**ADDIS ABABA UNIVERSITY**

**ADDIS ABABA INSTITUTE OF TECHNOLOGY**

**SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING**

# Reliability Distribution Modeling for Bus Dwell Time and its Contributing Factors: A Case Study in Selected Routes of Addis Ababa City

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A Thesis Presented to the School of Civil and Environmental Engineering as Part of the Prerequisites for Obtaining the Master of Science Degree in Civil Engineering with a Focus on Road and Transport Engineering.

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**DEPARTMENTS OF ROAD AND TRANSPORT ENGINEERING**

The undersigned have examined the thesis entitled **[Reliability Distribution Modeling for Bus Dwell Time and its Contributing Factors: A Case Study in Selected Routes of Addis Ababa City]** presented by **Asmamachew Yilak**, a candidate for the **Degree of Master of Science in Road and Transportation,** hereby certify that it is worthy of acceptance.

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## UNDERTAKING

I affirm that research work titled **[Reliability Distribution Modeling for Bus Dwell Time and its Contributing Factors: A Case Study in Selected Routes of Addis Ababa City]** is my work under the supervision of my advisors **Prof. Girma Gebresenbet (PhD)** and **Hilina Demeke (MSc)**. The work has not been submitted to any other Institution for evaluation or the conferral of any certificates, diplomas, or degrees, aside from the assessment at **Addis Ababa Institute of Technology.** All the pages formatted in the accepted font and margin alignment and proper acknowledgment has been given to all utilized information and materials.

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**Date: April, 2024 G.C**

## ABSTRACT

The initial point of contact between the passenger and the passenger service is at the bus stop. All buses in Addis Ababa City now operate in mixed traffic with no signal prioritization, with the exception of BDL (Bus Dedicated Lane) on a few chosen routes. Bus stops are significant components of the Public bus system, and the way they are run has a significant impact on the network's overall service level and transit effectiveness. The aim of this work was determining the most influential factor on dwell time and the likelihood of dwell time occurrence at stop.

Quantitative and qualitative data were gathered for a study on bus dwell times at stops, with quantitative data obtained from bus stops and qualitative data from passengers. Manual field data collection was conducted due to the lack of Automatic Passenger Count (APC) and Automatic Vehicle Location (AVL) data. To ensure accuracy, data collection was repeated for three days at each stop and time frame, three bus type, and the averages were used for dwell time determination. Directionality was considered, categorizing bus stops into upstream, stop, and downstream sections. The lengths of these sections were determined based on observed bus maneuvers within a 10-meter radius during a pilot survey. Video recording and direct transcription onto paper sheets were used to collect data for a specific bus. Only buses stopping at designated stations within the specified range were considered for the study. The data were analyzed using a statistical model and the probabilistic method of analysis.

The research successfully achieved its stated objectives, contributing to a novel approach for evaluating dwell time. The author developed two models to identify the most significant factors affecting bus dwell time specifically, the Gaussian and Weibull regression models. The Weibull regression model demonstrated superior accuracy and a better fit for predicting bus dwell time, with a significantly lower RMSE (0.075) and an Adjusted R-squared of 92.63%, compared to the Gaussian regression model (RMSE: 3.93, Adjusted R-squared: 93.00%). Moving to specific coefficients in the Weibull regression model, factors such as No_aligt. Weibull (Number of alighting), Alig.Weibull (Alighting time), Board.Weibull (Boarding time), Idle.Weibull (Idle time), No. Boa.Weibull(Numbers of Boarding), Odd.pen.Weibull (Odd. Penny Weibull), Re.boa.Webull(Re-boarding passengers), Accel.Weibull (Acceleration time), and Far side (Far side stop location) exhibited a statistically significant effect on bus dwell time at stops. However, the location of the far side stops and the time of day had no effect on dwell time. The combined effect of stop location and bus type did not show statistical significance (p-value: 0.845), surpassing the conventional threshold of 0.05. However, analyzing the variables individually revealed a significant difference between stop type location and bus type in relation to dwell time. Specifically, Alliance buses exhibited longer dwell times compared to single Sheger and Anbessa buses.


**Key words:** Bus stop; Dwell time; Gaussian regression; Regression models; Weibull distribution.

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# Acronyms

AACIA: Addis Ababa City Infrastructure and Design

AACRA: Addis Ababa City Roads Authority

AACTB: Addis Ababa City Administration Transport Bureau

Accel.weibull: Acceleration time as a function of Weibull

Adj MS: Adjusted Mean Square

Adj SS: Adjusted Sum of Squares

Alig.weibull: Alighting time as a function of Weibull

AD: Anderson-Darling

ANOVA: Analysis of Variance

APC: Automatic Passenger Count

ATSSC: Alliance Transport Service Share Company

AVL: Automatic Vehicle Location

BDL: Bus Dedicated Lane

Board.Weibull: Boarding time as a function of Weibull

CBC: Central Business Center

Cox: Cox Regression

CV: Coefficient of Variation

DF: Degree of Freedom

EMA: Exponential Moving Average

EM: Empirical Method

Far side: Far side stop as a function of Weibull

GOF: Goodness of Fit

GPS: Global Positioning System

HCM: Highway Capacity Manual

Idle.Weibull: Idle time as a function of Weibull

IQR: Interquartile range

MAE: Mean Absolute Error

MAPE: Mean Absolute Percentage Error

Mid-Block: Mid-block as a function of Weibull

MLM: Modified Maximum Likelihood Method

MLR: Multiple Linear Regression

MTTF: Mean Time to Failure

No alig. weibull: Number of alighting as a function of Weibull

No. Boa. weibull: Numbers of Boarding as a function of Weibull

Odd.pen. weibull: Odd penny fare as a function of Weibull

OLS: Ordinary Least Squares

PFC: Public Finance Corporation

PMT: Public Mass Transport

PSETSE: Public Service Employees Transport Service Enterprise

PDF: Probability Density Function

Re.boa.Webull: Re-boarding passengers as a function of Weibull

RMSE: Root Mean Square Error

R-sq: R-squared

R-sq(adj): Adjusted R-squared

R-sq(pred): R-squared for Prediction

SCOPUS: Bibliographic database of academic articles

S(t): Survival Function

Sch Hub: Scholarly Hub

SMTSE: Sheger Mass Transportation Service Enterprise

SPSS: Statistical Package for Social Science

VIF: Variance Inflation Factor

# CHAPTER 1 INTRODUCTION

## 1.1 Background of the study

At a bus stop, buses can interact in ways that restrict the discharge flows of the passengers they are serving. The initial point of contact between the passenger and the passenger service is at the bus stop(Gu et al., 2011).The location of bus stops has a big impact on how well a bus transit system works and how satisfied the passengers are. This can lengthen bus wait times at stops and worsen the transport system's overall traffic flow in a variety of traffic conditions. Therefore, it is essential to be aware of the bus's maximum stop-time delay. And analyze the reasons for the increase of bus dwell and then put forward the countermeasures to reduce the dwell time.

Currently, in urban transit systems, the concept of bus stop passenger service time delays is an everyday issue. Due to extended stop dwell times in Addis Ababa City's Bus Transportation system, passengers encounter uncertainties and inconsistencies in the schedules of bus arrivals and departures. All buses in Addis Ababa City now operate in mixed traffic with no signal prioritization, with the exception of BDL (Bus Dedicated Lane) on a few chosen routes. (Berhan et al., 2013; Girma, 2023). Bus stops are significant components of the public bus system, and the way they are run has a significant impact on the network's overall service level and transit effectiveness(Philiphos Dea et al., 2019). The definition of a bus dwell at a stop is not universally accepted. It is influenced by stop characteristics such as the number of berths, stop geometry, and passenger parking shades, as well as by vehicle characteristics. It also influenced by many factors in different aspects, including passengers, buses, stop type and their surrounding traffic conditions. In the side of passengers, the age and gender of passengers, health, the number and size of luggage, and payment ways. Furthermore, discontinuous passenger flow also greatly increases bus delay. The capacity and arriving rate of buses, number and width of door, the height of floor and the load factor of passenger are important factors for delay at stop(S. Chen et al., 2013).

## 1.2 Statement of the problem

Ethiopia is beginning a phase of rapid urbanization, and its capital city, Addis Ababa, is dealing with serious challenges with overcrowding and higher travelling time. The issue is ascribed to inadequate planning for city buses, poor bus stop service management, and poor compliance to land-use and transportation regulations. The integration of transportation and transportation infrastructure is inadequate, and manpower resources to plan for them are limited(Buchari, 2009). The amount of time buses spends to providing services at a bus stop or station might significantly influence transit system performance and passenger satisfaction. When buses take a long time to load and unload passengers at stops, it can lead to the front bus occupying another vehicle lane, hence blocking space of passengers to board and disembark. This creates a ripple effect, affecting other buses at upstream stops and limiting overall stop capacity. Consequently, dwell times increase across the entire network.

Even though public bus has many advantages, bus dwell experiences, more passengers waiting at a stop, the longer time a bus needs to spend there and more passengers arrive that need to be served at its next stop. One study has defined determinant of bus dwell time at stop in Addis Ababa City Transport (Tsegaye & Sc, 2018). And tried to mention dwell time in times of the day, by lane category, numbers of boarding and alighting passenger, fare conditions collect fares while the passengers are outside, which lengthens the dwell time overall. On some other buses, the fares are only collected after everyone has boarded and settled into their seats. Other times, the back doors are opened for passengers disembarking, while those boarding enter through the front door and pay their money there. Most of the researchers primarily focuses on linear relationship between average boarding and alighting times and their respective standard (Sun et al., 2013, 2014). Also new model incorporating critical occupancy was also proposed to estimate passenger activity time but often existing study failed to identify key influential variables such as odds penny, exact fare, and idle type, which can significantly impact bus operations. And Anbessa and Sheger bus enterprises initially utilized both service doors for boarding and disembarking, but due to the impact of Covid-19, they transitioned to using only the back door for service. Additionally, post-Covid-19, Alliance and Kitkit buses emerged as new passenger transportation services. However, no existing studies have provided insights for bus dwell time at stops in Addis Ababa City. This gap has to be considered in the current study.

Moreover, the unpredictable arrival nature of both buses and passengers makes it challenging to use average methods for analysis. To conduct a more comprehensive analysis and gain a better understanding, a new approach which is probabilistic methods to dwell time prediction is needed. Which offer a solution by effectively accounting for the variability in dwell time distribution. Studies in transportation engineering and operations research have demonstrated the advantages of dwell time probability over average values in predicting bus stop behavior. For instance,(Meng & Qu, 2013) have shown that considering the stochastic nature of dwell times leads to more accurate predictions and better decision-making for transit planning and management.

## 1.3 Hypothesis of the research

In statistical terms, a hypothesis test for dwell time involves examining whether there was a statistically significant difference certain factors and the dwell time of buses at stops.

**Null Hypothesis (H0)**: No statistically significant variation is present in dwell time during the day's peak periods (morning peak, afternoon peak).

**Alternative Hypothesis (H1):** There is a statistically significant difference in dwell time between the morning peak and afternoon peak periods.

**Null Hypothesis (H0):** No statistically significant variation is present in dwell time between bus types.

**Alternative Hypothesis (H1):** There is statistically significant variation present in dwell time between bus types.

**Null Hypothesis (H0):** No statistically significant variation was present in dwell time between stop types (Mid-block and Far side).

**Alternative Hypothesis (H1):** There is statistically significant variation present in dwell time between stop types (Mid-block and Far side).

**Null Hypothesis (H0):** The bus dwell time follows a Weibull reliability distribution.

**Alternative Hypothesis (H1**: The bus dwell time does not follow a Weibull reliability distribution.

## 1.4 Research question

1. What is the variation in bus dwell times during distinct time periods (morning peak and afternoon peak) and at different stop locations (mid-block and far side)?
2. How do bus users perceive the impact of extended bus dwell times on their overall travel experience?
3. How to develop model to investigate the contributing factors of bus dwell time?
4. How can reliability distribution models be utilized to predict bus dwell time?

## 1.5 Objective of the study

The general objective of this work was evaluating of bus dwell time variability and its contributing factors using statistical modeling.

### 1.5.1 Specific objectives

1. Quantify the variation across multiple groups of bus dwell times factors during specific time periods (morning peak and afternoon peak) and at different stop locations (mid-block and far side).
2. Assess the perceptions of bus users regarding the impact of prolonged bus dwell times on their overall travel experience through surveys, interviews.
3. Developing a regression model for identify the most influential factors on bus dwell time analysis.
4. Explore the utilization of weibull distribution models for predicting and modeling bus dwell time.

## 1.6 Scope of the study

The research was conducted in Addis Ababa City, focusing on public bus dwell time at bus stops along a major route characterized by high passenger demand, is methodologically sound for several reasons. Firstly, it directly addresses a critical issue in the city's public transportation system, aligning with the challenges of high population density and urbanization. Secondly, operating buses along this route provides a representative sample, ensuring the research is feasible and reflects typical conditions. Additionally, data availability on schedules, routes, focusing on a major route allows high passenger demand routes attract attention from key stakeholders, facilitating engagement and ensuring the research findings are actionable and relevant to transportation authorities, operators and likely to be higher, enhancing the reliability of findings.

All selected buses were actively assigned to this route. The study focused on two types of stop locations, each with its unique characteristics and implications for traffic flow, pedestrian safety, and overall efficiency. By integrating various factors including spatial analysis, traffic data, and transportation planning principles to accurately classify stop locations. Spatial analysis techniques identify patterns and characteristics of stop locations within the study area, while traffic data provide insights into operational impacts on roadway capacity and intersection performance. Principles of transportation planning guide the classification process, ensuring alignment with broader goals such as optimizing transit service, enhancing pedestrian safety, and improving overall transportation system efficiency. Their classification into shade types categorized as type one, type two, and type three was based on existing source and pre-selection criteria. Additionally, the research focused on three distinct bus types: single Anbessa, single Sheger, and Alliance Buses, regardless of their company names. Operational differences could involve, each bus company might have unique management practices, fleet maintenance schedules, and driver training programs, factors like route coverage, service frequency, passenger capacity. However, Data collection during the study was concentrated on peak hour time frames, specifically morning and afternoon, coinciding with peak passenger density periods at the selected stops. The study exclusively focused on the dwell time at stops, and as such, the traveling time of vehicles between stops was not included in the analysis.

## 1.7 Significant of the study

This study aimed to determine the waiting time for bus services, contributing to the enhancement of long-term public transportation goals. It establishes a framework for city planners, serving as a valuable resource for optimizing bus operations by considering various factors. The research focuses on maximizing the efficiency of bus operations and increasing schedule frequency without a proportional rise in the number of buses in service. Understanding how bus stops impact traffic flow is crucial for city planners, and the Addis Ababa City Road Infrastructure Office utilized this work to enhance bus assignment for better management. The study identifies factors leading to excessive delays at underperforming bus stops, providing insights for potential solutions.

### 1.7.1 Limitation of the study

This research focuses only on through public bus transportation.

- ❖ During the data collection period, certain variables such as weather conditions, road surface conditions, and the deceleration and acceleration capabilities of buses were not considered. The rationale for excluding these variables indicates that they were not part of the study's objectives or parameters. This could be because they introduce complexity beyond the focus of the research, or they may require additional resources and specialized expertise to measure accurately. However, acknowledging that considering them would require further research. Kitkit buses were removed from the data collection hence those factors were not significantly identified and rectify potential issues before conducting the full-scale study. Double decker, articulated city buses were not included. Because features are varied in total. The other major difficulty for the research to extract video data to analysis software are expensive. Manual data extraction taken roughly one month, which can be time-consuming and exhausting. And also, secondary data such as stop time, expected travel time of bus between stops were taken from transport officer and those officers could not always provide data in a format that can be directly applied.

On the other hand, during data collection time some bus stops were unused by the drivers and passengers, in such case the researcher jumps such stops because of lack of data.

## 1.8 Structure of the work

The typical thesis structure of this study is as follow.

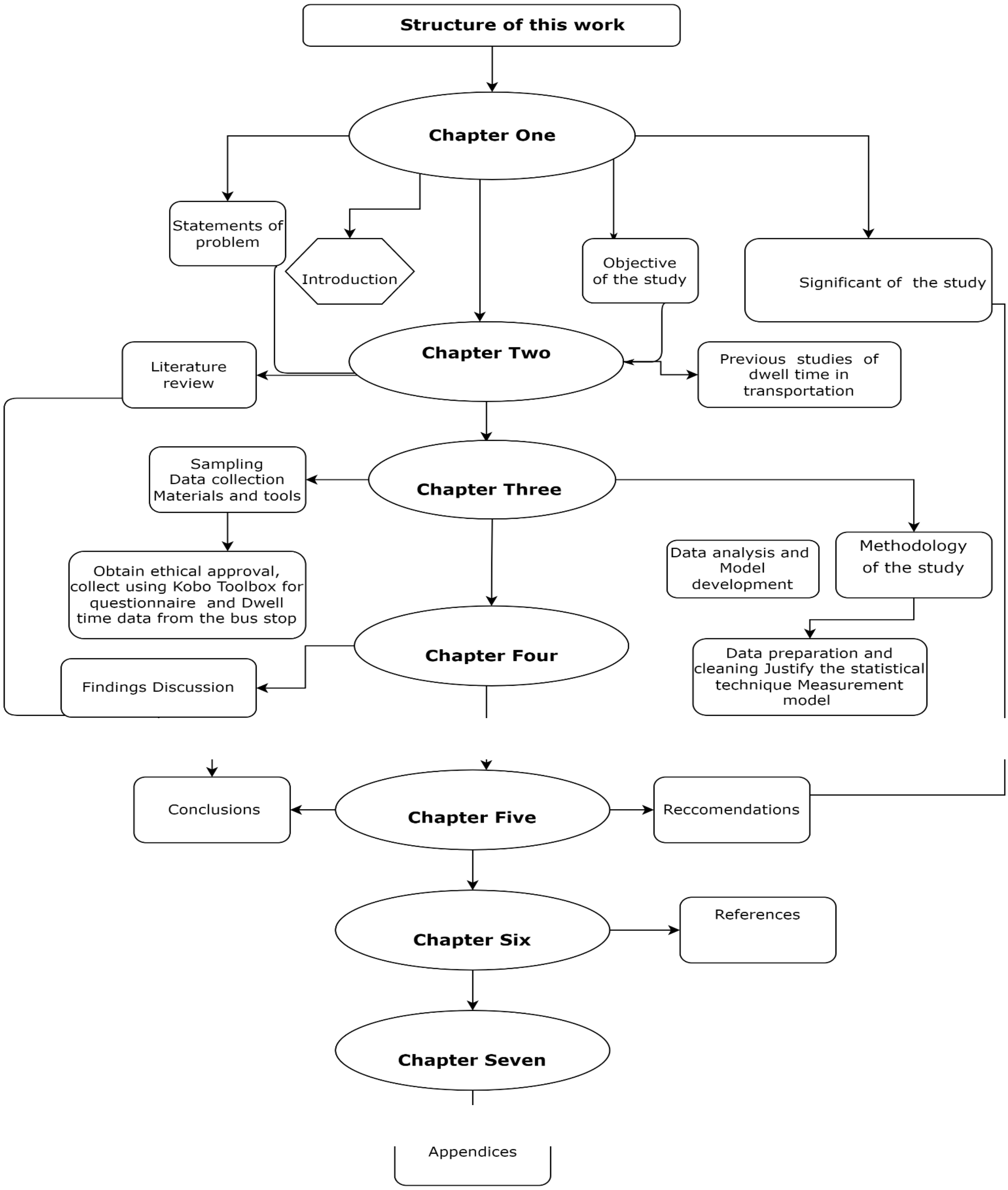


Figure 1: Structure of the work

# CHAPTER 2 LITERATURE REVIEW

## 2.1 The concept bus stop literature survey

After finalizing the study working title, which revolves around addressing a specific issue, the author proceeded to identify keywords for an extensive search of pertinent articles. These keywords were utilized in various databases, including Google Scholar, SCOPUS (a bibliographic database of academic articles), ResearchGate, Scholarly Hub (possibly Sch Hub), and PDF Drive. Additionally, explored an integrated database dedicated to transportation research documentation. These platforms enabled the researcher to locate and access relevant academic articles and documents. The initial selection of related articles involved screening titles and abstracts. Subsequently, a thorough review of literature, including textbooks, journals, and research papers, was undertaken to establish a framework and comprehend the characteristics of bus delays at stops.

literature review is to present a summary of various studies conducted in associated with bus dwell time, including an examination of methodologies employed in previous studies, the identification of factors influencing dwell time, exploration of various modeling techniques, and an analysis of insights derived from case studies. This investigation will be particularly focused on studies conducted within the context of Addis Ababa City. Furthermore, the review will emphasize the identification of gaps or areas requiring additional research, thereby establishing a solid foundation for the proposed study and articulating its contribution to the current body of knowledge in this specific field. The following aspects were considered in the reviews of past studies:

- Definition of bus stop
- Types of bus stop
- Location of bus stop
- Definition of bus delay at stop
- Factors affect delay at stop
- Definition and measurement of bus dwell time
- Methodologies employed in studying bus dwell time
- Factors influencing bus dwell time

The bus stop is a crucial component in a transit system's overall effort to provide prompt, secure, and convenient transportation since it serves as the first point of contact between the passenger and the public transit service. Research has investigated the impact of interactions between buses, passengers, and traffic on delays and capacity at bus stops (Prathibaa & Gunasekaran, 2022) and (Tirachini, 2014) defined bus stop is a set location where people can board or exit the vehicle.

Delays at bus stops have negatively impacted the efficiency of bus operations, the overall improvement of public transportation services, and the preferences of passengers to use bus services have all been adversely affected by delays at bus stops (S. Chen et al., 2013). This research proposes examining data from three bus routes, focusing on the arrival, boarding, and departure processes, along with a methodology for calculating bus delays at stops. Through statistical analysis, determines the average duration buses spend at both curbside and bay-style stops. It's noteworthy that the individual boarding and alighting times are significantly influenced by various passenger load factors. The number of passengers boarding and alighting can be modeled linearly in terms of bus stop times, with the coefficient's variability depending on the bus type and fare collection method (e.g., paper tickets or electronic cards). The study reveals a three-stage delay at the stop, where buses initially slow down at a distance of L1 from stops during the docking process's first phase, coming to a halt after T1 seconds. In instances with multiple buses in line, they might impede each other during this operation, causing potential delays. The second stage involves dwelling, encompassing the processes of opening doors, boarding and disembarking passengers, and closing doors while buses are at stops. Door operations typically occur within one to three dwell times, influenced by the electromechanical performance of the equipment. The duration of the stay is minimally affected by door-open and door-close timings, typically ranging from one to three seconds and primarily reliant on the electromechanical performance of related equipment.

According to study (Huo et al., 2018), the classification of bus delays at stops involves three distinct categories through a specified model. Firstly, occupy-based delay occurs when a bus is unable to enter a location due to the presence of other buses in service, and the model offers a method to estimate this delay. Secondly, transfer block-based delay occurs when a bus is impeded from entering a location by buses that have completed passenger serving, and the model facilitates the estimation of this specific delay. The third category is block-based delay, which occurs when a bus is hindered from exiting a location by the leading bus and external factors such as traffic lights. The model allows for the estimation of block-based delay. In summary, the total bus delay at the stop is determined by the cumulative sum of these three types of delay, providing a comprehensive measure that considers various factors contributing to delays in the bus service. The research discussed in (Z. Liu & Jian, 2019a) is focused on investigating the impact of bus stops located near signalized intersections. The study employs various analytical models to evaluate how these bus stops affect the functionality of the adjacent intersection, specifically examining changes in traffic volume near the intersection. The primary goal is to understand and analyze the dynamics between bus stops and signalized intersections, providing valuable insights for optimizing traffic flow.

Dwell time, as defined (Ling KHOO,2013), is the duration in seconds that a transit vehicle pauses to serve passengers, covering the time to open and close doors. It is a crucial factor influencing the overall level of service in bus transit systems and is integral to planning and modeling these systems. The researcher utilizes regression models to assess the impact of factors like passenger volume, fare collection method, and platform crowding on dwell time variability. Statistical modeling, supported by software, is employed to analyze and explain the variability in dwell time. Data collection involves recording dwell time at 20 bus stops using video recording, with three students assisting in the process. The research findings indicate that dwell time is influenced by factors such as payment method, time of day, and platform crowding level. (Prathibaa &

Gunasekaran, 2022) ,define, dwell times can be determined by the demand for boarding, alighting, or the overall interchange of passengers. In any scenario, the dwell time is directly related to the volumes of boarding and/or alighting passengers and the time required to serve each passenger. Dwell time, as examined by (Fernandez & Tyler, 2005), is influenced by various factors, including passenger activity, lift operations, and considerations such as the use of low-floor buses, time of day, and route type. The study found that dwell time can be calculated as 1.5 seconds plus 1.9 seconds for specific fare structures and 2 seconds plus 4.5 seconds per boarding passenger for cash and change fare structures. The research utilized data from service bus routes over a two-week period, enabling the identification of fundamental factors affecting bus dwell duration. Passenger activity emerged as a crucial determinant, and the substantial dataset allowed for the development of separate models for dwells with lift operation only. Additionally, variables like low-floor buses, time of day, and route type were evaluated for their impact on dwell time. Dwell time is defined as the duration during which a public transport vehicle stays stationary for passenger transfers. This duration is influenced by factors such as the count of boarding and alighting passengers, as well as operational characteristics like fare collection method, number of doors and steps, internal vehicle layout, among others. The conventional understanding portrays dwell time as a linear function of the boarding and alighting passenger numbers. The researcher examined three distinct factors: door width (800 and 1,600 mm), platform height (0, 150, and 300 mm), and fare collection technique (prepayment outside the vehicle and payment with an electronic card at the entrance of the vehicle). Video recordings from 15 to 20 runs were collected using four cameras and various perspectives for each variable. A total of 300 records documenting boarding and deplaning procedures were obtained. The study's findings indicate that door width has a more significant impact than platform height. Specifically, a wider door, regardless of platform height, can reduce average boarding time by 20% and alighting time by approximately 40%. In contrast, a lower platform has a comparatively modest effect, shortening average alighting time by 1 to 9% for the same door width. (Fernandez & Zegers, 2010).

