stratum 1 to Stratum 2 interval is 25.36; the Stratum 2 to Stratum 3 interval is 15.27; and lastly, the Stratum 3 to Stratum 4 interval is 13.67. This result indicates that barangay areas skew toward households with 1 to 4 members, as Stratum 1 and Stratum 2 were the most populous strata, with stratum sizes of 257 and 322, respectively.

Table 5. Stratum Boundary.

Stratum	Household Size (HS) Range	Stratum Size (N_h)	C_x	Theoretical Cut-Off
1	1–2	257	22.58	19.21
2	3–4	322	47.94	38.42
3	5–6	120	63.21	57.64
4	7 and above	42	76.85	76.85

3.2. Proportional Allocation

Conducted with one million iterations, the Monte Carlo analysis permitted the demonstration and comparison of the performance of different sampling rates in terms of their accuracy and precision to the true population parameters. The evaluation was based on four key metrics: Average Stratified Mean, Average Mean Absolute Percentage Error (MAPE), Standard Error (SE), and Coefficient of Variation (CV). The summarized results obtained using PA for sampling rates ranging from 20% to 1% are presented in Table 6.

Table 6. Monte Carlo Simulation Results using Proportional allocation.

Sampling Rate	Avg. Stratified Mean (TF)	Avg. MAPE (%)	SE	CV (%)
20%	5.95	2.31	0.17	2.89
15%	5.95	2.76	0.21	3.46
10%	5.95	3.47	0.26	4.35
8%	5.95	3.92	0.29	4.91
5%	5.95	5.03	0.38	6.31
4%	5.95	5.52	0.41	6.94
3%	5.95	6.18	0.46	7.78
2%	5.95	7.68	0.58	9.70
1%	5.95	10.47	0.79	13.31

A significant finding of the data presented in Table 6 was the stability of the Average Stratified Mean, which consistently remained at 5.95 trips across all experimental sampling rates. This is primarily attributed to the law of large numbers, which states that as the sample size increases—in this case, simulated one million times per sampling rate—the sample mean converges towards the true population mean [24,36]. Hence, it cannot be used as the only indicator of sampling rate efficiency. It is also important to note that as the sampling rate decreased from 20% to 1%, the MAPE, CV, and SE increased. The CV remained below 5% at an 8% sampling rate (4.91%) but nearly doubled to 9.7% at a 2% sampling rate, indicating increased dispersion around the mean. These results suggest that although the estimator remains accurate in the aggregate, its precision is significantly compromised at lower sampling rates [29].

To further quantify the accuracy at different sampling levels, the probability distribution of the MAPE was analyzed after one million simulation runs. Figure 5 provides a view of these error probabilities, illustrating the probability of achieving specific levels of precision within a single survey execution.

