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# Gap Acceptance Behavior of Minor Road Two-Wheeler Riders Performing Right Turn Maneuver at Unsignalized Three-Legged Intersections: Case Study of Pulchowk-Kupondole and Satdobato-Lagankhel Intersections, Kathmandu Valley

**by**

**Aashray Mahat**

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The undersigned certify that they have read and recommended to Institute of Engineering for acceptance, a thesis entitled **"Gap Acceptance Behavior of Minor Road Two-Wheeler Riders Performing Right Turn Maneuver at Unsignalized Three-Legged Intersections: Case Study of Pulchowk-Kupondole and Satdobato-Lagankhel Intersections, Kathmandu Valley"** submitted by **Aashray Mahat** in partial fulfillment of the requirement for degree of Master of Science in Transportation Engineering.

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# ABSTRACT

This study investigates gap acceptance behavior among minor-road two-wheeler riders at two unsignalized three-legged intersections in Kathmandu (Pulchowk-Kupondole and Satdobato-Lagankhel), analyzing 953 observed gap acceptance events. Using binary logistic regression, we examined how traffic conditions, rider characteristics, and riding behavior influence merging decisions. The models incorporated gap type (gap/lag), major road speed, gap duration, rider gender, and classified riding behavior as aggressive or ideal based on observed gap selection patterns. Using MLR, the relation between Accepted Gap and incorporated traffic as well as demographic variables were modeled in which the results gave a distinct relation of Accepted Gap and clearing time. Also taking account the behavioral factor, the results reveal distinct behavioral differences: aggressive riders accepted gaps shorter on average than ideal riders, with significantly higher risk-taking at both intersections. The logistic models showed riders were substantially less likely to accept gaps than lags, with this effect being more pronounced among aggressive riders. Higher approaching speeds reduced acceptance likelihood, while longer gaps increased acceptance probability, though aggressive riders demonstrated greater tolerance for high-speed approaches. Gender differences emerged at Satdobato-Lagankhel, with male riders more frequently exhibiting aggressive gap acceptance. These findings provide critical insights for traffic management, suggesting that intersection design should account for behavioral variations. The identification of aggressive versus ideal gap acceptance patterns enables targeted safety interventions, such as: infrastructure modifications to discourage risky maneuvers; educational campaigns focused on high-risk groups; and signal timing adjustments that accommodate different rider behaviors.

**Keywords:** Critical Gap, Gap Acceptance, Regression, Speed, Behavior, CBA

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# LIST OF ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| SPSS | Statistical Package for Social Sciences |
| INFOGA | Influence Area of Gap Acceptance |
| MLR | Multiple Linear Regression |
| CBA | Clearing Behavior Approach |

# CHAPTER 1: INTRODUCTION

## 1.1 Background

Kathmandu Valley, the most urbanized region in Nepal, faces significant traffic congestion due to rapid urbanization, increasing vehicle ownership, and inadequate road infrastructure. The ring road, a major arterial route, connects various parts of the valley, but its intersections often experience chaotic traffic movements. While some major intersections have been signalized to improve traffic flow, many remain unsignalized, leading to complex driver interactions, particularly at three-legged and four-legged junctions.

At unsignalized intersections, traffic movement is not regulated by traffic lights, and drivers on minor roads must yield to vehicles on the major road. The absence of proper traffic control mechanisms results in heavy reliance on gap acceptance behavior—where drivers assess and decide whether to merge or cross based on available gaps in the major traffic stream. This behavior is critical for safety and efficiency, especially for two-wheeler riders, who constitute a significant portion of Kathmandu's traffic. At unsignalized intersections, the right turning minor road two-wheeler drivers must find a safe time and moment to enter the intersection. The drivers are presented with a series of gaps between vehicles in the major stream, which they need to either cross or merge into it. A driver has to accept or reject a gap presented to him/her which is influenced by certain traffic as well as behavioral considerations.

There are different definitions of gap in different literatures. Ashworth and Button [1977] measured gap from the rear of one vehicle to the front of the following vehicle. Adibesi [1989] defined gap as the major stream headway which is wholly available to a waiting vehicle from the minor road. Polus [1983] defined it as the time interval between two successive vehicles in the major road stream. A term lag comes along with the word gap which many people account to as the same thing but lag is defined as the time interval between the arrival of a vehicle in the minor road at the stop line and the arrival of the first vehicle on the major road to a point just opposite to this line (Solberg and

Oppenlander, 1996. In actual terms the lag represents the remaining part of the gap which is presented to the driver on his arrival at the stop line.

The parameter 'Critical gap' is an important one in gap acceptance behavior. It is the minimum gap that is acceptable to a driver, intending to cross a conflicting stream. For a particularly consistent driver, its value lies in between the largest rejected gap and the smallest accepted gap. Critical gap cannot be directly measured in field. Its value differs from driver to driver, from time to time, intersection to intersection, type of movement and traffic situations. All these factors make into account while estimating the critical gap and makes the process a difficult one.

Gap acceptance behavior study is important for appropriate planning of operational analysis and capacity estimate. In Nepal, there have been carried out some studies on gap acceptance behavior of roundabouts (Gyawali B and Marsani A [2021]) but there are limited literatures in this direction for unsignalized intersections which is the focus of this study.

## 1.2 Problem Statement

Most studies on unsignalized intersections have been conducted in developed countries where traffic is generally homogeneous, and drivers follow more disciplined lane-based movement. Unsignalized three-legged intersections are critical yet hazardous points in the road network. With two-wheelers constituting 72% of the total vehicle fleet (DoTM, 2022) and contributing to nearly 40% of intersection-related crashes (KV Traffic Police, 2021), understanding their gap acceptance behavior is essential for improving road safety. Unlike signalized intersections, unsignalized ones rely heavily on drivers' judgment, leading to inconsistent gap selection and frequent conflicts, especially during right-turn maneuvers. This study focuses on minor road two-wheeler riders who are particularly vulnerable due to their aggressive riding tendencies and lack of priority rules to analyze how they assess and accept gaps in mixed traffic conditions.

Given Nepal's 1,200+ annual two-wheeler crashes (Nepal Police, 2023), many of which occur at intersections, this research will provide crucial insights into rider behavior, differentiating between aggressive and cautious gap acceptance strategies.

However, research in developing countries under mixed traffic conditions has examined various aspects of traffic heterogeneity, yet aggressive driver behavior has not been explicitly incorporated into critical gap analysis. This study specifically investigates differences in critical gap acceptance between aggressive and non-aggressive drivers, while developing a logistic regression model to assess gap acceptance decisions. The model considers key variables such as gap duration, rider gender, major traffic speed, gap versus lag type, and aggressive riding behavior—a factor often overlooked in existing literature.

While there is growing research on gap acceptance behavior in developing countries, studies in the Nepalese context remain extremely limited. To the best of the author's knowledge, no prior research has systematically analyzed for minor road two-wheeler gap acceptance behavior in Nepal, particularly at unsignalized three-legged intersections. This research gap is significant, given that minor road users, especially two-wheelers, play a dominant role in Kathmandu's traffic dynamics. Their gap acceptance behavior is crucial because minor road riders must continuously assess and negotiate gaps in major traffic streams, often under highly irregular and aggressive traffic conditions. Unlike in regulated environments, riders in Kathmandu frequently accept shorter gaps due to impatience, congestion pressures, or a tendency to force entry into traffic. Understanding these behaviors is essential for improving intersection safety and efficiency in Nepal's unique mixed traffic conditions.

The study focuses on two key unsignalized intersections in Kathmandu—Pulchowk-Kupondole and Satdobato-Lagankhel—where unsignalized minor road merging presents significant safety challenges. By analyzing real-world gap acceptance patterns, this research aims to provide insights into how aggressive versus non-aggressive riders differ in their decision-making, contributing to better traffic management strategies tailored to Nepal's distinct road environment. The findings will not only fill a critical gap in local transportation literature but also offer practical recommendations for policymakers and urban planners working on road safety improvements in similar developing urban contexts.

### 1.3 Research Questions

This research aims to determine the minimum safe gap duration needed for two-wheeler riders to cross three-legged intersections and examine how different rider types approach gap acceptance decisions. The investigation focuses on understanding crossing behaviors and decision-making patterns among motorcycle and scooter riders at unsignalized junctions. The questions that can be expected to be answered by this research are:

i. What is the estimate of gap required in the three-legged Intersections for the minor road two-wheeler riders to successfully perform the right turning operation?
ii. How does the aggressive behavior of minor road right turning two-wheelers impact on the critical gap required?
iii. What are the factors that influence the gap required by the two-wheelers?

### 1.4 Objective of Study

The main objective of the study is to investigate gap acceptance behavior of minor road two-wheeler riders at unsignalized Three-legged Intersections of Kathmandu by determining the critical gap through different approaches. The specific objectives are listed below:

i. To estimate critical gaps for minor road two-wheeler riders at unsignalized three-legged intersections using Raff's and Clearing Behavior methods and analyze gap acceptance behavior of aggressive vs. ideal drivers.
ii. To identify factors that affect gap acceptance and gap duration and develop probabilistic gap acceptance and gap duration models for the minor road two-wheeler riders.

### 1.5 Scope of Study

This study covers two unsignalized Three legged intersections inside Kathmandu valley where traffic flow is significant. The following points constitute the scope of the work:

i. Computation of the drivers' demographic characteristics and traffic characteristics from the video recording
ii. Estimation of Critical Gap using two established methods.
iii. Comparing the aggressive and ideal behavior of drivers in gap acceptance
iv. Comparison of probability of acceptance and rejection of gap
v. Developing relation between gap acceptance and the considered traffic as well as demographic parameters.

## 1.6 Limitations

The research limitations are listed as follows:

i. The study was carried out considering peak hours of traffic flow. Therefore, the study of gap acceptance behavior could not be analyzed for non-peak hours.
ii. The effect of vehicular flow on gap acceptance was not taken into consideration
iii. The gradient effect of Intersections and environmental condition were not taken into consideration.
iv. Severity analysis of drivers' behavior in gap acceptance was not performed in this study.

## 1.7 Organization of Report

The report consists of a total of five chapters, which are listed as follows:

Chapter 1: Introduction which describes in brief the gap acceptance model of right turning minor road drivers along with objectives, scope and limitations of study.

Chapter 2: Literature Review which discusses the available literature related to the effect of demographic and traffic related factors in the gap acceptance behavior

Chapter 3: Methodology which describes stepwise conceptual plans from data collection to data analysis and presents framework for the study.

Chapter 4: Data Analysis which includes analysis and modelling of the extracted data and validation of the model, along with the interpretation of results.

Chapter 5: Conclusion and Recommendation which summarizes the findings of the results obtained and its scope in the engineering design practice

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Critical Gap

The concept of critical gaps has evolved through various interpretations in traffic research. Greenshields initially defined it as the time interval where acceptance and rejection frequencies for gap opportunities become equal. Raff and Hart later refined this as the specific gap duration where the number of accepted shorter gaps matches rejected longer gaps. The Highway Capacity Manual (HCM, 2000) provides an operational definition as the minimum time required for a single vehicle to safely enter an intersection.

This study specifically examines critical gap behavior for two-wheelers executing right-turn maneuvers from minor roads in mixed traffic conditions. The analysis focuses exclusively on motorcycle riders due to their unique operational characteristics in developing urban environments like Kathmandu. Two-wheelers demonstrate distinct gap acceptance patterns compared to other vehicles, exhibiting greater acceleration capabilities, smaller spatial requirements, and more flexible positioning in traffic streams. These attributes, combined with riders' ability to utilize smaller inter-vehicle spaces, create specific challenges for gap analysis.

The research pursues three key objectives: first, determining critical gap values for right-turning two-wheelers using established methodologies including Raff's technique and clearing behavior analysis; second, comparing gap acceptance patterns between aggressive and conservative riding styles; and third, developing predictive models including a logistic regression model for gap acceptance decisions and a multiple regression model for Accepted Gaps. These models specifically address the behavior of two-wheelers at unsignalized intersections, where their unique maneuvering characteristics significantly influence traffic dynamics.

## 2.2 Gap Acceptance Methods

Critical gap estimation becomes highly complex in heterogeneous traffic conditions due to the wide variations in traffic characteristics, including speed, maneuverability, vehicle dimensions, and driver responses to other vehicles. In mixed traffic, vehicles such as two-wheelers often exploit even the smallest gaps, maneuvering through intersections in a zigzag pattern. A single gap in the major traffic stream may be accepted by multiple minor road vehicles in succession, even if the gap is insufficient for more than one vehicle to safely clear the intersection. This behavior sometimes forces major road vehicles to stop, allowing minor road users—particularly two-wheelers—to proceed, disregarding priority rules.

These complexities make critical gap estimation particularly challenging, necessitating a reevaluation of the factors influencing gap acceptance behavior at uncontrolled (unsignalized) intersections, where priority norms are frequently ignored. Over the past decades, researchers worldwide have developed various gap acceptance methodologies, most of which assume consistent driver behavior under homogeneous traffic conditions. However, these assumptions often do not hold in heterogeneous traffic environments. A summary of past methodologies is illustrated in Figure 2.1, followed by a brief review of key approaches in the subsequent paragraph.

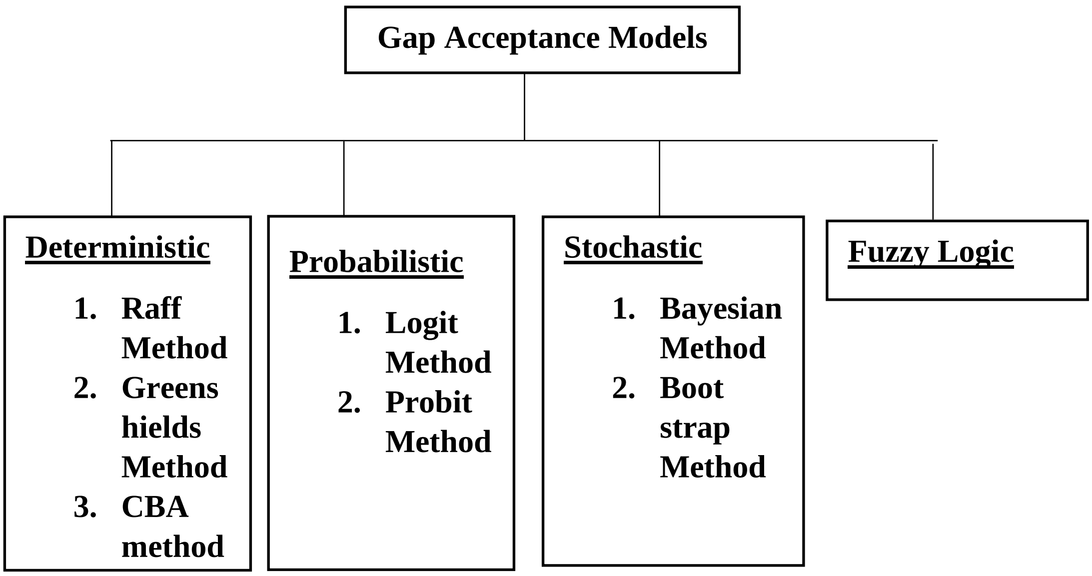



Figure 2.1 Methodologies on Gap Acceptance Behavior Studies

The probabilistic approach takes into account the fact that the gap acceptance behavior depends not only on intersection characteristics, vehicular characteristics, opposing flow, type of control, but also on qualitative factors like drivers' psychological and socioeconomic status, factors related to weather, pavement and light conditions, and factors related to the vehicle occupancy. The complexity is further increased in the case of heterogeneous traffic conditions that typically exist in developing countries, where the rules regarding assignment of the right of way are often neglected.