Study (Tirachini, 2013a),explores the significance of understanding transit dwell time for the benefit of both users and operators. The article employs multiple regression models to analyze how various factors, including payment methods, the presence of steps at doors, passenger age, and interactions between boarding, alighting, and standing passengers, influence dwell times at bus stops. Through simulations based on average boarding and alighting times, the study compares the performance of different payment scenarios, such as payment outside buses, prepaid cards validated inside buses, and cash transactions. Results reveal the specific impact of each variable on bus dwell time, emphasizing the potential time savings by transitioning from slower payment methods (e.g., cash transactions) to faster ones (e.g., fare paid outside buses). The study also highlights the influence of factors like steps at doors, age-related boarding speed differences, friction effects when passengers board from two queues, and crowding effects on both boarding and alighting times. Also, the study involves a comparison of dwell times, specifically focusing on different fare collection systems, including ticket fare, prepaid card, and cash payment. Additionally, the researcher categorizes passengers into three age groups: schoolchildren (under 18), adults (18-64), and seniors (65+). This categorization enables the estimation of distinct boarding and alighting periods for each age group, providing insights into the varying time dynamics associated with different passenger demographics.

## 2.2 Platform crowding level

In a study (Ling Khoo, 2013), dwell time data was classified into two categories. If the average number of passengers waiting at a train station was fewer than 15 people, the platform was considered to have less crowded dwell time. Conversely, if the average number of waiting passengers exceeded 15 people, the platform was labeled as "congested." The study highlighted that overcrowded boarding passengers could disrupt smooth alighting operations, leading to a reduction in passenger maneuverability on crowded platforms. Crowded platforms, as mentioned in (Jaiswal et al., 2010a), could create visibility challenges for passengers trying to discern oncoming buses clearly. This reduced visibility may contribute to slower reaction times among passengers, potentially affecting the efficiency of boarding or alighting processes. The outcome displayed as platform crowing level has the highest impact on dwell duration. The length of time passengers wait at bus stops depends on how frequently buses arrive there(Jaiswal et al., 2010b) .The amount of time passengers must wait for buses is reduced by reducing their frequency. It is measurable by observation surveys and has an impact on the amount of people disembarking at stops(Prathibaa and Gunasekaran, 2016). In order to board, exit, and decide where to stand or sit, passengers must be able to circulate inside the bus freely. However, this is impossible when there is crowding. Studies have shown that, (Cetin and Ilicali 2022; Zhang and Bai 2015)whether linearly or non-linearly, dwell times increase and passenger processing rates decline as a bus becomes fuller(Katz and Garrown, 2017) . In the case of a crowded bus, there is a greater likelihood of passengers hanging out the door. This includes both the average number of people in this conditioned state and the percentage of stops where such a situation occurs. It's important to note that the latter is conditional in that it specifically addresses stops where at least one passenger is hanging out the door. This condition is linked to higher load factors, indicating a greater number of passengers waiting at the door. According to (Cristoforo et al 2017) it is recommended to conduct experiments to explore the correlation between platform density and the time taken for boarding and alighting. This is because the speed of passengers tends to decrease as the available circulation space within the vehicle diminishes.

### 2.2.1 Fare collection system

Two types of payment system(Yook & Heaslip, 2014a),(Perrotta, 2013), cash/card system and manual system used by the bus operators. (Ling Khoo 2013), Demonstrates that the dwell time for the conductor system (Cervero, 1981; “Efficiency and Equity Implications of Transit Fare Policies,” 1983)is less on average than it is for the cash/card method(Cools et al., 2018).This is so because there is just one driver and no assistant on board the bus with the cash/card system. He oversees the entrance's payment mechanism. Because the duration of payments (Smith, 2009) depends on how each driver operates the system(Fayyaz., and Porter 2016). When compared to payment by card, cash transactions cause delays that are about 2.3 times greater.

Study found (Fernandez & Tyler, 2005) by ticketing system has an enormous effect on marginal boarding time. Fare collection practices, and one person versus two-person operations.

### 2.2.2 Passenger surveying time and date

According to the study conducted by (Zhang and Bai, 2015), the research focused on analyzing bus delay times at two distinct bus stations. The data collection took place between September 15, 2014, and October 20, covering both morning sessions (7:30-10:30) and afternoon sessions (15:30-18:30), with the remaining periods classified as non-peak. Station A featured a bus bay characterized by a 50-meter length and three parking spaces. In contrast, Station B had a linear stop with similar dimensions. Notably, during the final survey, Station A amassed 1100 data points in flat peak hours and 439 during peak hours. Conversely, Station B yielded 325 data points in flat peak hours and 309 during peak hours. It is crucial to highlight that the study's emphasis on these two bus stations aimed to provide insights into the variations in bus delay times under different station configurations and spatial layouts. The meticulous data collection during both peak and non-peak hours contributes to a comprehensive understanding of the factors influencing bus delays in the specified contexts. Likewise, as articulated by a scholar (Kim, 2007a) three regular bus routes operate in the area, each having varying service frequencies, or bus headways, ranging from 6 minutes to 40 minutes, depending on the time of day. The collected data encompassed information on alighting/boarding passengers, passenger loads, and bus dwell times. Observers stationed at each bus stop utilized digital timers to gather this data. The data collection occurred during the mornings, specifically between 7:00 AM and 10:00 AM, spanning five weekdays in 2003. Over the entire data collection period, a total of 217 buses were observed. The study by (Naiya Ibrahim and Ismail, 2013),both traffic directions (to and from) on all routes, examining various times—peak and off-peak periods during both morning and afternoon. Data collection occurred exclusively on weekdays to capture heightened activities compared to weekends. Stop-time intervals were subsequently derived from the collected data across all routes under investigation. Data collection requirements were categorized into on-spot data from curbside stops and bay-style stops, in morning rush hours (7:00–9:00) and noon hours (12:00–14:00). Nine buses' data were utilized for delay analysis, while the remaining data served to validate the results.

### 2.2.3 Ticket varieties

Single-trip tickets for passengers are predominantly offered by Anbessa, Sheger, bus enterprise. These tickets come pre-printed with designated fare amounts for each route, featuring batch and serial numbers for tracking purposes. To enhance revenue protection and discourage ticket reuse, outbound and return trips employ tickets of distinct colors. The conductor completes the waybill for each journey, ensuring accurate passenger count allocation. The sale of tickets is managed by a stationary conductor positioned directly in front of the bus's main gate (Fernandez & Zegers, 2010).

#### 2.2.3.1 Fare structure

Flat and graded fare structures are two types of fare structures used in public transit(Bandegani & Akbarzadeh, 2016). Based on variables including distance, time, quality, cost, region (zone), and client, flat fares can be converted into variable fares. A distance-based structure is one that is based on the distance travelled(Chen et al., 2021; Yook & Heaslip, 2014b). A time-based fare structure bases the charge amount on the length of the trip or whether it occurs during peak or off-peak hours(Smith, 2009). With cost-based pricing, the amount of the price is determined in accordance with the expenses the system incurs to provide the service(Jansson & Angell, 2012; Zhou et al., 2019). In a zonal-based fare system, the distance across zonal boundaries is used to calculate the fare. In a customer-based price structure, the fare is determined by the user's attributes, including age and economic standing.

### 2.2.4 Delay

Delay, as confirmed by author (Liu & Jian, 2019b) stands as a crucial metric for examining the operational attributes and service quality of a signalized intersection. According to (Sahraei & A, 2018) It is commonly defined as the surplus time expended at a transportation facility when juxtaposed with a reference value. Numerous models have been established to evaluate it. Delay often refers to the difference between the ideal time and the actual time when traversing a road section, such as an intersection. Here, the ideal time corresponds to the travel time under ideal conditions. Similarly, the actual time means the travel time under real conditions. A study( Zhang et al., 2018a) investigated the impact of bus stop designs on the operations of bicycles, vehicles, and buses, revealing that the bus dwelling process influenced the activities of diverse road users. The bus stop serves buses (Cortés et al., 2010a) providing a service that involves a specific duration. With an escalation in the volume of buses seeking to utilize the stop within a designated timeframe, a queue is formed. As mentioned in (Bian et al., 2019)bus stops often experience queues that result in significant delays. buses frequently pass other vehicles during curbside stops, with overtaking maneuvers categorized as either "overtaking in" or "overtaking out." Permitting overtaking poses challenges in analyzing bus lines, as it contradicts the first-in, first-out principle, affecting both bus stop capacity and average waiting times. It is crucial to comprehend the repercussions of overtaking maneuvers on bus stop operations, as service time is also contingent on passenger arrivals at the bus stop. The capacity of a bus stop is quantified by the number of buses that can enter the stop area in a given period, typically an hour. The operational stages of a bus stop, outlined in(Fernandez & Tyler, 2005) includes: At declaration time, an empty berth eagerly awaits the arrival of a bus. Upon its arrival, the bus comes to a stop in the berth, immediately opening its doors to allow passengers to embark and disembark. Once all passengers have boarded and alighted, the bus closes its doors and is ready for departure. The acceleration time, or the time it takes to exit the stop, is then determined by the speed at which the bus resumes its journey after leaving the berth. The bus checks if the exit path is clear; otherwise, it waits for an available gap in the traffic stream. Throughout these stages, other buses may arrive but must queue behind the stopped bus. In study (Rosenblum et al., 2015) three metrics vehicle delay, overall passenger delay, and system reliability are employed to assess delay. These metrics are amalgamated into a unified composite rating system for each route segment, aiding in the identification of segments where buses encounter the greatest delays. Also introduces a method for calculating bus delay by segment and presents findings for a specific analyzed route. However, it is noteworthy that the paper does not establish a clear correlation between delay at stops and the analysis of delay within a single segment, questioning the validity of analyzing delay at just one segment.

## 2.3 Stop location

Decisions regarding the location of bus stops(Furth & Rahbee, 2000) have significant societal implications, centering on a trade-off between increased stop frequency and the associated costs and benefits. The key impacts include:

- Riding time: Increased stop frequency leads to longer time spent by passengers inside the vehicle as they board and alight more frequently.
- Operating cost: More frequent stops result in a greater cycle time, subsequently raising the operating cost of the route.
- Walking time: Higher stop frequency reduces walking time for passengers to access the route.

Additionally, a fourth potential impact is that increased spacing between stops might lead to longer walking distances, potentially resulting in a loss of passengers.

(Prathapan & Rajamma, 2018) , endeavors to assess how far side (downstream) and near side (upstream) bus stops influence saturation flow rates. The initial phase involves quantifying the impact of bus stops on saturation flow rates by analyzing approaches with bus stops adjacent to intersections. Adjustment factors, accounting for the influence of far side bus stops and near side bus stops are introduced to refine the saturation flow rate assessment. Delay it also a transit stop located on the approach side of an intersection (Cortés et al., 2010b) .

### 2.3.1 Time required for clearance

After a bus closes its doors and prepares to leave a stop, an additional duration known as clearance time ensues. During this time, the loading area is temporarily unavailable for the next bus. Part of this period is fixed and involves the time for the bus to initiate, move its length, and clear the stop. In the case of on-line stops where buses halt in the traffic lane, this constitutes the sole component of clearance time. However, for off-line stops away from traffic, an additional component contributes to clearance time. Roadway agencies often favor off-line stops to prevent traffic delays and reduce the risk of rear-end collisions between other vehicles and stationary buses. The choice between on-line and off-line stops also relates to the challenge of re-entry delay time He examined the components of clearance time, with total clearance times ranging from 9 to 20 seconds. The time required for a bus to start up and travel its own length to clear a stop is about 10 seconds(TRB, 2003).

## 2.4 Bus stop space

Study suggested in (Li & Bertini, 2009a)ideal bus stop spacing is theoretically 1,200 feet, in contrast to the existing 950 feet. The report delves into trade-offs and provides an approximation of potential transit operating cost savings associated with the optimized spacing. Information on stop time interval characteristics can be used for estimation of bus stops spacing as well as provision of reasonable walking distance to and from bus stop, and minimize the number of permissible bus stops along a route so as to reduce the frequencies at which a bus is required to merge into and exit from traffic stream. Several studies were conducted on bus stops spacing using different approaches in various parts of the world(Cortés et al., 2010b), a dynamic programming and geographic modeling was used to estimate optimal bus stop locations on bus routes in which an average bus stops spacing of 400 m was established, another scholar(Li & Bertini, 2009b; Ling et al., 1989)estimated a bus stops spacing of 1222 ft (372.5 m).bus stops spacing has a considerable effect on passenger’s travel time for both in-vehicle travel time and distance on foot to and from bus stop(X. Zhang et al., 2009)When the spacing between bus stops increases, the distance on foot to and from bus stops also increases; however, the in-vehicle travel time becomes shorter because the vehicles have fewer locations to stop. If the distance between consecutive stops is shortened, access time (a distance on foot to and from bus stops) to them is correspondingly reduced, but the buses have to stop in more locations for passengers to board or alight with resulting increase in overall travel time. Studies (Chien et al., 2003; Kuah & Perl, 1990; Li & Bertini, 2008) have affirmed the drawbacks of having an excessive number of bus stops and closely spaced terminals on urban routes. Placing bus stops in close proximity to each other leads to inefficiencies in travel time and space utilization. It is crucial to understand the relationship between stop density and accessibility, considering the arrival rate of passengers at a given stop.

### 2.5 Bus stop type

In (Ke & Chen, 2016), it is mentioned that bus stops can be divided into curbside bus stops and bus bays. Curbside bus stops are the most prevalent and straightforward, situated alongside the shoulder lane and only needing a sign to mark the stop. Their uncomplicated design makes them cost-effective and easy to install or relocate, facilitating convenient access for bus drivers with minimal disruption to bus schedules. However, these stops might hinder traffic flow for cars and could lead drivers to make unsafe lane changes in order to avoid delays behind stationary buses.

Passengers waiting on the platforms prefer walking to the stopped bus, which leads to additional walking time(Xin et al., 2015) And the study findings suggest a significant rise in average additional walking time when the number of berths at a bus stop exceeds three. Additionally, the analysis indicates that an increase in the headways between two adjacent buses results in a corresponding increase in additional walking time. In essence, these observations constitute the primary conclusions derived from the study. The distances between bus stops can have a big effect on how quickly people enter and exit. Researchers (J. Zhang et al., 2018b) have affirmed that various stop configurations exert unique impacts on road users. Specifically, bus bays are designed as dedicated spaces set apart from the regular traffic lanes and situated outside the standard roadway sections, serving the purpose of facilitating the boarding and alighting of passengers. bus bays enable uninterrupted flow of through traffic by keeping buses separate from the main road way. As it mansion in (Meng & Qu, 2013), duration buses spend at a bus bay differs from that at a curbside bus stop, primarily because of the distinct dynamics involving the bus, arriving passengers, and traffic in the shoulder lane. Once all passengers have disembarked or boarded at a bus bay, the bus promptly exits the bay to merge with traffic on the shoulder lane, if feasible. In contrast to buses at curbside stops, those at bus bays must allocate time to identify a suitable gap between successive vehicles on the shoulder lane. Simultaneously, there is the possibility of a new passenger arriving at the bus bay while the bus is seeking an appropriate gap at the exit point.

## 2.6 Design and location considerations

(TRB, 2003) indicates the numbers of loading areas should adequately sufficient to the scheduled number of buses intending to use the stop. Exceeding three loading areas at a stop may cause confusion among passengers, who might be uncertain about where to wait for a bus. This confusion can result in extended dwell times as passengers may need to walk to the rear of the bus queue for boarding. Offline bus stops (those located away from traffic flow) offer increased bus capacity compared to online stops when four or more loading areas are available while on-line bus stops provide a higher bus capacity when one or two loading areas are provided. studies have shown that bus stop always has great effect on traffic flow near the bus stop(Hu et al., 2021). Study in (J. Zhang et al., 2018c)assess the impact of various bus stop designs on the operations of adjacent traffic.

The majority of bus stop layouts can be categorized into two primary types curbside stops and layby stops. When buses pick up or drop off passengers at curbside stops, they are required to halt directly on the road, often causing disruptions to the traffic flow behind them. On the other hand, at layby stops, buses have the option to stop in a designated area beside the road, allowing the continuous flow of traffic. While there may be variations in design features within each category, classifying bus stops as either curbside or layby highlights a significant design distinction that is likely to impact the movement of passing traffic(Phillips et al., 2021). The time buses spend at stops constitutes a substantial portion of their operational time and adds to its variability. While the dwell time is closely tied to the count of passengers getting on and off, additional factors like crowding, fare type, and bus design can also play a role. These secondary factors can significantly impact the effectiveness of various strategies employed to enhance service(Milkovits, 2008).As mentioned in(X. Liu et al., 2017a),the configuration of bus stops plays a crucial role in impacting bus operations. Ineffectively designed bus stops can lead to delays, negatively impacting the overall efficiency of the system. The study results indicate that curb-side stops outperform bus bays in terms of average passenger boarding and alighting time as well as acceleration time. These findings hold operational and planning implications for transportation authorities and operators, emphasizing the need to assess bus operation performance and enhance bus stop designs for improved efficiency. Autor(Wang et al., 2016a) the placement of bus stops can notably influence the delay experienced by a bus during a stop. Therefore, a sensitivity analysis was undertaken to examine how bus stop locations impact both bus dwell time and the time lost while serving the stop. The various types of bus stop locations include near-side, far-side, and mid-block. Predicting bus dwell time and time lost while serving a stop involves estimating various components, including deceleration time, time spent serving boarding and alighting passengers, dead time, and acceleration time at the bus stop. A polynomial model that incorporates the kinematics of a particle was developed to estimate both bus acceleration and deceleration times.

### 2.6.1 Studies in bus dwell time modeling

The modeling of bus dwell time has collected considerable attention in both academic and industrial sectors. Despite this interest, there is currently no universally accepted model in place(Yang et al., 2019). bus dwell time, the period a bus stops for passenger boarding/alighting, crucially influences transit efficiency. Numerous studies model factors like passenger behavior, stop characteristics, and environmental conditions to optimize operations. Methodologies range from statistical approaches (e.g., regression analysis) to advanced techniques (e.g., machine learning) capturing dynamic passenger-system interactions. environmental factors, GPS, and real-time data integration improve dwell time predictions, contributing to efficient transit. Research strives to enhance public transportation reliability, efficiency, and urban mobility while considering diverse factors and methodologies.(Kamaruddin ,2009) the focus of the paper is on determining variables influencing travel time and developing a bus travel time prediction model. The study utilizes data collected through GPS from a regular bus system operating in rural areas with minimal congestion. Two separate models were developed for divided multiple-lane highways. The results indicate that multiple linear regressions (MLR) effectively modeled bus travel time prediction. Both models were found to be statistically significant based on the analysis of variance (ANOVA) test at a 95% confidence level. For Case 1 (Ipoh to Lumut direction), the MLR model had a mean absolute percentage error (MAPE) of 14.8%, while for Case 2 (Lumut to Ipoh direction), the MAPE was 12.1%. The small and reasonable MAPE values suggest that the models are suitable for recommending bus travel time predictions.

### 2.6.2 Weibull distribution

Study conducted in Cameroon(Kidmo Kaoga et al., 2014), involves in the exploration and comparison of five numerical methods for fitting the Weibull distribution to hourly presenting wind speed in the Maroua district of Cameroon. The five methods considered were the maximum likelihood method, the modified maximum likelihood method (MLM), the energy pattern factor method (EPF), the graphical method (GM), and the empirical method (EM). The study assesses the performance of these methods and reveals that the MLM is the most accurate model, followed by the EPF and the GM. Furthermore, in comparing the wind speed standard deviation predicted by the proposed models with the measured data, it was found that the MLM has a smaller average relative error of -3.33%, compared to -11.67% for the EPF and -8.86% for the GM. This analysis provides valuable insights into the effectiveness of these numerical methods for modeling and predicting reliable data.

Various studies justify the utilization of different methods to ascertain the parameters of the Weibull distribution function. The shape parameter of a Weibull distribution holds particular significance as it plays a crucial role in exploring and understanding the characteristics of the variable under consideration(Hussain et al., 2023).

This paper introduces and explores an adapted form of the Weibull distribution characterized by four parameters, designed to accurately represent a hazard rate function. Its relevance in the domains of lifetime and reliability lies in its capacity to model both increasing and decreasing failure rates. The newly proposed distribution encapsulates various established models, including the Weibull, extreme value, exponentiated Weibull, generalized Rayleigh, and modified Weibull distributions(Shama et al., 2023).

According to a study(Mueller & Rigdon, 2015) Weibull regression, a common assumption is that the scale parameter is a function of the predictor variables, while the shape parameter remains constant. This implies that the variability in the response variable, often related to the scale or spread of the distribution, is influenced by the predictor variables in the model. Meanwhile, the shape of the Weibull distribution, represented by the shape parameter, is assumed to be consistent across different levels of the predictors. This assumption simplifies the modeling process, allowing for a focus on how the predictors impact the spread of the distribution, while assuming a consistent shape for the underlying probability distribution.

Weibull models serve as versatile tools for describing diverse types of observed failures in components and phenomena. Widely employed in reliability and survival analysis, these Weibull-related distributions exist, providing flexibility and adaptability to various applications. This broad range of Weibull models allows researchers and analysts to tailor their approach based on the specific characteristics and requirements of the data under investigation, enhancing the utility of Weibull modeling in different fields(Lai et al., 2006).

### 2.6.3 **Survival analysis and model**

This research employs survival models to estimate bus arrival times at downstream stops and intersections. Those considers both accelerated failure time (AFT) and Cox regression-based hazard models. Which are two distinct events, namely buses arriving at bus stops and signalized intersections, are analyzed for measuring arrival times. Weibull and log-logistic distribution models are applied to estimate arrival times for each event separately. Various factors, including distance, speed, bus stop dwell time, passenger count, road gradient, intersection length, and signal details (e.g., green time, red time, cycle length), are considered as explanatory variables. The results indicate that the developed models for predicting arrival times reduce uncertainties by 10% and yield smaller uncertainties for 70% of the predictions. The mean absolute percentage error for AFT survival models is 10.04, and concludes the AFT model approach emerges as a promising method, outperforming Cox regression in predicting bus arrival times and minimizing associated uncertainties(Sharmila et al., 2020).

The study introduces accelerated failure time survival models as a method for simultaneous predictions of bus travel times on a headway-based route serving the Pennsylvania State University-University Park campus. The proposed survival models and traditional linear regression frameworks were applied to data for comparison, and while both approaches exhibited similar accuracy in point estimates, measured by root-mean-squared errors (RMSEs) and mean absolute errors (MAEs), the survival models were found to more accurately capture the uncertainty associated with predictions. Notably, survival model estimates had smaller uncertainties on average, particularly for predicted travel times of shorter durations. Tests for transferability over time indicated that the models did not overfit the dataset, validating their predictive ability with historical data. In conclusion, the survival model approach emerges as a promising method for predicting both expected bus travel times and the corresponding uncertainties associated with these travel times(Yu et al., 2017).

## 2.7 Chosen area

One study(Csiszár & Sándor, 2017) has identified four key factors that exert a significant influence on dwell times at stops, namely the specific stop, the time period, prevailing weather conditions, and the floor height of the vehicle. The duration of dwell times at stops is significantly affected by the floor height of the vehicle. Specifically, boarding and alighting processes tend to be more expeditious for vehicles with lower floor heights. For this study, consideration will be put as follows:

### 2.7.1 Based on trip demand

The bus route's stops are strategically located for data collection on stop dwell times. Operating through a congested corridor, buses become unpredictable, leading to longer wait times for passengers. The route serves economically active areas like employment centers, schools, banks, and residential districts, resulting in high demand for transportation services.

## 2.8 Door issues

The study compares manual and automatic door operation on buses. It recommends closing and opening the door only once at each stop to avoid delays caused by re-opening for various reasons, ensuring accurate data collection for the study.

### 2.8.1 Fare pavement procedure

Passengers inside the bus have various payment options, including fixed amounts, fractional coin prices, and pre-paid passes validated by the driver. Outside the bus, fares can be paid through fixed amounts or pre-paid passes, offering flexibility and streamlining the collection process for both inside and outside transactions.

### 2.8.2 People based

The study will analyze passengers' ages and the time taken for boarding and alighting. It also considers passengers with baggage and the boarding time from different seat positions - back, middle, and front.

### 2.8.3 In vehicle circulation

This study focuses on overloading, passenger boarding/alighting, and standees on buses along the route. However, it doesn't consider the influence of different bus stop designs on bus operations.

## 2.9 Institutional organization of Addis Ababa Public Transport

In Addis Ababa, there are numerous authorities and agencies that handle public transportation, both at the city and federal levels. Among this authority are:

- Addis Ababa Road and Transport Bureau (AARTB)
- Anbessa City Bus Services Enterprise (ACBE)
- Sheger Mass Transportation Service Enterprise
- Alliance Transport Service S.C (a private company)

## 2.10 Gaps in literature review

The literature review provides a comprehensive overview of existing studies on bus dwell time and passenger service time characteristics, aiming to identify research gaps and discuss how these studies have addressed them.

Historically, earlier research has primarily focused on identifying key variables that influence dwell time, while some studies have utilized these factors to develop predictive models for dwell time. These investigations have employed methods such as deterministic and simulations based on real cases or collected data from available sources, including archived Automatic Vehicle Location (AVL)/Automatic Passenger Counter (APC), and Automatic Fare Collection (AFC) data reported at the level of individual bus stops.

However, it is important to highlight that the present study adopts a unique approach to bus dwell time data collection. In contrast to prior research, this study relies on labor-intensive ride checks and video recording for data collection. The decision to use these methods stems from the absence of advanced technologies such as AVL (Automatic Vehicle Location), APC (Automatic Passenger Counter), and AFC (Automatic Fare Collection) within the scope of this study. This lack of technological infrastructure might render previous methodologies less applicable, particularly in developing countries like Ethiopia, where such advanced systems may not be readily available or functional.

Previous study focused on deterministic methods of dwell determination. Quantifying them through average or deterministic methods poses a challenge due to substantial variations and complexity, especially at bus stops characterized by high passenger volumes and diverse bus types. Establishing the likelihood of dwell time occurrences is crucial for developing a more reliable transport system.

- Impact of passenger behavior being aware of how factors like passenger flow dynamics, fare payment procedures, and boarding and alighting patterns impact bus dwell time.With the existing models, it is challenging to predict dwell times with any degree of accuracy. From a reliability perspective, the current approach is crucial to define a dwell time using statistical modeling techniques to estimate the parameters of the distribution that best describe the observed data and fit dwell time data with a theoretical distribution function. This allows for inferences about the underlying stochastic process and insights into its behavior. In order to boost accuracy, this study considers estimating the likelihood of dwell time rather than using point estimate. Most of the existing dwell time models were based on the application of linear and multiple regression approaches to the numbers of boarding and alighting passengers' effects on dwell time. However, this model may not consider all estimators accurately, so logo normal, Weibull distribution and exponential models have to be developed and considered. The current practices in passenger service time involve making judgments at individual stop types, such as bay and curve stops, without considering how the distribution of dwell time depends on different stop locations.