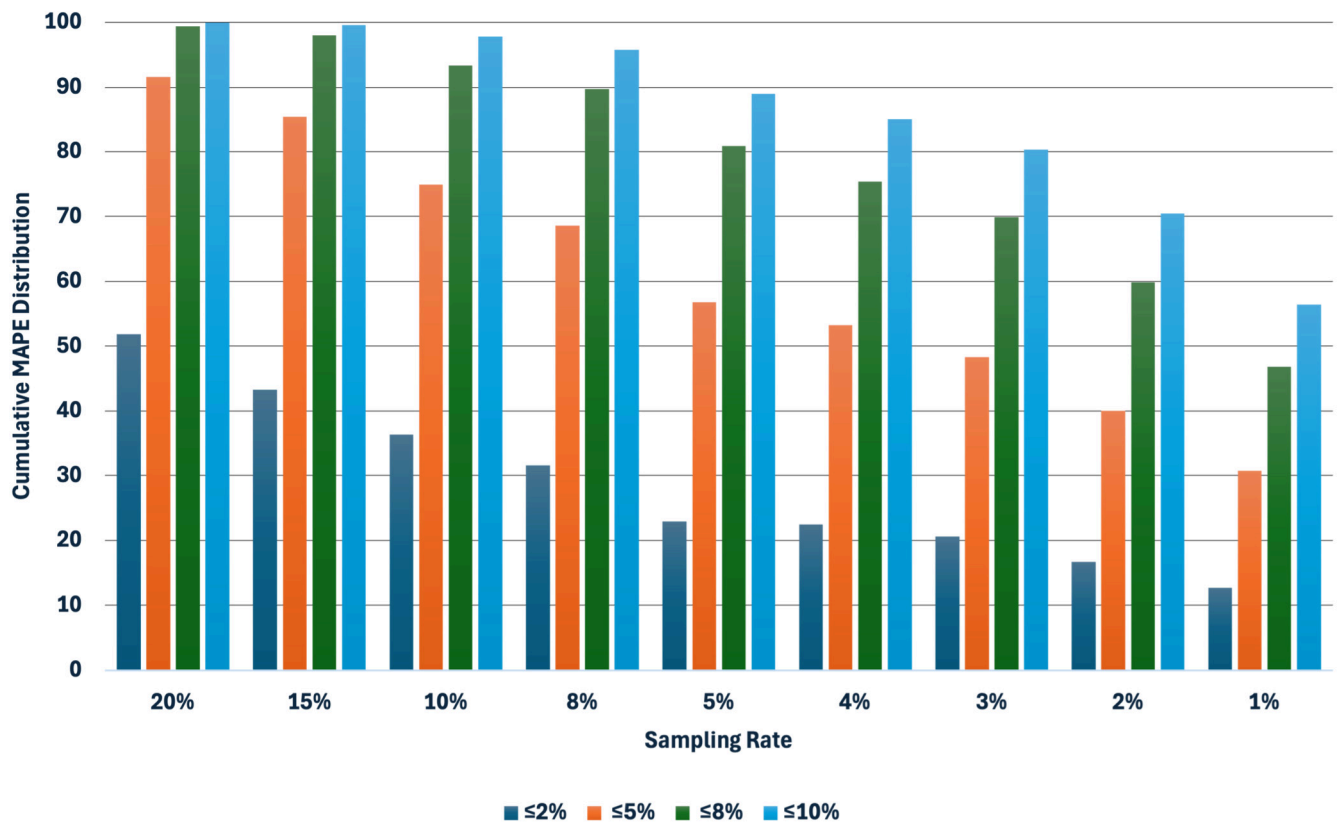


Figure 5. Cumulative Probability Distribution of MAPE using Proportional Allocation.

The MAPE distribution further clarifies the risks associated with low sampling rates. The results showed a decreasing trend in the empirical probability of committing certain MAPE thresholds as the sampling rate decreased. Additionally, it was evident that higher sampling rates, specifically 20% and 15%, showed large empirical probabilities, 91.56% and 85.47%, of committing $\leq 5\%$ MAPE. This was complemented by their corresponding CVs of 2.89% and 3.46% in Table 6, indicating higher accuracy, as they are below the 5% optimal threshold [30,31]. Although highly recommended as sampling rates for transportation studies, they may not justify the doubling of resources required for data collection [37].

On the other hand, the sampling rates 10% and 8% yielded good results with CVs below 5% and Average MAPE values of 3.47% and 3.92%, respectively. However, these sampling rates exhibited a declining MAPE cumulative probability distribution after one million runs, as shown in Figure 5. The 10% and 8% sampling rates reached only 74.91% and 68.64% probabilities of committing small MAPE values of $\leq 5\%$, respectively. Nevertheless, some transportation studies have adopted a tolerance to a $\leq 10\%$ MAPE threshold to maintain the quality of data [33]. The MAPE distributions of the 10% and 8% sampling rates show high results, reporting 97.83% and 95.82%, respectively, of committing $\leq 10\%$ MAPE; among these two, the 8% sampling rate was identified as the optimum threshold where the simulation attained a high probability of maintaining 5% and 10% thresholds without the diminishing returns associated with higher sampling rates.

3.3. Neyman's Allocation

Prior to running the Monte Carlo simulations, the dataset was stratified by NA. Table 7 tabulates the recommended percent composition per stratum per sampling rate assigned by NA. For a 20% sampling rate, NA recommended the optimum sample size consisting of 22.30% stratum 1, 47.97% stratum 2, 20.27% stratum 3, and 9.46% stratum 4. The same logic follows for the rest of the sampling rates. Among strata, NA recommended the largest number of samples in stratum 2 and the smallest number of samples in stratum 4. This is explained by the fact that the data distribution of trip rates observed in household sizes 3–4 often exhibits the highest heterogeneity in travel behavior. While smaller households typically have very predictable commuting patterns, the 3–4-person bracket introduced a complex mix of trip purposes. It can also be observed that as the sampling rate decreased, the percent composition per stratum evened out. For example, a 1% sampling rate was recommended to consist of 22.22% strata 1, 3, and 4, and 33.33% stratum 2.

Table 7. Strata Weights in Neyman's Allocation.

Sampling Rate	% Stratum 1	% Stratum 2	% Stratum 3	% Stratum 4
20%	22.30	47.97	20.27	9.46
15%	22.32	47.32	20.54	9.82
10%	22.97	47.30	20.27	9.46
8%	22.03	47.46	20.34	10.17
5%	21.05	47.37	21.05	10.53
4%	23.33	46.67	20.00	10.00
3%	22.73	50.00	18.18	9.09
2%	20.00	46.67	20.00	13.33
1%	22.22	33.33	22.22	22.22

Then, the Monte Carlo simulation showed the performance of various sampling rates in estimating the household trip frequency using the NA in Table 8, which summarizes the findings for sampling rates that vary from 20% to 1%.

Table 8. Monte Carlo Simulation Results using Neyman's Allocation.

Sampling Rate	Avg. Stratified Mean (TF)	Avg. MAPE (%)	SE	CV (%)
20%	5.95	2.19	0.16	2.74
15%	5.95	2.60	0.19	3.26
10%	5.95	3.30	0.25	4.14
8%	5.95	3.74	0.28	4.69
5%	5.95	4.74	0.35	5.95
4%	5.95	5.36	0.40	6.73
3%	5.95	6.30	0.47	7.92
2%	5.95	7.70	0.58	9.69
1%	5.95	10.50	0.79	13.31

The results indicate that the Average Stratified Mean remained highly stable under NA (5.95). When compared with the PA results (Table 6), NA generally produced lower Average MAPE, SE, and CV values across all sampling rates. For instance, at the 8% sampling rate, the CV for NA was 4.69%, which was lower than the 4.91% value observed for PA. This improvement in precision highlights the efficiency of the NA method in reducing sampling error by accounting for stratum variance. The NA method significantly impacts this process, as it relies heavily on the standard deviation of the strata. Strata with higher standard deviations were prioritized in the allocation to reduce the SE, thereby estimating the sample mean closer to the actual mean.