The modeling of gap acceptance behavior has evolved significantly through various methodological approaches. Early work by Maze (1981) demonstrated that logit models could effectively approximate probit models in analyzing gap acceptance decisions. Subsequent comparative studies by Gattis and Low (1999) evaluated multiple estimation techniques including Siegloch's method, Greenshields' approach, Raff's technique, acceptance curve analysis, and logit modeling to determine critical lag and gap values. Environmental factors influencing driver behavior were examined by Zohdy et al. (2010), who developed logit models revealing two key relationships: acceptable gap durations decrease with longer waiting times at three-legged intersections, but increase during periods of heavier rainfall. Brilon et al. (2011) further advanced the field through their comparative analysis of lag and gap estimation methods.

Recent methodological developments have incorporated various traffic parameters into gap acceptance models. Devarasetty et al. (2012) employed logistic regression to analyze how geometric and traffic characteristics influence driver decisions, developing separate models for gap and lag acceptance. Serag (2015) extended this work by explicitly incorporating driver aggressiveness as a predictive factor in binary logit models, building on earlier investigations of aggressive driving behavior at unsignalized intersections by Kaisy et al. (2007). The interaction between conflicting traffic streams was examined by Liu et al. (2015), who identified approach speed differentials as the most significant factor affecting preemptive/yielding decisions.

For developing country contexts, Ashalatha and Chandra (2011) proposed the Clearing Behavior Approach (CBA) as an alternative critical gap estimation method specifically adapted for heterogeneous traffic conditions. Comparative studies by Amin and Maurya (2015) further validated the effectiveness of logit models alongside traditional estimation techniques. While existing literature provides substantial insight into gap acceptance behavior, significant research gaps remain regarding aggressive driving tendencies in mixed traffic environments. Most studies have focused on homogeneous traffic conditions in developed countries (Zhang et al., 2019), where aggressive driving manifests differently than in developing nations. Recent work by Rahman et al. (2021) has highlighted how motorcycle-dominated traffic requires specialized modeling approaches.

## 2.3 Summary of Literature Review

Over the past few decades, numerous methods have explored gap acceptance theory. This literature review categorizes these approaches into probabilistic methods, clearing behavior models, and Raff's method. The probabilistic approach recognizes that gap acceptance depends not only on intersection geometry, vehicle dynamics, opposing traffic flow, and control type but also on qualitative factors such as driver psychology, vehicle occupancy, and weather conditions.

Existing research indicates that limited studies have recently addressed aggressive driver behavior and critical gap estimation in mixed traffic conditions. Most unsignalized intersection studies originate from developed countries, where drivers generally exhibit less aggressive tendencies. While past research on uncontrolled intersections under mixed traffic has examined traffic heterogeneity, aggressive driving behavior remains largely unaddressed. This study aims to analyze variations in critical gaps between aggressive and ideal driver behavior while developing a logistic regression model for gap acceptance/rejection. Key variables include gap duration, gender, major traffic speed, gap/lag type, and aggressive driving tendencies.

# CHAPTER 3: METHODOLOGY

## 3.1 Research Design

For the proposed study, all the relevant literature was thoroughly assessed to identify the important variables to be considered. A model framework is established by keeping in mind the purpose of study and types of variables considered for the research. It is followed by selection of appropriate locations for the study. Minimum sample size is determined so that it would facilitate sufficient data needed for the study. After that, data collection procedure is carried out using video recording and all the necessary information was extracted from the video and filled up in the observational sheets for further analysis and interpretation. Appropriate models were formulated and validated to justify the topic selected for research. The flowchart below in Figure 3.1 shows the brief details about the methodology adopted in this study and the headings are described in detail

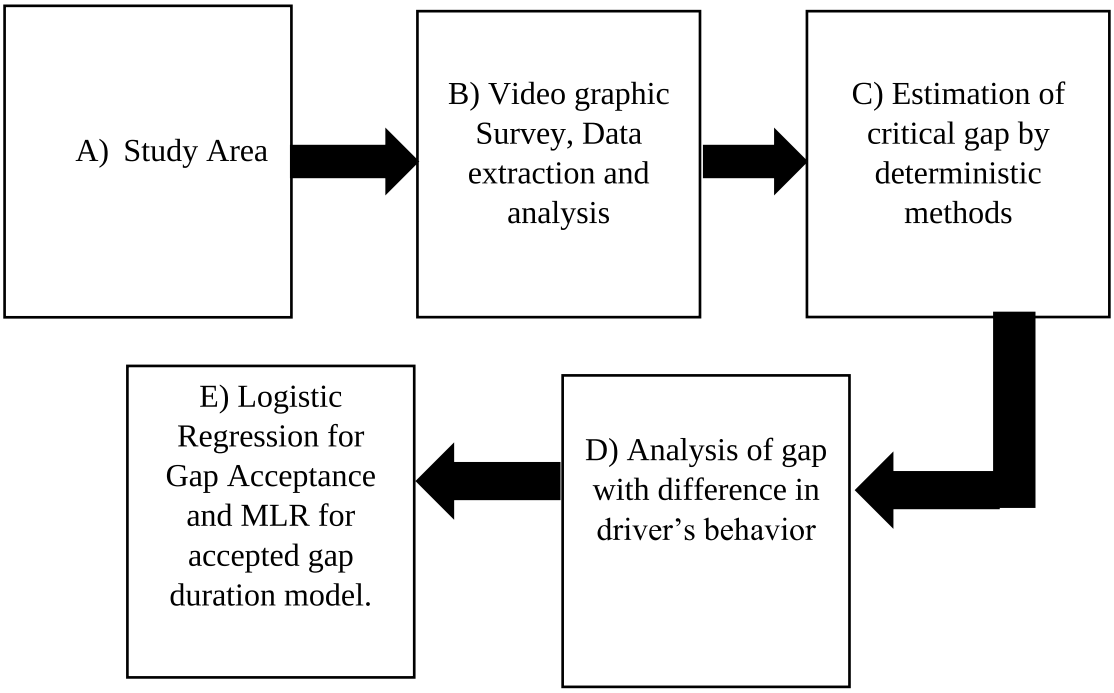



Figure 3.1: Methodological Framework of the Study

## 3.2 Variables Definition

Based upon various literatures and pilot study of unsignalized three legged intersections of Kathmandu Valley, the following have been identified as major forms of variables that influence gap acceptance/rejection of minor road two-wheeler riders trying to perform the right turning operation: speed of major traffic vehicles, gap/lag (duration in seconds), whether gap or lag presented to the driver, aggressive and ideal behavior. Besides that, literature also suggests that demographic factor gender also largely influences the probability of acceptance/rejection of right turning operation of minor road two-wheeler riders. Therefore, five independent variables (demographic and traffic related factors) and a dependent variable (Accepted Gap) are considered for the development of gap acceptance model and Accepted Gap model. Similarly, the findings from various literatures indicate how the demographic factors also influence the gap acceptance behavior. Thus, separate models for both sites were developed in the form of gap acceptance model(binary logistic) and Accepted Gap model(a multiple regression midel) in which five independent variables (gender, speed, gap/lag duration, gap/lag, aggressive/ideal) and a dependent variable (gap acceptance/Accepted Gap) are considered for model formulation. The variables have been listed below based on demographic/general characteristics and traffic related characteristics:

**Demographic/General Characteristics Related Variables**

1. *Driver Gender:*

   It is a categorical variable which has been categorized into two groups:

      i. Male two-wheeler riders
      ii. Female two-wheeler riders

**Traffic Related Variables**

1. *Clearing Time:*

   It is a continuous variable which is extracted from the video and the description is as mentioned in the Clearing Behavior approach explained below.

2. *Speed of Major Road Vehicle:*

   It is a continuous variable extracted from the video by fixing a stretch of 30m in the intersection and measuring the time taken by the fastest approaching vehicle to enter and exit the stretch of 30m.

3. *Gap/Lag:*

   It is a continuous variable extracted from the video and is extracted as shown in the Figure 3.2.

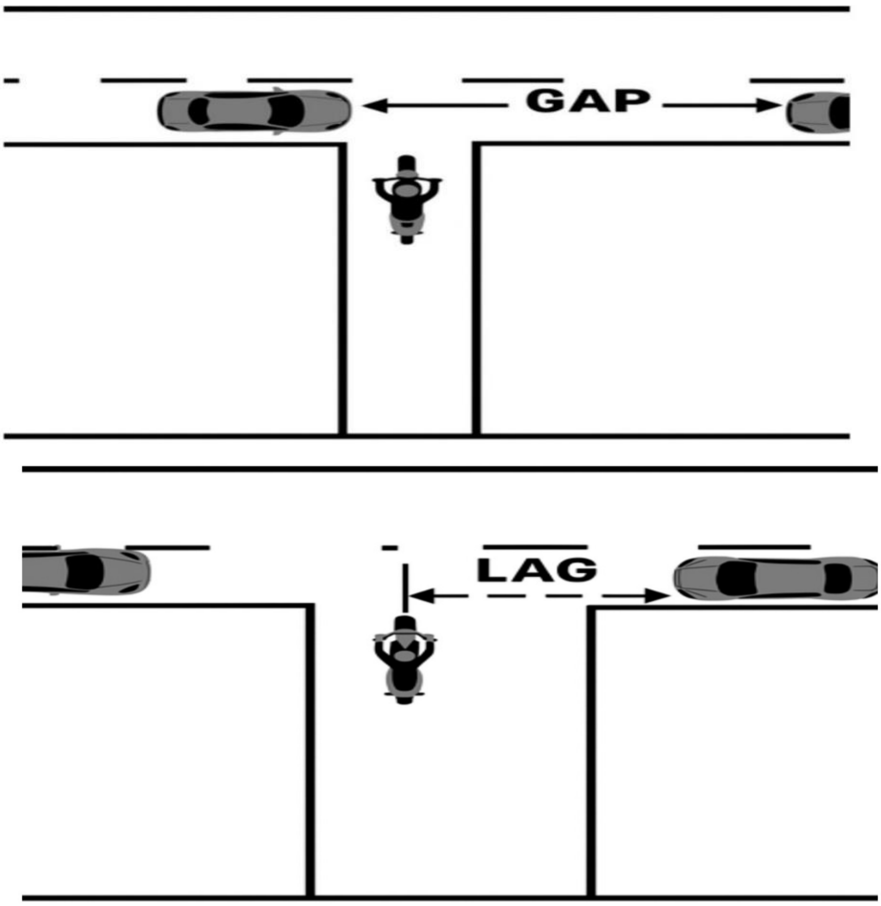



Figure 3.2: Gap and Lag

(Source: Regenerated from Ashalatha and Chandra,CBA(2011) )

4. *Gap or Lag Present:*

   It is a binary categorical variable which takes the value ‘0’ if a minor road vehicle accepts lag for his crossing operation and the value ‘1’ minor road vehicle accepts gap for his crossing operation.

5. *Aggressive and Ideal Behavior:*

   It is a binary categorical variable which takes the value ‘1’ if a minor road vehicle aggressively performs the crossing operation and the value ‘0’ if the minor road vehicle ideally performs the crossing operation by following the rule of priority. The aggressive behavior is identified by the abrupt entry of minor road two-wheelers into the major road.

6. *Accept or Reject:*

   It is a binary categorical variable which takes the value ‘1’ if a minor road vehicle performs the right turning operation by accepting the lag/gap and the value ‘0’ if the driver rejects the lag/gap. It is used as a dependent variable in the logistic regression model for gap acceptance.

## 3.3 Determining Critical Gap from Deterministic Methods

Critical gaps at the intersection can be determined using deterministic methods such as Raff’s method and clearing behavior approach. The methods are discussed in detail in following subsections

### 3.3.1 Critical Gap by Raff’s Method

Raff used cumulative distribution of number of rejected and accepted gaps to find out the critical method. The critical gap ‘C’ is the size lag which has the property that the number of accepted lags shorter than is the same as the number of rejected lags longer than (Raff and Hart,1950). So, the critical gap can be derived from the cross point between the number of curves of accepted gaps and rejected gaps as shown in Figure 3.3. This method is used in this study to find out the critical gap required by the minor road drivers to perform the right turning operation successfully. In Raff's method,we estimate the critical gap by analyzing the distribution of accepted and rejected gaps. The critical gap is defined as the time value where the curve of accepted gaps intersects the curve of rejected gaps. This approach provides an objective, behavior-based estimate of the minimum gap duration that riders are willing to accept, without relying on theoretical assumptions. The method is particularly suitable for unsignalized intersections with mixed traffic conditions

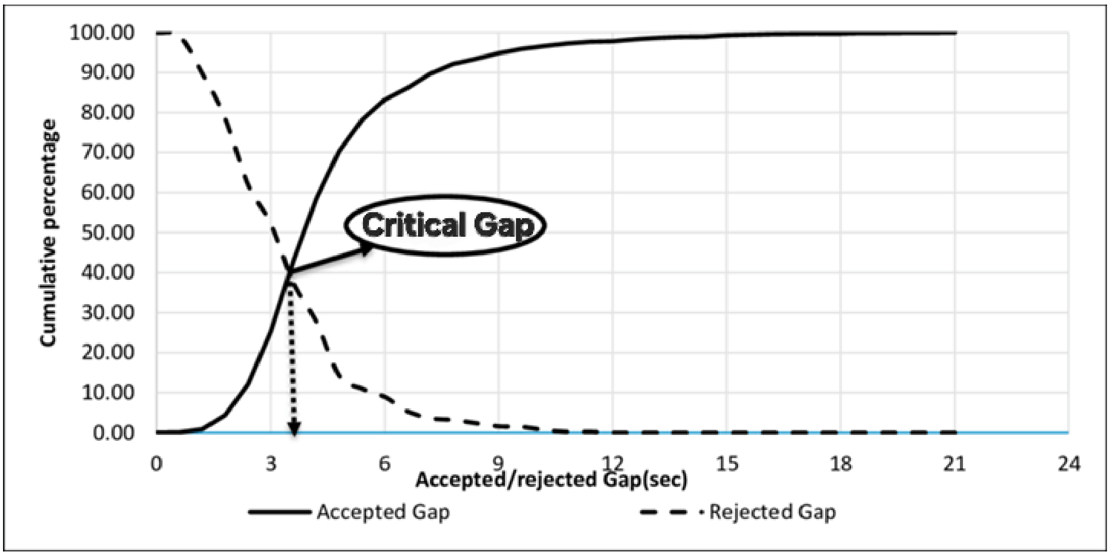



Figure 3.3**:** Raff's method of Critical Gap

### 3.3.2 Critical Gap from Clearing Behavior Approach

Ashalatha and Chandra (2011) have developed an alternate procedure for estimation of critical gap known as 'clearing behavior approach (CBA)'. This method is suitable in situations where rules of priority is not observed, and minor street vehicles clear the intersection in a zig-zag manner. In such kind of situations, the requirement of gap will depend on two factors; the clearing behavior of the minor street vehicle and the clearing distance. In this method, a vehicle can be assumed to have cleared the intersection when it crosses the influence area for gap acceptance (Inafoga) as shown in Figure 3.4 and reaches a point where it requires only merging in the next stream. The modified version of this method is also used in this study to find out the critical gap required by minor road drivers to perform the right turning operation successfully.