# CHAPTER 3 METHODOLOGY

## 3.1 Basic concepts of methodology

The study was conducted in the city of Addis Ababa, with a specific focus on pre-selected routes characterized by significant congestion and a high demand for the boarding and alighting of passengers. Notably, No previous research has been done. Before selecting the stop routes several factors related to their selection, first, the routes were chosen for their consistently good condition, unaffected by seasonal variations; then, these routes attract a substantial number of city bus services; and third, the routes traverse a diverse range of land-use areas, including residential, business, institutional, and the Central Business Center (CBC). This strategic selection aims to provide a comprehensive understanding of bus dwell time across varied urban contexts and conditions. To achieve this, the research requires a prioritized list of routes with the highest levels of excess travel time, utilizing data from the Transport Authority as a reference point. Key information, including the total number of stations, terminal details, distance coverage, types of buses and their respective numbers, as well as passenger density, was gathered from the Addis Ababa City Administration Transport Bureau (AACTB).The selected route, which distinguishes itself from others due to its unique characteristics. This road traverses residential areas characterized by high population density, accompanied by numerous business areas along the route, including major markets and a lot of roadside trading activities. Moreover, unrestricted parking is prevalent along this road. These distinctive features are anticipated to generate and attract a considerable number of trips. Consequently, a high frequency of passengers is expected to board and alight frequently along this route, resulting in shorter stop-time intervals.

## 3.2 Study description

Addis Ababa is the capital of Ethiopia. The largest city and the country's economic center, it is situated in the middle of the nation. A substantial urban center located in the Horn of Africa. Addis Ababa houses 25% of Ethiopia's population and is expected to approach nearly five million residents by 2030. It is the largest city in Ethiopia. Situated at the base of the 3,200-meter-tall Mount Entoto, Addis Ababa is home to the African Union's headquarters and the home of a wide variety of cultures and races. Living, working, and playing are all made more enjoyable and comfortable by the region's moderate climate. The city is well-known for its distinctive architecture, active nightlife, and energetic marketplaces. Numerous educational institutions and international conferences are held in the city. (Girma & Woldetensae, 2021; Kenea et al., 2017; Mohammed & Senadheera, 2022).

## 3.3 Research approach

This study endeavors to utilize a combination of quantitative and qualitative methodologies to holistically formulate a model for the reliability distribution of bus dwell time (Creswell, 2017). Moreover, statistical modeling was used to identify various bus stop-related characteristics and a comprehensive understanding of the factors influencing bus dwell time within the specific context of chosen routes in Addis Ababa City. Because the collective goal is to better understand the world in which we live and allow for cross-validation or triangulation, which involves merging two or more ideas or sets of data to analyze the same phenomenon.

### 3.3.1 Study area selection criteria

The data for this study was gathered in 2023 G.C, which serves as the reference year. The collection occurred throughout a week, focusing on three distinct buses and routes characterized by elevated trip demand and passenger density. Notably, all selected routes for the bus dwell time study were situated within Addis Ababa City. To determine the specific stops for data collection, extensive reviews of literature from various sources and an analysis of the transportation conditions in Addis Ababa City were conducted. Route selection criteria will be outlined in the following section.

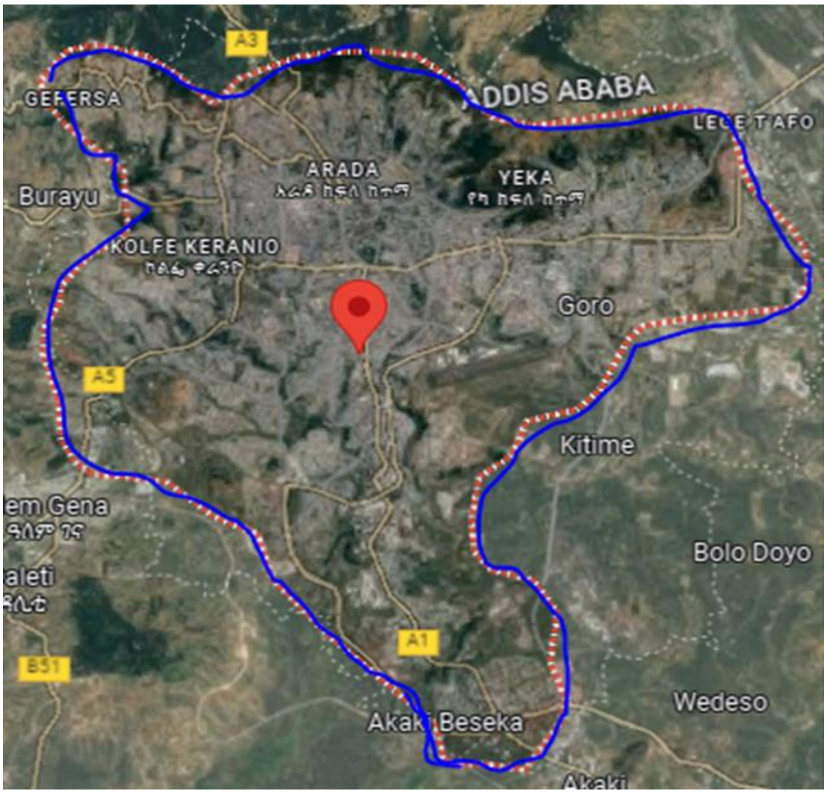


Figure 2: Map of Addis Ababa city

(Source: Google map,2023)

### 3.3.2 Bus features

Despite having identical door numbers, there are distinctions in the service doors among different bus types. Specifically, Anbessa and Sheger buses limit service exclusively to the back door, whereas Alliance buses extend service through each door. Nevertheless, this is subject to the ticketing position. Consequently, the researcher had selected to identify the service door based on the ticketing area's location, emphasizing service by bus rather than by a specific service door. Anbessa and Sheger buses feature a design with low floors and no steps at the entrance, as the front part of the vehicle is positioned at a lower height. However, despite the absence of steps at the entrance, passengers are still required to ascend into the bus. This is due to the fact that the ground level at bus stops is lower than that of the vehicles, necessitating passengers to elevate themselves for boarding.

Table 1: Characteristics of bus stop service

| Bus type | Alliance bus | Anbessa bus | Sheger bus |
|---|---|---|---|
| Payment method | Cash | Ticket outside and free -pass | Ticket outside and free pass |
| Number of active doors | Two, three | One | One |
| Ticketer position | One ticketer for each door 2,3, doors | Front window | Front window |
| Boarding door | 2,3, doors | Back door only | Back door only |
| Alighting door | 2,3, doors | Back door only | Back door only |
| Number of steps | 2-3 | Lower floor | Lower floor |

Table 2: Characteristics of surveyed buses

| Type of bus | Average number of trips/days | Door use | Total bus in the city | Manual Vs automatic door | Number of ticketer | Carrying capacity |
|---|---|---|---|---|---|---|
| Single Anbessa | Five | Having two, but the service is at the back only | 549 | Automatic | One/door | >70 pas. |
| Single Sheger | Five | Having two, bus the service is at the back only | 460 | Automatic | One/door | >70 pas. |
| Alliance/Adey Ababa/bus | Five | Have three doors and all are giving service | 68 | Automatic | Two or three | >70.pas |

Source: Addis Ababa City Transport Bureau, 2023

Dwell time as a function of following elements from the literature review, along with the route directions, was taken into consideration while choosing the study routes. Such as routes were chosen based on several criteria: higher passenger activity, various location conditions such as mid-block, far side, the types of bus stop shades were considered, categorized into three types: type one with shade and mirrors on both sides, type two with shade and seating, and type three with only shade and no mirrors or seating, linked to five terminals with at least one terminal used as a reference for departure or destination, assignment to selected buses for the study, inclusion of routes with at least one traffic congestion corridor identified by Addis Ababa City Transport Bureau, consideration of fare variation at stops for joint service routes, inclusion of interconnected routes connecting bus routes from different lines, and focus on centrality to major activities in the city, particularly targeting Transport Congestion Corridors (By et al., 2021) .

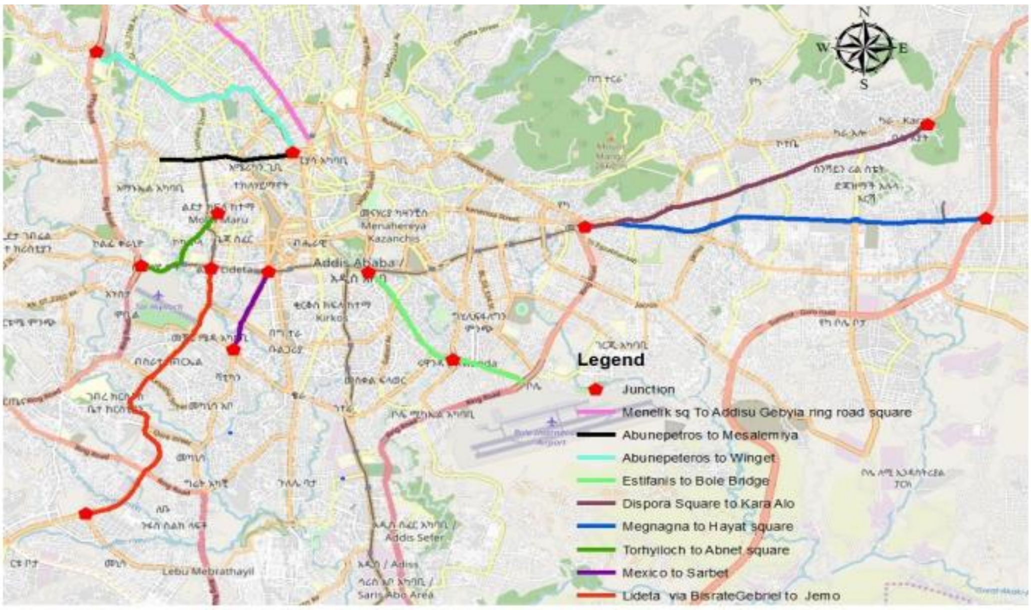


Figure 3: High traffic jam in Addis Ababa

Based on this criteria and literature reviews discussed above four routes were initially selected. To enhance the reliability of the study, data collection at each stop of these routes was systematically repeated for three day. This repetitive approach to data gathering serves the dual purpose of thorough analysis and validation, ensuring the integrity of the study findings were;

1. Kara via Megenagna to Piassa
2. Goro to Megenagna
3. Ayat via Megenagna to Mexico
4. Piassa to Winget

Although the Piassa-Winget route was initially chosen as a study route, it was subsequently excluded from data collection. This decision was made because Alliance buses were not permitted to serve on that route due to a route assignment issue with the City Transport Bureau leading to their exclusion from data collection and subsequent analysis.

Table 3: Route line and dipo checklists

| Dipo<br>Origin | Destination | Were the routes Included traffic jam | Were the routes provide joint service | Passengers density | Were three buses assigned | Terminal name destination, through | Did they have all stop type | Routes<br>Chosen |
|---|---|---|---|---|---|---|---|---|
| Arabsa | Legehar | Ayat | Yes | High | Yes | Megenagna | Yes | Ayat |
| 49 | Legehar | Ayat | Yes | High | Yes | Megenagna | Yes | to |
| Tafo | Megenagna | Ayat | Yes | High | Yes | Megenagna | Yes | Leghar |
| Abado | Piassa | Abado | Yes | High | Yes | Piassa | Yes | |
| Mishin | Megenagna | Abado | Yes | High | Yes | Megenagna | Yes | Kara |
| Kara | Piassa | Abado | Yes | High | Yes | Piassa | Yes | To |
| Abado | Mexico | Abado | No | High | Yes | Mexico | Yes | Piassa |
| Koye-fiche | Megenagna | Jakros | Yes | High | High | Megenagna | Yes | Megenagna |
| Pisa | Koye-fiche | Jakros | Yes | High | High | Megenagna | Yes | To |
| Kaliti | Megenagna | Jakros | Yes | High | High | Megenagna | Yes | Goro |
| Tuludimitu | Megenagna | Jakros | Yes | High | High | Megenagna | Yes | |
| Saris | Piasa | Sarbet | Yes | High | Yes | Leghar | Yes | Not |
| Kaliti | Piasa | Sabert | Yes | High | No | Leghar | Yes | chosen |
| Piasa | Winget | Winget | Yes | High | No | Piasa | Yes | |
| Piasa | Addis sefer | Winget | Yes | High | No | Piasa | Yes | Piasa |
| Piasa | Birchiko | Winget | Yes | High | No | Piasa | Yes | to |
| Piasa | Sansusi | Winget | Yes | High | No | Piasa | Yes | Winget |
| Piasa | Dire Roca | Winget | Yes | High | No | Piasa | Yes | |
| Shiro meda | Bole | Estifanos | Yes | High | No | Shiromeda | Yes | |
| 4 kilos | Bole | Estifanos | Yes | High | No | Shiromeda | Yes | Not chosen |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Pisa to | Bole | Estifanos | Yes | High | No | Piasa | Yes | |
| Adisu gebeya | Bole | Estifanos | Yes | High | Yes | 6kilo | Yes | Not chosen |
| Ayer Tena | Piasa | Mexico | Yes | High | Yes | Mexico | Yes | Not chosen |
| Piasa | Betel | Mexico | Yes | High | No | Mexico | Yes | Not chosen |
| Piasa | Torhyiloch | Mexico | Yes | High | No | Mexico | Yes | Not chosen |
| Piasa | Abenet | Abenet | Yes | High | No | Abenet | Yes | Not chosen |

Source: Addis Ababa Transport Bureau, 2023

Table 4: Route dipo and chosen lines data

| Dipo | Megenagna | | |
|---|---|---|---|
| Routes lines | | | Chosen route – 1 Chosen |
| Megenagna | | Ayat | Ayat to Megenagna and Mexico |
| Megenagna | | 49 mazoriya | |
| Megenagna | | Arabsa | |
| Routes lines | | | Chosen route – 2 Chosen |
| Megenagna | | Tafo | From Megenagna to Piasa and Kara to Megenagna |
| Megenagna | | Mishin | |
| Abado | | Piasa | |
| Megenagna | | Abado | |
| Merkato | | Tafo | |
| Legedade | | Piassa | |
| Routes lines | | | Chosen route – 3 Chosen |
| Megenagna | | Mexico | No chosen |
| Ferensi | | Mexico | Megenagna to Goro |
| Megenagna | | Goro | |
| Dipo | kaliti | | |
| Saris | | Piassa | Not chosen |
| Kaliti | | Piasa | |
| Piasa | | Winget | No chosen |
| Pisa | | Sansusi | |

| | | | |
|---|---|---|---|
| Piasa | | Birchiko | |
| Piasa | | Addis sefer | |
| Route line | | | Not chosen |
| Piasa | | Bole | |
| Shiromeda | | Bole | |
| Arat kilo | | Bole | |
| Adiso-gebeya | | Bole | |
| Autobistera | | Kasanchis | |
| Ferensi | | Mexico | No chosen |
| Dipo | Mekanisa | | Route line chosen |
| Alembank | | Piasa | |
| Ayirtena | | Autobistera | |
| Mexico | | Torhyiloch | |
| Alembank | | Mexico | Not chosen |

Source: Addis Ababa City Transport Bureau,2023

As indicated in tables 3 and 4, considering the factors discussed above, only three routes, namely Ayat to Leghar, Kara to Megenagna and Goro to Megenagna were selected for data collection further analysis. The rout map will be shown in the next section.

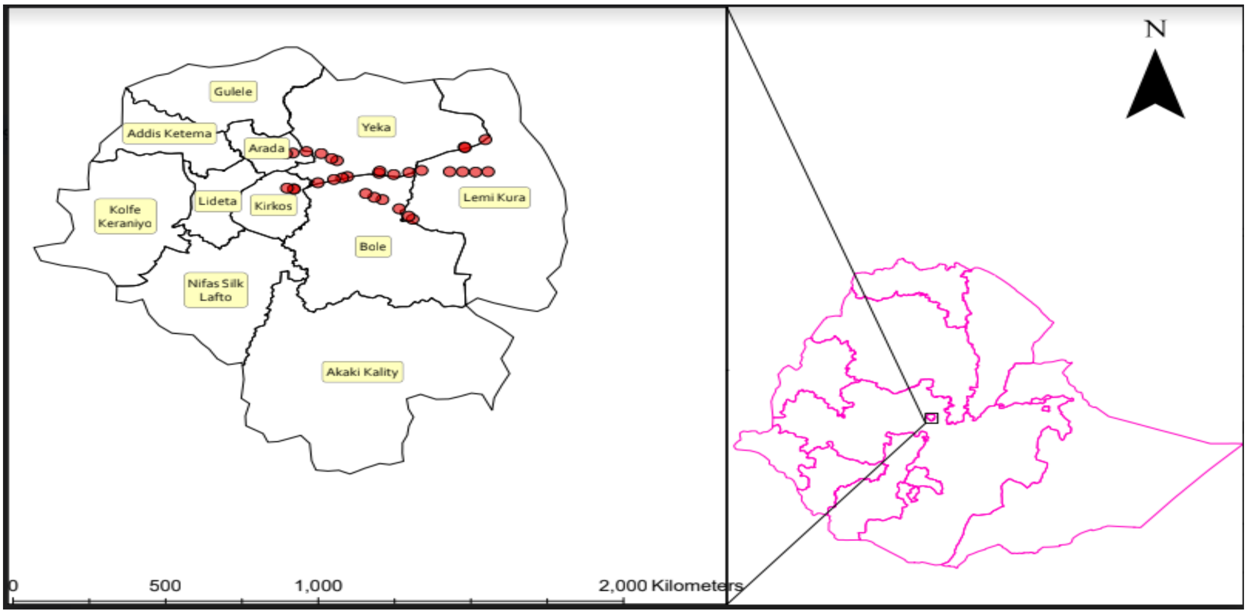


Figure 3: Study route line

Source: Arch GIS,2023

As it shown in figures 3, the selected route is highlighted by red circle color. Both of the study's stop locations were chosen along this route.

### 3.4 Sample size and sampling technique

The target population comprises of this study encompasses bus stops situated along the major routes within Addis Ababa City, as officially identified by relevant authorities. The dataset was derived from three distinct public bus groups. Random stratified sampling is a method of sampling that involves dividing a population into smaller subgroups, known as strata, which are distinct and non-overlapping. These strata are based on specific characteristics or criteria relevant to the study. Once the population is stratified, random samples are taken from each stratum (Oladele et al., 2021), could therefore be considered suitable for determining an appropriate sample size (Pratiwi et al., 2022). Researchers run evaluations on samples that was selected from a larger population while designing an evaluation and establishments of qualitative data, the researcher determine the number of participants to include in the sample (Mohiuddin et al., 2022; Najafi et al., 2022)(Sarabestany, 2016).

Table 5: Literature's how different scholars sampling dwell time data

| Autor's | Numbers of stop | Sampling size |
|---|---|---|
| (Phillips et al., 2021) | The number of data points used for analysis was 12 months x 2 days per month x 2 trips per day = 48 trips per year. | Highest, peak period, mid-day (11:00-15:00) |
| (Z. Liu & Jian, 2019b) | 300 records were collected,180 boarding processes and 120 alighting 24 process | 20 Variables 15 runs were performed for the boarding process and 20 for the 23 alighting one |
| (Fernandez & Tyler, 2005) | Covers total of 25Km and on two buses within three areas of Sydney. | 1604 numbers of observation |
| (S. Chen et al., 2013) | 79 stops and three routes in total | 163 samples on curbside stops and 125 samples on bay-style stops |
| (Milkovits, 2008) | 60 stops | Total of 1783 recorded were taken by him 10 data at one stop for three times |
| (X. Liu et al., 2017b) | 11 stops | 176 observations, for two day in the peak of week day and two days for weekend day |
| (Ling KHOO, 2013) | 89 stops | 18,957 observations from 128-week day and from 4900 runs |

Table 6: Sampling size table

| Location | | Type of stop | | | Population | Number of proportional samples | |
|---|---|---|---|---|---|---|---|
| Departing | Arriving | Near | Far | Mid | Far+Mid | Number of Far sides | Number of Mid-Block |
| Ayat | Leghar | 4 | 4 | 9 | 13 | 3 | 9 |
| Piasa | Kara | 4 | 6 | 8 | 14 | 6 | 8 |
| Megenagna | Goro | 3 | 3 | 4 | 7 | 3 | 4 |
| Sample size = 34/ (1+34*(0.05*0.05) | | | | Sum of Po | 13+14+7=34 | 11 | 21 |

n = Sample size N = population size e = precision or error limit at 95% confidence interval.

n = $N/(1 + N(e * e))$

Yamane's formula = N/(1+N(e*e)    F1=4/(1+4(0.05*0.05)) =3.96 = 4

M1=9/ (1+9(0.05*0.05) = 8.80= 9

(0.05*0.05*32)+1= 1.08, 34/1.08 = 31.3364=32 = n

## 3.5 Study variables

In this study both dependent and independent variables were used.

### 3.5.1 Dependent variables

- ✓ Bus dwell time at stop

### 3.5.2 Independent variables

The variables considered study encompass deceleration time, service time (from door opening to door closing), bus type, passenger characteristics (age, body size) and factors related to friction effects. The specific elements have to be discussed in the next table 7.

Table 7: Descriptions of variables

| Variables | Description |
|---|---|
| Deceleration time | Starting from when the bus driver activates the right turn signal pointer light, the bus waits until it reaches the berth, which may be blocked by the crowding effects of passengers and other vehicles. The bus remains in this state until it fully stops to open the door. |
| Door opening time | Time to open door. |
| Exact fare | When the ticket price will be fixed (if not odd penny). |
| Odd-penny /change fare | A single coin or token used for payment, searching coin, and evaluated by the ticket seller and the passenger, resembling a coin issued for use. |
| Free pass service | Time required to steeped in bus floor who have free pass ID. |
| Any Contact with ticketer | Confusion of the bus destination, fare disputes, and price inquiries (no service time during ticketing time) Coin search considered by the ticket seller and the passenger |
| Alighting time | A time from the door fully opened ended when the last alighting rider stepped off the bus. |
| Boarding time | The final rider to get off the bus marks the beginning of the boarding period. It begins when the passenger enters the bus and ends until the driver closes the door or the bus moves. It also includes the time it takes to go some distance from the thicket window to the boarding door. |
| Re-boarding passengers | Number of passenger alighting and re-entering before their destination in order to create free space for alighting passengers. |
| Number of boarding | Total number of people who board a bus at a certain stop during specific time period. |
| Number of alighting | Number of riders disembarking from the bus at a specific stop. |
| Closing Door | The time that door closed as soon as the last boarding passenger stepped inside the bus. |
| Acceleration time | The time required to rejoin the downstream lane. |

The variables in this study encompass a range of factors influenced by local conditions and other unquantifiable elements. These include passenger types, physical characteristics of passengers, passenger preferences, luggage amount, speed of alighting passengers, age, crowding conditions at the bus stop classified as less crowded if fewer than 15 passengers were waiting and congested if more than 15 passengers were waiting and more (Ling Khoo, 2013). The researcher endeavored to collect information on these variable characteristics through the use of questionnaires and observation conducted during passenger travel.

## 3.6 Data collection procedures

The researcher used for manual field data collection at bus stops due to the absence of readily available Automatic Passenger Count (APC), Automatic Vehicle Location (AVL) data. Before initiating data collection, field technicians had a two-day training period. Field observations, involving data collection at various bus stops in Addis Ababa City. There have been many of data collection tools, but each of them depends on the resource availability, investigation reliability and consistency. The regular bus services operating time data (afternoon and morning) peak were considered for this work. To collect data, video recording and direct transcription onto paper sheets were employed for a pre-selected bus type at stops during both morning and afternoon peak periods. This method was chosen to account for potential differences in peak times between the morning and afternoon. Recognizing directional variations in population density, a data collection technique that considers directionality was also implemented. bus stops were categorized into three sections: the upstream section (where the bus initiates deceleration), the bus stop section (where passengers embark and disembark), and the downstream section (where the bus begins acceleration). During a pilot survey, video data revealed that most bus maneuvers occurred within a 10-meter radius near the stop, influencing the determination of the lengths of both the upstream and downstream sections (set at 10 meters each) and an average of 25 meters for the bus stop section. The average length of each investigated stop segment was 45 meters. It's essential to note that buses could potentially stop anywhere for passenger boarding and alighting, but for this study, only buses stopping at designated stations within the specified range were considered. Buses stopping outside the designated berths were subject to protection by law enforcement and traffic management adjustments.

### 3.6.1 Date and days for data recording

Two difference data type were collected such as quantitative data from bus stops and qualitative data from passengers. Video recording tool for bus dwell at stop analysis were held from February 20 to March 12, 2023. In this study, data for analysis was collected during peak morning (12:30-3:30) A.M, and afternoon (10:00-1:30) P.M. as identified by the Addis Ababa City Traffic Agency. For validation purpose data collection were repeated for three-days in each stop and time frame and finally the average was applied to determination of dwell time study. The number of standees inside the bus were not counted during data collection. Since buses were loaded over 70 passengers which was greater than the maximum capacity of buses standardized by Addis Ababa City Transport Authority and bus manufacturing company.

### 3.6.2 Numerical data collection techniques from bus stop

The researcher employed a specific procedure to gather data for this study. Initially, a purposive sampling technique was utilized to select three types of buses. The rationale behind using purposive sampling is to focus on common characteristics that are most relevant to the research. The selection of these buses was based on buses operate on same origin-destination, varying in population density, bus stop characteristics, service frequency, and similar features, structures, prices, and carrying capacities.

By considering the criteria mentioned before, Anbessa, Alliance, and Sheger Buses were selected. Subsequently, the following general data collection procedures were implemented.