As shown in Figure 6, the cumulative probability distribution reinforces the superior performance of the NA method over the PA. At 20% and 15%, the results obtained a large empirical probability, 93.19% and 87.53%, respectively, of committing $\leq 5\%$ MAPE. Further, at an 8% sampling rate, NA yielded a 71.39% probability of committing $\leq 5\%$ MAPE, an improvement over the 68.64% probability observed in PA in Figure 5. Similarly, at a 10% sampling rate, the probability increased from 74.91% to 77.34%. At $\leq 10\%$ MAPE, the 8% rate showed a 96.69% probability, two points above the PA. This trend suggests that NA provides more robust protection against extreme outliers in a single survey execution. Given that the CV at the 8% rate (4.690%) remained below the 5% threshold and the probability of accuracy was significantly higher, NA further recommended the 8% sampling rate as the optimal range for urban travel data collection, offering maximum precision with minimal resource waste.

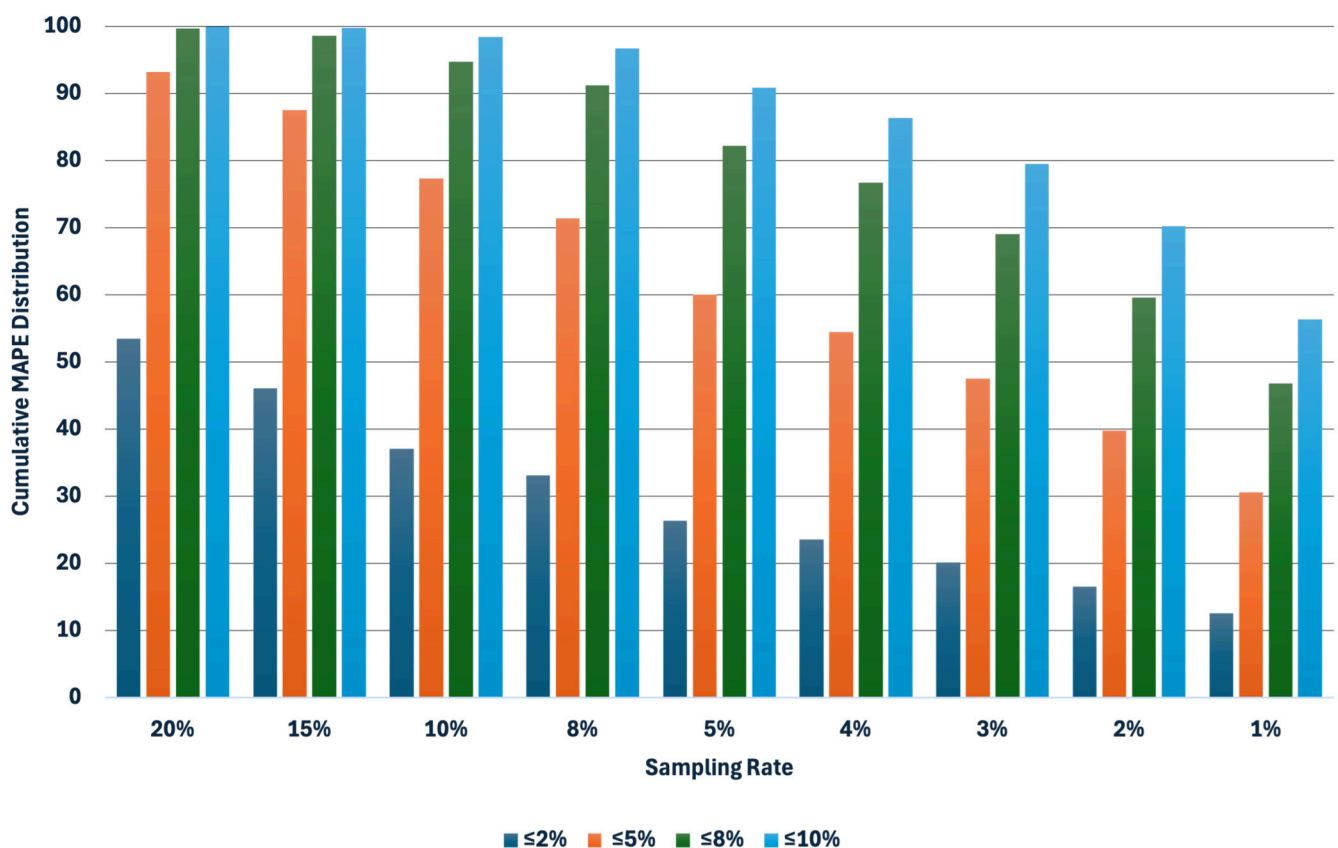


Figure 6. Cumulative Probability Distribution of MAPE using Neyman's Allocation.

3.4. Validation Through Trip Generation Modeling

Trip generation modeling using the Multiple Linear Regression (MLR) model was executed as part of the validation process to assess the efficiency of the selected optimized sampling rate of 8% under proportional and Neyman's allocation. Using the identified sociodemographic and economic variables detailed in Table 3 as predictors, an MLR analysis was conducted to estimate trip frequency generated on a household basis.

As a preliminary requirement before the MLR procedure, predictors were tested for multicollinearity. The variance inflation factor (VIF), as shown in Table 9, was above 10 [38] for V_1 , indicating multicollinearity for household size [39]. There were also higher VIFs for V_2 and V_3 , indicating that household size is directly linked to gender distribution. Although V_1 has been established as a primary indicator for trip generation modeling, this research used household-size stratification, resulting in redundant variable usage. To mitigate this, V_1 , with VIF values exceeding 10, was excluded from the MLR analysis. This

exclusion ensures model stability and enables a deeper understanding of the specific effects of gender distribution on households' overall trip patterns. After removal, there was a notable decrease in the VIFs for V_2 and V_3 . Overall, 12 sociodemographic and economic variables were used in the trip generation modeling.