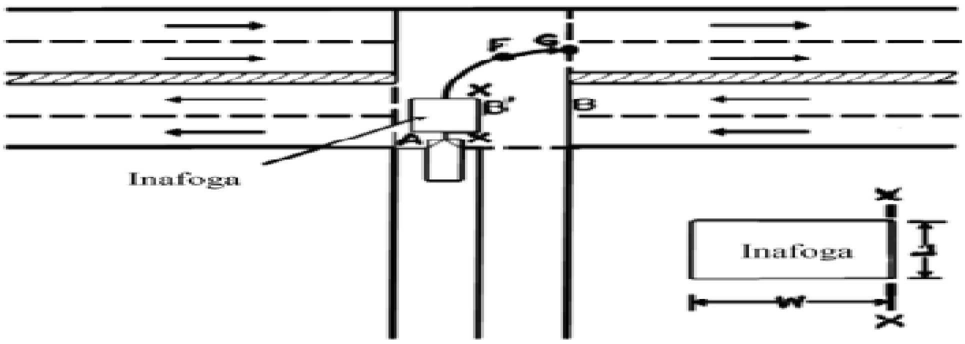



Figure 3.4: Influence Area for Gap Acceptance for Clearing Behavior Approach
(Source: Ashalatha and Chandra (2011))

This study adopted Ashalatha and Chandra's (2011) method for manually calculating clearing time at unsignalized intersections, while introducing key modifications to better suit field conditions. The original method involves measuring the time required for a two-wheeler to completely traverse a predefined conflict zone, using a rectangular box model with fixed dimensions (3.0m length × 1.75m width including safety buffers). In our implementation, we maintained the core principles of their manual measurement approach but enhanced it with several practical adaptations. We used stopwatches to record the precise moment when a vehicle's front buffer entered the conflict zone until its rear buffer fully cleared the area, consistent with Ashalatha and Chandra's methodology. The measurements were conducted through videography observation. This adapted version of Ashalatha and Chandra's method proved particularly valuable for capturing the unique merging behaviors in mixed traffic conditions, where riders often deviate from theoretical paths. By combining their established framework with our field-based refinements, we achieved a balance between methodological consistency and practical applicability for gap acceptance studies in complex urban intersections. Similar graph as Raff's method is plotted to determine the critical gap(point of intersection) but the plot is between clearing time and accepted gaps.

**3.4 Probabilistic Modeling of Gap Acceptance Behavior.**

This section focuses on development of probabilistic Accepted Gap model and gap acceptance models. The Accepted Gap model helps to predict Accepted Gaps at the intersection as a function of different demographic and behavioral parameters and the gap acceptance model helps to determine the changes in the probability of gap acceptance behavior with the change in different parameters.

### 3.4.1 Accepted Gap Model

A multiple regression model was created to predict how much time gap two-wheeler riders take when turning right from minor roads, considering both rider characteristics and traffic conditions. This multiple regression analyzes the linear relation of a dependent variable with two or more independent variables. Dependent variable is the one which we want to predict, and independent variables are those which we use to forecast the value of dependent variables.

The model outcome takes the following form given in Eq (3.1):

$$Y = \beta_o + \beta_1 X_1 + \ldots + \beta_n X_n + \epsilon \qquad (3.1)$$

Where,

$Y$ : Predicted value of the dependent variable

$\beta_0$ : Y-intercept (value of y when all other parameters are set to zero)

$\beta_1$ : Regression coefficient ($\beta_1$) of the first independent variable ($X_1$)

$\beta_n$ : Regression coefficient of the last independent variable

$\epsilon$ : Model error or residuals (Variation in the estimate of y)

For the study, the independent variables used are the gap lag type, speed of the major road traffic, rider behavior(aggressive/ideal), clearing time of the rider. Only significant variables are to be taken for the final developed model. The model works by finding the combination of factors that best explain the observed gap durations. The significant variables were only kept in the final model using the level of significance 5 percent. Key assumptions include:

1. Each characteristic affects gap duration in a consistent way
2. The characteristics aren't too similar to each other.

We measure model quality using $R^2$ (explanation power), which shows what percentage of gap duration differences the factors can account for (0% = no explanation, 100% = perfect prediction). The actual importance of each factor is shown by its "effect size" (how much gap time changes per unit change in the factor) and "confidence level" (how certain we are this isn't random).

Before building the model, we checked relationships between all characteristics using a correlation table:

- +1 = Perfect matching (both increase together)
- -1 = Perfect opposition (one increases as other decreases)
- 0 = No Connection

  When two characteristics were too similar (>0.7 correlation), we only kept the more meaningful one.

### 3.4.2 Gap Acceptance Model

When approaching an unsignalized intersection from a minor road, drivers face a critical decision-making process. They must evaluate available time intervals in the major road traffic (either initial lag or subsequent gaps) and decide whether to accept or reject each opportunity to merge or cross. This binary choice (accept=1/reject=0) varies significantly among drivers due to individual differences in risk perception, skill, and judgment, making it fundamentally probabilistic in nature.

To model this discrete choice behavior, we employ binary logistic regression, which is particularly suited for analyzing dichotomous outcomes. The model examines how various measurable factors influence a driver's likelihood of accepting an available gap. Key explanatory variables included:

- type of traffic interval (gap or lag)
- Approaching vehicle speed
- Available gap duration
- Driver gender
- Other relevant characteristics

Unlike linear regression which requires continuous outcomes, logistic regression handles binary dependent variables effectively. The method follows these key assumptions:

1. The outcome variable has exactly two possible states
2. Predictor variables are not highly correlated
3. Each predictor relates linearly to the log odds of acceptance
4. All observations are independent

The model structure consists of two key equations:

$$\text{Log-odds of acceptance} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n \quad (3.2)$$

Where:

- Log-odds of acceptance = Natural logarithm of (acceptance probability/rejection probability)
- $\beta_0$ = Baseline acceptance tendency when all predictors equal zero
- $\beta_1$ to $\beta_n$ = Coefficients quantifying each predictor's influence
- $X_1$ to $X_n$ = Values of the predictor variables

The model's performance is evaluated using R-squared measures to assess how well independent variables explain the variation in gap acceptance behavior. The Cox & Snell R-squared value indicates the proportion of variance explained by the model compared to a null model, while the Nagelkerke R-squared provides an adjusted version that ranges from 0 to 1, where values closer to 1 represent better model fit. These metrics demonstrate the model's effectiveness in capturing the relationship between the predictor variables and drivers' gap acceptance decisions, confirming its reliability for analyzing intersection behavior

### 3.4.3 Model Validation

Model validation is the process that is carried out after model training where the trained model is evaluated with a testing data set. It can also be defined as the set of processes and activities intended to verify that the models are performing as expected. The testing data may or may not be a chunk of the same data set from which the training set is procured. Model validation determines whether the trained model is trustworthy and ensures its accuracy. Without checking and validating the model, it is not right to rely on its prediction.

For the validation of binary logistic regression, a confusion matrix was created as shown in Table (3.1). A confusion matrix, also known as error matrix, is a specific table layout that allows visualization of the performance of a model and used to describe the performance of a classification model on a set of test data, of which the true values are known.

Table 3.1 Confusion Matrix

| | | **Actual Value** | |
|---|---|---|---|
| | | **Negative (0)** | **Positive (1)** |
| **Predicted Value** | **Negative (0)** | True Negative | False Negative |
| | **Positive (1)** | False Positive | True Positive |

**True Positive (TP)** is the number of outcomes in which the predicted values are positive and correctly predicted because the actual test data observations are also positive.
**True Negative (TN)** is the number of outcomes in which the predicted values are negative and correctly predicted because the actual test data observations are also negative.
**False Positive (FP)**, also called Type I error, is the number of outcomes incorrectly classified as positive by the model.
**False Negative (FN)**, also called Type II error, is the number of outcomes incorrectly classified as negative by the model.

Using the values obtained from the confusion matrix, sensitivity and specificity of the model are calculated from Equations (3.4) and (3.5) respectively:

$$\text{Sensitivity} = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3.3}$$

$$\text{Specificity} = \frac{True\ Negative}{True\ Negative + False\ Positive} \tag{3.4}$$

Sensitivity is the ability of a model to correctly identify the cases in which the outcome is positive whereas specificity is the ability of a model to correctly identify the cases in which the outcome is negative.

In this research, sensitivity tells us what percentage of the observations with gap acceptance were correctly identified and specificity tells us what percentage of the observations with gap rejection were correctly identified.

### 3.4 Site Selection

Several literatures have been reviewed for the determination of study area to study and analyze the gap acceptance behavior of minor road two-wheeler riders performing right turning operation at unsignalized three legged intersections at various sites. The selection of sites with high traffic flow, varying geometry and mixed land use were considered to obtain variety in behavioral characteristics of drivers based upon each site. Considering all the above criteria, two sites were selected for study: Kopundole-Pulchowk and Lagankhel-Satdobato. Pilot observations were carried out to determine peak hours of traffic flow and smooth gap acceptance performance/behavior for adequate and representative sample of minor road drivers performing right turn operation.

#### 3.5.1 Description of Case Study

For conducting the research, two unsignalized three legged intersections of Kathmandu Valley were selected. To observe the difference in critical gap duration by deterministic methods and gap acceptance behavior with differences in site conditions. The two selected Three-legged intersections are different in site specifications. The study has been carried out based on the data collected from Kopundole-Pulchowk Intersection and Lagankhel-Satdobato intersection.

**Case Study I: Kopundole-Pulchowk Intersection(Site 1)**

Kopundole-Pulchowk intersection is a three-legged intersection as shown in Figure 3.5 and a part of commercial area.

*Features of the study area:*

- Intersection selected: Kopundole-Pulchowk
- Number of major lanes: Four
- Number of minor lanes: Two

- Approx Total width: 14.6m (Major Road)
- Approx Total width: 8.1m (Minor Road)


Figure 3.5: Kopundole-Pulchowk Intersection

**<u>Case Study II: Lagankhel-Satdobato Intersection(Site 2)</u>**

Lagankhel-Satdobato intersection is a three-legged intersection as shown in Figure 3.5 and a part of commercial area.

*Features of the study area:*

- Intersection selected: Lagankhel-Satdobato
- Number of major lanes: Four
- Number of minor lanes: Two
- Approx Total width major road: 15.2
- Approx Total width minor road: 9.1


Figure 3.6: Lagankhhel-Satdobato Intersection

### 3.6 Sample Size

The appropriate sample size for statistical analysis depends on the specific research methodology employed. This study utilized established statistical formulas to determine the minimum required observations for both study locations.

**For Kopundole-Pulchowk Intersection:**

Two distinct approaches were used to calculate the necessary sample size. Following Tabachnick and Fidell's (1996) guidelines for linear regression analysis, the minimum sample size was computed as:

**N > 50 + 8m**

where m represents the number of predictor variables (m=5). This yielded a minimum requirement of 90 observations.

For logistic regression analysis, Peduzzi et al.'s (1996) formula was applied:

**N = 10k/p**

where k indicates the number of covariates (k=5) and p is the proportion of the targeted outcome which in our case is the gap acceptance (p=0.42, representing gap acceptance rate). This calculation produced a requirement of 120 cases. The probability(p) for this case is calculated as 210 number of gaps accepted from the total of 500.

**For Lagankhel-Satdobato Intersection:**

The same calculation methods were employed. The linear regression formula again suggested a minimum of 90 observations. However, the logistic regression calculation, using a higher observed acceptance proportion (p=0.52), resulted in a requirement of 97 cases. The probability(p) for this case is calculated as 235 number of gaps accepted from the total of 453. The study adopted more conservative estimates from these calculations to ensure robust statistical analysis at both locations.

## 3.7 Data Collection

To investigate gap acceptance behavior at unsignalized three-legged intersections, an observational field study was conducted using video recordings at two high-traffic locations in Kathmandu Valley: Kopundole-Pulchowk and Lagankhel-Satdobato intersections. The study employed an EZVIZ CCTV camera, strategically positioned to capture a comprehensive view of the intersection, ensuring unobstructed visibility of vehicle movements on both the major and minor roads.

### Camera Setup and Recording Protocol

- The camera was mounted at an elevated location to minimize blind spots and provide a top-down perspective of traffic interactions.
- Daylight hours (8:00 AM–11:00 AM) were selected for recording to ensure optimal visibility and consistent lighting conditions.
- Data collection was restricted to clear weather days to avoid behavioral variances caused by rain or fog.
- To ensure naturalistic driving behavior, recordings were conducted only in the absence of traffic police, eliminating external enforcement influences.

**Sampling Strategy**

- At each intersection, three hours of video footage per day were recorded over three weekdays, totaling 9 hours per site dated June 20-22,2022 for Kopundole-Pulchowk and June 26-28,2022 for Lagankhel-Satdobato(18 hours combined).
- Peak morning hours (8–11 AM) were prioritized to capture high-density traffic scenarios, where gap acceptance decisions are most critical.

The video-based data collection method offered several significant advantages for this study. First and foremost, the non-intrusive nature of CCTV recording ensured drivers remained completely unaware of being observed, thereby capturing completely natural behavioral patterns without any influence from the Hawthorne effect where subjects might alter their behavior when knowing they are being studied. The high-resolution footage enabled meticulous frame-by-frame analysis, allowing researchers to precisely measure critical parameters including gap and lag durations (the exact time intervals between consecutive vehicles), analyze detailed turning maneuvers (including clearing times and acceleration patterns), and make reasonable demographic estimates (such as gender categorization based on visible physical characteristics). Furthermore, the archived video recordings provided exceptional reproducibility of the study, as the footage could be reviewed multiple times to verify findings, cross-check measurements, and correct any potential errors in data interpretation, thereby significantly enhancing the reliability and validity of the collected data. This comprehensive approach to video analysis proved particularly valuable for examining the complex interactions in unsignalized intersections where split-second decisions occur.

## 3.8 Data Extraction

Video recordings totaling 18 hours were collected from two three-legged intersections: Kopundole-Pulchowk and Lagankhel-Satdobato. To ensure representative data, observations were conducted during peak traffic hours, with two-hour recordings per day at each site. Since capturing every crossing event was impractical, systematic sampling was employed, focusing only on smoothly executed right-turn maneuvers from the minor road when major road traffic density permitted safe crossings.

The following variables were recorded for each valid crossing event:

i. **Gap/lag duration (in seconds)**

- Gap refers to the time interval between consecutive vehicles in the major traffic stream as the minor road driver approaches the intersection but has not yet initiated a crossing maneuver.
- Lag specifically denotes the time between successive major road vehicles at the exact moment when the minor road driver begins entering the intersection.

ii. **Clearing time** – Total time taken by the minor road vehicle to complete the turning maneuver.

iii. **Major road vehicle speed** – Calculated by measuring traversal time over a 30-meter pre-marked section using a stopwatch (Speed = Distance/Time).

iv. **Behavioral traits** – Classified as "aggressive" (abrupt acceleration, close gaps) or "ideal" (cautious, larger gap acceptance).