- ✓ Identification of routes through pilot surveys to gather information on predetermined bus stops.
- ✓ Prior to the final phase, preparation of essential tools for data collection, including a red pen, sheets, a stopwatch, and two video recording phones. Ethical approval was also obtained from the relevant body.
- ✓ Preparation of two data collectors, designated as Person A & B, and one assistant for coding purposes.
- ✓ Data collectors performed tasks according to the prepared format during field observations.
- ✓ Person A collected information related to fare, including exact and odd penny, boarding time, and any idle time.
- ✓ Person B gathered door opening and closing times, the number of free passes and re-boarding passengers, as well as the number of boarding and alighting passengers.
- ✓ The data assistant recorded stop location, crowding status, stop types, bus type, number of service doors, dwell time, time to alighting per person, crowding status of the bus stop, acceleration and deceleration times, and manually reviewed registered data before coding it onto the final data collection sheet.
- ✓ Odd penny times were measured by counting individual passengers receiving change, recorded using a stopwatch, and the total time per passenger was divided to obtain odd penny passenger time.
- ✓ Collection of fare system data: Only fare outside the bus or fare on board was considered for this study. Passengers entering the bus before paying fare were regarded as free pass users.
- ✓ Identification of passengers with equal fare prices (exact fare) and those without equal fare prices (individuals waiting for the ticket collector to receive coins).
- ✓ Data collection from the back door only for Anbessa and Sheger buses, with subjective judgments made by the data collector for Alliance bus based on busy doors following with the ticketer position.
- ✓ Recording of re-boarding passengers who re-entered the bus to create free space for alighting passengers.
- ✓ Recording of dead time, which is time neither spent boarding nor alighting, occurring after closing the bus door, during fare disputes, or contact with the ticket collector.
- ✓ Alighting time was measured from the complete stop of the bus, starting when the door was opened earlier, and ending when the last alighting rider stepped off the bus.
- ✓ Boarding time was measured from the last alighting rider stepping off the bus, concluding with either the driver closing the door or the bus starting to move. The duration of alighting time commenced when the last passenger disembarked from the bus and concluded at the earliest instance of either, the driver closing the door, or the bus initiating movement.
- ✓ Finally, using a mobile GPS app, latitude, longitude, and elevations of each stop were recorded to develop a route map.

### 3.6.3 Qualitative data collection procedures

This is particularly important as it enables the researcher to comprehend passengers' beliefs, experiences, and perspectives to receive things their behavior and dwell habits that influence on total traveling time. For this purpose, the data collection method employed was one-on-one interviews, chosen for its ability to provide a more personal approach to data collection a preference often favored by qualitative researchers due to its depth. While interviews are more time-intensive compared to surveys, they offer a richer understanding of individuals' perspectives. For this study, the researchers utilized the Kobo Toolbox version 2022.4.4 application to collect qualitative data. A total of thirty-two questions were formulated and incorporated into an Excel spreadsheet. These research questions were primarily designed to address the objectives of the dwell time study and were informed by insights from various previous studies. Upon connecting this application to Moto Android 11 phone, data were gathered from passengers traveling on seven different bus routes. Initially, a test of the tool's performance was conducted on 26 passengers, which proved to be successful. To prevent respondent redundancy and enhance the diversity of perspectives, the researcher selected different locations. The target sample area included passengers across various age groups and educational backgrounds.

### 3.6.4 Source of research data

The researcher utilized a combination of primary and secondary data sources to obtain current and factual information for the study.

#### 3.6.4.1 Primary data

These primary data sources significantly contributed to the depth of the study by providing firsthand and up-to-date insights into various aspects. Which encompassed the number of bus stops at each route, arrival and departure times of buses at stop points, and the location of stop points categorized as bus stations, bus stops, or non-bus stop locations. Additionally, data on fare types (cash, ticket, add penny, and exact fare), the number of alighting and boarding passengers, and the types of stop locations, whether they were far side or mid-block stops, were recorded. Origin-destination names of routes (route lines), the type of bus, and numerical independent variables were also included.

### 3.6.5 Secondary data

Secondary sources played a crucial role in supporting the primary data collection process by providing essential background information and enhancing the overall understanding of the research context. They also facilitated the collection of primary data by supplying key details such as the total capacity of each selected bus, the number of passenger seats, and information extracted from Addis Ababa City Infrastructure and Design files. Additionally, these sources offered insights into the number of bus stops, distances between them, and layout arrangements, as well as references to the revised road network of Addis Ababa road segments. Insights from the Highway Capacity Manual (HCM 2010) further enriched the understanding of transportation infrastructure and capacity within the study area.

## 3.7 Data preparation

Data has been grouped into homogeneous categories in order to analyses behavior of dwell time. Following is a summary of the initial data adjustments made to exclude records that misleads dwell time.

Table 8: Data preparation

| Item | Action | Reasons | Code |
|---|---|---|---|
| Days of the week | Used week days | Patterns of passenger activity differ between weekdays and non-weekdays. For this analysis, only weekdays were considered due to their higher passenger flow, and it was preferable to maintain homogeneity in the data. These weekdays also represented normal conditions and suitable weather conditions. | Week days |
| Focused stops | Conducting observations exclusively on mid-block and far-side locations | Determining dwell time for starting and terminating stops is challenging as they lack specific arrival or departure times. Additionally, excessive delays can result in overestimation. | Far, Mid-block, in between start and ending stops. |
| In side ticket | Free pass service | During peak hours and busy stops the ticketer allowed to getting on the passengers before getting fare outside the bus, in this cause the ticketer consider these passengers as a free pass. | Free pass |
| Odd penny | No fare time | In the process of fare collection, the ticket conductor looks for coins to provide change to a passenger. No ticket service is documented during this odd penny time. If multiple passengers with odd pennies are present, the total fare time is calculated as the sum of each individual time, which is then divided by the number of passengers to obtain the fare time per passenger. | Odd penny |
| Stop Area | Use 45 meter only | Given that bus stops lack a defined berth, the researchers consider the acceleration and deceleration distances of 10 meters before and after the stop, as well as a 45-meter service berth at the stop (TCQSM, 2017) | Berth number |
| Bus door | Use busy door only | The Alliance bus is equipped with three doors, but for the purposes of this study, only the busy doors where significant activities took place were taken into consideration. The data collector made critical | busy door |

| | | | |
|---|---|---|---|
| | | observations to select these busy doors. Specifically, doors where major activities such as boarding and alighting occurred were chosen, and the decisions were made by the data collector during the random movements of passengers. | |
| Dwell time | Value of dwell time | The analysis focused on the dependent variable, which is the duration between the initial door opening and the final door closing, constituting the passenger dwell time. If the doors are never opened, even when the bus stops, this variable returns 0. | DT |

## 3.8 Data processing and analysis

Following the collection of data from both primary and secondary sources, employing a mixed research methodology (Israel, 1992; Creswell, 2017), a combination observation of data pattern on their completeness and statistical software, was utilized to assess consistency, and accuracy of the dataset. Internal consistency was evaluated using Cronbach's alpha, a statistic derived from the pairwise correlations between items.

The analysis was bifurcated into two main sections: qualitative and quantitative data analysis. In the first section, descriptive statistics analysis for qualitative data (including percentages, means, medians, frequencies, and ratios), the coefficient of variation (CV), and statistical tests such as ANOVA (Analysis of Variance) were presented. Also, some graphical techniques were employed to examine dwell time patterns. Moving on to the second section, a regression model was utilized for raw and Weibull-transformed distribution analysis to ascertain the shape and scale parameters of the factor.

### 3.8.1 Quantitative dwell time data analysis

The methodology for the quantitative analysis cover two sections, this were descriptive statistics analysis of variance, hypothesis test in one section while in the second section part developing a statistical model for both classical and Weibull distribution data and comparing the two model which is being more essential for the next dwell time determination. Parameters such as CDF, PDF, H(t), S(t) values will calculated using following formula.

$CDf\ = 1 - e\hat{}(\vdash - (t/\eta)\hat{}\beta)\ where, t \geq 0, \beta > 0$……. Cumulative distribution function…i

$PDf = \ (\beta(t)\hat{}(\beta - 1))/\eta\hat{}\beta\ \ e\hat{}(-(t/\eta\dashv)\hat{}\beta\ )$…… ... Probability density function…….. ii

$H(t) = \ (\beta(t)\hat{}(\beta - 1))/\eta\hat{}\beta\ \ where, t \geq 0, \beta > 0$……… Failure function ……………… iii

$R(t) = e\hat{}(-(t/\eta\dashv)\hat{}\beta)$ where, Pr $(t \geq 0, \beta > 0)$…… .... Survival function…………………iv

where;

- ✓ CDF Weibull cumulative distribution function
- ✓ PDF Probability density function
- ✓ R(t) Reliability function

- ✓ H(t) hazard failure
- ✓ t is the random variable of dwell time
- ✓ η is the scale parameter
- ✓ β is the shape parameter

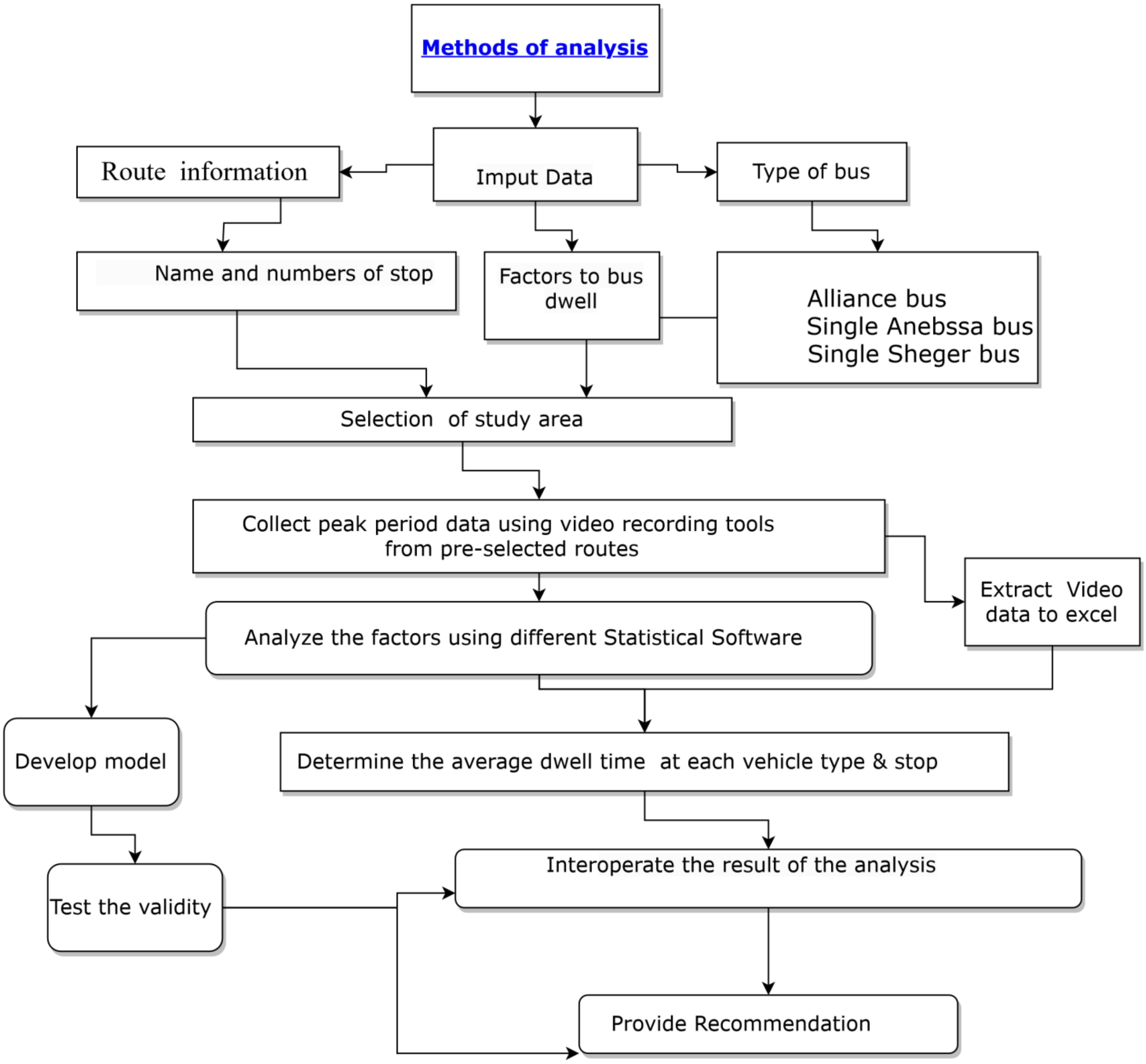


Figure 4: Methods of analysis for numerical data

#### 3.8.1.1 Analysis the effect of different contributing factors on dwell time at stop

A statistical hypothesis test was performed to assess whether dwell variations in traffic flow conditions.

**Null Hypothesis (H0)**: No statistically significant variation is present in dwell time during the day's peak periods (morning peak, afternoon peak).

**Alternative Hypothesis (H1):** There is a statistically significant difference in dwell time between the morning peak and afternoon peak periods.

**Null Hypothesis (H0):** No statistically significant variation is present in dwell time between bus types

**Alternative Hypothesis (H1):** There is statistically significant variation present in dwell time between bus types.

**Null Hypothesis (H0):** No statistically significant variation was present in dwell time between stop types (Mid-block and Far side).

**Alternative Hypothesis (H1):** There is statistically significant variation present in dwell time between stop types (Mid-block and Far side).

**Null Hypothesis (H0):** The bus dwell time follows a Weibull reliability distribution.

**Alternative Hypothesis (H1**: The bus dwell time does not follow a Weibull reliability distribution.

### 3.8.2 Analysis the effects of contribution factors on dwell time

Dwell time variations among bus types (Single Anbessa, Single Sheger, Alliance) were represented as explanatory variables with codes 0, 1, and 2, respectively, for hypothesis testing. The separation of the three bus types was carried out using Minitab version 20 and validated with IBM SPSS Statistics Version 25.

Table 9: One-way ANOVA test for dwell time on bus type

| Source | DF | Adj SS | Adj MS | F-Value | P-value |
|---|---|---|---|---|---|
| Bus type | 2 | 5331 | 2665.6 | 14.23 | 0.000 |
| Error | 189 | 35404 | 187.3 | | |
| Total | 191 | 40735 | | | |

Source: Minitab output, 2023

Table 10: Mean dwell time of bus type

| Bus type | N | Mean | Std. Error | 95% CI | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| Anbessa | 64 | 60.53 | 13.9 | 57.16 | 63.91 |
| Sheger | 64 | 62.48 | 11.98 | 59.11 | 65.86 |
| Alliance | 64 | 72.56 | 15.01 | 69.18 | 75.93 |
| Pooled St. Dev = 13.6865 | | | | | |

Source: Minitab output, 2023

As presented in table 9, the degrees of freedom (DF) associated with each source of variation are presented. Bus type has observed to have 2 degrees of freedom, while the error term has 189 degrees of freedom, resulting in a total of 191 degrees of freedom. The Adjusted Sum of Squares (Adj SS) represents the total variability in the data for each source of variation. For bus type, the adjusted sum of squares is 5331, while for error, it is 35404, leading to a total adjusted sum of squares of 40735. Adjusted Mean Square (Adj MS) is calculated by dividing the sum of squares by the corresponding degrees of freedom. The adjusted mean square for bus type is 2665.6 (5331/2), and for error, it is 187.3 (35404/189). The F-value were calculated by dividing the mean square for bus type by the mean square for error and used to test whether there are significant differences among the means of the groups. In this case, the F-value for bus type is 14.23.

The p-value for bus type is 0.000, which is less than the common significance level of 0.05. This suggests that there were significant differences among the means of buses type. Therefore, Tukey test would be applied to identify where was the difference occurred.

Table 11: Grouping information using the Tukey method and 95% confidence

| Bus type | N | Mean | Grouping | |
|---|---|---|---|---|
| 2 | 64 | 72.56 | A | |
| 1 | 64 | 62.48 | | B |
| 0 | 64 | 60.53 | | B |

Source: Minitab output, 2023

Table 12: Pairwise comparisons for stop type

| (I) Bus type | (J) Bus type | Mean Difference (I-J) | Std. Error | Sig.b | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| 0 | 1 | -1.415 | 2.632 | 0.592 | -6.607 | 3.778 |
| | 2 | -11.905* | 2.632 | 0 | -17.098 | -6.712 |
| 1 | 0 | 1.415 | 2.632 | 0.592 | -3.778 | 6.607 |
| | 2 | -10.490* | 2.632 | 0 | -15.683 | -5.298 |
| 2 | 0 | 11.905* | 2.632 | 0 | 6.712 | 17.098 |
| | 1 | 10.490* | 2.632 | 0 | 5.298 | 15.683 |

Source: Minitab output, 2023

* The mean difference is significant at the 0.05 level.

The result of a post-hoc analysis, specifically the Tukey method, which is commonly used to compare multiple group means after conducting an Analysis of Variance (ANOVA). The Tukey method, also known as the Tukey Honest Significant Difference (HSD) test, is a statistical technique used for comparing the means of multiple groups to identify which pairs are significantly different from each other. It's commonly employed after conducting an Analysis of Variance (ANOVA) to determine where the differences lie when there are more than two groups. Table 11-12 shows, bus Type 2 has the highest mean and was labeled with letter group A, also bus Type 1 and bus Type 0 had lower means and were labeled with letter group B. The letter "A" indicates that the mean of bus Type 2 was significantly different from the means of bus Type 1 and bus Type 0. Both bus Type 1 and bus Type 0 share the letter "B," indicating that their means were not significantly different from each other. Tukey method suggests that Alliance bus had significantly different at a mean second of 10.490 and 11.905 for sheger and Anbessa bus respectively. On the other hand, both Sheger and Anbessa bus were not significantly different from each other. And it is concluded that there was statistical difference between bus type on dwell time at stop.

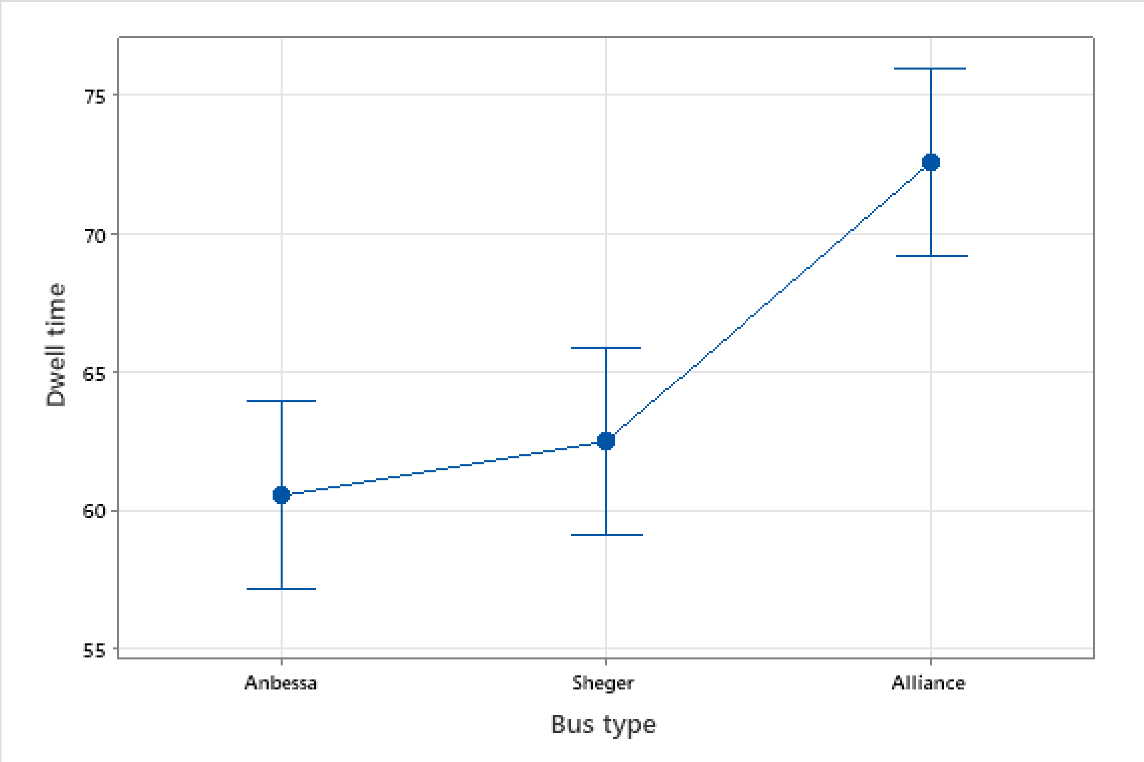


Figure 5:Dwell time of bus type Addis Ababa City,2023

Table 13: Analysis of variance on stop location

| Source | DF | Adj SS | Adj MS | F-Value | P-value |
|---|---|---|---|---|---|
| Stop type | 1 | 929.9 | 929.9 | 4.44 | 0.036 |
| Error | 190 | 39804.9 | 209.5 | | |
| Total | 191 | 40734.8 | | | |

Source: Minitab output, 2023

Table 13 shows the degrees of freedom associated with each source of variation. which were a measure of the amount of variability in the data. For Stop type, it's 1, and for error, it’s 190. Table 13 provides information on degrees of freedom (DF) associated with each source of variation, measuring the variability in the data. For Stop type, it's 1, and for error, it’s 190. The Adjusted Sum of Squares (Adj SS) represents the sum of squared deviations from the mean, adjusted for the number of observations, with values of 929.9 for Stop type and 39804.9 for error. The Adj MS (Adjusted Mean Square) for stop type and error are both 929.9 and 209.5, respectively. The F-value for stop type is 4.44, with a corresponding p-value of 0.036, indicating evidence to reject the null hypothesis for stop type at the 0.05 significance level. This suggests a significant difference among the groups defined by stop type. The F-value of 4.44 serves to assess the statistical significance of the difference, with the obtained p-value confirming the acceptance of the alternative hypothesis that there was a difference among the groups.

Table 14: Mean dwell time of stop type

| Stop type | N | Mean | St. Dev | 95% CI |
|---|---|---|---|---|
| 0 | 132 | 63.71 | 14.35 | (61.22, 66.19) |
| 1 | 60 | 68.45 | 14.74 | (64.77, 72.14) |
| Pooled St. Dev = 14.4741 | | | | |

Source: Minitab output, 2023

Table 15: Grouping information using the Tukey Method and 95% confidence

| Stop type | N | Mean | Grouping | |
|---|---|---|---|---|
| 1 | 60 | 68.45 | A | |
| 0 | 132 | 63.71 | | B |

Source: Minitab output, 2023

Table 16: Pairwise comparisons for stop type

| (I) Stop type | (J)Stop type | Mean Difference (I-J) | Std. Error | Sig.b | 95% Confidence Interval for Differenceb | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| 0 | 1 | -4.748* | 2.149 | 0.028 | -8.988 | -0.508 |
| 1 | 0 | 4.748* | 2.149 | 0.028 | 0.508 | 8.988 |

Source: Minitab output, 2023

Group A (Stop type 1):

Number of observations (N): 60

Mean: 68.45

Grouping: A

Group B (Stop type 0):

Number of observations (N): 132

Mean: 63.71

Grouping: B

The letter assigned to each group is based on the Tukey method. Groups with different letters (A and B) were considered to have significantly different means at a 95% confidence level. Since Group A is labeled with the letter A and Group B with the letter B, this implies that the means of Stop type 1 (Group A) and Stop type 0 (Group B) are statistically significantly different. The Tukey method suggests that there was a significantly different at a mean second of 4.748 in between far side stop and mid-block stop type location. And it is concluded that there was statistical difference between bus stop type on dwell time at a p value of 0.05.

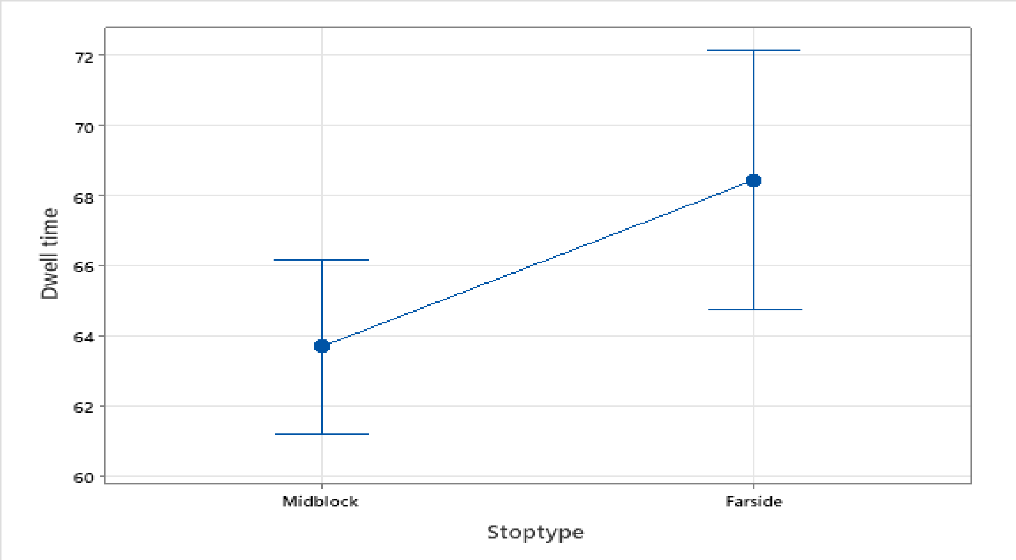


Figure 6:Dwell time of stop type Addis Ababa city,2023

Table 17: Analysis of variance for time of the day

| Source | DF | Adj SS | Adj MS | F-Value | P-value |
|---|---|---|---|---|---|
| Time | 1 | 21.7 | 21.72 | 0.1 | 0.751 |
| Error | 190 | 40713.1 | 214.28 | | |
| Total | 191 | 40734.8 | | | |

Source: Minitab output, 2023

In summary, the results indicated in table 17, there was not significant difference among the groups defined by 'time of the day' The F-Value of 0.1 is used to assess whether the difference is statistically significant, and since the p-value was above the significance level, this would be accepted null hypothesis that there was no difference among the groups.