Table 9. Multicollinearity Test Result.

Variable	VIF (Pre-Screening)	VIF (Post-Screening)
V_1 Household Size	12.85	-
V_2 No. of Male Members	6.81	2.32
V_3 No. of Female Members	7.24	2.52
V_4 Children (under 7 y/o)	2.24	2.24
V_5 No. of SC (>59 y/o)	1.17	1.17
V_6 No. of Working Members	1.32	1.32
V_7 No. of Students	2.79	2.79
V_8 No. of Motorized Vehicles	2.17	2.17
V_9 Income	1.54	1.53
V_{10} No. of Driver's License Holders	1.38	1.37
V_{11a} Household Ownership Status (Tenant = 1; Other = 0)	1.40	1.39
V_{11b} Household Ownership Status (Owned = 1; Other = 0)	1.30	1.30
V_{12} Household Structure (Nuclear = 1; Extended = 0)	1.33	1.30

Using the population dataset, Table 10 shows the beta coefficients and corresponding p -values for each variable. Eight predictors came out statistically significant ($p < 0.05$) such as V_2 , V_3 , V_4 , V_6 , V_7 , V_8 , V_{11a} , and V_{11b} . On the other hand, four predictors (V_5 , V_9 , V_{10} , V_{12}) were found to be statistically non-significant ($p > 0.05$). Though this study did not intend to remove literature-proven variables, as this might lead to omitted-variable bias [40], Income (V_9) was excluded from the model as its effect on the estimated TF is negligible due to its zero coefficient. Overall, the equation of the trip generation model was expressed in the form of a multiple linear regression model to estimate Household Trip Frequency TF, as shown in Equation (8).

$$\text{TF} = 1.419V_2 + 1.187V_3 - 1.003V_4 - 0.161V_5 + 0.223V_6 + 0.847V_7 + 0.277V_8 + 0.071V_{10} + 0.528V_{11a} + 0.572V_{11b} - 0.265V_{12} + 0.64 \quad (8)$$

Negative relationships with trip frequency were identified for (V_4) Children under 7 years old (V_4), Number of Senior Citizens (V_5), and Household Structure (V_{12}). V_4 and V_5 relate to the mobility of household members, meaning that senior citizens and children travel less than other age groups. Lastly, V_{12} is associated with household size, indicating that an extended household structure generates more trips than a nuclear household structure, with a negative standardized coefficient of -0.265 . Furthermore, Household ownership (V_{11}) status was represented by two dummy variables, with Informal Settler designated as the reference category. The regression results indicate that both Tenant (V_{11a}) and Owned (V_{11b}) were statistically significant predictors of household trip generation. Specifically, tenant households exhibited a positive standardized coefficient of 0.055 ($p = 0.015$), while owner-occupied households showed a larger positive standardized coefficient of 0.079 ($p < 0.001$), indicating greater influence on trip frequency than the referenced Informal Settler households.

Table 10. Multiple Linear Regression Analysis using Population Dataset.

Variable	Coefficients	Standardized Coefficients	p-Value	Remarks
V ₂	1.419	0.448	0.000	Significant
V ₃	1.187	0.369	0.000	Significant
V ₄	−1.003	−0.267	0.000	Significant
V ₅	−0.161	−0.025	0.221	Non-Significant
V ₆	0.223	0.070	0.001	Significant
V ₇	0.847	0.272	0.000	Significant
V ₈	0.277	0.162	0.000	Significant
V ₉	0.000	0.001	0.972	Non-Significant
V ₁₀	0.071	0.013	0.550	Non-Significant
V _{11a}	0.528	0.055	0.015	Significant
V _{11b}	0.572	0.079	0.000	Significant
V ₁₂	−0.265	−0.027	0.217	Non-Significant
Intercept	0.648	-	0.037	Significant

3.4.1. MLR Analysis Using Proportional Allocation

As for the validation process, the analysis revealed that an 8% stratified sampling rate is highly reliable in estimating the primary predictors of trip frequency, particularly Number of Male Members (V₂) and Number of Female Members (V₃), as shown in Table 11. In addition, it was also reliable in explaining Children under 7 years old (V₄) at 72.22% probability. The 8% sampling rate was able to capture the core demographic variables with respect to trip generation, as these relationships remain nearly universal and highly resistant to sampling noise even at this reduced scale.

Table 11. Predictors Probability using PA.

Variable	Population Dataset Significance	Monte Carlo Simulation Percent Significance (%)	8% Sampling Rate Interpretation
V ₂	Significant	96.34	Highly Reliable
V ₃	Significant	85.77	Highly Reliable
V ₄	Significant	72.22	Reliable
V ₇	Significant	43.29	Moderately Reliable
V ₉	Non-Significant	19.54	Non-significant
V _{11b}	Significant	17.65	Poorly Reliable
V _{11a}	Significant	11.46	Non-Significant
V ₈	Significant	10.43	Poorly Reliable
V ₁₂	Non-Significant	8.62	Non-Significant
V ₅	Non-Significant	8.43	Non-Significant
V ₁₀	Non-Significant	8.34	Non-Significant
V ₆	Significant	6.97	Poorly Reliable

While the 8% rate reliably explained the primary indicators, this study found inconsistent results for secondary variables such as V₆, V₈, V_{11a}, and V_{11b}. Although these variables yielded significant *p*-values in the full population model, the Monte Carlo simulation reveals that the 8% sampling rate had poor reliability in capturing this result. For instance, V₈ and V₆ achieved significance in only 10.43% and 6.97% out of the one million iterations, despite being found statistically significant in the baseline population model. This discrepancy suggests that these variables are sensitive to sample size.