The data extraction of above mentioned variables is done manually through below described process.

**Manual Data Extraction Process**

For this study, all traffic parameters were manually extracted from video recordings using frame-by-frame analysis with the following specific measurement protocols:

i. **Gap and Lag Time Measurement**

- **Gap**: Measured as the time difference (in seconds) between when the rear bumper of one major road vehicle passes the conflict point and when the front bumper of the next major road vehicle reaches the same point.
- **Lag**: Recorded as the time interval between when a minor road vehicle arrives at the stop line and when the front bumper of the next approaching major road vehicle passes the reference line.This is the first presented gap to the approaching minor road rider.


Figure 3.7: Lag and Gap presented to minor road rider at Site 1

i. **Gap Measurement**:

- We Start the stopwatch when the rear bumper of a major-road vehicle passes the conflict point.
- Stop when the front bumper of the next major-road vehicle reaches the same point.
- Record the elapsed time as the gap duration.

ii. **Lag Measurement**:

- Start the stopwatch when the minor-road vehicle arrives at the stop line.(a marked point in case of no stop line for the site, the marking can be an indicator present on the site)
- Stop when the first major-road vehicle's front bumper passes the conflict point.
- Record the elapsed time as the lag duration.

The conflict point (or reference line) is the exact location in an intersection where the trajectories of major-road and minor-road vehicles intersect, creating potential collision risk. It serves as the standard reference for measuring gap/lag durations consistently.

ii. **Clearing Time Calculation**

- Timing began when the minor road vehicle's front axle crossed the stop line( a marked point in case of no stop line for the site, the marking can be an indicator present on the site)
- Timing ended when the vehicle's rear axle completely cleared the conflict area( an area defined in the Ashaltatha and Chandra[2011] Infoga modified in case of our study)
- Measured to 0.1 second precision using video timestamps

iii. **Speed Determination**

- A 30-meter marked section was established upstream of each intersection approach
- Traversal time was recorded manually using synchronized stopwatches
- Speed calculated as: Speed (m/s) = 30 meters / traversal time (seconds)

iv. **Driver Characteristics**

- Gender was identified through visual observation of:
  - Helmet style/color (male vs. female patterns)
  - Clothing characteristics
  - Body posture and riding style

- Each observation was verified by two independent raters

v. **Gap Acceptance Behavior**.

- For classifying the behavioral difference of the minor road two wheeler riders behavioral indicators provided below were used.

**Table 3.2: Behavioral Indicators of Minor Road two wheelers**

| **Trait** | **Aggressive Rider** | **Ideal Rider** |
|---|---|---|
| **Gap Duration** | Short (≤ critical gap) | Long (≥ critical gap + buffer) |
| **Approach Speed** | No deceleration | Slows if gap is tight |
| **Merge Style** | Erratic, abrupt | Smooth, predictable |
| **Reaction to Risk** | Ignores oncoming vehicles | Yields if unsafe |

Despite Considering these indicators, some sample do not match the classification as in case abrupt merging of minor road rider in lesser or no traffic in the major road can result in larger gap time but an aggressive characteristics as we have prioritized yielding as first criteria.

For the Quality control measures we applied the following process in our study

- Any cases with unclear video evidence were excluded
- 10% of samples were re-measured by a second observer to ensure consistency

This manual extraction process allowed for detailed examination of driver decision-making while maintaining rigorous measurement standards. The 30-meter speed measurement section provided more stable speed estimates compared to shorter distances.

# CHAPTER 4: RESULTS AND DISCUSSIONS

## 4.1 General

The data analysis process commenced with correlation analysis between variables to identify relationships influencing two-wheeler riders' decision-making patterns. This preliminary examination informed the development of two specialized models. First, a logistic regression model analyzed two-wheeler riders' gap acceptance behavior, predicting their likelihood of accepting available gaps. Second, a multiple linear regression model investigated factors affecting the duration of gaps accepted by riders. Both models were implemented in SPSS Version 27, incorporating only statistically significant variables to ensure reliable and meaningful results. For comprehensive understanding, critical gap thresholds for two-wheeler riders were determined using two established methods: Raff's technique comparing accepted and rejected gaps, and the Clearing Behavior approach based on actual crossing completion times. The study further examined risk-taking patterns among riders through graphical representations of aggressive gap acceptance behavior. This integrated analytical approach provided robust insights into two-wheeler riders' intersection navigation strategies while maintaining methodological precision. The Kopundole-Pulchowk and Lagankhel-Satdobato Sites are named as Site 1 and Site 2 Respectively for the rest of the discussion.

## 4.2 Correlation Matrix

Two types of variables, namely nominal variable and scale variable are part of this research. To determine the correlation between nominal variables Chi-square tests of independence were used. Similarly, the correlation between two scale variables was determined using Spearman’s correlation coefficient. From the correlation matrix below in Tables 4.1, 4.2, 4.3 and 4.4 for both the intersections, it can be observed that there is no strong correlation between any variables considered. Hence, the listed variables can be considered for analysis.

**Table 4.1 : Correlation Matrix of Nominal Variables( Site 1)**

| Correlation Matrix | Gap/Lag | Gender | Aggressiveness |
|---|---|---|---|
| Gap/Lag | 1 | | |
| Gender | -.048 | 1 | |
| Aggressiveness | .116 | 0.204 | 1 |

**Table 4.2: Correlation Matrix of scale variables(Site 1)**

| | Speed | Gap/lag Duration |
|---|---|---|
| Speed | 1 | -.410** |
| Gap/lag Duration | -.410** | 1 |

**Table 4.3 : Correlation Matrix of Nominal Variables(Site 2)**

| Correlation Matrix | Gap/Lag | Gender | Aggressiveness |
|---|---|---|---|
| Gap/Lag | 1 | | |
| Gender | -.051 | 1 | |
| Aggressiveness | .109 | 0.218 | 1 |

**Table 4.4: Correlation Matrix of scale variables(Site 2)**

| | Speed | Gap/lag Duration |
|---|---|---|
| Speed | 1 | -.358** |
| Gap/lag Duration | -.358** | 1 |

### 4.3 Critical Gap Using Raff's Definition

In this research this method is selected as one of the two deterministic method used to calculate the critical gap for two wheelers performing right turn operations under mixed traffic conditions in two selected three legged intersections inside the Kathmandu valley.

The graph (Figure 4.1) presents the critical gap analysis using Raff's method for Kopundole-Pulchowk Intersection, where the cumulative frequency of observations is plotted against gap duration. The vertical y-axis displays gap duration in seconds, while the horizontal x-axis shows the cumulative number of observations for both accepted and rejected gaps.

The graph is constructed by firstly sorting all observed gaps by their duration. Separate cumulative frequency curves were then plotted for accepted gaps (represented by a solid orange line) and rejected gaps (shown as a solid blue line). The critical gap value by Raff's definition was determined to be 4.3 seconds, the point where these two curves intersect, indicating the gap duration where drivers demonstrated equal probability of accepting or rejecting an available gap.

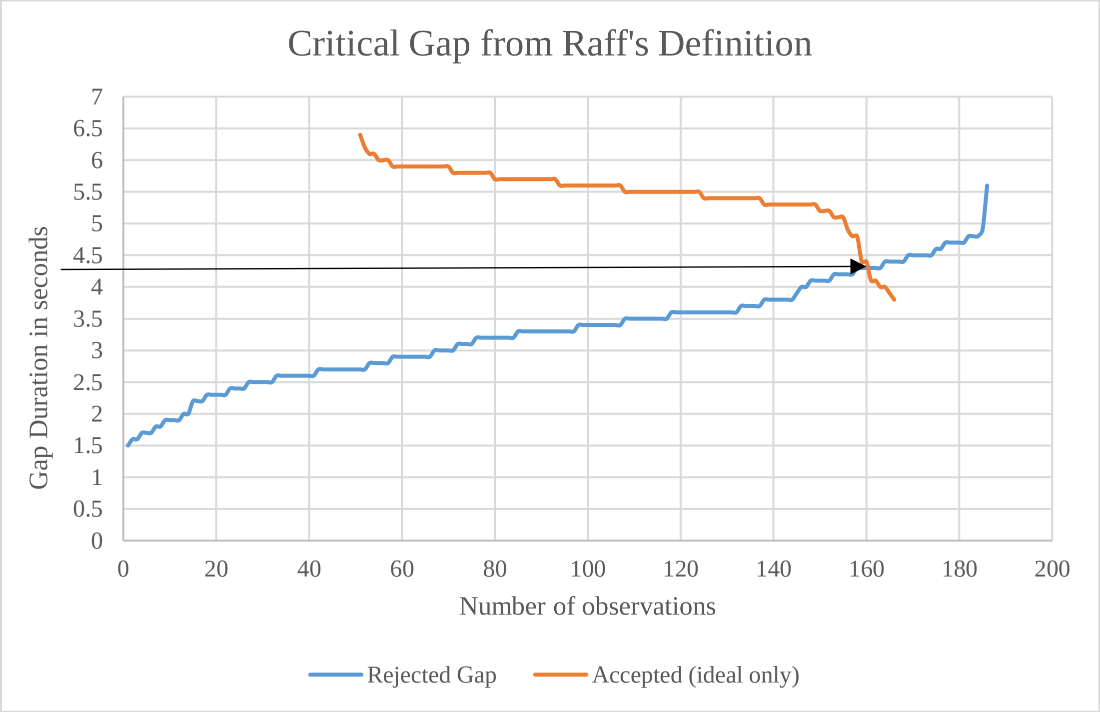



Figure 4.1: Critical Gap using Raff's Definition (Site 1)

The critical gap value by Raff's definition for Site 2 was determined to be 2.7 seconds, the point where the two curves intersect, indicating the gap duration where drivers demonstrated equal probability of accepting or rejecting an available gap.

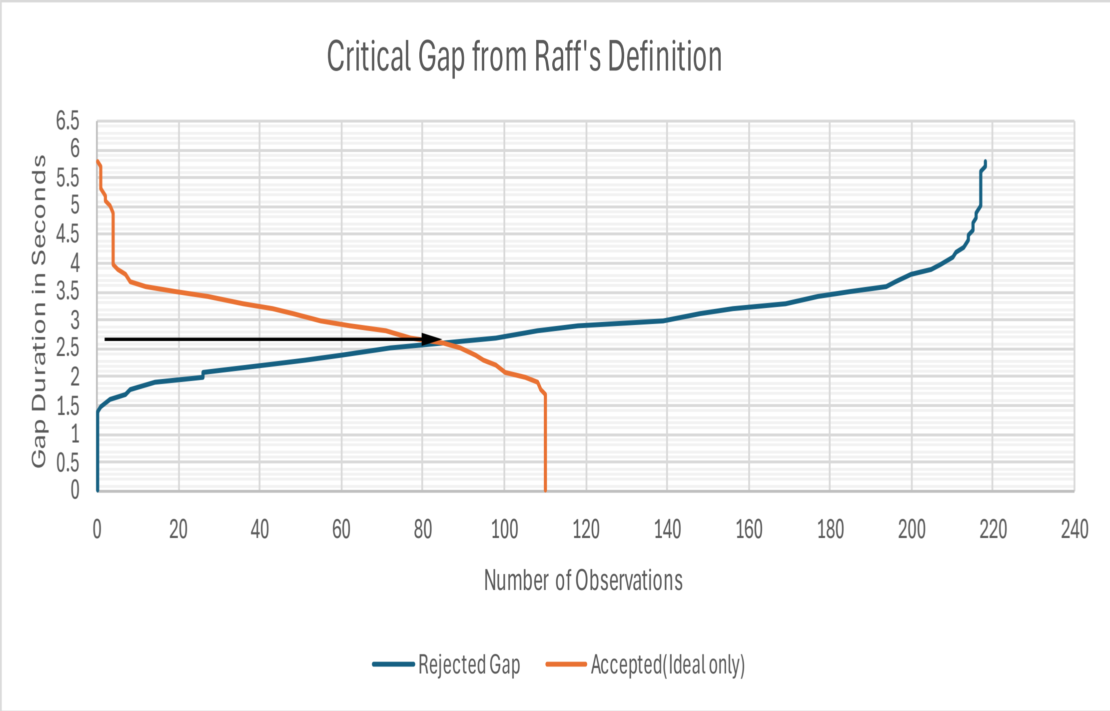



Figure 4.2: Critical Gap using Raff's Definition (Site 2)

## 4.4 Critical Gap Using Clearing Behavior Approach

The Clearing Behavior Approach by Ashalatha and Chandra (2011) is the second of the two deterministic method used in this research for estimating the critical gap. In this method a graph similar to Raff's method. In this method the distribution of Clearing time(solid blue line) and Accepted Gap (solid orange line) is plotted. The intersection point of this curve will provide us the Critical gap. While the Raff's method uses the accepted and rejected gaps to estimate the critical gap, the CBA uses the actual clearing time used by the drive to perform the crossing(right turn) operation. It uses how long the driver takes to pass through INFOGA (an influence area described above defined in the CBA by Ashalatha and Chandra(2011).

The graph (Figure 4.3) presents the critical gap analysis using CBA method for Kopundole-Pulchowk Intersection, where the cumulative frequency of observations is plotted against gap duration. The Clearing time and accepted gaps are extracted manually from the video recorded as explained in the data extraction section above. The vertical y-axis displays gap duration in seconds, while the horizontal x-axis shows the cumulative number of observations for both clearing time and accepted gaps

The graph is constructed by firstly sorting all observed clearing time and accepted gaps by their duration. Separate cumulative frequency curves were then plotted for Clearing Time (represented by a solid blue line) and accepted gaps (shown as a solid orange line). The critical gap value by CBA approach was determined to be 5.7 seconds, the point where these two curves intersect. This method is useful because it considers how long drivers actually need to cross safely, not just their decisions. The clearing time gives us a more realistic picture of what gaps work at an intersection.