Table 18:Tests of between-subject's effects

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Corrected Model | 6323.345a | 5 | 1264.669 | 6.836 | 0 |
| Intercept | 720501.463 | 1 | 720501.463 | 3894.438 | 0 |
| Bus type | 4652.61 | 2 | 2326.305 | 12.574 | 0 |
| Stop type | 929.925 | 1 | 929.925 | 5.026 | 0.026 |
| Bus and Stop type | 62.256 | 2 | 31.128 | 0.168 | 0.845 |
| Error | 34411.452 | 186 | 185.008 | | |
| Total | 856698.47 | 192 | | | |
| Corrected Total | 40734.797 | 191 | | | |
| R Squared = 155 (Adjusted R Squared = 133) | | | | | |

Source: Minitab output, 2023

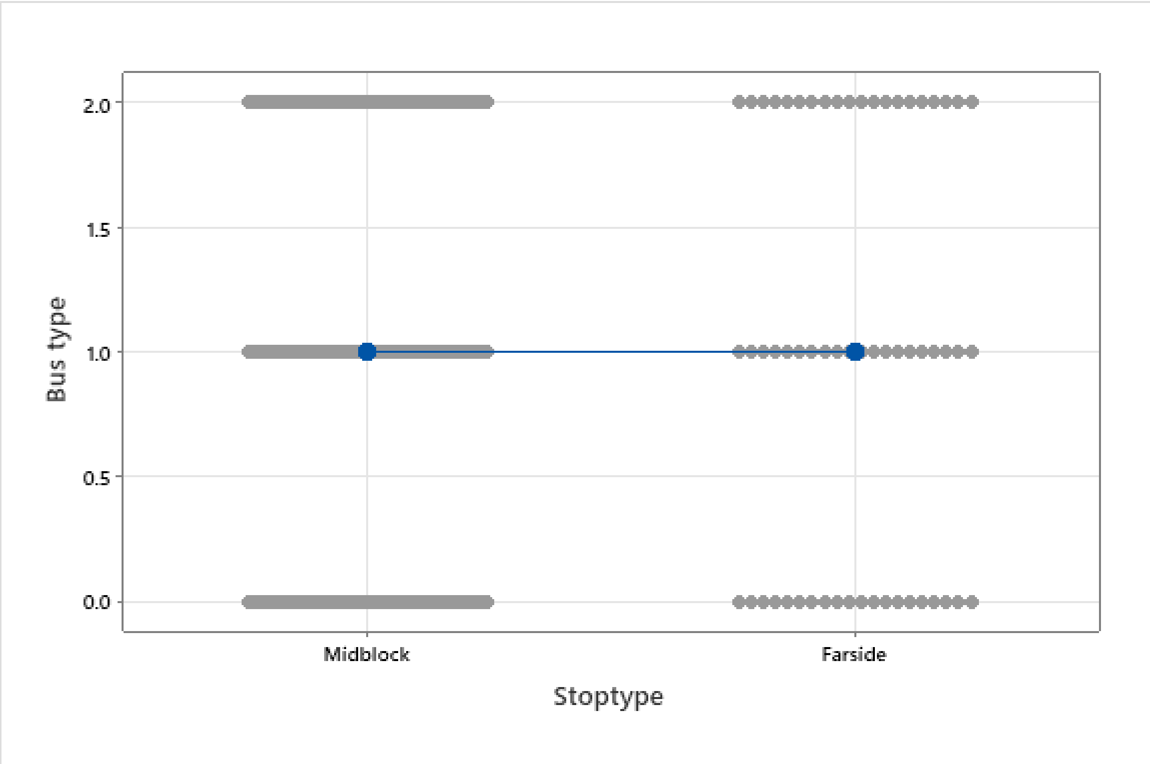


Figure **7**: Stop type and bus type comparation in Addis Ababa City, 2023

Table 18 shows the test at 95% confidence interval, the results of the two-way ANOVA, at F (2,186) =12.574, F (1,180) =5.026, F (2,186) = 0.168, p-value of 0.0,0.0,0.845, for bus type, stop type and bus type versus Stop type respectively. The one could conclude that there was not statistically significant difference between stop type and bus type at p-value of 0.845 which is greater than 0.05. But there was a statistically significant difference between stop type on dwell time and bus type on dwell time individually.

## 3.9 Regression analysis and model development

Following the analysis methodology described in the method section, the researcher conducted multiple linear regression analyses to build regression models for the independent variables.

Each independent variable, such as deceleration time, door closing time, alighting time, boarding time, exact fare time, odd penny time, and idle time, was measured in seconds. Passenger-related variables like alighting, re-boarding, and free pass boarding were recorded as numerical counts. Additionally, nominal data, such as time of day (coded as 0 for morning, 1 for afternoon), bus types (0 for Anbessa, 1 for Sheger, 2 for Alliance), stop type (0 for mid-block, 1 for far side), and crowdedness of bus stops (0 if passengers closed the lane, 1 if not), were coded accordingly. The recorded data also included the numbers of stops and route lines in the Minitab software.

Validate assumptions before performing the regression analysis, and thorough checks were conducted for each possible scenario. Regression models for every possible scenario were constructed using both SPSS and Minitab 20 statistical software. Each qualitative variable was coded accordingly: zero for Anbessa, one for Sheger, and two for Alliance bus. Stop types were coded as zero for Middle block and one for Far-side stops, while time of day received numerical values (one for morning, zero for afternoon). Passenger crowding effect was coded as zero if passengers closed the lane during ticketing and one if not. The thirty-two bus route lines and stop location names were detailed in Appendix D for conciseness.

### 3.9.1 Assumption one: linear relationship

Examine the linear relationship between the dependent variable and each independent variable by creating scatter plots using Minitab 20 software. The validation process involves assessing scatter plots for every combination of independent variables in comparison to the dependent variable to identify a consistent pattern. If the points exhibit a linear trend, it suggests that the assumption of a linear relationship was satisfied.

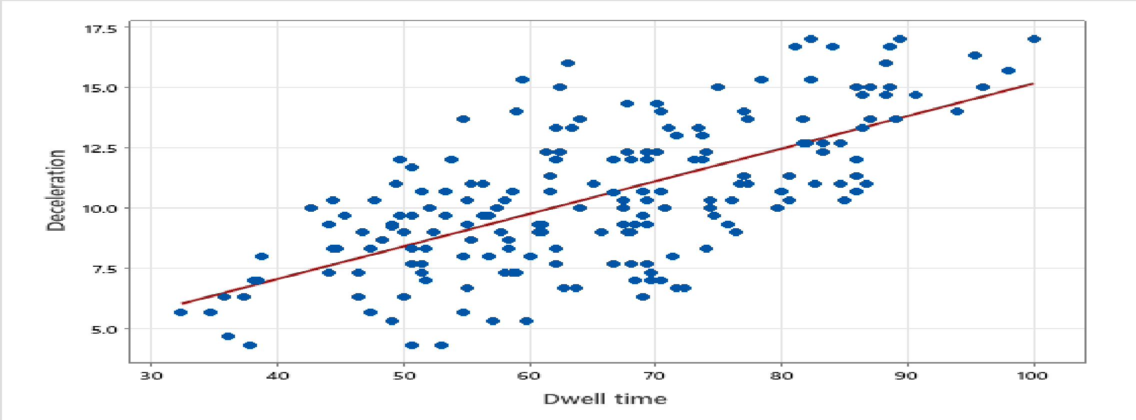


Figure 8: Scatter plot for dwell time Vs deceleration time

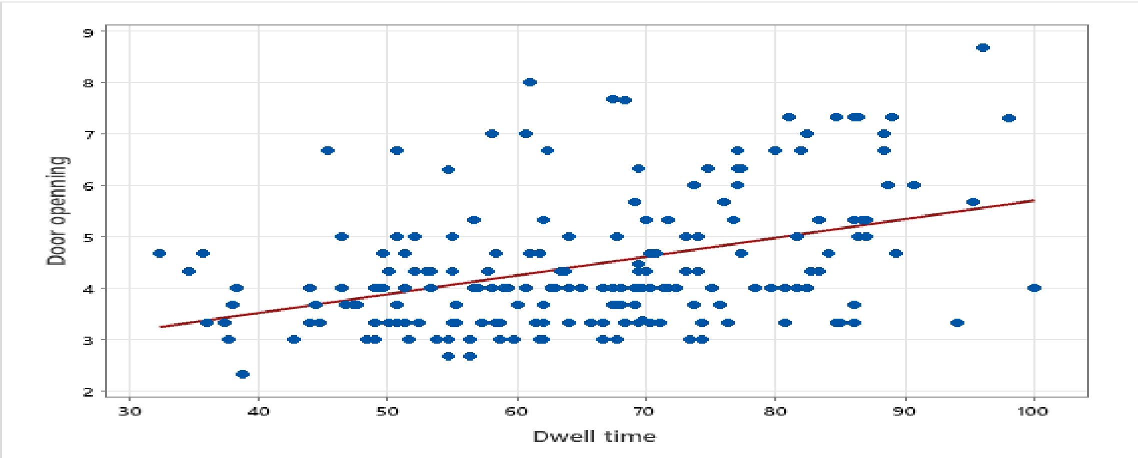


Figure 9: Scatter plot for dwell time vs door opening time

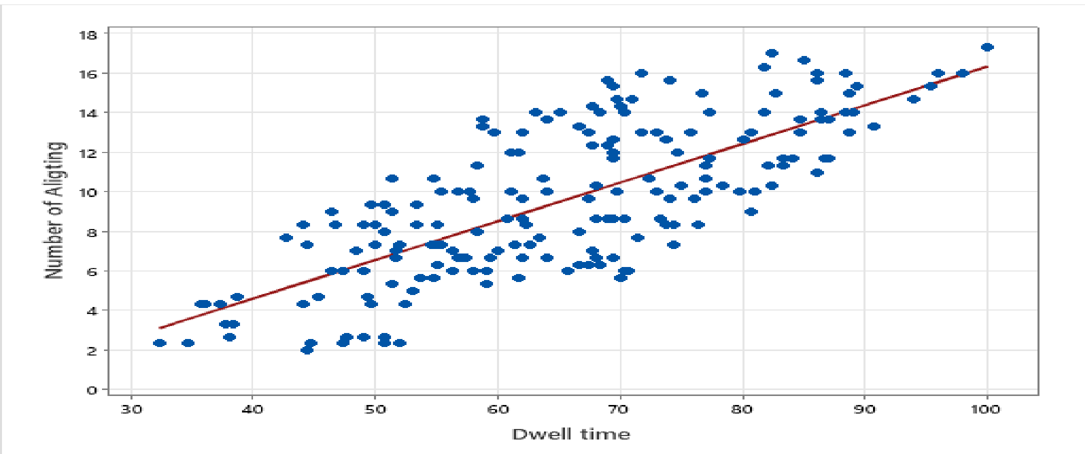


Figure 10: Scatter plot for dwell time vs number of alighting passengers

Figures 8,9 and 10 reveals that there was no linear correlation between door opening time and dwell time. The reason might be that operational differences, mechanical configuration, and the dynamic nature of the bus doors create a non-linear correlation with dwell time. All other variables meeting the specified criteria have been incorporated into 'Appendix D' to illustrate the linear relationship between the dependent variable, dwell time, and each independent variable.

### 3.9.2 Assumption two: no perfect multicollinearity

To assess multicollinearity, two methods were employed correlation coefficients and variance inflation factor (VIF) values which is provided in the next table of regression summary table 22. VIF values were examined for each independent variable, with high values which is greater than 10 indicating multicollinearity problem. (Shrestha, 2020). While "Idle time" has the highest VIF at indicating some correlation with other predictors, it's below the common threshold of 10. Additionally, the VIF values for the other variables are all below 3.5, suggesting only moderate multicollinearity, which is generally manageable. Therefore, while there is moderate multicollinearity present, it doesn't seem to be severe enough to significantly impact the interpretation of the model. Several approaches have been suggested to translate the correlation coefficient into describe like "weak," "moderate," or "strong" relationship. These cutoff points are arbitrary and inconsistent and should be used judiciously. While most researchers would probably agree that a coefficient of <0.1 indicates a negligible relationship and >0.9 a very strong relationship, values in between are disputable. For example, a correlation coefficient of 0.65 could either be interpreted as a good or moderate (Schober & Schwarte, 2018)(Williams et al., 2013). It's important to note that multicollinearity, if present, could hinder the computation of a unique least square regression analysis solution(Ayinde et al., 2015; Partika et al., 2020).

Table 19:Autocorrelation summary

| Explanators | Dec. Time | Op. time | No_alig. pass. | Alig. time | No_bo pass | Bor. time | Idle time | Exact far. time | Odd pe. time | Re_bor. time | Clos. time | Acc. time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dec. Time | 1 | | | | | | | | | | | |
| Op. time | 0.419 | 1 | | | | | | | | | | |
| No_Alight. pass. | 0.476 | 0.326 | 1 | | | | | | | | | |
| Alig. time | 0.526 | 0.4 | 0.634 | 1 | | | | | | | | |
| No_bor. pass | 0.496 | 0.387 | 0.57 | 0.632 | 1 | | | | | | | |
| Bor.time | 0.56 | 0.268 | 0.596 | 0.682 | 0.558 | 1 | | | | | | |
| Idle time | 0.535 | 0.344 | 0.597 | 0.635 | 0.608 | 0.632 | 1 | | | | | |
| Exact fa. time | 0.44 | 0.327 | 0.587 | 0.582 | 0.533 | 0.566 | 0.568 | 1 | | | | |
| Odd pen. time | 0.571 | 0.423 | 0.665 | 0.716 | 0.685 | 0.639 | 0.675 | 0.72 | 1 | | | |
| Re_bor. time | 0.41 | 0.462 | 0.346 | 0.527 | 0.451 | 0.422 | 0.42 | 0.442 | 0.484 | 1 | | |
| Clos.time | 0.187 | 0.384 | 0.064 | 0.151 | 0.136 | 0.027 | 0.207 | 0.066 | 0.145 | 0.283 | 1 | |
| Acc. Time | 0.317 | 0.249 | 0.38 | 0.435 | 0.289 | 0.436 | 0.42 | 0.451 | 0.462 | 0.312 | -0.054 | 1 |

*Source: Micros soft excel output, 2023, correlation matrix outputs. Variables were abbreviated as (deceleration, door opening, number of alighting, alighting, number of boarding,boarding,Idle,exactfare,oddy_penny,reboarding,closing,Acceleration)time(Dec.time,Op.time,No.alig.pass.Alig.pass.Alig.time,No.bor.pass,Bor.time,Idle.time,Exactfa.time,Odd pe.time,Re-bor.time,clos.time) respectively.*

As per table 19, the Variance inflation factor among independent variables were generally below 5, allowing for regression analysis to proceed with the remaining explanatory variables.

### 3.9.3 Assumption three: independent errors: Durbin-Watson test

The Durbin-Watson test (White, 1992; Zeisel, 1989) examines serial correlation in residuals, generating a value within the range of 0 to 4. A value of 2 signifies uncorrelated residuals. Values above 2 suggest negative correlation, whereas values below 2 indicate positive correlation among adjacent residuals.

Table 20: Durbin Watson result for independence of error

| Durbin-Watson Statistic | |
|---|---|
| Durbin-Watson Statistic | 1.60702 |

In Table 20, the DW statistic is recorded as 1.607. Since this value is close to 2, it suggests that there is little to no autocorrelation in the residuals of the regression model. While it is not exactly 2, a value of 1.607 is still within a reasonable range to infer that the autocorrelation is not a significant issue in this context.

Even though the outliers were not considered as an assumption the dataset should not contain significant outliers, high leverage points, or highly influential points. and influential points are distinct terms referring to observations in the dataset that exhibit some form of unusual behavior during multiple regression analysis. These diverse classifications of unusual points signify varying effects on the regression line.

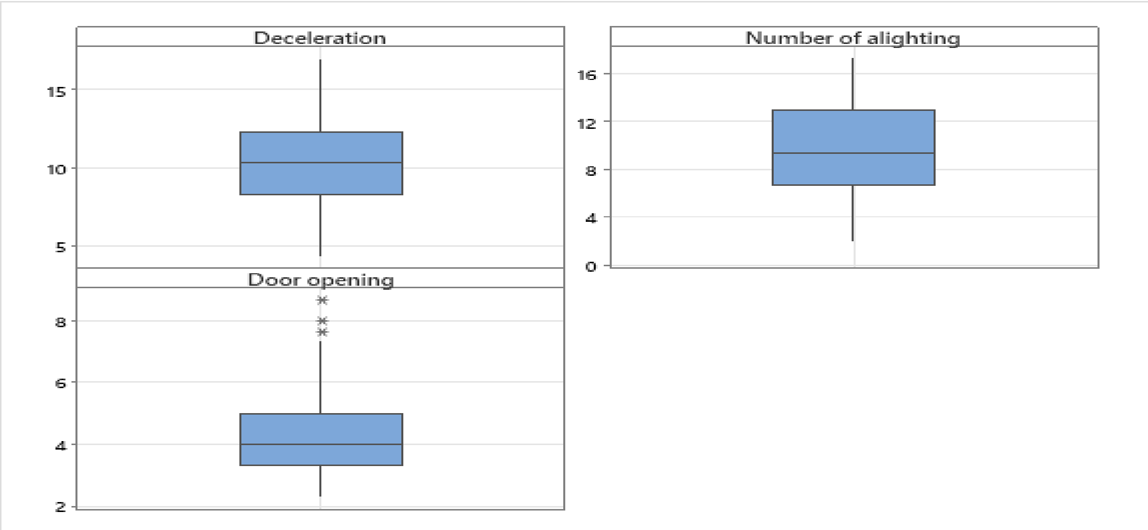


Figure 11: Outlier representation in box plot

As mentioned in figure 11, no outliers were detected in the predictor variables number of alighting passengers and deceleration time based on a box plot. However, upper outliers were observed in rows 6, 49, and 66 for the variable related to ‘door opening,’ with corresponding values of 7.67, 8, and 8.67, respectively. To ensuring the robustness of regression and addressing the significance of outlier issues in Ordinary Least Squares (OLS) regression analysis. Applying transformations, such as log transformation, to the data may mitigate the impact of outliers (Choi, 2009).

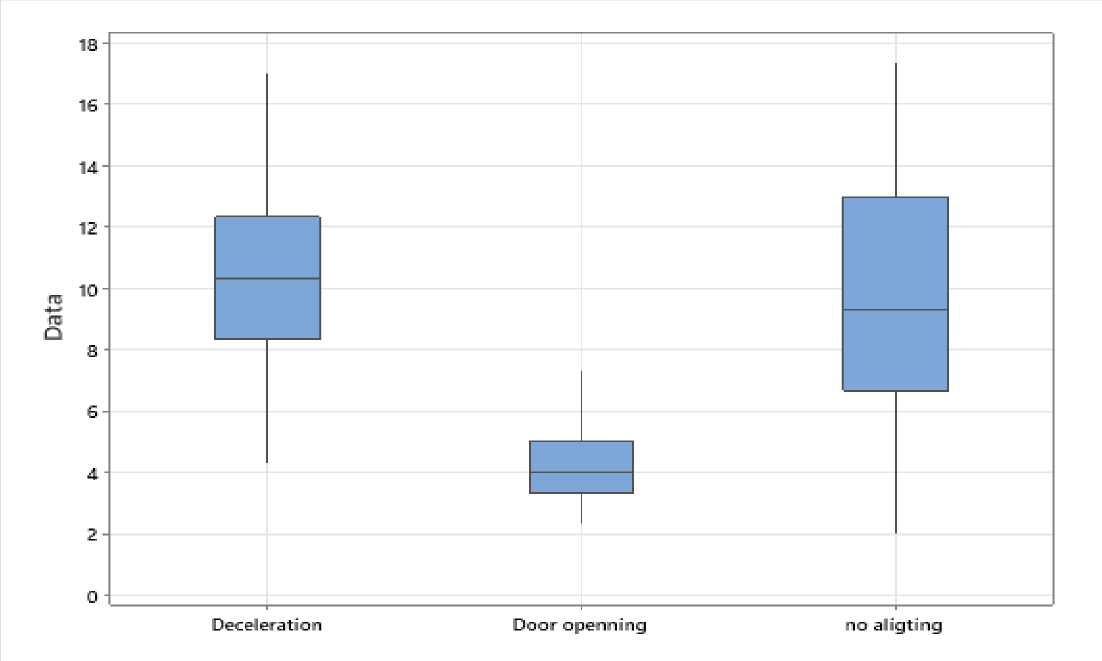


Figure 12: After removing extreme outlier

As mention in figure 12, the researcher effectively resolved the presence of extreme outliers in the ‘door opening’ variable by excluding them from the dataset and replaced the data that were recorded in the same time in the same place, because the cause of outliers was due to data entry errors. Consequently, the data became devoid of outliers, aligning with the essential assumptions for conducting regression analyses. Box plots for the remaining predictors are detailed in Appendix D.

### 3.9.4 Assumption Five: the homogeneity of residual variances (homoscedasticity)

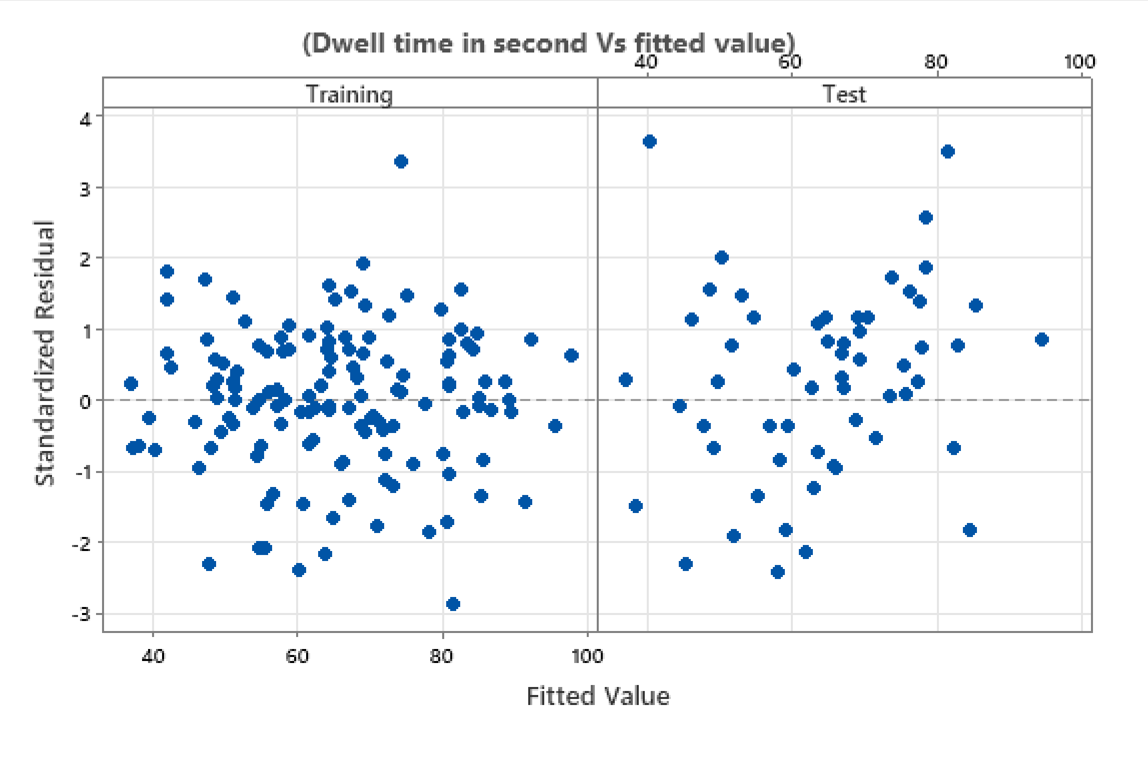


Figure 13: The homogeneity of residual variances (homoscedasticity)

The assumption under consideration pertains to the constancy of error variance in a regression model across all levels of the independent variables. The researcher aimed to demonstrate homoscedasticity, a quality wherein the variances along the line of best fit remain consistent throughout its trajectory. Homoscedasticity is indicated when, in examining scatter plots, there is a roughly uniform spread of residuals across the spectrum of predicted values. Conversely, the presence of a discernible pattern or systematic changes in spread may suggest heteroscedasticity. In this case, the scatter plot analysis revealed a consistently uniform spread of residuals across the range of predicted values, affirming that the assumption of homoscedasticity was met.

### 3.9.5 Assumption six: normality

Finally, make sure the residuals (errors) should be approximately normally distributed. This could be checked by a histogram with a superimposed normal curve.