The simulation further explains the difference between fundamentally non-significant variables and those that require a higher sample size for stabilization. Variables V₅, V₉, V₁₀, and V₁₂ were fundamentally non-significant in both the population and the simulation, confirming their lack of effect on trip generation regardless of the sample size. In contrast, V₇

was only moderately captured at 43.29%, although it was significant in the full-population model. A similar pattern can also be observed for V_6 , V_8 , V_{11a} , and V_{11b} , suggesting sensitivity to sample size. Thus, it should be noted that even though the sampling rate of 8% can reliably explain the population's primary variables, caution is still advised when interpreting secondary variables, as these may require a larger sample size. Ultimately, these findings observe both advantages and disadvantages of using an 8% sampling rate as an optimized benchmark for trip generation modeling. It successfully captures the primary demographic predictors that drive population behavior while balancing data collection costs and model reliability, provided the model prioritizes these high-stability predictors.

Further validation was conducted in terms of the coefficient of determination (R-squared). Figure 7 shows the probability distribution of R-squared. The model shows that R-squared is normally distributed, with its mean converging to 0.80 over one million iterations. The result also revealed that 95.97% of the time, R-squared is above 0.7, which is considered a good level of prediction [41].

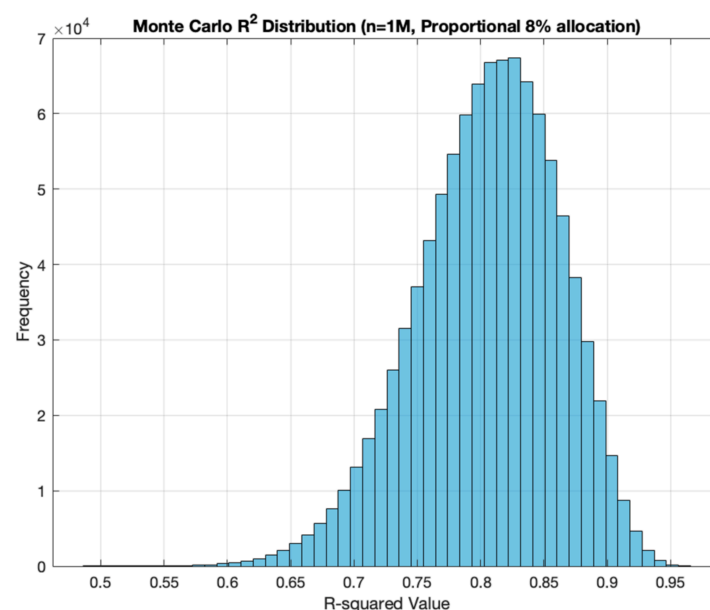


Figure 7. R-squared Monte Carlo Distribution using PA.

3.4.2. MLR Analysis Using Neyman's Allocation

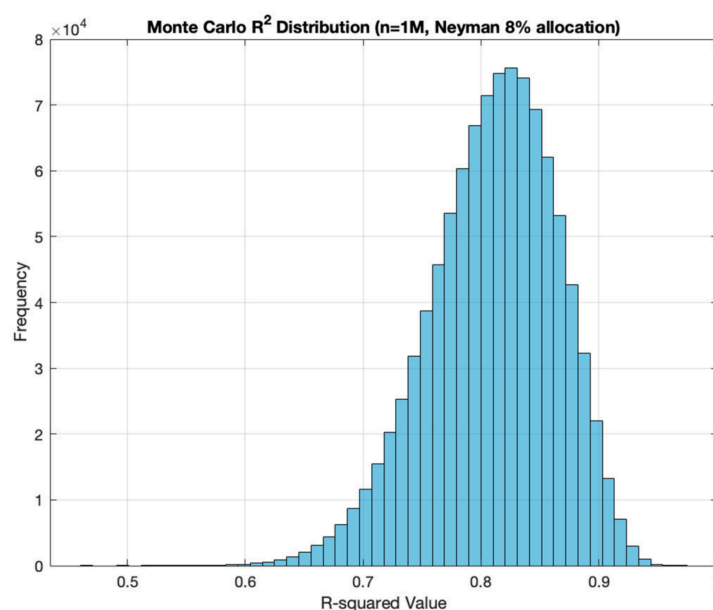
The behavior of MLR stability was also investigated using Neyman's allocation approach. As with PA, the reliability of the sampling rate for estimating primary predictors in a Monte Carlo simulation was compared with that of the population trip generation model. As seen in Table 12, the 8% sampling rate was highly reliable in capturing V_2 , V_3 , and V_4 with a probability of 95.78%, 85.15%, and 77.04%, respectively, which showed a slight discrepancy with the result from PA. Despite having a better CV and MAPE, as discussed in the previous sections, NA showed a slightly lower probability for some of the variables as compared to PA, such as V_2 (95.78%), V_3 (85.15%), V_{11a} (9.86%), V_{11b} (14.58%), V_{12} (8.70%), and V_6 (6.23%). Nevertheless, the reliability of the 8% sampling rate was similar to PA for all variables.

Table 12. Predictors Stability using NA.