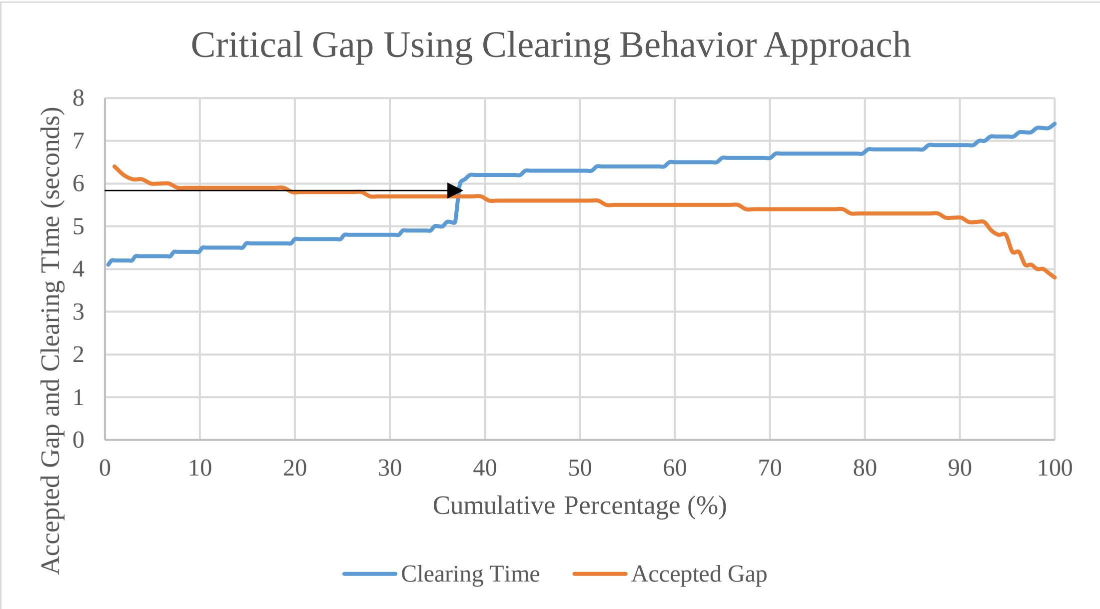



Figure 4.3: Critical Gap using Clearing Behavior Approach (Site 1)

The graph (Figure 4.4) presents the critical gap analysis using CBA method for Lagankhel-Satdobato Intersection. The critical gap for this intersection was found to be 4.1 seconds while using CBA approach.

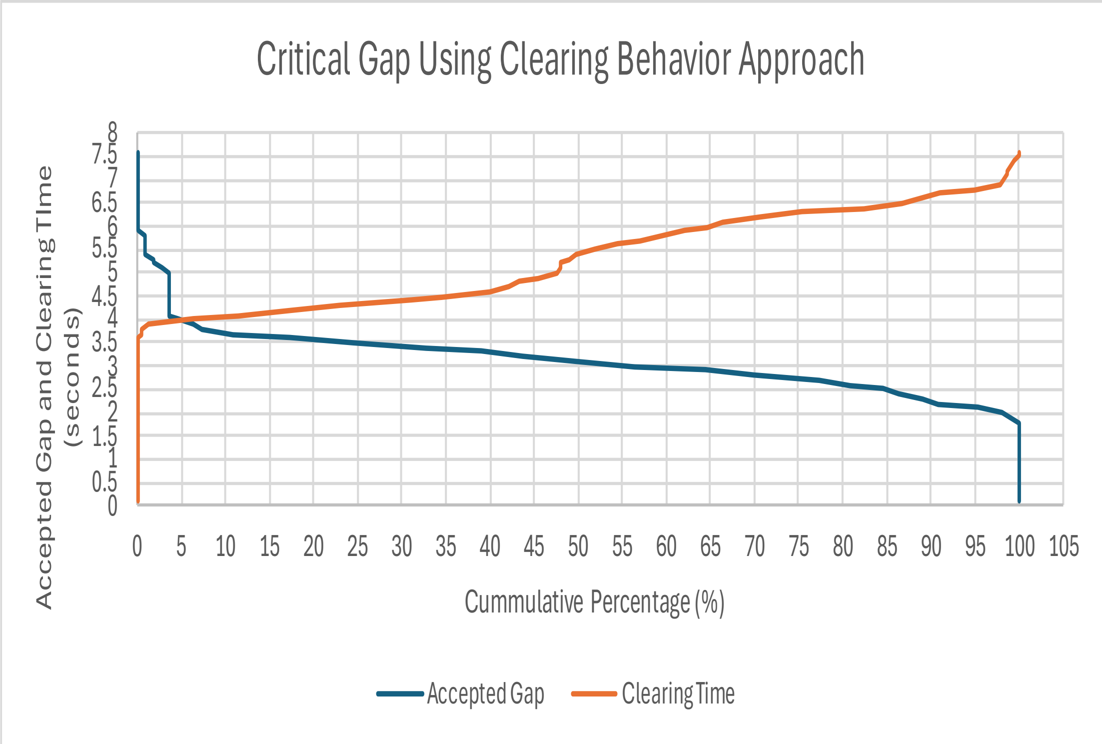



Figure 4.4: Critical Gap using Clearing Behavior Approach (Site 2)

### 4.5 Effect of Aggressive Behavior

The figures below show us variations in accepted gaps for both aggressive and ideal cases of minor road two-wheeler riders performing right-turning maneuvers at our study sites. Figures 4.5 and 4.6 presents the aggressive and ideal cases respectively for the Kopundole-Pulchowk Intersection (a T-type configuration), while Figures 4.7 and 4.8 show the corresponding behaviors for the Lagankhel-Satdobato Intersection (a Y-type configuration). The graphs plot cumulative percentage of gap acceptance against Accepted Gap for two-wheeler drivers.

#### 4.5.1 Comparison of Critical Gap

i. **Gap Duration Ranges**:
   - At the T-type Kopundole-Pulchowk Intersection:
     - Aggressive drivers accepted gaps from 1.8-5.6 seconds
     - Ideal drivers required 3.8-6.4 seconds
   - At the Y-type Lagankhel-Satdobato Intersection:
     - Aggressive drivers accepted shorter gaps (1.8-3.8 seconds)

        - Ideal drivers accepted 3.2-5.8 second gaps

ii. **Intersection Geometry Impact**:

    The Y-type intersection consistently shows lower gap acceptance thresholds due to:

    - Better forward visibility from the acute approach angle
    - More natural vehicle alignment with the main traffic flow
    - Reduced crossing distance compared to the T-type intersection

      This geometric advantage explains why drivers at the Y-intersection accept shorter gaps with higher confidence.

iii. **Behavioral Patterns**:

    The graphs clearly demonstrate that:

    - Aggressive drivers accept smaller gaps than ideal drivers at both sites
    - A higher percentage of aggressive drivers accept any given gap compared to ideal drivers
    - The gap acceptance curves for the Y-intersection are steeper, indicating more uniform decision-making
    - The T-intersection shows greater dispersion in accepted gaps, suggesting more variability in driver comfort levels

These findings highlight how intersection geometry significantly influences driver behavior, with Y-type configurations making it more efficient for gap acceptance due to superior visibility and alignment characteristics as the cumulative frequency curves confirmed that drivers at the T-junction required longer gaps for acceptance, likely due to restricted visibility or complex traffic flow, whereas the Y-junction facilitated quicker decisions. These findings highlight the influence of intersection design on gap acceptance dynamics. The data shows that aggressive driving tendencies prevail similarly across different Three-legged Intersection types, but the absolute gap values vary based on the crossing scenario's physical and visibility conditions.

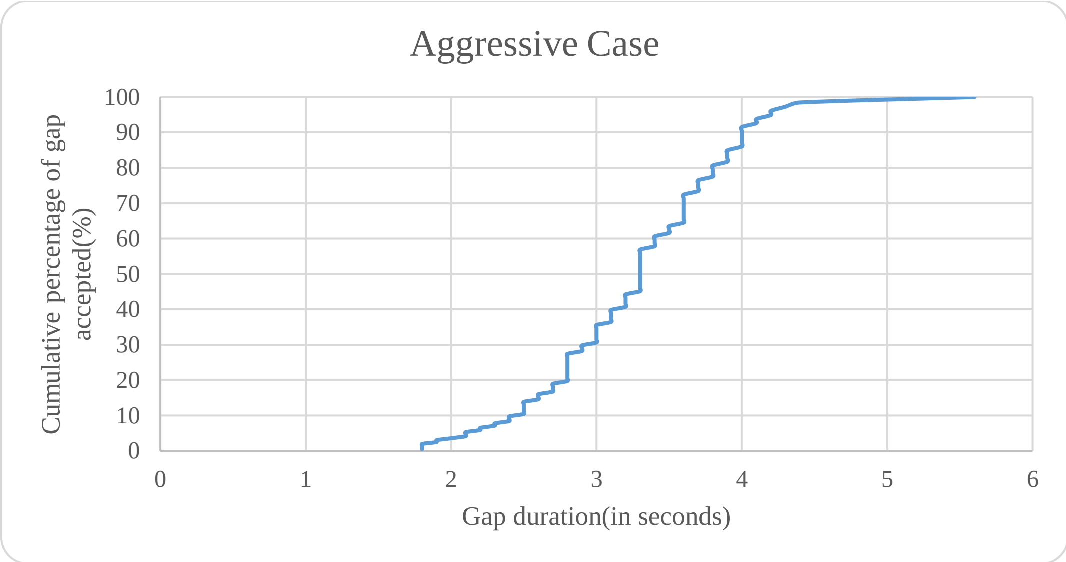



Figure 4.5: Cumulative Percentage Distribution of Gap Accepted (Aggressive Case for Site 1)

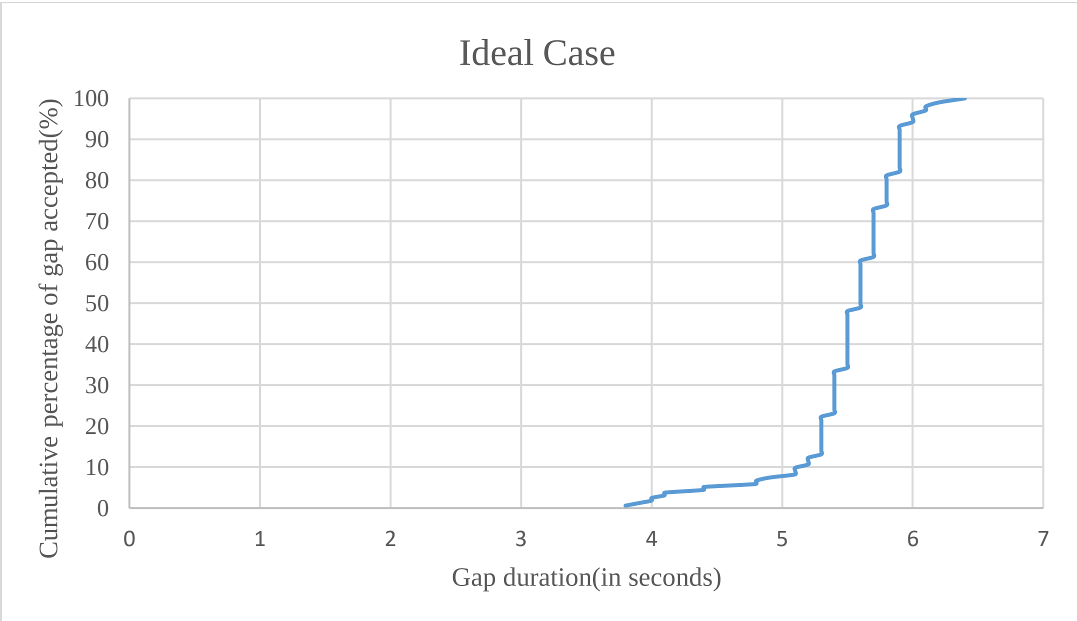



Figure 4.6: Cumulative Percentage Distribution of Gap Accepted (Ideal Case for site 1)

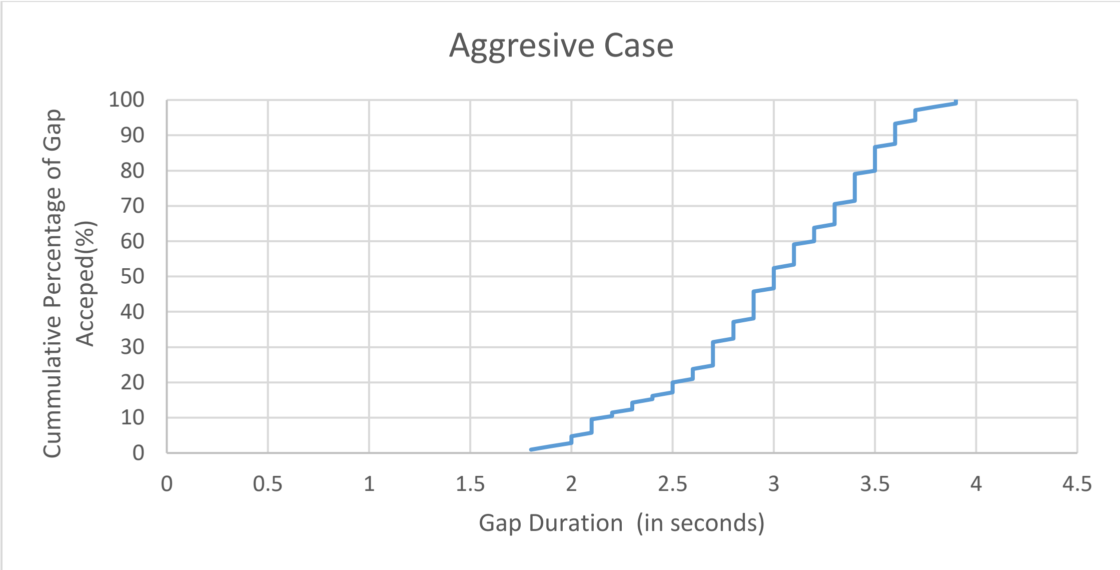



Figure 4.7: Cumulative Percentage Distribution of Gap Accepted (Aggressive Case for Site 2)

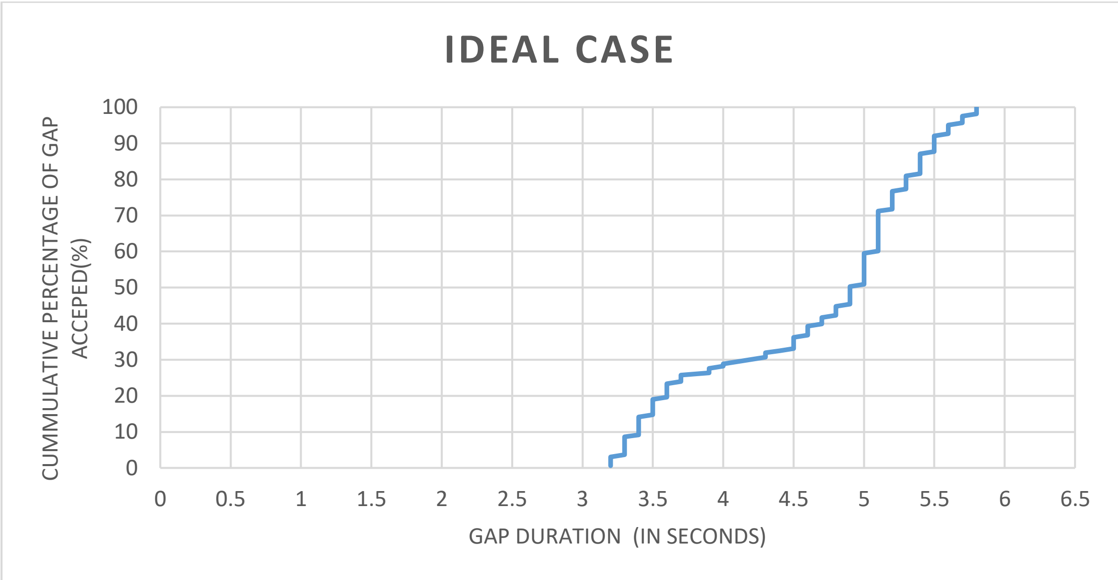



Figure 4.8: Cumulative Percentage Distribution of Gap Accepted (Ideal Case for Site 2)

The aggressive behavior resulted a variation from 1.8 to 5.6 seconds for the first site, this was due to the yielding as the first criteria of selecting behavioral differences which caused few samples of no yielding and a larger gap provided. In comparison to the above four figures/graphs, we can observe a different nature of curve in case of Figure 4.8. This difference in nature is due to a larger portion of accepted gaps for this case falling in that range

## 4.6 Gap Acceptance Model

The Binary logistic regression model was developed using Statistical Package for the Social Sciences (SPSS) Version 27 software package to determine the probability of provided gap being accepted based upon traffic parameters as well as demographic characteristics. The logistic regression model represents the probability of gap being accepted at 95% confidence interval. Here, gap acceptance is taken as dependent variable and gender, gap or leg presented, speed of major traffic and duration of gap/lag were taken as independent variables. Gap Accepted cases were coded as '1' whereas the rejected cases were coded as '0'. Reference category was used to indicate base for gender. Male category was considered as base for interpreting the probability of gap acceptance based on gender. The lag presented to the driver were coded as '0' and gaps presented were coded as '1'. Based upon the results presented by the software, the coefficients of variables and the equation of binary logistic regression model can be represented in tabular form below. The models were formulated for both the cases(sites) separately.