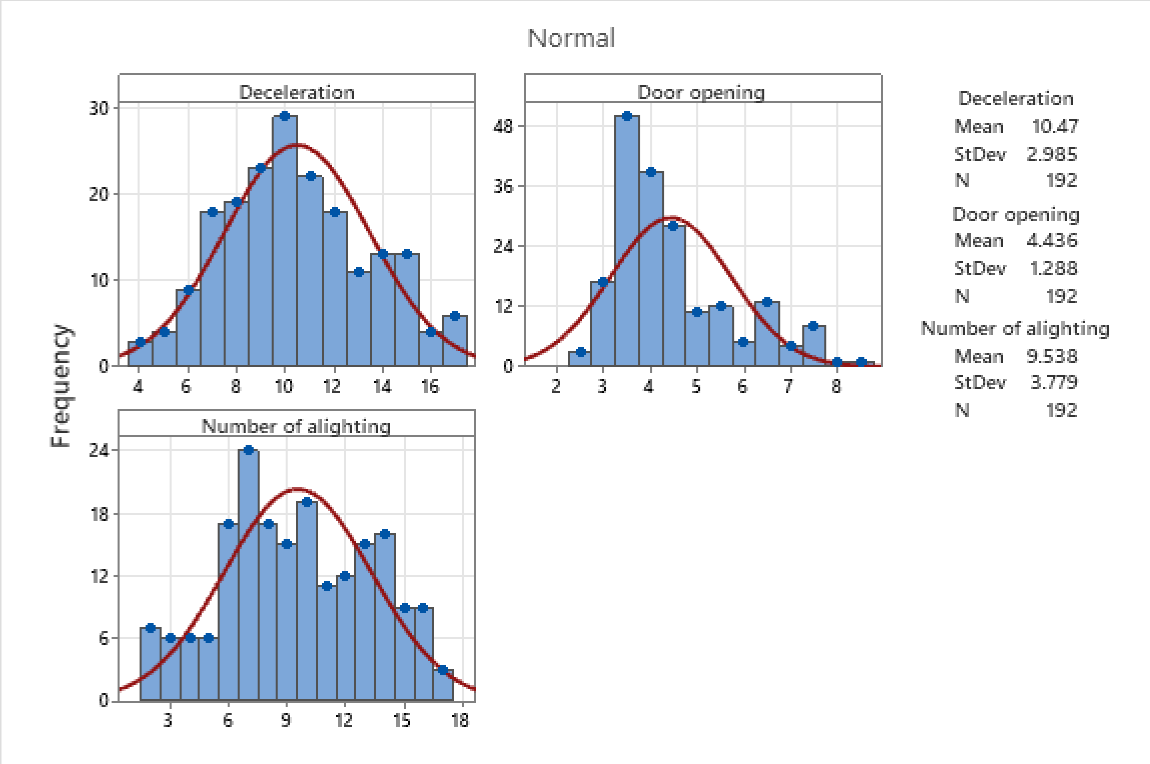


Figure 14: Histogram plot of deceleration, door opening, number of alighting

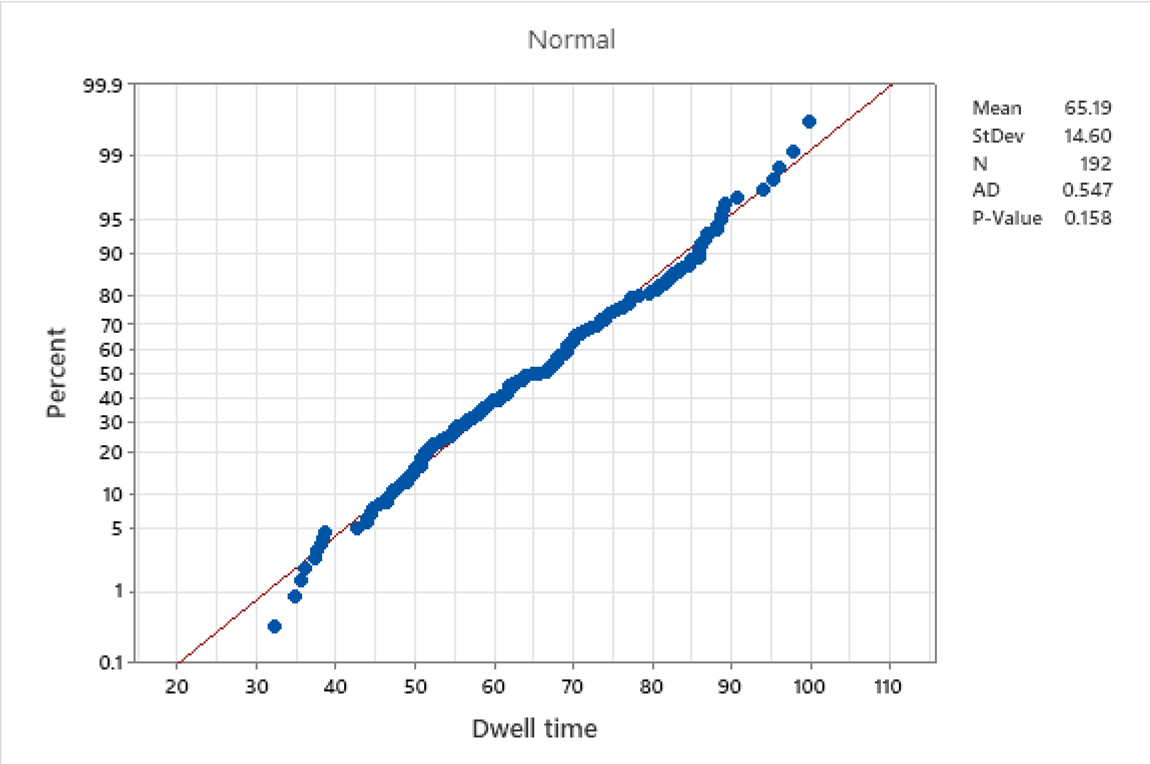


Figure 15: Normality plot following with fitted line

Table 21: Shapiro-Wilk and Anderson-darling test of normality

| | | |
|---|---|---|
| Mean | 65.19 | Anderson Darling Test |
| St. Dev | 14.6 | |
| N | 192 | |
| AD | 0.547 | |
| P-value | 0.158 | |
| Mean | 65.19 | Shapiro-Wilk Test |
| St. Dev | 14.6 | |
| N | 192 | |
| RJ | 0.996 | |
| P-value | >0.100 | |

As it shown in figure 15 and table 21, the residuals had aproximatelly symmetrical bell shape and Shapiro-Wilk test p-value of 0.158 was greater than the common significance level of 0.05, Which was fail to reject the null hypothesis. Likewise, the p-value was 0.1 suggesting that it's greater than 0.05. Therefore, not enough evidence to suggest that the data significantly deviates from a normal distribution based on the Anderson-Darling test. Both tests, Anderson-Darling and Shapiro-Wilk, indicate that there was no strong evidence to reject the assumption of normality for the given dataset. Now regression had to be applied since it was satisfied the assumption.

Table 22: Regression coefficient and model summary

| Model Summary | | | |
|---|---|---|---|
| S | R-sq | R-sq(adj) | R-sq(pred) |
| 3.93 | 92.96% | 92.63% | 92.13% |

| Variables | Coef | Stand. error | t-Value | P-value | VIF |
|---|---|---|---|---|---|
| Constant | 7.77 | 1.88 | 4.13 | 0.000 | |
| No- alighting | 0.492 | 0.135 | 3.63 | 0.000 | 2.45 |
| No_boarding | 0.391 | 0.137 | 2.85 | 0.005 | 2.25 |
| Boarding time | 0.4979 | 0.0531 | 9.37 | 0.000 | 2.42 |
| Idle time | 0.3221 | 0.092 | 3.5 | 0.001 | 2.3 |
| Odd penny | 0.6946 | 0.0869 | 7.99 | 0.000 | 3.38 |
| Re_boarding | 0.522 | 0.137 | 3.8 | 0.000 | 1.41 |

Source:regression output from Minitab software;2023

Where, No. alig. pass = Number of alighting passengers

No.bor.pass = No_boarding for passengers

Bor.time = Boarding time

Idle = Idle time

Odd_penny = Odd penny

Re-boarding pass = Re_boarding passengers

#### 3.9.5.1 Output interpretation of multiple regression

The R-squared (R-sq) value, which measures how well the independent variable(s) explain the variability of the dependent variable, was found to be 92.96% in this study, indicating that approximately 92.96% of the variance in the dependent variable was being explained by the independent variable(s). Adjusted R-squared (R-sq(adj)), a modification accounting for the number of predictors in the model, yielded 92.63%, suggesting that even after considering the number of predictors, the model still explains a high percentage (92.63%) of the variance in the dependent variable. Additionally, the R-squared for Prediction (R-sq(pred)), assessing the model's ability to make accurate predictions on new, unseen data, was 92.13%, indicating the model's expected performance on new data.

Overall, these high R-squared values suggest that the model had been good fit for the data, and a large proportion of the variance in the dependent variable is accounted for by the independent variables.

The researcher employed the statistical approach of stepwise regression for variable selection. In stepwise regression, variables were added to or eliminated from the model based on their statistical significance. The analysis revealed that 92.63% of the variance in the dependent variable explained by independent variable in the regression model. Using the stepwise regression selection method, six independent variables were identified to have a statistically significant effect on dwell time. These variables include the number of passengers alighting, number of boarding passengers, boarding time, idle time, odd penny, and re-boarding passengers. The coefficients of these predictors and their corresponding p-values will be discussed as follows.

A. Number of alighting passengers

The variable ‘No-alighting’ had a coefficient of 0.492, indicating that, holding other variables constant, a one-unit increase in ‘No-alighting’ is associated with a 0.492 unit increase in the bus dwell time second at stop. The t-value of 3.63 and the low p-value (0.000) suggest that this variable is statistically significant. And VIF of 2.45 is below the typical threshold of 10, indicating low multicollinearity.

B. Number of boarding passengers

The coefficient for ‘No-boarding’ was 0.391, indicating that a one-unit increase in ‘No-boarding’ is associated with a 0.391 unit increase in the bus dwell time in second at stop. The t-value of 2.85 and the p-value of 0.005 suggest statistical significance at a VIF of 2.25.

C. Boarding time

The regression coefficients of passenger ‘Boarding time’ is 0.497 indicating that while all other factors remaining constant, bus dwell time has to been expected to increase by 0.497 for every one unit second increase of boarding time. A one-unit increase in ‘Boarding time’was associated with a 0.497 unit increase in the bus dwell time second at stop. The high t-value and low p-value (0.000) indicate that ‘Boarding time’ was highly statistically significant at VIF of 2.42.

D. Idle time

The coefficient for ‘Idle time’ was 0.3221, indicating that a one-unit increase in ‘Idle time' was associated with a 0.3221 unit increase in the bus dwell time at stop. The t-value of 3.5 and the p-value of 0.001 suggest statistical significance at VIF of 2.3.

E. Odd penny time

The regression coefficients of odd penny were 0.694 indicating that while all other factors remaining constant, bus dwell time has been expected to increase by 0.694 for every one-unit increase seconds of odd penny fare time. The coefficient for ‘Odd penny’ was 0.694, suggesting that a one-unit increase in ‘Odd penny’ was associated with a 0.6946 unit increase in the bus dwell time at stop. The high t-value (7.99) and low p-value (0.000) indicate that ‘Odd penny’ was highly statistically significant at VIF of 3.38.

F. Re_boarding passengers

The regression coefficients of ‘Re-boarding’ passengers were 0.522 indicating that while all other factors remaining constant, bus dwell time has been expected to increase by 0.552 for every one-unit increase numbers of passengers that are re-boarding. The coefficient for ‘Re-boarding’ is 0.522, indicating that a one-unit increase in ‘Re-boarding’ is associated with a 0.522 unit increase in the bus dwell time at stop. The t-value of 3.8 and the p-value of 0.000 suggest statistical significance at of VIF of 1.41.

Dwell time = 7.77 + 0.492No. alig. pass. + 0.391 No.bor.pass. + 0.4979 Bor.time + 0.3221 Idle + 0.6946 oddy_penny + 0.522 Re-boarding pass + ε

Coefficient (Coef): 7.7, Standard Error: 1.8, t-Value: 4.13 and p -Value: 0.000.

The constant is 7.77. The t-value of 4.13 suggests that the constant is statistically significant ($p$-value $< 0.05$), meaning it was unlikely to have occurred by chance. Each variable's coefficient represents the change in stop bus dwell time associated with a one-unit change in that variable, while holding other variables constant.

## 3.10 Probability model for estimating dwell time

The Weibull distribution is frequently employed as an alternative to parametric testing when data has outliers. This distribution is versatile and can accommodate various forms of data, including those that are heavy-tailed or skewed. Fitting the data to the Weibull distribution proves to be a useful approach in such situations. The Anderson-Darling (AD) statistic is used to assess how well the data aligns with a specific distribution. The Goodness of Fit (GOF) test evaluates the suitability of a distribution to a particular curve, with smaller statistic values indicating a better fit for the given data and distribution. In this research, Maximum Likelihood Estimation methods would be employed for fitting the distribution lines, as it enables an effective alignment with the data set.

- ✓ **Null Hypothesis (H0):** The bus dwell time follows a Weibull reliability distribution.
- ✓ **Alternative Hypothesis (H1**: The bus dwell time does not follow a Weibull reliability distribution.

### 3.10.1.1 Procedures for probability distribution analysis

The methodology for determining the appropriate probability distribution for fitting dwell time data and calculating distributional parameters involved recording numerical variables, including time (in seconds) and the number of passengers. The data was entered into Minitab version 20 for reliability and distribution analysis. Minitab offers eleven probability distributions however; the researcher chose four specific distributions. To identify the best-fitting distribution, the author used plots displaying the distribution trends of the selected four distributions. The analysis involved comparing these trends to identify the one with the majority of data points closest to the trend line. Ultimately, the selection of the best-fitting model was based on observing the outputs of Minitab and choosing the distribution with the lowest Anderson-Darling value and higher correlation.

Table 23: Summarized Anderson -Darling goodness tests of Minitab output

| Predictors | Distribution | Anderson-Darling | Correlation Coefficient |
|---|---|---|---|
| Dec. Weibull | Weibull | 1.782 | 0.99 |
| | Lognormal | 5.613 | 0.946 |
| | Exponential | 25.687 | |
| | Smallest Extreme Value | 13.08 | 0.929 |
| Dor.ope.Weibull | Weibull | 8.143 | 0.959 |
| | Lognormal | 3.027 | 0.977 |
| | Exponential | 34.502 | |
| | Smallest Extreme Value | 32.064 | 0.874 |
| No. Ali.weibul | Weibull | 4.389 | 0.968 |
| | Lognormal | 10.319 | 0.902 |
| | Exponential | 25.778 | |
| | Smallest Extreme Value | 11.012 | 0.936 |
| Aligt.Weibull | Weibull | 3.779 | 0.981 |
| | Lognormal | 8.564 | 0.926 |
| | Exponential | 24.701 | |
| | Smallest Extreme Value | 10.858 | 0.932 |
| Boa.Weibull | Weibull | 5.081 | 0.975 |
| | Lognormal | 11.002 | 0.906 |
| | Exponential | 26.927 | |
| | Smallest Extreme Value | 7.52 | 0.943 |
| Idle. Weibull | Weibull | 3.342 | 0.983 |
| | Lognormal | 7.964 | 0.937 |
| | Exponential | 24.906 | |
| | Smallest Extreme Value | 10.048 | 0.933 |
| No.bor.Weibull | Weibull | 3.336 | 0.982 |
| | Lognormal | 8.079 | 0.93 |
| | Exponential | 24.75 | |

| | | | |
|---|---|---|---|
| | Smallest Extreme Value | 10.635 | 0.933 |
| Odd.penn. Weibull | Weibull | 2.107 | 0.986 |
| | Lognormal | 6.513 | 0.942 |
| | Exponential | 25.611 | |
| | Smallest Extreme Value | 13.758 | 0.929 |
| Re-boa. Weibull | Weibull | 2.176 | 0.989 |
| | Lognormal | 4.031 | 0.962 |
| | Exponential | 27.046 | |
| | Smallest Extreme Value | 15.885 | 0.918 |
| Dor.Clos. Weibull | Weibull | 9.455 | 0.952 |
| | Lognormal | 2.007 | 0.985 |
| | Exponential | 48.022 | |
| | Smallest Extreme Value | 30.661 | 0.871 |
| Accel.Weibull | Weibull | 3.538 | 0.947 |
| | Lognormal | 7.991 | 0.864 |
| | Exponential | 31.638 | |
| | Smallest Extreme Value | 9.356 | 0.945 |
| Dwell.Weibull | Weibull | 2.108 | 0.989 |
| | Lognormal | 5.652 | 0.947 |
| | Exponential | 25.349 | |
| | Smallest Extreme Value | 12.358 | 0.928 |

Source:Output from Minitab software;2023

The Minitab outputs in table 23 indicate that the Weibull and Lognormal distributions best fit the dwell datasets. The parameters for the Weibull distribution were chosen using Maximum Likelihood Estimation (MLE), emphasizing lower Anderson-Darling values and least square methods for correlation coefficients. The Weibull distribution values were highlighted in a yellow background, while the Lognormal distribution values are highlighted in red. Additionally, both the door opening and closing times of the bus were fitted with a Lognormal distribution.

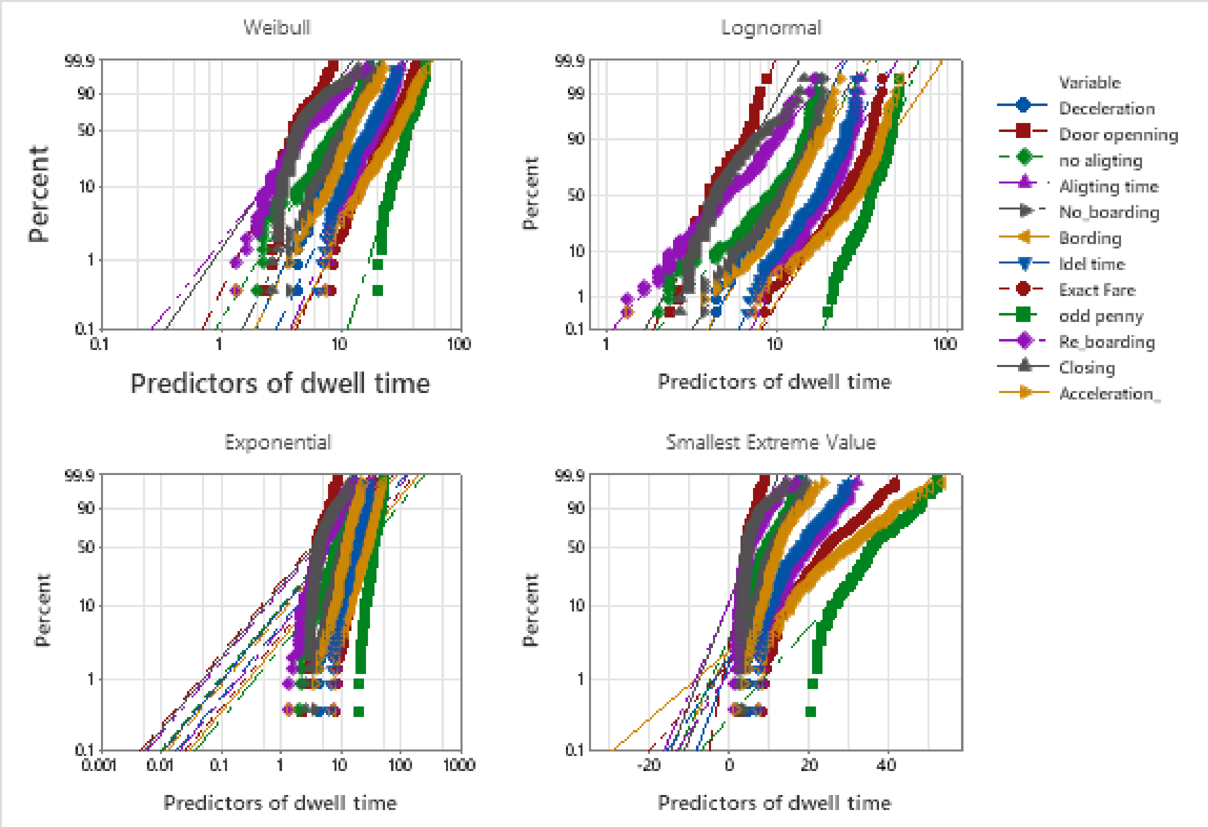


Figure 16: ID plot reliability distribution

Figure 16 illustrates the Minitab outputs of four ID plot distributions, depicting each independent variable against the percentages of dwell time. The graph indicates that the data align closely with the lines of fit in the Weibull distribution, except for the door opening and closing times of the bus, which are better fitted with a Lognormal distribution. Despite both distributions being considered, the researcher opted for the Weibull distribution based on the lowest Anderson-Darling (A-D) goodness of test and the highest correlation coefficient, as highlighted in table 23.

#### 3.10.1.2 Weibull probability distribution function

Following the methodology outlined in the analysis section, the researcher aimed to generate models for Cumulative Density Function (CDF), Probability Density Function (PDF), Survival Function S(t), and Hazard Rate H(t) for each independent variable. These models were crucial for conducting Weibull regression on dwell time and observing the Weibull regression. Before delving into the model analysis, it was imperative to validate assumptions through statistical and graphical techniques. The researcher used the graphical approach to validate models and assess data assumptions, providing essential parameters for numerical procedures needed for statistical estimates. Minitab software was employed to generate Weibull and lognormal outputs for various scenarios, aiding in determining the probability of dwell time creation at bus stops.

#### 3.10.1.3 Two-parameter Weibull distribution

The Weibull distribution utilizes shape and scale parameters to define the Probability Density Function (PDF) of the distribution (Christofferson & Gillette, 1987; Haghighat et al., 2022). In the domain of bus dwell time, the shape parameter governs the form of the distribution curve, and the scale parameter influences the size or magnitude of the distribution. The interpretation of these parameters is crucial for understanding the characteristics of the distribution curve(Engeman & Keefe, 1985; George, 2014).

The shape parameter of a Weibull distribution plays a crucial role in determining the hazard function's behavior. If the shape parameter is less than 1, it indicates a decreasing hazard function, suggesting that the likelihood of a shorter dwell time increases as time progresses. A shape parameter equal to 1 denotes an exponential distribution, where the hazard rate remains constant over time. Conversely, if the shape parameter is greater than 1, it signifies an increasing hazard function, indicating that the probability of a longer dwell time grows as time advances. On the other hand, the scale parameter establishes the characteristic or average dwell time. A larger scale parameter implies a lengthier average dwell time, while a smaller scale parameter implies a shorter average dwell time.

Table 24: Parameter estimate for deceleration

| Parameter | Estimate | Standard error | 95.0% Normal CI | |
|---|---|---|---|---|
| | | | Lower | Upper |
| Shape | 3.86364 | 0.214669 | 3.465 | 4.30815 |
| Scale | 11.5794 | 0.228597 | 11.1399 | 12.0363 |

Source: outputs of Minitab software;2023

Table 25: Characteristics of distribution for deceleration

| Characteristics of Distribution | Estimate | Standard Error | 95.0% Normal CI | |
|---|---|---|---|---|
| | | | Lower | Upper |
| Mean (MTTF) | 10.4751 | 0.219561 | 10.0535 | 10.9144 |
| Standard Deviation | 3.0323 | 0.13571 | 2.77765 | 3.3103 |
| Median | 10.5315 | 0.231901 | 10.0866 | 10.9959 |
| First Quartile(Q1) | 8.38767 | 0.257122 | 7.89856 | 8.90707 |
| Third Quartile(Q3) | 12.6009 | 0.236337 | 12.1461 | 13.0728 |
| Interquartile Range (IQR) | 4.21327 | 0.198788 | 3.84112 | 4.62147 |

Source:output from Minitab software;2023

Table 26:Table of percentiles

| Percent | Percentile | Standard Error | 95.0% Normal CI Lower | Upper |
|---|---|---|---|---|
| 1 | 3.52051 | 0.263717 | 3.03978 | 4.07725 |
| 2 | 4.21782 | 0.275142 | 3.7116 | 4.79308 |
| 3 | 4.69071 | 0.279567 | 4.17356 | 5.27194 |
| 4 | 5.06005 | 0.281424 | 4.53746 | 5.64281 |
| 5 | 5.3681 | 0.282017 | 4.84287 | 5.95031 |
| 6 | 5.63513 | 0.281891 | 5.10886 | 6.21562 |
| 7 | 5.87254 | 0.281321 | 5.34625 | 6.45063 |
| 8 | 6.08745 | 0.280462 | 5.56184 | 6.66273 |
| 9 | 6.28463 | 0.279408 | 5.76018 | 6.85683 |
| 10 | 6.46746 | 0.278219 | 5.94451 | 7.03641 |
| 20 | 7.85391 | 0.264089 | 7.35299 | 8.38895 |
| 30 | 8.86758 | 0.250654 | 8.38967 | 9.37272 |
| 40 | 9.73154 | 0.23966 | 9.27297 | 10.2128 |
| 50 | 10.5315 | 0.231901 | 10.0866 | 10.9959 |
| 60 | 11.3204 | 0.228487 | 10.8813 | 11.7772 |
| 70 | 12.1493 | 0.231395 | 11.7042 | 12.6114 |
| 80 | 13.0972 | 0.244715 | 12.6263 | 13.5858 |
| 90 | 14.3694 | 0.280224 | 13.8305 | 14.9292 |
| 91 | 14.5367 | 0.286316 | 13.9862 | 15.1089 |
| 92 | 14.7175 | 0.293239 | 14.1539 | 15.3036 |
| 93 | 14.9151 | 0.301199 | 14.3363 | 15.5173 |
| 94 | 15.1342 | 0.310493 | 14.5377 | 15.7552 |
| 95 | 15.3822 | 0.321573 | 14.7646 | 16.0255 |
| 96 | 15.6709 | 0.335192 | 15.0275 | 16.3418 |
| 97 | 16.0219 | 0.352732 | 15.3453 | 16.7284 |
| 98 | 16.4822 | 0.377233 | 15.7592 | 17.2384 |
| 99 | 17.193 | 0.418106 | 16.3927 | 18.0323 |

Source:output from Minitab software;2023

Table 24,25,26 indicates shape and scale parameter, estimate characteristics of distribution and percentiles tables of deceleration time was presented and the rest of predictors has been putted in appendix D.

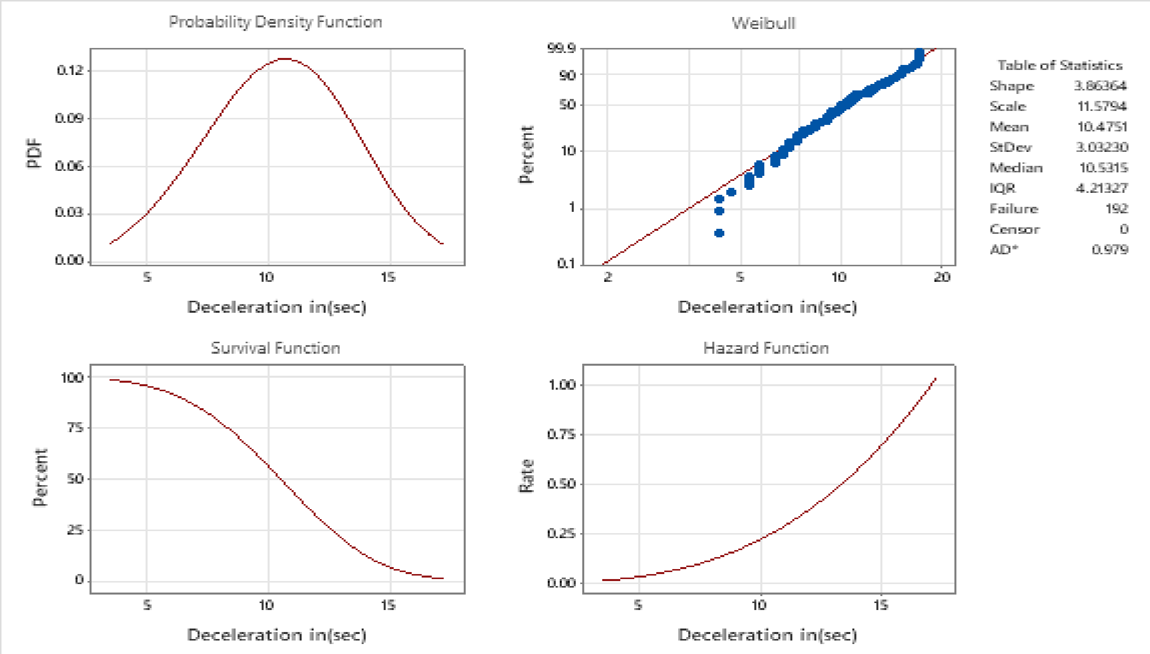


Figure 17:Weibull distribution plot for acceleration of time

The Weibull dwell time failure distribution's shape has been employed to ascertain the probable duration a dwell will endure at a bus stop and the likelihood of a bus spending a specific amount of time in seconds at a failed state. The hazard rate graph for dwell time increases over time, while the survival graph for dwell time decreases over time. This implies that the risk or probability of an event, such as the dwell time at a bus stop, increases as time progresses, as illustrated in figure 17.