Variable	Population Dataset Significance	Monte Carlo Simulation Percent Significance (%)	8% Sampling Rate Interpretation
V ₂	Significant	95.78	Highly Reliable
V ₃	Significant	85.15	Highly Reliable
V ₄	Significant	77.04	Reliable
V ₇	Significant	46.79	Moderately Reliable
V ₉	Not Significant	20.16	Non-Significant
V _{11b}	Significant	14.58	Poorly Reliable
V ₅	Not Significant	11.50	Non-Significant
V ₈	Significant	10.58	Poorly Reliable
V _{11a}	Significant	9.86	Poorly Reliable
V ₁₀	Not Significant	9.26	Non-Significant
V ₁₂	Not Significant	8.70	Non-Significant
V ₆	Significant	6.23	Poorly Reliable

At an 8% sampling rate, NA showed results similar to PA in identifying non-significant variables and inconsistencies. In NA, the study captured non-significant variables that support the trip generation model in the population dataset. V₅, V₉, V₁₀, and V₁₂ were found to be non-significant predictors in both the baseline population model and the Monte Carlo simulation, with probabilities of only 11.50%, 20.16%, 9.26%, and 8.70%, respectively. Nevertheless, some variables showed inconsistency: V₆, V₈, V_{11a}, and V_{11b} were statistically significant in the baseline population but had lower probabilities during the Monte Carlo simulation, at 6.23%, 10.58%, and 14.58%, respectively, suggesting sensitivity to the reduced sampling rate.

The stability of R-squared was also observed, as shown in Figure 8. Similarly to PA, the R-squared is normally distributed, with the mean converging to 0.81 after one million iterations. Moreover, 96.86% of the iterations had R-squared values of 0.7 or higher, indicating good stability. The resulting R-squared is higher than that from PA, which showed a slight improvement of 0.9%.

**Figure 8.** R-squared Monte Carlo Distribution using NA.

4. Discussion

PA and NA revealed a slight difference in terms of estimating population trip frequency across different sampling rates. After one million iterations, all stratification strategies produced similar Average Stratified Means across all sampling rates, an expected effect of the law of large numbers, which states that as the sample size increases, the mean approaches the true population mean; in this study, the Average Stratified Mean was 5.95 household trips. The results also show an increasing trend in all statistical parameters as the sampling rate decreased. For example, the CV and sampling rate showed an inverse relationship. As expected with a small sample size, heterogeneity becomes magnified, leading to a high variance and high dispersion of the estimated trip frequency across one million iterations.

Further, this study analyzed the empirical probability of accurately estimating the trip frequency, where accuracy is measured to a MAPE threshold as strict as 2%. For both NA and PA, an 8% sampling rate was considered an optimal rate since there were empirical probabilities of at least 95.82% estimated trip frequencies that were within the $\leq 10\%$ MAPE thresholds, but this dropped to as low as 68.64% probability when adopting a much more conservative MAPE threshold of $\leq 5\%$, as shown in Table 13. Although these results fall within the threshold [35], the risk of large errors increases as the sampling rate decreases.

Table 13. Probability–Accuracy Matrix for Varying Sampling Rate.

Sampling Rate	MAPE	Proportional Allocation (Probability %)	Neyman's Allocation (Probability %)
20%	$\leq 10\%$	99.94	99.97
	$\leq 5\%$	91.56	93.19
15%	$\leq 10\%$	99.62	99.78
	$\leq 5\%$	85.47	87.53
10%	$\leq 10\%$	97.83	98.42
	$\leq 5\%$	74.91	77.34
8%	$\leq 10\%$	95.82	96.69
	$\leq 5\%$	68.64	71.39

This was further validated using trip generation modeling. The optimized sampling rate of 8% successfully captured primary predictors, such as gender distribution variables V_2 and V_3 , which were statistically significant in both the Monte Carlo simulations and the population baseline trip generation model. This can be attributed to household size as the primary predictor in trip generation modeling, and thus justifies its adoption for stratum characterization in this study. However, for the No. of Senior Citizens (V_5), the No. of Driver's License Holders (V_{10}), and Household Structure (V_{12}), despite their contribution to household size, do not reflect a statistically significant effect in both the population and simulation models. Elderly people have mobility concerns and unpredictable travel patterns, and having a driver's license does not necessarily affect trip frequency because urban trip makers often prefer public utility vehicles in their daily travel. Interestingly, economic predictors like Income (V_9), frequently considered major predictors in transport literature, did not become statistically significant in either the baseline model or simulation models. This reflects that urban residents' travel decisions are not affected by their economic status, which is overpowered by household composition, such as the presence of children and students [42].

The findings also revealed that both tenant (V_{11a}) and owner-occupied households (V_{11b}) generate significantly more trips than Informal Settler households, with both positive standardized coefficients. Moreover, the larger standardized coefficient for owner-occupied

households suggests that the increase in household trip generation is more pronounced among owner-occupied households than among tenant households, relative to the Informal Settler group, which can be attributed to the economic background of the household.

The increase in heterogeneity at low sampling rates is reflected in its inconsistency in capturing other statistically significant variables, such as Household Ownership Status (V_{11a} and V_{11b}), No. of Motorized Vehicles (V_8), and No. of Working Members (V_6), which showed low stability in the Monte Carlo simulation. This implies that these variables are sensitive to low sampling sizes due to their high variability. For instance, worker count is less reliable than demographic factors like student presence, likely because of high behavioral variability driven by unpredictable travel patterns or a hybrid work setup.

The evaluation of R-squared showed consistent good predictive accuracy, averaging 0.8 across a Monte Carlo simulation. Specifically, at least 95% of all iterations yielded values above 0.7. This result reflects the structural design of the household-size stratification framework, which preserves the dominant demographic predictors present in the baseline census population. Nevertheless, while the optimum 8% sampling rate demonstrates high accuracy in estimating mean trip rates, the reduced sample size expectedly diminishes statistical power for secondary explanatory variables (V_6 , V_8 , V_{11a} , and V_{11b}) due to increased standard errors.