From the 500 total extracted data for the Kopundole-Pulchowk intersection, approximately 70 percent were used for training the model and the remaining data were used for validating the model. Wald chi-square test was conducted with reference to the degree of freedom of the variables. The value that could be predicted by this model is Ln (Odds), where odds indicate the ratio between probabilities of gap being accepted to that of rejected. The variables were encoded as '1' for Gap Accepted and '0' for Gap rejected. The data sets were then extracted and entered into the SPSS v27 and a filter variable was created so as to select 70 percent of the data set for training the model and 30 percent for validating. The software used 371 cases for training the model and the remaining 129 were kept for validating the model. After analyzing the logistic regression from the software, the results of the analysis are presented in a tabular as well as descriptive way below.

Table (4.5) presents the case summary of Model I for first Site i.e. Kopundole-Pulchowk Intersection which includes that 371 cases were selected with zero missing cases.

**Table 4.5: Case Processing Summary for Model 1 of Site 1.**

| Case Processing Summary | | | |
|---|---|---|---|
| **Unweighted Cases** | | **N** | **Percent** |
| **Selected Cases** | **Included in Analysis** | 371 | 100.0 |
| | **Missing Cases** | 0 | .0 |
| | **Total** | 371 | 100.0 |
| **Unselected Cases** | | 0 | .0 |
| **Total** | | 371 | 100.0 |

Table (4.6) shows how the Dependent variable was encoded to run the analysis. Acceptance of gap i.e. Accept was encoded as ‘1’ whereas rejection of gap i.e. Reject was encoded as ‘0’.

**Table 4.6: Dependent Variable Encoding of Model 1 for Site 1**

| Original Value | Internal Value |
|---|---|
| **Accept** | 1 |
| **Reject** | 0 |

Table (4.7) presents how the categorical variables were encoded before running the model. Male category was taken as reference for interpreting the probability of gap acceptance based on gender. And Gap was coded as reference for interpreting the probability of gap acceptance based on gap or lag presented to the driver.

**Table 4.7: Categorical Variable for Gap Acceptance Model for Model 1 of Site 1**

| Categorical Variables Coding | | | | |
|---|---|---|---|---|
| | | | **Parameter coding** | |
| | | **Frequency** | **(1)** | **(2)** |
| **Gender** | 0 | 108 | 1.000 | |
| | 1 | 263 | 0.000 | |
| **Gap/Lag** | 0 | 193 | 1.000 | |
| | 1 | 178 | 0.000 | |

From the Omnibus test shown in Table (4.8), the values are significant for 95% confidence interval which proves the model accuracy.

**Table 4.8: Omnibus Tests of Model 1 for Site 1 Coefficients**

| | Chi-square | df | Sig. |
|---|---|---|---|
| **Model** | 242.415 | 4 | .000 |

Based on Table (4.9), the Cox and Snell $R^2$ value is 0.480, while the Nagelkerke $R^2$ is 0.642, suggesting a well-fitted model. These results imply that approximately 64.2% of the variability in gap acceptance can be explained by the independent variables, which is considered reasonably strong for behavioral studies, as supported by existing research.( Zhang et al. (2014))

**Table 4.9: Model Summary of Model 1 for Site 1**

| Model | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| **I** | 268.204 | 0.480 | 0.642 |

From Table (4.10), it reveals that Model 1, developed for Site 1, demonstrates strong predictive accuracy. Specifically, the model correctly classified 79.9% of accepted gaps (sensitivity) and 87.4% of rejected gaps (specificity). The overall prediction accuracy of 83.3% further confirms the model's reliability in assessing gap acceptance behavior as our accuracy is > 75-80% threshold for "strong" classification in transportation behavior models (Hauer, 2004)

**Table 4.10: Classification Table of Model 1 for Site 1**

<table>
<tr><th colspan="3" rowspan="3">Observed</th><th colspan="3">Predicted</th></tr>
<tr><th colspan="2">Gap Acceptance</th><th rowspan="2">Percentage Correct</th></tr>
<tr><th>Accepted</th><th>Rejected</th></tr>
<tr><td rowspan="3">Model</td><td rowspan="2">Gap Acceptance</td><td>Accepted</td><td>146</td><td>21</td><td>87.4</td></tr>
<tr><td>Rejected</td><td>41</td><td>163</td><td>79.9</td></tr>
<tr><td colspan="2">Overall Percentage</td><td></td><td></td><td>83.3</td></tr>
</table>

Table (4.11) presents the coefficients of the model, along with their significance at 95% confidence interval. It can be observed that all the variables except gender are significant, and we need to develop a further model without using the variable Gender. In the further step, the insignificant variable is removed, and the regression is carried out again. All the included variables were found to be significant here and the coefficients are given in Table 4.12 below.

**Table 4.11: Coefficients of Gap Acceptance Model for Site 1 including all Variables**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Gap Acceptance Model Including Gender Variable | **Male Female (1)** | -.282 | .340 | .686 | 1 | .408 | .754 |
| | **Gap or Lag (1)** | -2.072 | .325 | 40.620 | 1 | .000 | .126 |
| | **Speed** | -1.027 | .140 | 53.511 | 1 | .000 | .358 |
| | **Gap_Lag_Interval** | .654 | .161 | 16.405 | 1 | .000 | 1.923 |
| | **Constant** | 16.621 | 2.579 | 41.524 | 1 | .000 | 16527347.815 |

**Table 4.12: Coefficients of Gap Acceptance Model for Site 1 excluding Gender Variable**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Gap Acceptance Model Excluding Gender Variable | **Gap or Lag (1)** | -2.064 | .324 | 40.620 | 1 | .000 | .127 |
| | **Speed** | -1.037 | .140 | 55.021 | 1 | .000 | .355 |
| | **Gap_Lag_Interval** | .631 | .159 | 15.829 | 1 | .000 | 1.880 |
| | **Constant** | 16.770 | 2.567 | 42.669 | 1 | .000 | 19188616.687 |

The final logistic regression Model for the Kopundole-Pulchowk Intersection using only the significant variables can be written as:

$$\mathbf{Y = 16.770 - 1.037S - 2.064\ IGL + 0.637G} \qquad (4.1)$$

Where,

Y = Log-odds of Gap Acceptance.

S= Speed of major traffic

IGL = Gap or Lag presented to the minor road driver

G= Gap or Lag duration presented to the minor road driver

The logistic regression model developed for gap acceptance at Site 1 examines how various factors influence drivers' decisions to accept gaps in traffic. The model equation 4.1 above where Y represents the log of probability of gap acceptance. The term Gap or Lag (1) is a categorical variable, with the coefficient of -2.064 indicating that when the situation is classified as a gap rather than a lag, the log-odds of acceptance decrease by 2.064. This translates to an odds ratio of 0.127, meaning drivers are about 87% less likely to accept a gap compared to a lag, holding other factors constant. The speed variable shows a negative relationship, with each unit increase in speed reducing the odds of acceptance by approximately 65%. In contrast, the duration of the gap or lag has a positive effect, with each additional second increasing the odds of acceptance by about 88%. The intercept term of 16.770 represents the baseline log-odds when all predictors are at zero. These results suggest that drivers are more cautious when dealing with gaps in moving traffic compared to lags, and that both higher speeds and shorter durations significantly reduce the likelihood of gap acceptance. The model's statistically significant coefficients (all with $p < 0.001$) support its reliability for analyzing driver behavior in traffic situations. These findings have practical implications for traffic management, particularly in designing intersections or merge points where gap acceptance plays a crucial role in safety and efficiency.

The logistic regression for Site 2 i.e. Lagankhel-Satdobato Intersection was analyzed by applying the same process as above used for the Kopundole-Pulchowk Intersection. Same Variables were extracted from the video data of this site. The variables coding were as in the Site 1.

From the 453 total extracted data for the Lagankhel-Satdobato intersection, approximately 70 percent were used for training the model and the remaining data were used for validating the model. Wald chi-square test was conducted with reference to the degree of freedom of the variables. The value that could be predicted by this model is Ln (Odds), where odds indicate the ratio between probabilities of gap being accepted to that of rejected. The variables were encoded as ‘1’ for Gap Accepted and ‘0’ for Gap rejected. The data sets were then extracted and entered into the SPSS v27 and a filter variable was created so as to select 70 percent of the data set for training the model and 30 percent for validating. The software used 318 cases for training the model and the remaining 135 were kept for validating the model. After analyzing the logistic regression from the software, the results of the analysis are presented in a tabular as well as descriptive way below.

Table (4.13) presents the case summary of Gap Acceptance Model for first Site 2 i.e. Lagankhel-Satdobato Intersection which includes that 318 cases were selected with zero missing cases.

**Table 4.13: Case Processing Summary for Model 1 of Site 2.**

| Case Processing Summary | | | |
|---|---|---|---|
| **Unweighted Cases** | | **N** | **Percent** |
| **Selected Cases** | **Included in Analysis** | 318 | 100.0 |
| | **Missing Cases** | 0 | .0 |
| | **Total** | 318 | 100.0 |
| **Unselected Cases** | | 0 | .0 |
| **Total** | | 318 | 100.0 |

Table (4.14) shows how the Dependent variable was encoded to run the analysis. Acceptance of gap i.e. Accept was encoded as ‘1’ whereas rejection of gap i.e. Reject was encoded as ‘0’.

**Table 4.14: Dependent Variable Encoding of Model 1 for Site 2**

| Original Value | Internal Value |
|---|---|
| **Accept** | 1 |
| **Reject** | 0 |

Table (4.15) presents how the categorical variables were encoded before running the model. Male category was taken as reference for interpreting the probability of gap acceptance based on gender. And Gap was coded as reference for interpreting the probability of gap acceptance based on gap or lag presented to the driver.

**Table 4.15: Categorical Variable for Gap Acceptance Model for Model 1 of Site 2**

| Categorical Variables Coding | | | | |
|---|---|---|---|---|
| | | | **Parameter coding** | |
| | | **Frequency** | **(1)** | **(2)** |
| **Gender** | 0 | 94 | 1.000 | |
| | 1 | 224 | 0.000 | |
| **Gap/Lag** | 0 | 164 | 1.000 | |
| | 1 | 154 | 0.000 | |

From the Omnibus test shown in Table (4.16), the values are significant for 95% confidence interval which proves the model accuracy.

**Table 4.16: Omnibus Tests of Model 1 for Site 2 Coefficients**

| | Chi-square | df | Sig. |
|---|---|---|---|
| **Model** | 222.221 | 4 | .000 |

Based on Table (4.17), the Cox and Snell $R^2$ value is 0.503, while the Nagelkerke $R^2$ is 0.671, suggesting a well-fitted model. These results imply that approximately 67.1% of the variability in gap acceptance can be explained by the independent variables, which is considered reasonably strong for behavioral studies, as supported by existing research.

**Table 4.17: Model Summary of Model 1 for Site 2**

| Model | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| **I** | 217.601 | 0.503 | 0.671 |

From Table (4.18), it reveals that Model 1, developed for Site 2, demonstrates strong predictive accuracy. Specifically, the model correctly classified 83.3% of accepted gaps (sensitivity) and 86% of rejected gaps (specificity). The overall prediction accuracy of 84.6% further confirms the model's reliability in assessing gap acceptance behavior.

**Table 4.18: Classification Table of Model 1 for Site 2**

| Observed | | | Predicted | | |
|---|---|---|---|---|---|
| | | | Gap Acceptance | | Percentage Correct |
| | | | Accepted | Rejected | |
| **Model** | **Gap Acceptance** | **Accepted** | 129 | 21 | 86 |
| | | **Rejected** | 28 | 140 | 83.3 |
| | **Overall Percentage** | | | | 84.6 |

Table (4.19) presents the coefficients of the model, along with their significance at 95% confidence interval. It can be observed that all the variables are significant. All the included variables were found to be significant here and the coefficients are given in Table 4.12 below.

**Table 4.19: Coefficients of Gap Acceptance Model 1 for Site 2 including significant Variables**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Gap Acceptance Model Including Gender Variable | Gap or Lag (1) | -2.223 | .376 | 34.984 | 1 | .000 | .108 |
| | Speed | -.895 | .126 | 50.059 | 1 | .000 | .409 |
| | Gap_Lag_Interval | .973 | .197 | 24.345 | 1 | .000 | 2.646 |
| | Male Female (1) | -1.006 | .420 | 5.744 | 1 | .017 | .366 |
| | Constant | 14.052 | 2.334 | 36.250 | 1 | .000 | 1266579.66 |

The logistic regression equation for gap acceptance behavior at the Lagankhel-Satdobato intersection, incorporating all significant predictors from the table (including gender), is:

$$\mathbf{Y = 14.052 - 2.223(IGL) - 0.895(S) + 0.973(G) - 1.006(Gen)} \qquad (4.2)$$

Where:

Y = Log-odds of gap acceptance

IGL = Gap/Lag indicator (0 = Lag, 1 = Gap)

S = Speed of major traffic (km/h)

G = Gap/Lag duration (seconds)

Gen = Gender (0 = Male, 1 = Female)

The logistic regression model developed for the Lagankhel-Satdobato intersection provides valuable insights into the factors influencing drivers' gap acceptance behavior. The model reveals three key determinants that significantly affect drivers' decisions: the type of traffic interval (gap versus lag), the speed of approaching major road traffic, and the duration of available gaps. When encountering a gap in traffic (as opposed to an initial lag), drivers exhibit significantly greater caution, with the model showing they are 88.4% less likely to accept these gaps. This hesitation likely stems from the perceived higher risk of merging into moving traffic compared to entering during the initial break in traffic flow. The speed of approaching vehicles also plays a crucial role, with each 1 km/h increase in speed reducing the likelihood of gap acceptance by 59.7%, as drivers become more cautious when facing faster-moving traffic. Conversely, the duration of available gaps has a strong positive effect on acceptance rates, with each additional second more than doubling the odds that a driver will accept the gap. These findings suggest that drivers at this intersection carefully weigh both traffic conditions and time constraints when making gap acceptance decisions. The model's strong statistical significance ($p < 0.001$ for all key variables) confirms the reliability of these patterns. From a practical perspective, these results highlight opportunities to improve intersection safety through measures such as traffic calming to reduce vehicle speeds, optimized signal timing to create longer lag phases, and driver education programs focused on safe gap selection strategies. The model's robust performance, with all significant variables demonstrating expected directional relationships, provides a solid foundation for both immediate safety interventions and future research into driver behavior at unsignalized intersections.