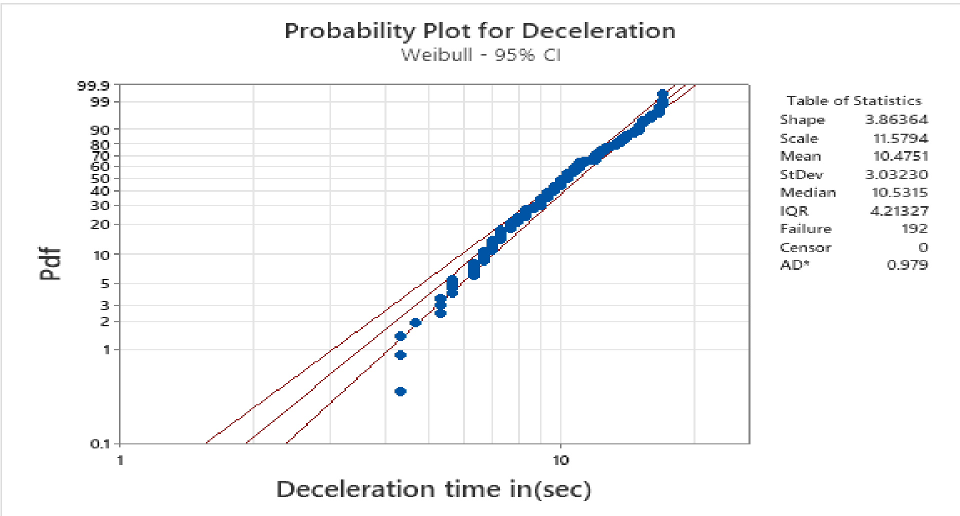


Figure 18:Probability density functions for deceleration time in (sec)

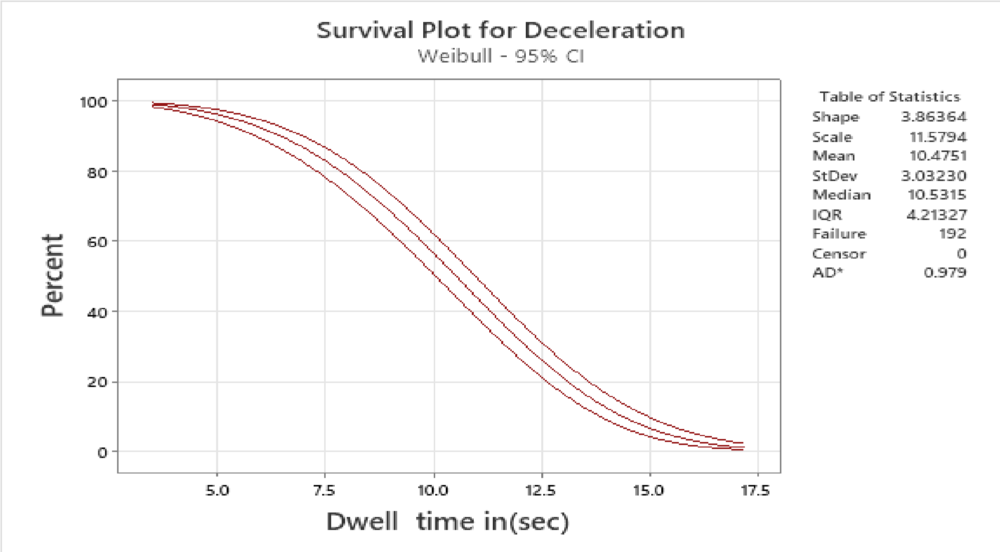


Figure 19: Survival plot for deceleration time in (sec)

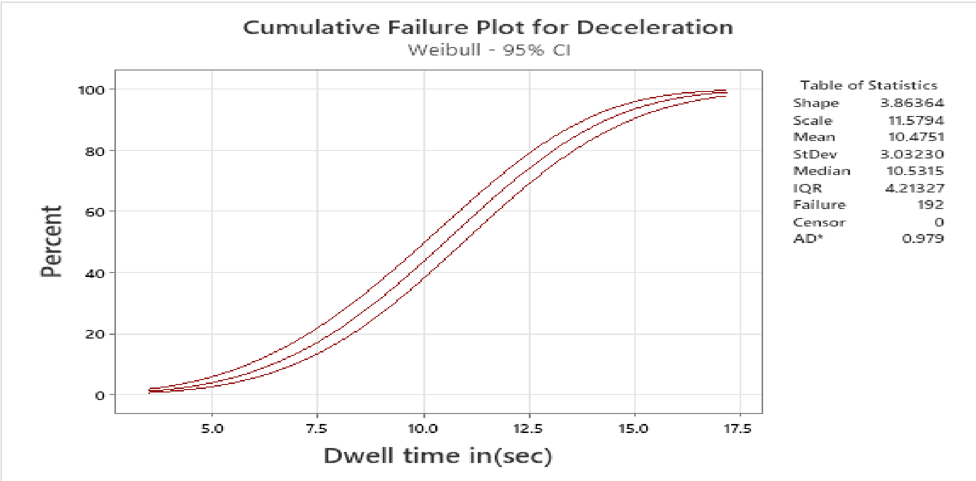


Figure 20: Cumulative failure plot for hazard rate

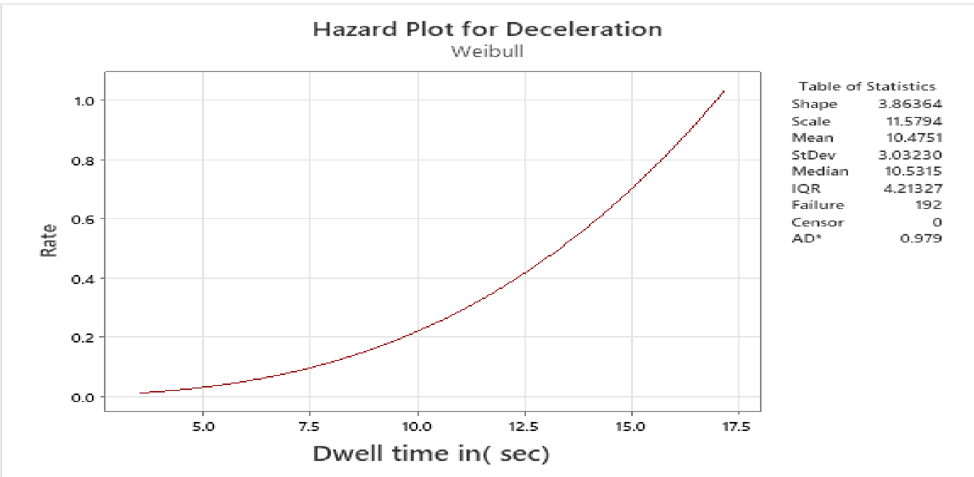


Figure 21: Hazard plot for alighting time

Greater log-likelihood values indicate a better fit to the data, typically less than zero. The results, presented in PDF graph 18 for bus deceleration time, roughly follow the line of fit at MTTF (Mean Time to Failure) of

10.475 seconds and a standard deviation of 3.03 seconds. The log-likelihood is -481.817, and the Anderson-Darling (A-D) value is 0.979, which is a higher statistical value compared to the lognormal, exponential, and small extreme distributions, resulting in a higher reliability coefficient of 98.9%. The Weibull distribution ID plot demonstrates the substitution of each scale and shape parameter into equations for cumulative distribution function (CDF), probability density function (PDF), hazard function (H(t)), survival function (S(t)), providing dwell time as a function of these parameters.

- ✓ Comulative distribution of alighting passenger $= 1 - e^{(-(t/11.579)^{3.863})} = 1 - e^{(-(12/11.579)^{3.863})} = 0.682667$
- ✓ Probablity of alighting passenger dwell time $= (3.863(t)^{2.863})/12719.40\, e^{(-(t/11.579)^{2.863})} = (3.863(12)^{2.863})/12719.40\, e^{(-(12/11.579)^{2.863})} = 0.0910663$
- ✓ Weibull dwell time failure distribution $= \frac{3.863(t)^{2.86}}{12719.4} = (3.863(12)^{2.86})/12719.40 = o.3706$
- ✓ Weibull dwell time survival distribution $= e^{(-(t/11.57)^{2.86})} = e^{(-(12/11.57)^{2.86})} = 12.28$ where, at acceleration value of 12 and the rest of Weibull data will be presented in the next portion.

Table 27: Summary of shape and scale parameters

| | Shape | Scale | Correlation | |
|---|---|---|---|---|
| Deceleration | 4.22423 | 11.4818 | 0.989 | Log-Likelihood = -483.799 |
| Door opening | 5.14507 | 4.7744 | 0.911 | Log-Likelihood = -382.344 |
| No alighting | 2.65165 | 10.7283 | 0.989 | Log-Likelihood = -525.109 |
| Alighting time | 3.94279 | 21.6439 | 0.992 | Log-Likelihood = -603.468 |
| No_boarding | 3.34424 | 12.0685 | 0.991 | Log-Likelihood = -520.623 |
| Boarding time | 3.11032 | 32.1836 | 0.995 | Log-Likelihood = -710.217 |
| Idle time | 3.75672 | 19.4372 | 0.988 | Log-Likelihood = -597.239 |
| Exact Fare | 3.67862 | 27.2934 | 0.994 | Log-Likelihood = -655.551 |
| Odd penny | 6.04957 | 38.9227 | 0.988 | Log-Likelihood = -655.404 |
| Re_boarding | 2.55095 | 6.3543 | 0.975 | Log-Likelihood = -468.259 |
| Closing | 4.22367 | 5.4131 | 0.878 | Log-Likelihood = -605.049 |
| Acceleration_ | 3.60168 | 13.5952 | 0.982 | Log-Likelihood = -526.778 |
| Dwell time | 5.43802 | 70.5368 | 0.988 | Log-Likelihood = -789.729 |

Source:output from Minitab software,2023

These values are crucial for the subsequent analysis of data distribution, and they have been utilized in the application of a regression model.

### 3.11 Application of regression on Weibull distribution.

The researcher utilized a regression model to assess the impact of explanatory variables on the dependent variable within the extended Weibull distribution. Unlike Gaussian regression, the assumption of normality for the dependent variable was not obligatory in the context of the Weibull distribution.

### 3.11.1 Assumption one: linear combination of the covariates

The dependent and independent variables have a linear relationship. The relationship between the covariates and the logarithm of the hazard rate should be linear. The Weibull regression model assumes that the log-hazard function has to be a linear combination of the covariates.

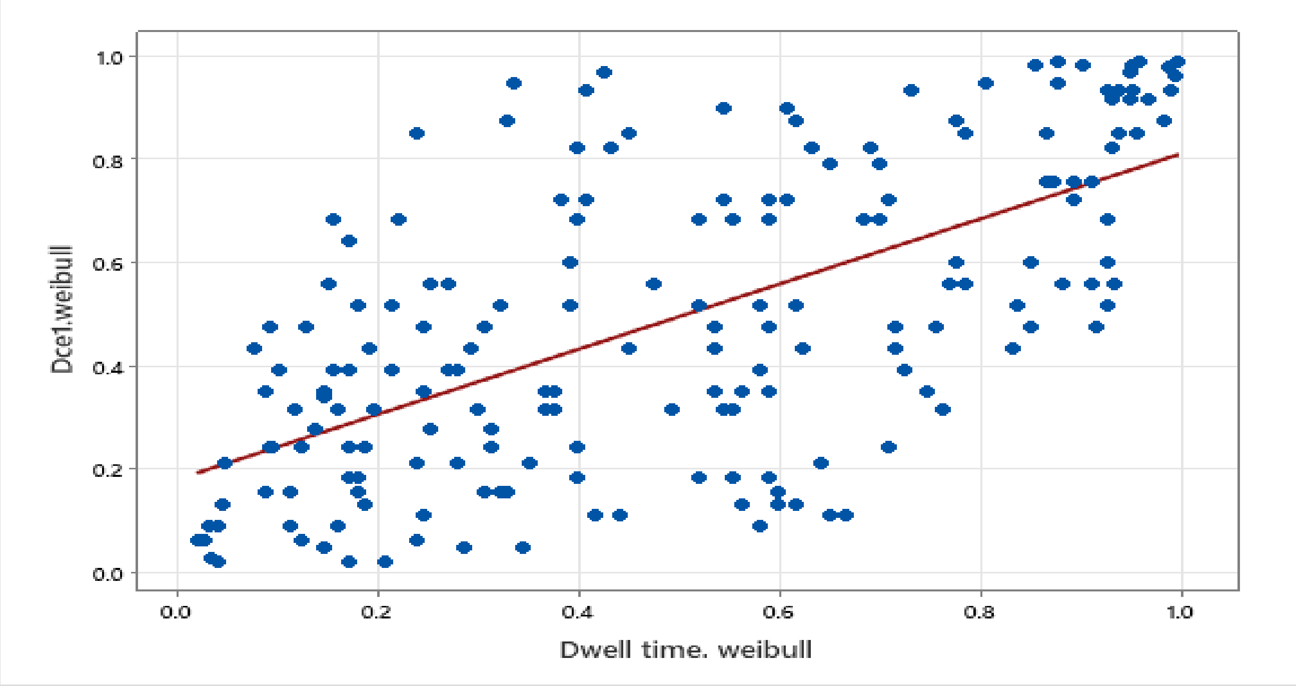


Figure 22: Scatter plot for dwell time vs deceleration time in Weibull distribution

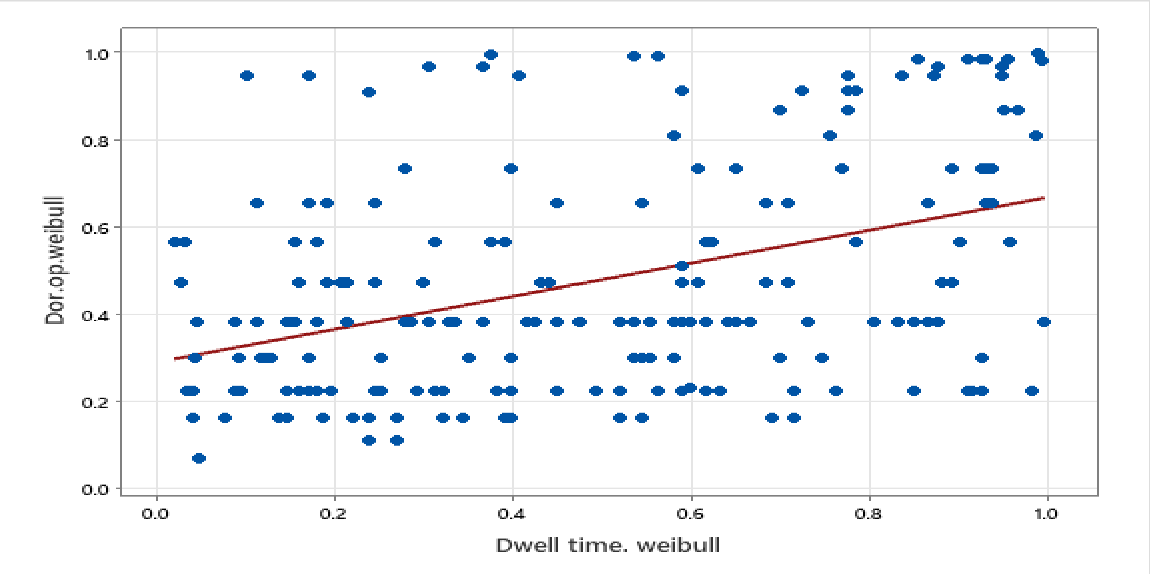


Figure 23: Scatter plot for dwell time vs No_alight time in Weibull distribution

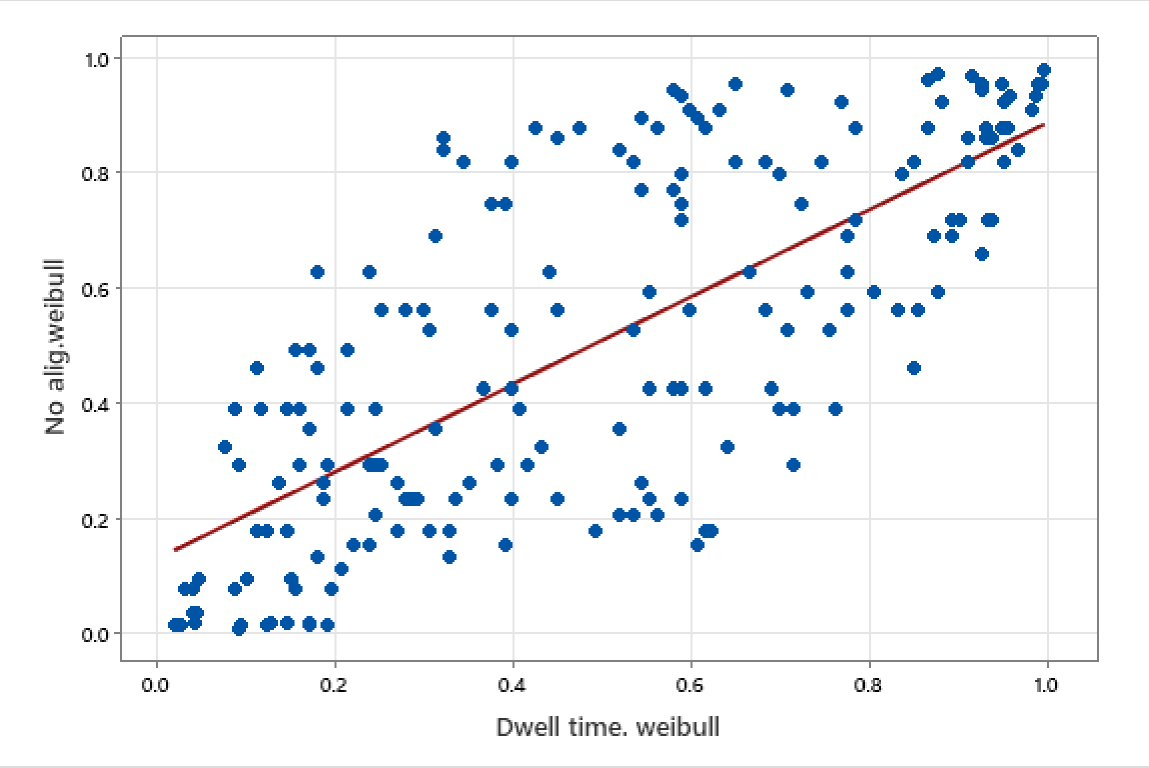


Figure 24: Scatter plot for dwell time Vs alighting time in Weibull distribution

Figures 22, 23, and 24 illustrate the linear relationship between bus deceleration, the number of passengers alighting, and alighting time with dwell time in the Weibull distribution. However, there was no observed linear relationship between door opening time and dwell time. Consequently, regression was not applied to door opening time due to a failure to meet assumptions. The remaining variables have been included in Appendix E.

### 3.11.2 Assumption two: multicollinearity

When two or more predictor variables in a regression model exhibit a strong correlation with each other, this phenomenon is known as multicollinearity. It can lead to issues in regression analysis, including unstable and inaccurate coefficient estimates or challenges in identifying the specific impacts of the predictor variables. One common method for detecting multicollinearity involves calculating the correlation matrix of the predictor variables and identifying high correlation coefficients (around +1 or -1). Another approach is to compute the variance inflation factor (VIF) for each predictor variable, with multicollinearity possibly present if the VIF value exceeds 5 or 10.

Table 28: Multicollinearity matrix plot

| Weib.variable | Dce1.Weibull | Dor.ope.Weibull | No Alig.Weibull | Aligt.Weibull | Board.Weibull | Idle.Weibull | No.Boa.Weibull | Odd.penn.Weibull | Re.boa.webull | Clos.Weibull | Accel.Weibull |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Dce1.Weibull | 1 | | | | | | | | | | |
| Dor.ope.Weibull | 0.432 | 1 | | | | | | | | | |
| No Aligt.Weibull | 0.464 | 0.330 | 1 | | | | | | | | |
| alig.Weibull | 0.500 | 0.415 | 0.626 | 1 | | | | | | | |
| Board.Weibull | 0.548 | 0.268 | 0.611 | 0.673 | 1 | | | | | | |
| Idle.Weibull | 0.514 | 0.328 | 0.591 | 0.634 | 0.629 | 1 | | | | | |
| No.Boa.Weibull | 0.500 | 0.384 | 0.549 | 0.612 | 0.563 | 0.607 | 1 | | | | |
| Odd.Pen.Weibull | 0.578 | 0.429 | 0.662 | 0.71 | 0.642 | 0.658 | 0.669 | 1 | | | |
| Re.boa.webull | 0.354 | 0.476 | 0.305 | 0.521 | 0.397 | 0.369 | 0.417 | 0.447 | 1 | | |
| Cls.Weibull | 0.284 | 0.541 | 0.157 | 0.265 | 0.113 | 0.277 | 0.236 | 0.278 | 0.434 | 1 | |
| Accel.Weibull | 0.282 | 0.244 | 0.358 | 0.405 | 0.406 | 0.425 | 0.258 | 0.430 | 0.287 | 0.043 | 1 |

Source:output from Minitab software;2023

The multicollinearity matrix presented in table 28 indicates that the regression model underwent evaluation for multicollinearity. This suggest that multicollinearity was not a significant concern, as the values are below more or less the value 0.71. This enhances the overall reliability of the regression analysis.

### 3.11.3 Assumption three: independent error (Durbin-Watson test)

In regression analysis, the assumption of independent error was crucial. It suggests that there was no correlation between the regression model's errors or residuals. Estimates of the regression coefficients that have been skewed and ineffective could result from violating this assumption. A statistical technique called the Durbin-Watson test was used to determine whether autocorrelation exists in regression model errors. When the Durbin-Watson test statistic near 2, it indicates no autocorrelation.

Table 29: Durbin Watson value

| Durbin-Watson Statistic | |
|---|---|
| Durbin-Watson Statistic | 1.87389 |

The Durbin-Watson Statistic was 1.87, close to the value of 2 as it mentioned in table 29, indicating that there was no significant autocorrelation among the predictors. This suggests that the assumptions for the analysis were satisfied.

### 3.11.4 Assumption five: the homogeneity of residual variances (homoscedasticity)

Homoscedasticity would have to satisfied in the context of a Weibull distribution, it means that the variability in the survival times was being consistent across different levels of the covariates included in the model. This assumption has been crucial for the validity of statistical inferences drawn from the model, as violations of homoscedasticity could lead to inefficient parameter estimates and biased hypothesis test.

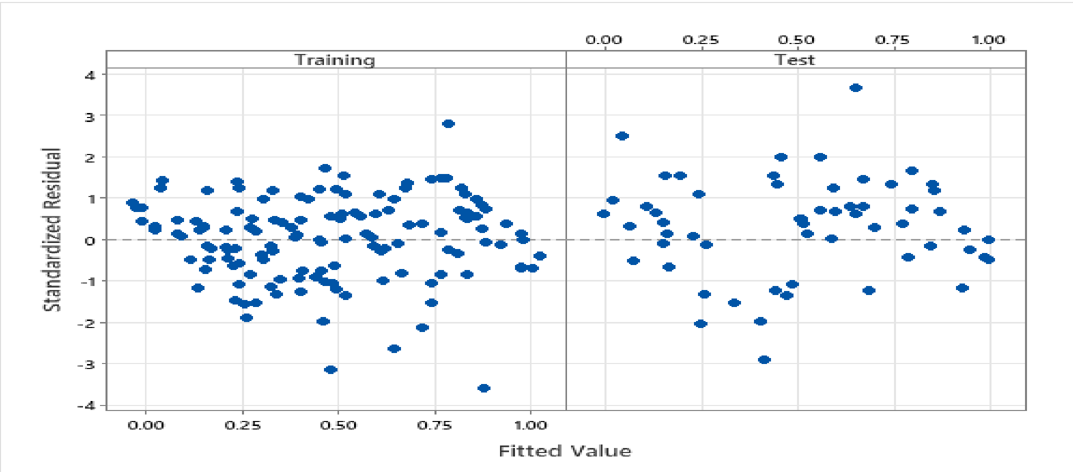


Figure 25: Homoscedasticity in Weibull distribution

The researcher attempted to demonstrate homoscedasticity, a characteristic of the line of best-fitted variances that remains similar throughout the line as it progresses. Plotting the studentized residuals against the unstandardized expected values was necessary when the researcher analyzed the data, as shown in figure 25.

Regression output

The model summary, P value and stepwise summary were displayed as follow.