5. Conclusions

The Micro-Analysis Zone is preferred for localized planning since it reduces aggregation bias and increases sensitivity to transportation system effects. However, it requires a larger sample size. Because standard sample size formulae aim for high confidence levels regardless of population size, this often requires surveys to have a disproportionately large percentage of the total MAZ population, making granular data collection both a logistical and financial challenge. To address this problem, this study aimed to develop a Monte Carlo-based stratified sampling framework for probabilistic accuracy comparisons across different sampling rates in a household survey in MAZ. Unlike traditional random sampling, stratified sampling ensures the equitable representation of various sociodemographic groups by allocating specific proportions of the total sample to each subgroup. Specifically, this study adopts household size as the stratification variable, leveraging its proven direct correlation with household trip patterns to maximize the framework's predictive accuracy.

Two stratification approaches, PA and NA, were utilized in the sampling methodology. Using a Monte Carlo simulation with one million iterations, all stratification strategies produced similar Average Stratified Means for all sampling rates at 5.95 household trips. The results also showed an increasing trend in all test parameters as the sampling rate decreased. An optimal sampling rate was selected based on CV, MAPE, and empirical probability. Specifically, an 8% sampling rate yielded a CV of less than 5%, implying low variability among trip frequency means relative to the true population mean. Furthermore, simulation showed that there was at least a 95% empirical probability that an 8% sampling rate achieved trip frequency estimates within the $\leq 10\%$ MAPE thresholds, but the probability decreased to as low as 68.64% when considering a much more conservative threshold of $\leq 5\%$ MAPE, noting that there is a trade-off for higher accuracy.

Different stratification approaches are essential for determining the optimal sampling rate. No large discrepancies in test parameters were observed among the different allocation methods. It was observed that NA produced lower CV and higher empirical probabilities and similar MLR stability with PA. Nevertheless, PA produced a less complex stratification method compared to NA. Hence, the choice of method remains at the discretion of the survey investigator, who must balance target accuracy, project timelines, and survey costs.

To further substantiate the 8% optimum sampling rate, additional validation tests were conducted by running trip generation modeling through MLR. For both PA and NA, the predictor variables showed mixed results, as some variables that were found to be significant in the baseline model were inconsistent with the sample models. Similar primary predictors of the population were identified in the sampled groups, particularly the number of male and female members and the number of children under 7 years old, which emerged as significant indicators most of the time, while contrasting indicators were found to be the number of motorized vehicles, the number of working members, and household ownership status. This discrepancy suggests that while these variables are significant in a larger dataset, they become more sensitive as the sample size decreases.

On the other hand, Monte Carlo simulation revealed a high mean R-squared of 0.8 and at least a 95% probability of achieving an R-squared above 0.7. This high R-squared value can be attributed to the household size-stratification framework, which reflects the strong influence of identified primary predictors, particularly the gender distributions and the number of children. Despite a stable, high R-squared, reducing the sampling rate also reduces its ability to capture highly sensitive variables. Hence, it is important that a low sample size is carefully selected based on the data of interest, whether the aim is strictly to estimate household trip frequencies or to reliably identify secondary trip predictors.

The developed stratified sampling framework and Monte Carlo simulation approach offer a thorough, data-driven methodology for sample size optimization. However, certain limitations must be acknowledged. First, the empirical baseline data utilized to validate the framework were collected from a single and highly urbanized administrative unit, Barangay 15-B, Davao City. This study zone is characterized by high population density, mixed-use commercial zoning, and a high reliance on localized paratransit modes and active transport. This means that the specific 8% optimum sampling rate identified in this study represents a localized calibration result rather than a universal threshold for all MAZs. Second, it is critical to distinguish between the mathematical validation of the estimator and real-world field-survey deployment. The Monte Carlo simulation took samples from a census frame with ideal assumptions of perfect sampling and a high response rate in a sandbox environment. In actual field surveys, household travel surveys routinely encounter non-response bias, unreachable households, and structural field barriers—dynamics that this simulation did not model. Therefore, while the framework demonstrates high statistical precision, real-world implementations must account for field contingencies, which may necessitate recalibration of the sample size. Overall, this study recommends that future transport surveys be cautious of their local context and that 8% is mostly applicable to studies using household-size strata gathered from single, low-population areas in urban settings. Context aside, the optimum sampling rate is more reliable for studies that aim to estimate trip frequencies, highlighting that such low sampling can lose its ability to explain sensitive predictor variables in trip generation modeling. Larger sampling rates are recommended should these assumptions be violated to preserve the accuracy and reliability of results. Further research is also recommended to calibrate the optimum sampling threshold for other communities, especially for rural and suburban MAZs that differ in terms of sociodemographic distribution and built environments.

Author Contributions: Conceptualization, J.T.C. and A.M.F.; methodology, J.T.C.; software, V.J.G.M.; validation, J.T.C.; formal analysis, J.T.C.; investigation, J.T.C.; resources, J.T.C.; data curation, J.T.C.; writing—original draft preparation, J.T.C.; writing—review and editing, J.T.C., A.M.F. and V.J.G.M.; funding acquisition, J.T.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Engineering Research and Development for Technology (ERDT) of the Philippine Department of Science and Technology (DOST).

Institutional Review Board Statement: Ethical review and approval were waived for this study because no identifiable personal information was collected or disclosed.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to ethical and privacy restriction.