The logistic regression models for both intersections reveal consistent patterns in gap acceptance behavior while highlighting key differences in driver responses. At Kopundole-Pulchowk (Site 1), the model shows that drivers are 87% less likely to accept gaps than lags, with speed and duration having slightly weaker effects compared to Lagankhel-Satdobato (Site 2). At Site 2, the dislike to gaps is more pronounced, and the inclusion of gender reveals female drivers are 63.4% less likely to accept gaps than males. Both models agree that higher speeds reduce acceptance and longer durations increase acceptance. However, Site 2's gap duration effect is nearly twice as strong, suggesting drivers there prioritize time availability more critically. The baseline log-odds (intercept) are exceptionally high in both models.

### 4.7 Accepted Gap Model

A multiple linear regression model was developed using IBM SPSS Statistics Version 27 to analyze the factors influencing Accepted Gap. Two different models are developed for our two sites. In the model, Accepted Gap served as the dependent variable, with clearing time, gender, gap/lag classification, and approaching vehicle speed as independent variables. Only the significant variables were used for the final model for both the site. The MLR model estimates the critical gap duration based on these significant predictors at a

95% confidence interval. This model enables the calibration of gap acceptance data under various traffic conditions.

The backward elimination method was employed to systematically remove non-significant variables, with t-tests used to evaluate the statistical significance of each predictor. The final model retained only those variables demonstrating significant influence on gap acceptance duration.

This modeling approach allows for the quantification of how the significant variables from the given variables which are clearing time, gender differences, gap/lag scenarios, and vehicle speeds impact drivers' gap acceptance duration. The statistically validated model provides valuable insights for traffic engineering applications, particularly in intersection design and safety analysis where understanding gap acceptance behavior is crucial.

MLR model for the first site was developed by using Accepted Gap as dependent variable and Clearing Time, Speed of the major traffic, Gender and Gap or Lag were used as independent variables. The significance of variables was tested for 0.05 or 5 percent level and only significant variables were kept in the final model.

From Table (4.21), the R-square and adjusted R-square value obtained for the final model are 0.847 and 0.846 respectively which tells us that dependent variable is accounted by 84.6% of the independent variables and high $R^2$ value indicates a good model. For significant variables, t-test conducted have values more than 1.96 and the p-values are less than 0.05.

**Table 4.20: Model 2 for Site 1 Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| **2** | .920 | 0.847 | 0.845 | 0.05133 |

**Table 4.21: MLR Model 2 for Site 1 including all variables**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 2 for First Site | (Constant) | -2.257 | .511 | | -4.417 | .000 |
| | Gap or Lag | .201 | .079 | .069 | 2.537 | .012 |
| | Speed | .015 | .025 | .016 | .611 | .542 |
| | Male Female | -.046 | .079 | -.016 | -.581 | .562 |
| | Clearing Time | 1.115 | .037 | .890 | 29.833 | .000 |

**Table 4.22: MLR Model 2 for Site 1 including significant variables**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 2 for First Site | (Constant) | -2.062 | .178 | | -11.620 | .000 |
| | Gap or Lag | .197 | .077 | .067 | 2.547 | .011 |
| | Clearing Time | 1.118 | .033 | .893 | 33.841 | .000 |

The multiple regression analysis present in Table 4.22 and 4.23 above shows the model examining factors influencing Accepted Gap, with clearing time, gap or lag, gender, and speed as predictors for the Kopundole-Pulchowk Intersection. From the 4 variables used only the significant variables were used for the final model.

The second table presents the refined Multiple Linear Regression (MLR) Model 2 for Site 1 (Kopundole-Pulchowk Intersection), which includes only the statistically significant predictors of Accepted Gap. The regression equation derived from this model is:

**Accepted Gap = -2.062 + 0.197(Gap or Lag) + 1.118(Clearing Time)** (4.3)

The constant term (-2.062) represents the baseline gap duration when all predictors are zero. The coefficient for Gap or Lag (0.197) indicates that each one-unit increase in gap or lag time leads to a 0.197-unit increase in Accepted Gap, holding other variables constant.

This variable, while significant ($p = 0.011$), has a relatively small effect size (Beta = 0.067). The Clearing Time (1.118) demonstrates a much stronger influence (Beta = 0.893), with each unit increase resulting in a 1.118-unit rise in Accepted Gap, and its high statistical significance ($p = 0.000$) underscores its critical role in the model.

The first table included additional variables (Speed and Gender), but these were removed in the refined model due to their statistical insignificance ($p = 0.542$ and $p = 0.562$, respectively). The final model's focus on only significant predictors ensures a more reliable explanation of the factors affecting gap duration, with Clearing Time emerging as the dominant predictor. The high standardized coefficient (Beta = 0.893) for Clearing Time further confirms its substantial impact compared to Gap or Lag. This streamlined model effectively captures the key determinants of driver behavior at the intersection while eliminating noise from irrelevant variables.

MLR model for the second site was developed by using similar variables as the first site i.e. Accepted Gap as dependent variable and clearing time gender (male female), gap or lag and speed as the independent variables. From the taken four variables only the significant variables were used.

From Table (4.24), the R-square and adjusted R-square value obtained for the final model by considering the significant variables are 0.821 and 0.819 respectively which tells us that dependent variable is accounted by 81.9% of the independent variables and high $R^2$ value indicates a good model. For significant variables, t-test conducted have values more than 1.96 and the p-values are less than 0.05.

**Table 4.23: Model 2 for Site 2 Summary**

| **Model** | **R** | **R Square** | **Adjusted R Square** | **Std. Error of the Estimate** |
|---|---|---|---|---|
| **2** | .914 | 0.821 | 0.819 | 0.05133 |

**Table 4.24: MLR Model 2 for Site 2 including all variables**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 2 for SecondSite | Constant | -1.889 | .375 | | -5.037 | .000 |
| | Speed | .032 | .018 | .040 | 1.760 | .080 |
| | Gap or Lag | .187 | .065 | .071 | 2.895 | .004 |
| | Male Female | -.133 | .065 | -.050 | -2.050 | .001 |
| | Clearing Time | 1.037 | .030 | .900 | 34.145 | .000 |

**Table 4.25: MLR Model 2 for Site 2 including significant variables**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 2 for Second Site | (Constant) | -1.301 | .171 | | -7.587 | .000 |
| | Gap or Lag | .195 | .065 | .074 | 3.012 | .003 |
| | Male Female | -.141 | .065 | -.053 | -2.169 | .001 |
| | Clearing Time | 1.028 | .030 | .892 | 34.224 | .000 |

The multiple regression analysis present in a Multiple Linear Regression (MLR) presented in Table 4.24 and 4.25 above shows the model examining factors influencing Accepted Gap, with clearing time, gap or lag, gender, and speed as predictors for the Lagnkhel-Satdobato Intersection. Of the 4 variables used only the significant variables were used for the final model.

The second table presents the refined Multiple Linear Regression (MLR) Model 2 for Site 2 (Lagankhel-Satdobato Intersection), retaining only the statistically significant predictors of Accepted Gap. The regression equation derived from this model is:

**Accepted Gap = -1.301 + 0.195(Gap or Lag) - 0.141(Male Female) + 1.028(Clearing Time)** (4.4)

The constant term (-1.301) represents the baseline gap duration when all predictors are zero. The coefficient for Gap or Lag (0.195) indicates that each one-unit increase in gap or lag time results in a 0.195-unit increase in Accepted Gap ($p = 0.003$), though its effect size is modest (Beta = 0.074). The Gender variable (-0.141) shows that male drivers (assuming male = 1) accept gaps 0.141 units shorter than females ($p = 0.001$), with a small but significant effect (Beta = -0.053). The dominant predictor, Clearing Time (1.028), demonstrates a strong positive relationship (Beta = 0.892), where each unit increase leads to a 1.028-unit rise in gap duration ($p = 0.000$).

The first table included Speed, which was excluded from the final model due to insignificance ($p = 0.080$). By focusing solely on significant variables, the refined model improves parsimony while robustly explaining driver behavior, with Clearing Time again emerging as the most influential factor. The standardized coefficients highlight its substantial impact (Beta = 0.892) compared to Gap or Lag and Gender, which contribute modestly but meaningfully. This streamlined approach ensures clarity and reliability in interpreting the determinants of gap acceptance at this intersection.

The two MLR models for gap acceptance at the two intersections show both similarities and differences. Both find that the time needed to safely cross (clearing time) strongly affects how long a gap drivers will accept. The type of gap (gap or lag) also matters in both cases, but has a smaller effect. However, the Lagankhel-Satdobato model found that gender plays a role too - male drivers tend to accept shorter gaps than females. This gender difference wasn't seen at the other intersection. Both models dropped factors that didn't show clear importance, like speed at one site. The main takeaway is that while the safe crossing time is always very important, some other factors can vary between different intersections. This shows we need to consider each location's specific conditions when studying driver behavior.

### 4.8 Model Validation

For the validation of the gap acceptance model, the accuracy of the model was tested using remaining 30 percent of data for both cases i.e. Kopundole-Pulchowk Intersection and Lagankhel-Satdobato Intersection (which were not used for developing the actual model). The sensitivity and specificity values were found to be 82.4% and 75% for first case and

81.7% and 80% for the second case respectively which signifies that the cases of gap acceptance correctly identified as accepted and rejected respectively. The overall prediction ability of the validated model for the first case is 78.3% and second case is 80.7% as shown in Table (4.14) and Table (4.27) below

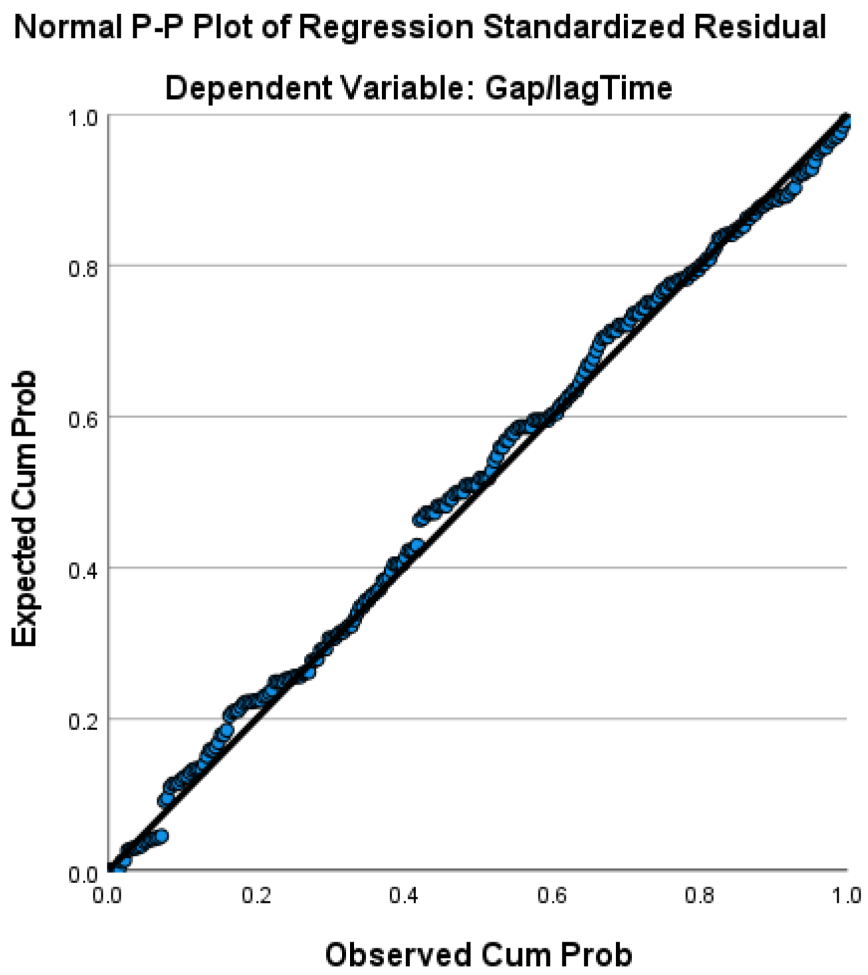
**Table 4.26 Validation Table for Model 1 of Site 1**

| Observed | | | Predicted | | |
|---|---|---|---|---|---|
| | | | Gap Acceptance | | Percentage Correct |
| | | | Rejected | Accepted | |
| For 129 cases | Gap Acceptance | Rejected | 47 | 10 | 82.4 |
| | | Accepted | 18 | 54 | 75 |
| | Overall Percentage | | | | 78.3 |

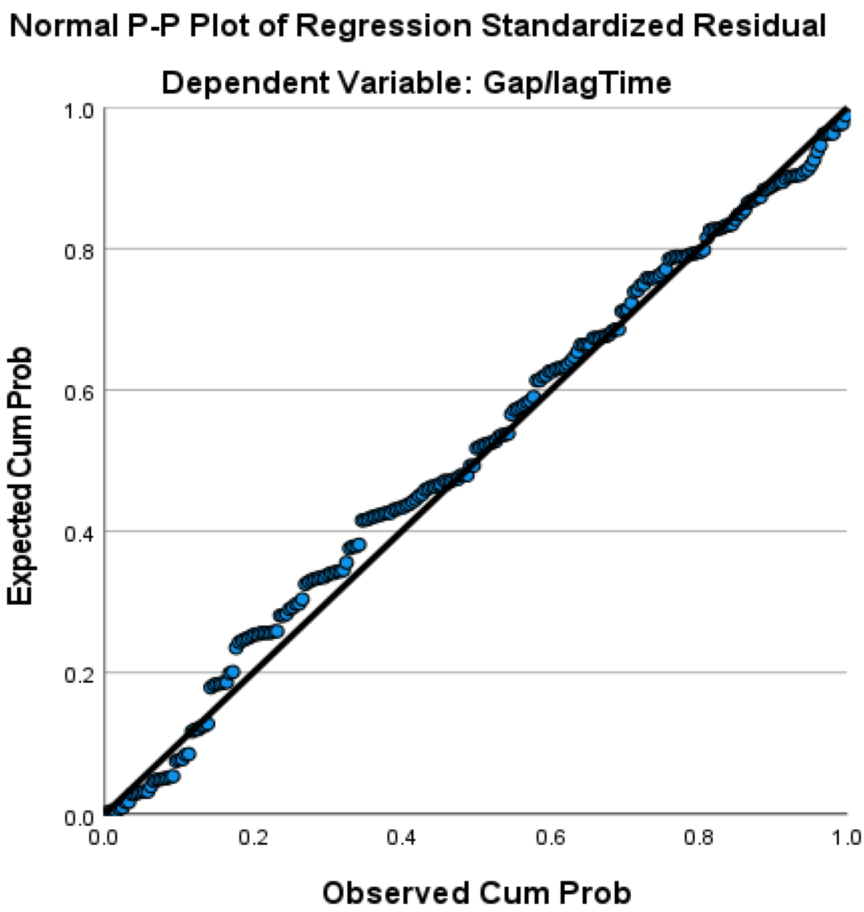
**Table 4.27 Validation Table for Model 1 of Site 2**

| Observed | | | Predicted | | |
|---|---|---|---|---|---|
| | | | Gap Acceptance | | Percentage Correct |
| | | | Rejected | Accepted | |
| For 135 cases | Gap Acceptance | Rejected | 49 | 11 | 81.7 |
| | | Accepted | 15 | 60 | 80 |
| | Overall Percentage | | | | 80.7 |