Acknowledgments: During the preparation of this manuscript, the author used Google’s Gemini (<https://gemini.google.com/app>, accessed on 19 July 2026) for limited language editing and stylistic refinement. No generative AI tools were used for study design, data collection, data analysis, or interpretation of results. The authors reviewed and edited all AI-assisted outputs and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CV	Coefficient of Variation
HS	Household Size
HTSQ	Household Travel Survey Questionnaire
MAPE	Mean Absolute Percentage Error
MAZ	Micro-Analysis Zone
MLR	Multiple Linear Regression
NA	Neyman’s Allocation
PA	Proportional Allocation
TF	Trip Frequency
VIF	Variance Inflation Factor

Appendix A. Household Travel Survey Questionnaire

Instruction to the enumerator: Write the appropriate answer legibly on the line provided or mark ✓ for the option(s) that correspond to the respondent's answer. Write N/A for questions that are not applicable.

Date of the Interview: _____
Household No.: _____

PART 1: Household General Information. Interview the household head or any adult representative.

1. Address of Household: _____
Street Purok Barangay
2. Number of Household Members: _____
3. Number of Male Members: _____
4. Number of Female Members: _____
5. Number of children under 7 years old? _____
6. Number of school children (from pre-school to college)? _____
7. Number of helpers? _____
8. Number of vehicles owned? _____
a. Bicycle: _____ d. Jeep: _____ g. Trucks: _____
b. Car: _____ e. Van: _____ h. Others, please specify: _____
c. Motorcycle: _____ f. Tricycle: _____
9. Household Ownership Status: Rented: _____ Owned: _____ Informal Settler: _____

PART 2: Household Member Information. Interview each household member aged 7 years and above.

Household Member No. _____

2. A. Personal Information

10. Name (optional): _____
Last Name First Name Middle Initial
11. Role in the household (write the code from Table A): _____
12. Sex: Male _____ Female: _____
13. Age: _____
14. Monthly Income in Philippine Peso: _____
15. Work Address: _____
Street Purok Barangay City/Municipality
16. School Address: _____
Street Purok Barangay City/Municipality
17. Occupation (write the code from Table B): _____
18. Employment Sector (write the code from Table C): _____
19. Highest Educational Attainment (write the code from Table D): _____
20. Does the respondent own a driver's license?: Yes: _____ No: _____
21. Type of gadgets owned: _____
Smart Phone: _____ Computer: _____ Others (pls specify): _____
22. Does the respondent have internet access: Yes: _____ No: _____

2. B Trip Information. Interview each household member aged 7 years and above about their daily travel.

List of destinations traveled in daily trips. Add more lines if necessary:

Destination 1: _____
Destination 2: _____
Destination 3: _____
Destination 3: _____

23. Total no. of daily trips made _____

Destination No. _____

24. Purpose of Travel (write the code from Table E): _____

25. Place of origin: _____
Street Purok Barangay Municipality/City

26. Institution of the origin (write the code in Table F): _____

27. Estimated Time of departure: _____

28. Destination of Travel: _____
Street Purok Barangay Municipality/City

29. Institution of the destination (write the code from Table F): _____

30. Estimated Time of arrival: _____

31. Transportation modes used in the trips (use the code in Table G).
For travel that requires multiple modes, please list all transportation modes for each transfer on a single trip. For a single mode, just fill out one line.

(Origin) _____ → _____ → _____ → _____ → _____

Add more sheets, if necessary

Table A. Role in the household

Relationship to Household Head	Code
Household Head (HH)	01
Spouse	02
Son / Daughter	03
Daughter-in-law / Son-in-law	04
Grandson / Granddaughter	05
HH's mother/mother-in-law	06
HH's father / father-in-law	07
HH's brother / brother-in-law	08
HH's sister / sister-in-law	09
HH's auntie / uncle	10
HH's niece / nephew	11
HH's grandfather	12
HH's grandmother	13
Others (Please specify)	14

Table B. Occupation

Occupation	Code
Service Worker	01
Administrative & Executive Worker	02
Sale Worker	03
Clerical Worker	04
Factory Worker/Craftsman	05
Transport Worker	06
Professional Worker	07
Student/Elem School	08
Student/High school	09
Housewife	10
Jobless	11
Other, specify	12

Table C. Employment Sector

Employment Sector	Code
Service Industry	01
School	02
University	03
Government	04
Agriculture/Mining	05
Manufacturing	06
Public Utility Company	07
Construction	08
Transportation/Communication	09
Homebased	10
Commerce	11
Other, please specify	12

Table D. Educational Attainment

Highest Educational Attainment	Code
Elementary Graduate	01
Highschool Graduate	02
College Graduate	03
Postgraduate	04
Technical and Vocation Course	05
None	06

Table E. Educational Attainment

Trip Purpose	Code
Home	01
Work	02
School	03
Private Business	04
Employer's Business	05
Medical	06
Social	07
Eating	08
Shopping	09
Church	10
Others, specify	11

Table F. Institution of origin and destination

Institution	Code
Residence (Home)	01
Commercial	02
Office/Bank	03
Factory/Warehouses	04
School/Universities	05
Recreational Place/Park	06
Medical	07
Religious/Social	08
Wholesale/Retail Shop	09
Restaurant and Entertainment	10
Others, specify	11

Table G. Institution of origin and destination

Mode Choice	Code
Walking	01
Bicycle	02
Jeepney	03
Tricycle	04
Taxi	05
Uber/Grab	06
Private Car	07

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