For the validation of Accepted Gap model, data set of 30 percent were selected as select cases from SPSS for both the site. Regression analysis was performed between the observed values and predicted values of Accepted Gap model as shown in Figure (4.9) and Figure(4.10) for Kopundole-Pulchowk Intersection and Lagankhel-Satdobato intersection respectively and it yielded the following results:




Figure(4.9) Validation Plot for Model 2 of Site 1




Figure(4.10) Validation Plot for Model 2 of Site 2

R Squared Value for Site 1 and Site 2 was found out ot be 0.816 and 0.805 respectively (i.e., 81.6% and 80.5% of variance of original field data is explained by the variance of field data obtained from MLR equation respectively)

# CHAPTER 5: CONCLUSION AND RECOMMENDATION

## 5.1 Conclusion

In this study, gap acceptance behavior analyses of minor road drivers (two-wheelers) at unsignalized intersections is done. The purpose was to model gap acceptance behavior of drivers and to find the critical gaps which are widely used in the intersection operational analysis and capacity estimates. Erratic maneuvers in the intersection area and aggressive driving are two common behavior of drivers observed at these intersections Considering the importance of incorporating crossing behavior of all types of drivers of minor roads trying to perform the right turning operation to enter the major road in an intersection, different factors influencing the right turning operation are studied in this study so as to provide an almost accurate guess of the critical gap required for the right turning operation of the minor road drivers. A gap acceptance model was developed that shows the probability of an individual minor road driver being able to accept the provided gap and perform the right turning operation. Numerical results obtained from the models help to derive the following conclusions:

i. The critical gap at the first site (Kopundole-Pulchowk) was 4.3 seconds, while the second site (Lagankhel-Satdobato) showed a lower critical gap of 2.7 seconds. The cumulative frequency curves confirmed that drivers at the first site required longer gaps for acceptance, likely due to restricted visibility or complex traffic flow, whereas the second site facilitated quicker decisions.

ii. The Clearing Behavior Analysis (CBA) method revealed a critical gap of 5.7 seconds when comparing clearing times and accepted gaps, providing a practical safety-based assessment. At Lagankhel-Satdobato Intersection, the CBA-derived critical gap was lower (4.1 seconds), suggesting geometric or traffic flow differences influence crossing efficiency. These results demonstrate CBA's effectiveness in evaluating real-world gap usability beyond driver decisions alone.

iii. The analysis on driver’s behavior revealed that distinct gap acceptance behaviors between aggressive and ideal drivers at both intersections. At the Kopundole-Pulchowk intersection, aggressive drivers accepted shorter gaps (1.8–5.6s) compared to ideal drivers (3.8–6.4s), while at the Lagankhel-Satdobato, aggressive drivers accepted 1.8–3.8s gaps versus ideal drivers' 3.2–5.8s range. Aggressive tendencies persisted across both sites in which 43.1% and 46.8% of the riders were found aggressive for first and second site respectively.

iv. The logistic regression models consistently identified three key predictors of gap acceptance behavior across both sites:

- Gap vs. Lag Condition: Drivers showed significantly lower acceptance probabilities for gaps compared to lags, reflecting their inherent caution when merging into moving traffic.
- Approach Speed: Higher vehicle speeds of major road consistently reduce gap acceptance likelihood, demonstrating that drivers become more conservative as the speed of the major traffic increases.
- Gap_Lag_Interval**:** Longer available gaps substantially improved gap acceptance rates.

v. The final gap acceptance model for Kopundole-Pulchowk shows only clearing time and gap/lag type significantly affect Accepted Gap. Clearing time has the strongest effect - drivers wait longer when they need more time to cross. Gap/lag type matters less but still plays a role.

vi. The final Accepted Gap model for Lagankhel-Satdobato Intersection shows that of Three factors which are significant there: clearing time (most important), gap/lag type, and driver gender. Males accept slightly shorter gaps than females. Like the first site, clearing time is the biggest factor in how long drivers wait.

## 5.2 Recommendation

The findings from the study suggest that the gap acceptance procedure is significantly affected by different variables under consideration in our study. Hence, there is a comprehensive need to incorporate these sorts of variables while designing minor road facilities. As the critical gap is used for intersection operational analysis and capacity estimates, a model developed to find the critical gap will help in the long run for the type of intersections considered in our study. The planners need to consider demographic as well as behavioral aspects to estimate the critical gap. As the findings of this study highlight the prevalence of aggressive gap acceptance behavior among minor road two-wheeler riders at unsignalized intersections in Nepal, posing significant safety risks. To address this issue, a multi-pronged approach can be recommended such as infrastructure improvements like traffic calming measures (speed bumps, raised crosswalks), protected right-turn lanes, and enhanced visibility through better signage and intersection design can help mitigate risky maneuvers. Also, behavioral interventions through targeted awareness campaigns and stricter enforcement of traffic rules are needed to educate riders about safe gap acceptance and deter dangerous behaviors.

A larger set of data could be utilized to develop a more robust model. Similarly, the analysis could be performed using alternative approaches and methods for the evaluation of outcome and the most accurate model could be chosen. In this study, only minor street right turning movement at unsignalized three legged intersections has been considered; the procedure can be extended to analyze the gap acceptance behavior of major street right turning vehicles as well. Studies on minor road four wheelers can be performed for further research. Also, Studies on four-legged intersections and effect of other parameters such as geometric features such as gradient effect, side friction, environmental condition, traffic flow characteristics can be considered to gain further understanding of traffic behavior at unsignalized intersections.

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# APPENDIX A: Sample Data

## Sample Data for Kopundole-Pulchowk Intersection

| S.N | Gap/lagTime | Clearing Time | Aggressive or ideal | accept or reject | Gap or Lag | Speed | Male Female |
|---|---|---|---|---|---|---|---|
| **1** | 5.5 | 6.8 | 0 | 1 | 1 | 16.6 | 1 |
| **2** | 1.8 | 4.3 | 1 | 1 | 0 | 12.2 | 1 |
| **3** | 2.1 | 4.5 | 1 | 1 | 0 | 13.1 | 1 |
| **4** | 2.8 | 4.7 | 1 | 1 | 0 | 14.1 | 1 |
| **5** | 5.7 | 6.7 | 0 | 1 | 0 | 17.6 | 0 |
| **6** | 3.8 | 4.4 | 1 | 1 | 1 | 14 | 1 |
| **7** | 4.9 | 6.4 | 0 | 1 | 1 | 17.8 | 1 |
| **8** | 3.5 | 4.6 | 0 | 1 | 0 | 15 | 1 |
| **9** | 5.7 | 7 | 0 | 1 | 1 | 15.8 | 0 |
| **10** | 2.9 | 4.3 | 1 | 1 | 0 | 16 | 1 |
| **11** | 5.4 | 6.5 | 0 | 1 | 1 | 18.1 | 1 |
| **12** | 3.2 | 4.7 | 1 | 1 | 1 | 16.1 | 1 |
| **13** | 3.2 | 4.2 | 1 | 1 | 1 | 15.8 | 1 |
| **14** | 5.7 | 6.8 | 0 | 1 | 1 | 17.1 | 0 |
| **15** | 6 | 6.7 | 0 | 1 | 1 | 16 | 1 |
| **16** | 2.6 | 4.3 | 1 | 1 | 1 | 18.1 | 1 |
| **17** | 5.7 | 6.2 | 0 | 1 | 0 | 16.6 | 0 |

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| **18** | 5.7 | 6.5 | 0 | 1 | 1 | 15.7 | 1 |
| **19** | 3.1 | 4.9 | 1 | 1 | 1 | 18.7 | 1 |
| **20** | 5.5 | 7.1 | 0 | 1 | 1 | 16.5 | 0 |
| **21** | 3.4 | 4.4 | 1 | 1 | 1 | 15.8 | 1 |
| **22** | 5.7 | 6.8 | 0 | 1 | 1 | 15.4 | 1 |
| **23** | 2.8 | 4.6 | 1 | 1 | 0 | 17.5 | 1 |
| **24** | 5.3 | 6.3 | 0 | 1 | 1 | 14.9 | 0 |
| **25** | 5.4 | 6.2 | 0 | 1 | 1 | 15.4 | 1 |
| **26** | 2.9 | 4.4 | 1 | 1 | 1 | 17.2 | 1 |
| **27** | 3.7 | 4.2 | 1 | 1 | 1 | 17.6 | 1 |
| **28** | 5.3 | 6.3 | 0 | 1 | 1 | 15.3 | 0 |
| **29** | 5.6 | 6.7 | 0 | 1 | 1 | 14.8 | 1 |
| **30** | 5.4 | 6.2 | 0 | 1 | 1 | 15.1 | 1 |
| **31** | 5.8 | 6.6 | 0 | 1 | 1 | 14.8 | 1 |
| **32** | 2.8 | 4.6 | 1 | 1 | 0 | 17.6 | 0 |
| **33** | 1.8 | 4.8 | 1 | 1 | 1 | 17.9 | 1 |
| **34** | 5.3 | 7.3 | 0 | 1 | 1 | 16.1 | 0 |
| **35** | 2.4 | 4.5 | 1 | 1 | 0 | 17.1 | 1 |
| **36** | 5.2 | 6.3 | 0 | 1 | 1 | 15 | 1 |
| **37** | 5.6 | 6.2 | 0 | 1 | 1 | 15.7 | 0 |
| **38** | 3.9 | 4.7 | 1 | 1 | 1 | 17.6 | 1 |
| **39** | 3.7 | 4.6 | 1 | 1 | 0 | 18.1 | 0 |
| **40** | 5.4 | 6.8 | 0 | 1 | 1 | 15.2 | 1 |
| **41** | 2.1 | 4.1 | 1 | 1 | 1 | 17.9 | 1 |
| **42** | 5.2 | 6.2 | 0 | 1 | 1 | 16 | 1 |
| **43** | 5.7 | 6.7 | 0 | 1 | 1 | 14.9 | 0 |
| **44** | 2.9 | 4.8 | 1 | 1 | 0 | 17.2 | 1 |
| **45** | 3.2 | 4.4 | 1 | 1 | 1 | 17.9 | 1 |

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|---|---|---|---|---|---|---|---|
| **46** | 5.5 | 6.6 | 0 | 1 | 1 | 16 | 0 |
| **47** | 4.2 | 4.7 | 1 | 1 | 0 | 18 | 1 |
| **48** | 5.8 | 6.7 | 0 | 1 | 1 | 15.4 | 1 |
| **49** | 3.4 | 4.2 | 1 | 1 | 1 | 17.8 | 0 |
| **50** | 5.2 | 6.3 | 0 | 1 | 1 | 15.7 | 1 |
| **51** | 5.7 | 6.3 | 1 | 1 | 1 | 15.2 | 1 |
| **52** | 5.5 | 6 | 0 | 1 | 0 | 15.4 | 1 |
| **53** | 5.1 | 6.4 | 0 | 1 | 1 | 15.5 | 1 |
| **54** | 3.1 | 4.6 | 1 | 1 | 1 | 17.5 | 1 |
| **55** | 3.8 | 4.4 | 1 | 1 | 1 | 18.1 | 1 |
| **56** | 5.4 | 6.5 | 0 | 1 | 1 | 14.9 | 0 |
| **57** | 5.6 | 6.9 | 0 | 1 | 1 | 14.9 | 1 |
| **58** | 5.4 | 6.4 | 0 | 1 | 1 | 15 | 1 |
| **59** | 5.9 | 6.7 | 0 | 1 | 1 | 14.6 | 1 |
| **60** | 3 | 4.8 | 1 | 1 | 0 | 17.6 | 0 |
| **61** | 2.1 | 5 | 1 | 1 | 1 | 18.1 | 1 |
| **62** | 5.5 | 7.4 | 0 | 1 | 1 | 15.8 | 0 |
| **63** | 2.6 | 4.7 | 1 | 1 | 0 | 17.1 | 1 |
| **64** | 5.3 | 6.3 | 0 | 1 | 1 | 15.3 | 1 |
| **65** | 5.7 | 6.4 | 0 | 1 | 1 | 14.6 | 0 |
| **66** | 4 | 4.9 | 1 | 1 | 1 | 17.3 | 1 |
| **67** | 3.7 | 4.8 | 1 | 1 | 0 | 18.5 | 0 |
| **68** | 5.5 | 7 | 0 | 1 | 1 | 15.3 | 1 |
| **69** | 2.3 | 4.2 | 1 | 1 | 1 | 18 | 1 |
| **70** | 5.3 | 6.4 | 0 | 1 | 1 | 15.8 | 1 |
| **71** | 5.9 | 6.8 | 0 | 1 | 1 | 14.8 | 0 |
| **72** | 3.1 | 4.7 | 1 | 1 | 0 | 17.2 | 1 |
| **73** | 3.4 | 4.6 | 1 | 1 | 1 | 17 | 1 |

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|---|---|---|---|---|---|---|---|---|
| **74** | 5.6 | 6.7 | 0 | 1 | 1 | 15.5 | 0 |
| **75** | 4.2 | 4.9 | 1 | 1 | 0 | 17.8 | 1 |
| **76** | 5.9 | 6.5 | 0 | 1 | 1 | 15 | 1 |
| **77** | 3.5 | 4.3 | 1 | 1 | 1 | 18 | 0 |
| **78** | 5.3 | 6.5 | 0 | 1 | 1 | 14.5 | 1 |
| **79** | 5.8 | 6.4 | 1 | 1 | 1 | 14.9 | 1 |
| **80** | 5.5 | 6.2 | 0 | 1 | 0 | 15.2 | 1 |
| **81** | 5.7 | 6.7 | 0 | 1 | 1 | 16.8 | 1 |
| **82** | 2 | 4.5 | 1 | 1 | 0 | 12.5 | 1 |
| **83** | 2.3 | 4.7 | 1 | 1 | 0 | 13.3 | 1 |
| **84** | 3 | 4.9 | 1 | 1 | 0 | 14.3 | 1 |
| **85** | 5.9 | 6.9 | 0 | 1 | 0 | 17.8 | 0 |
| **86** | 4 | 4.6 | 1 | 1 | 1 | 14.2 | 1 |
| **87** | 5.1 | 6.6 | 0 | 1 | 1 | 17.6 | 1 |
| **88** | 3.7 | 4.8 | 0 | 1 | 0 | 15.2 | 1 |
| **89** | 5.9 | 7.1 | 0 | 1 | 1 | 16 | 0 |
| **90** | 3.1 | 4.5 | 1 | 1 | 0 | 16.1 | 1 |
| **91** | 5.6 | 6.7 | 0 | 1 | 1 | 18.3 | 1 |
| **92** | 3.4 | 4.9 | 1 | 1 | 1 | 16.3 | 1 |