Table 30: Model summary

| Model Summary | | | |
|---|---|---|---|
| S | R-sq | R-sq(adj) | R-sq(pred) |
| 0.075678 | 93.47% | 93.00% | 92.39% |

Source: Minitab output;2023

Table 31: Analysis of variance

| Source | DF | Adj SS | Adj MS | F-Value | P-value |
|---|---|---|---|---|---|
| Regression | 9 | 10.1708 | 1.13009 | 197.32 | 0 |
| No -Alight. Weibull | 1 | 0.0363 | 0.0363 | 6.34 | 0.013 |
| Alig.Weibull | 1 | 0.0649 | 0.06494 | 11.34 | 0.001 |
| Board.Weibull | 1 | 0.5367 | 0.53675 | 93.72 | 0 |
| Idle. Weibull | 1 | 0.0328 | 0.03275 | 5.72 | 0.018 |
| No. Boa.Weibull | 1 | 0.0535 | 0.05353 | 9.35 | 0.003 |
| Odd. pen. Weibull | 1 | 0.3909 | 0.39086 | 68.25 | 0 |
| Re.boa.webull | 1 | 0.0263 | 0.02626 | 4.59 | 0.034 |
| Accel.Weibull | 1 | 0.0375 | 0.03754 | 6.56 | 0.012 |
| Stop Type location | 1 | 0.0385 | 0.03849 | 6.72 | 0.011 |
| Error | 124 | 0.7102 | 0.00573 | | |
| Total | 133 | 10.8809 | | | |

Source: Minitab output;2023

Table 32: Regression coefficients

| Model | Coefficient | Stand. error | t-Value | P-value | VIF |
|---|---|---|---|---|---|
| Constant | -0.1139 | 0.0208 | -5.46 | 0 | |
| No Alig.Weibull | 0.0801 | 0.0318 | 2.52 | 0.013 | 2.18 |
| Alig.Weibull | 0.1189 | 0.0353 | 3.37 | 0.001 | 2.58 |
| Board.Weibull | 0.3463 | 0.0358 | 9.68 | 0 | 2.48 |
| Idle.Weibull | 0.0788 | 0.033 | 2.39 | 0.018 | 2.32 |
| No.boa.Weibull | 0.0971 | 0.0318 | 3.06 | 0.003 | 2.23 |
| Odd.pen.Weibull | 0.32 | 0.0387 | 8.26 | 0 | 2.96 |
| Re.boa.webull | 0.0642 | 0.03 | 2.14 | 0.034 | 1.16 |
| Accel.Weibull | 0.0747 | 0.0292 | 2.56 | 0.012 | 1.39 |
| Far side stop location | 0.0363 | 0.014 | 2.59 | 0.011 | 1.04 |

Source:regression output from Minitab software;2023

Where,

No Alig. Weibull = Number of alighting as a function of Weibull

Alig.Weibull = Alighting time as a function of Weibull

Board.Weibull = Boarding time as a function of Weibull

Idle. Weibull = Idle time as a function of Weibull

No. Boa.Weibull = Numbers of Boarding as a function of Weibull

Odd.pen. Weibull = Odd penny Weibull as a function of Weibull

Re.boa.webull = Re-boarding passengers as a function of Weibull

Accel.Weibull = Acceleration time as a function of Weibull

Far side = Far side stop location as a function of Weibull

Mid-Block = Mid-block stop location as a function of Weibull

Dwell timeWeibull=$e$^$(-0.1139 + 0.0801 \times \text{No Alig\_Weibull} + 0.1189 \times \text{Alig\_Weibull} + 0.3463 \times \text{Board\_Weibull} + 0.0788 \times \text{Idle\_Weibull} + 0.0971 \times \text{No. boa\_Weibull}\ ) + 0.3200\ \text{Odd. pen. Weibull} + 0.0642\ \text{Re. boa. webull} + 0.0747\ \text{Accel. Weibull} + 0.0363\ \text{Far side stop}) + \varepsilon$

The model exhibits a root mean square error (S) of 0.075, indicating the average deviation between observed and predicted values, with a lower S suggesting a better fit. The R-squared value stands at 93.47%, showing that approximately 93.47% of the variability in the dependent variable is explained by the independent variables, signifying strong explanatory power. The adjusted R-squared, at 93.00%, adjusts for the number of predictors, maintaining the model's high explanatory power despite additional complexity. Consequently, the model displays a strong fit with high R-squared and adjusted R-squared values. Moreover, the relatively low root mean square error implies good accuracy in predicting the dependent variable, while the predicted R-squared suggests favorable performance on new data.

a. Number of alighting times

The coefficient for ‘No Alig-Weibull’ in the Weibull regression model is 0.0801, it suggests that ‘No Alig-Weibull’ increases by one-unit number of passenger while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.0801. This implies a faster increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor of e0.0801 for every one-unit increase in No Alig-Weibull passengers.

b. Alighting time

The coefficient for ‘Alig.Weibull’ in the Weibull regression model is 0.118, it suggests that when ‘Alig-Weibull’ time increases by one unit second while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.346. This implies a faster increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor of e0.346 for every one-unit increase in Alig.Weibull time second.

c. Number of boarding

The coefficient for ‘No.boa_Weibull’ in the Weibull regression model is 0.097, it suggests that when ‘No Alig-Weibull’ increases by one unit in person while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.097. This implies a faster increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor of e0.097 for every one-unit increase in No.boa-Weibull passengers.

d. Boarding time

The coefficient for ‘Board.Weibull’ in the Weibull regression model is 0.3463, it suggests that when ‘Board-Weibull’ time increases by one unit second while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.3463. This implies a faster increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor of e0 for every one-unit increase in Board.Weibull time second.

e. Idle time

The coefficient for ‘Idle.Weibull’ time in the Weibull regression model is 0.0788, it suggests that when ‘Idle. Weibull’ time increases by one unit second while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.0788. This implies a faster increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor ofe0.0788 for every one-unit increase in Idle. Weibull time in second.

f. Odd penny time

The coefficient for ‘Odd.pen.Weibull’ in the Weibull regression model is 0.3200, it suggests that when ‘Odd.pen.Weibull’ increases by one unit second while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.0788. This implies a faster increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor of e0.3200 for every one-unit increase in Odd.pen.Weibull time in second.

g. Re_boarding passenger

The coefficient for ‘Re.boa.webull’ in the Weibull regression model is 0.0642, it suggests that when Re.boa.webull increases by one unit in person while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.0642. This implies a faster increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor of e0.0642 for every one-unit increase in ' Re.boa.webull passengers.

h. Acceleration time

The coefficient for ‘Accel.Weibull’ in the Weibull regression model is 0.0747, it suggests that when ‘Accel.Weibull’ increases by one unit in second while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.0747. This implies a faster increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor of e0.0747 for every one-unit increase in Accel.Weibull passengers.

i. Far- side stop

The coefficient for ‘far side’ stops location in the Weibull regression model is 0.0363, it suggests that when ‘Far side’ stop increases by one unit while all other factors remain constant, the scale parameter is expected to increase by a factor of e0.0363. This implies a faster 'increase in the hazard rate. Consequently, the bus dwell time is expected to increase by a factor of e0.0363 for every one-unit increase in far side stop. The coefficients provide insights into how changes in each factor impact the bus dwell time. Understanding these relationships is crucial for optimizing bus schedules and operations, ultimately leading to improved efficiency and service for passengers. By considering these factors, transportation authorities can make informed decisions to enhance the overall bus transit experience. The analysis of the Weibull regression model coefficients allows for a nuanced understanding of the specific contributions of each variable, aiding in the development of strategies to minimize dwell times and improve the overall functioning of the transit system.

### 3.11.5 Qualitative data analysis

Data which is relevant to the accomplishment of the study was collected through questionnaires, interview. Total of 32 questionnaires (i.e. Three concerned for demography of the passenger and 27 close ended general questioners which were prepared by the researcher to receive the response of the passenger. The total of 384 respondents and plus 10% of non-respondents of this sample size. Even though no any un answered questioners the researcher collected additional 10% which was much important for confidence and reducing error. In total of 424 questionnaires were filled and collected by the researcher.

#### 3.11.5.1 Assessment of responses from passengers

Respondents were sampled randomly who were public bus users using purposive sampling. Five age categories selected from literature review, such as 6-8 school student, 19-25 early working stage, 26-54 prime working stage,55-64 mature working age, seniors.

Table 33: Age categories of the respondents

| Age catagories | Frequency | Percent | Valid Percent |
|---|---|---|---|
| 6-18 school student | 41 | 4.89 | 9.66 |
| 19-25 early working stage | 100 | 11.94 | 23.58 |
| 26-54 prime working stage | 116 | 13.85 | 27.35 |
| 55-64 mature working age | 92 | 10.99 | 21.69 |
| seniors | 75 | 8.96 | 17.68 |
| Total | 424 | 50.65 | 100 |

As illustrated in table 33, among the 424 respondents, 41 (9.66 percent) fell within the 6-18 school student range, 100 (23.58 percent) were in the 19-25 early working stage, 116 (27.35 percent) were in the 26-54 prime working stage, 92 (21.69 percent) were in the 55-64 mature working age range, and the remaining 75 (17.68 percent) were above 65 years (seniors). No respondents were below six years old. This distribution indicates that the majority of the respondents were in the 26-54 prime working stage.

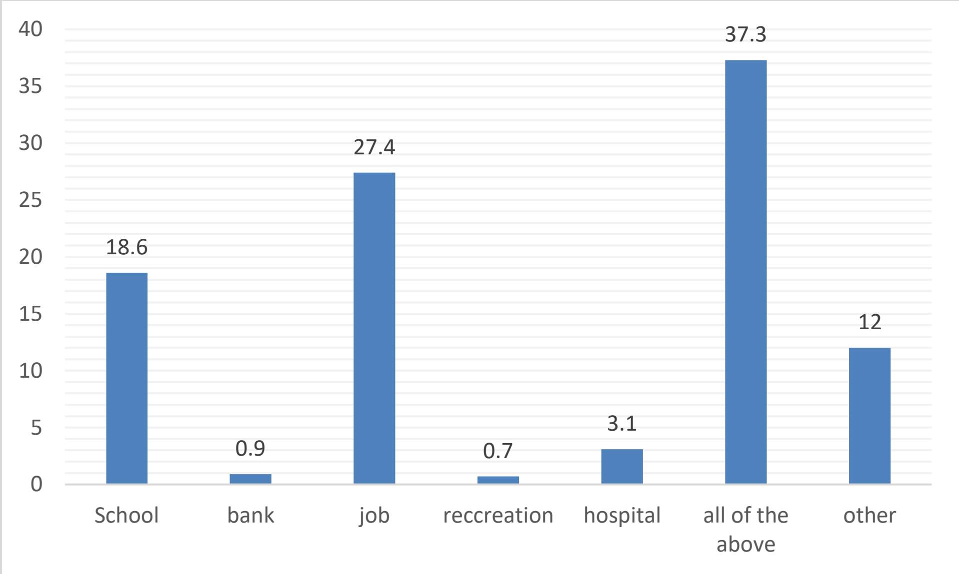


Figure 26: Purposes of passengers utilizing the bus for their daily commute

As indicated by the above figure 26, among the total passengers categorized by their bus usage, 79 (18.6%) utilized it for school purposes, 4 (0.9%) for banking, 116 (27.4%) for job, 3 (0.7%) for recreational purposes, 13 (3.1%) for hospital visits, 158 (37.3%) for various daily commute purposes, and 51 (12%) for purposes that remained unknown.

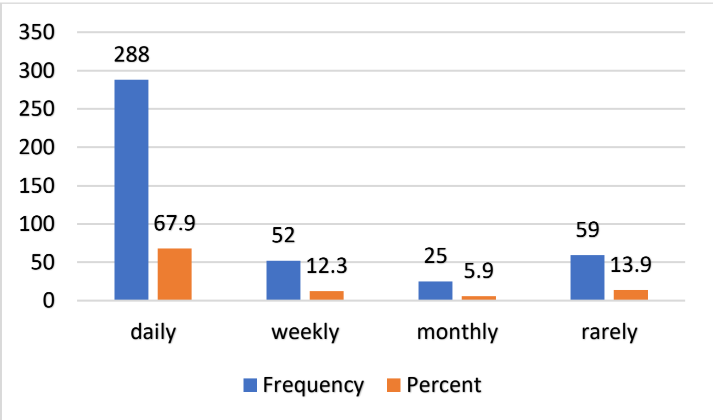


Figure 27: Frequency of bus usage

As shown in figure 27, passengers responding their frequency of buses usage, with 288 (67.9%) using it daily, 52 (12.3%) weekly, 25 (5.9%) monthly, and 59 (13.9%) using buses rarely.

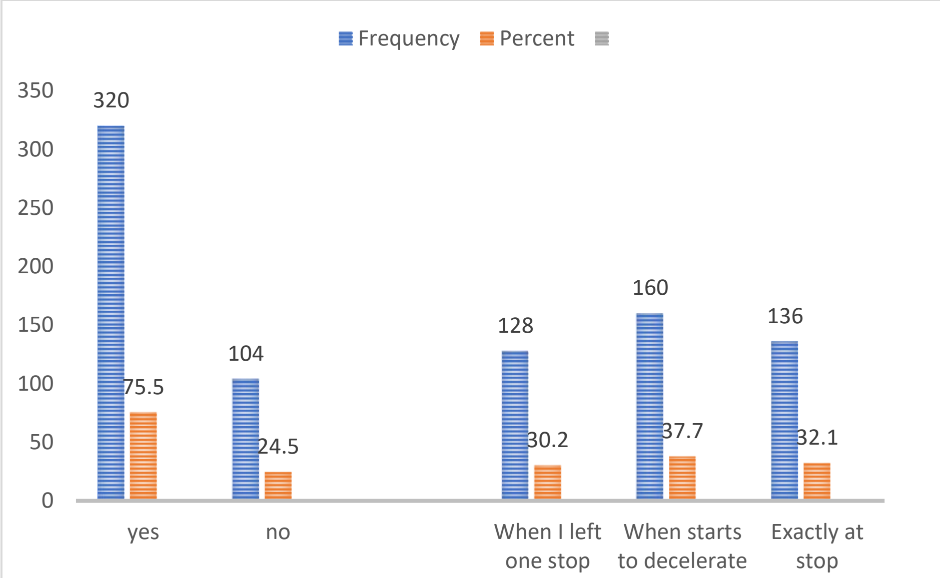


Figure 28: Passenger view to alighting time

The questionnaire was designed to explore how passengers disembark from buses, assessing their readiness to alight before reaching their destination and examining the characteristics of passengers during the alighting process. As depicted above figure 28, 320 (75.5%) passengers positioned themselves at the alighting door before reaching their final bus stop, while 104 (24.5%) passengers remained seated until the bus reached its ultimate destination. This suggests that the majority of passengers signal their intent to exit before the actual arrival at the stop. However, it's noteworthy that when passengers move toward the exit door before reaching the alighting door, the time taken for passengers to disembark tends to be longer. In general, passengers exhibited three common scenarios: moving to the door when the bus left one stop (128 passengers or 30.2%), moving to the bus door when the bus attempted to decelerate (160 passengers or 37.2%), and attempting to alight exactly at the stop (136 passengers or 32.1%). Despite the overall readiness of passengers during alighting, it is essential to acknowledge that 32.1% of passengers faced challenges embarking or disembarking when buses were at full capacity.

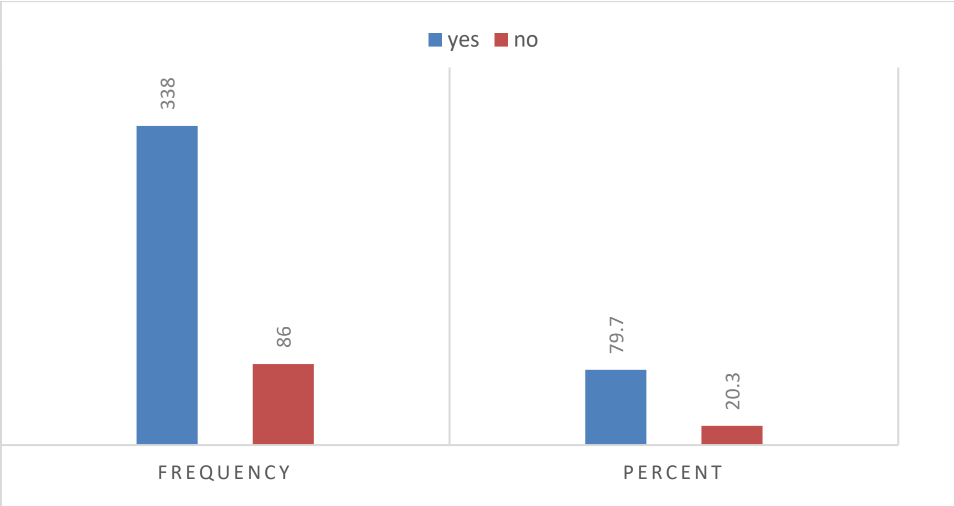


Figure 29: Get off the passengers

As it can be shown in figure 29, among the 424 respondents, 338 (79.7%) of the passengers engaged in the practice of moving in and out of the bus door to create a free space for alighting passengers, while 86 (20.3%) did not partake in this movement to facilitate passenger disembarkation.

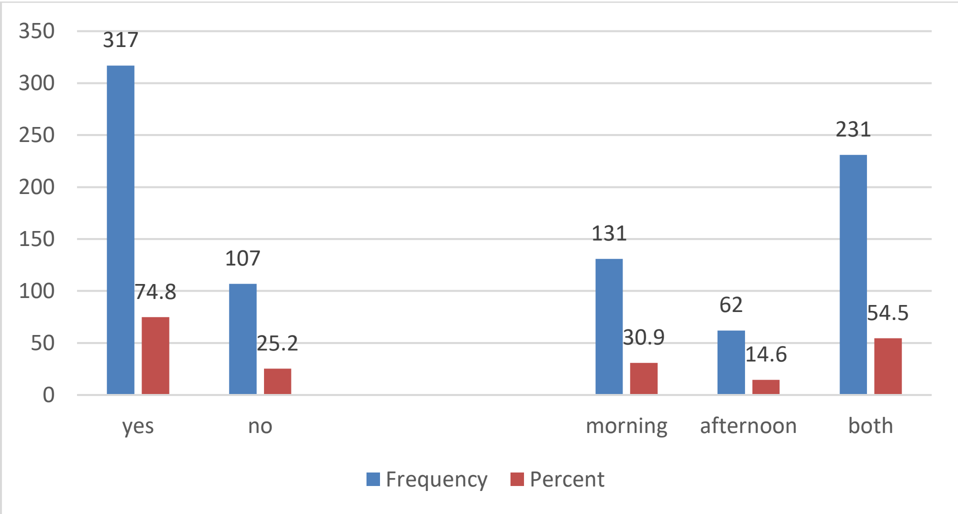


Figure 30: Bus arrival frequency on passenger demand

Table 34: Passengers bus waiting time at stop

| | Frequency | Percent |
|---|---|---|
| 21-30 minutes | 133 | 31.4 |
| 11-20 minutes | 59 | 13.9 |
| other | 11 | 2.6 |
| <10 minutes | 39 | 9.2 |
| >31 minutes | 181 | 42.7 |
| Total | 424 | 100.0 |

Source: Filed questioners from passengers,2023

According to the findings in figure 30, 317 passengers (74.8%) easily identified their bus stops, while 107 passengers (25.2%) experienced confusion in determining where the bus departs and ends. This suggests that the identification issue is not a primary factor contributing to the creation of bus dwell time at stops.

Analyzing waiting patterns, 131 passengers (30.9%) waited in the morning, 62 (14.6%) in the afternoon, and 231 (54.5%) during both morning and afternoon at a single stop. Although passengers can identify their bus destinations, long waiting times at bus stops lead to a higher concentration of passengers at one stop, resulting in excessive boarding at the next stop, which significantly impacts dwell time.

As per table 34, 133 passengers (31.4%) waited for 21-31 minutes, 59 (13.9%) for 11-20 minutes, 39 (9.2%) for less than 10 minutes, 181 (42.7%) for more than 31 minutes in average and 11 (2.6%) had other waiting times at a single stop. Thus, the responses indicate that an excess of passengers waiting at a stop strongly contributes to the prolonged bus dwell time at stops.

Table 35: Standees space of passengers

| Do buses have better standees space to a lighting and boards? | | Frequency | Percent |
|---|---|---|---|
| | Yes | 205 | 48.34 |
| | No | 219 | 51.65 |

Source: field survey, 2023

As indicated in table 35, 205 passengers (48.34%) acknowledged that buses have sufficient standing room, while 219 passengers (51.65%) expressed dissatisfaction, stating that buses lack an adequate standing area for both boarding and alighting.

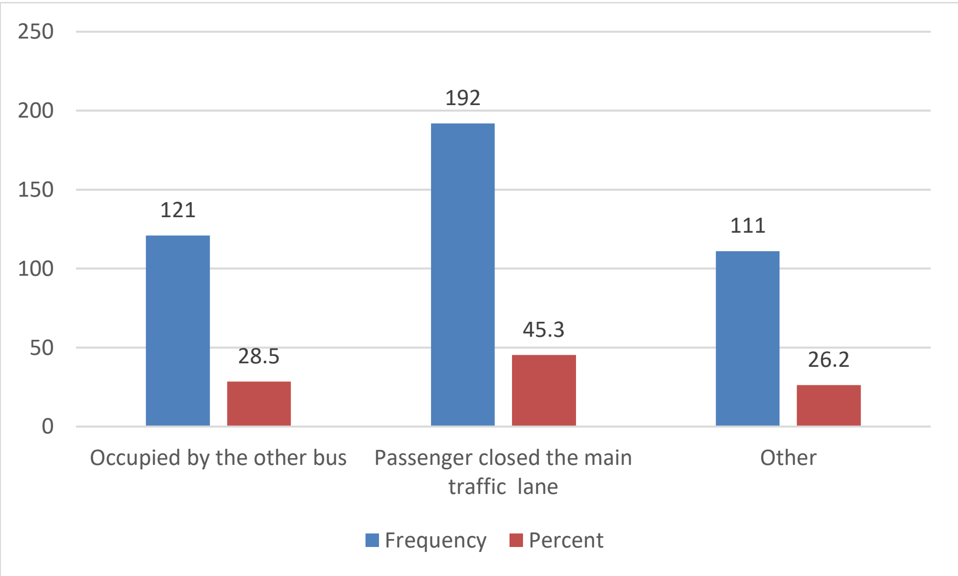


Figure 31: Passengers' reason on bus batching effect

Among the respondents, 121 (28.5%) attributed the issue to the occupation of the space by other buses, while 192 (45.3%) pointed out that passengers obstructed the main traffic lane. The remaining 111 respondents (26.2%) cited various other reasons for buses being unable to stop at the right curve stone of the traffic lane.

The respondents' feedback on why buses did not stop near the right edge of the lane curve stone is indicated in figure 31.

Table 36: Bus tariff issues and ability of boarding and alighting

| | Frequency | Percent | |
|---|---|---|---|
| yes | 154 | 36.3 | Do you need any assistance to board and alight bus steps? |
| no | 270 | 63.7 | |
| yes | 141 | 33.3 | Are you okay if the office of transport provides a single ticket for all public transport modes in a journey equal tariff? |
| no | 283 | 66.7 | |

Source: questionnaires from bus passengers,2023

Table 37:Odd penny characteristics of passengers

| Do you have equal amount of coin with fare value? | | |
|---|---|---|
| | Frequency | Percent |
| yes | 353 | 83.3 |
| no | 71 | 16.7 |
| total | 424 | 100 |
| If your answer is yes how often you have odd- penny in your hand to get fare. | | |
| Always | 146 | 34.4 |
| Sometimes | 278 | 65.6 |

Source: questionnaires from bus passengers,2023

Table 36 reveals that, majority of passengers, 270 (63.7%), expressed the need for assistance, while 154 passengers (36.3%) stated they did not require any assistance when boarding or alighting from the bus with their belongings and baggage. Although not a widespread issue, a few elderly and larger-bodied passengers experienced challenges, contributing to bus dwell time at stops. Additionally, 141 passengers (33.3%) favored the establishment of a single ticket for the entire journey, while a majority of 283 passengers (66.7%) found the financial cost to be prohibitive. Despite the potential financial concerns, implementing a single-ticket system for the entire journey could effectively reduce bus dwell time by addressing issues such as fare time, idle time, and unexpected disputes.

Likewise, from table 37, 146 passengers (34.4%) consistently encounter situations where they lack the exact fare, and with a significant frequency, 278 passengers (65.7%) often find themselves with an odd penny when attempting to pay for their fare.

Table 38: Bus stop comfort for passengers

| Which bus step is not good for you to board and alight? | | |
|---|---|---|
| Bus | Frequency | Percent |
| Single Anbessa bus | 25 | 5.9 |
| Single Sheger bus | 12 | 2.8 |
| Alliance | 291 | 68.6 |

Source: questionnaires from bus passengers,2023

As indicated in table 38, Alliance buses stand out with a significant frequency, as 291 passengers (68.6%) acknowledge the discomfort associated with entering and exiting these buses compared to Single Anbessa and Sheger buses. The passengers' feedback suggests that these buses contribute to prolonged dwell times, particularly impacting individuals with disabilities and larger body sizes. Thus, it can be inferred that the design of bus steps has a positive impact on the creation of dwell time.

Table 39: Passengers' friction and baggage status

| | | | |
|---|---|---|---|
| | | Frequency | Percent |
| | yes | 424 | 100 |
| Is there friction to board &alighting | no | 0 | 0 |
| If your answer is yes do you think you have additional time do you to friction | | | |
| | | Frequency | Percent |
| | yes | 397 | 93.6 |
| | no | 27 | 6.4 |
| | Total | 424 | 100 |
| | | | |
| | | Frequency | Percent |
| | yes | 347 | 81.8 |
| | no | 77 | 18.2 |
| Do you have luggage in your trip? | Total | 424 | 100 |
| if your answer is yes do the luggage protect you from boarding and alighting | | | |
| | | Frequency | Percent |
| | yes | 242 | 57.1 |
| | no | 182 | 42.9 |
| | Total | 424 | 100 |
| Does the time taken by the bus at stop affect your decisions for taking the bus? | | | |
| | | Frequency | Percent |
| | yes | 332 | 78.3 |
| | no | 92 | 21.7 |
| | Total | 424 | 100 |

Source: SPSS output from questionnaires of passenger,2023

As illustrated in table 39, all respondents unanimously agreed on the existence of friction, totaling 424 (100%). Among them, 397 passengers (93.6%) believe that friction significantly contributes to dwell time during daily trips, while the remaining 27 passengers (6.4%) do not associate friction with dwell time.

Furthermore, the table confirms that a substantial number, 347 passengers (81.8%), utilize baggage on their daily trips, while 77 passengers (18.2%) do not. Among those using baggage, 242 passengers (57.1%) assert that their baggage facilitates boarding and alighting, while 182 passengers (42.9%) express challenges in boarding and alighting with baggage, attributing this to passenger friction, particularly near the bus door, and the difficulty for larger passengers to ascend high-floor doors.

# CHAPTER 4 RESULT AND DISCUSSION

Due to the extensive volume of data and a thorough examination of two distinct models, various methodologies have been employed to analyze the data. This section will explore the key points of discussion and the most noteworthy discoveries. The discussion topics will be categorized into three segments: In the initial section, a comparison is made between two models which is Weibull regression and Gaussian regression examining their reliability, mean square error, and the number of determinant factors significantly influencing each model. Moving on to the second section, an exploration of Gaussian and Weibull distribution models is conducted in conjunction with the previously discussed models. Finally, the discussion explores deeply into selected qualitative results derived from passenger responses.

## 4.1 Comparison between the Gaussian regression model and the Weibull regression model

In this section, comparison of key metrics, including Root Mean Square Error (RMSE), R-squared, Adjusted R-squared (R-sq(adj)), number of variables which has significant effect in bus dwell time at stop will be discussed in the context of the provided information.

### 4.1.1 Root mean square error (RMSE)

The root means square error (RMSE) for Gaussian regression is 3.93, while for Weibull regression, it is reported as 0.075. This value indicates a notably low average deviation between the observed and predicted values. A decreased RMSE generally implies a superior fit of the model. Consequently, it can be inferred that the Weibull regression model exhibits high accuracy in predicting values.

For Gaussian regression demonstrated R-squared, Adjusted R-squared (R-sq(adj)), and R-squared predicted (R-sq(pred)) values of 92.96%, 92.63%, and 92.13%, respectively. Conversely, Weibull regression displayed slightly higher values with R-squared, Adjusted R-squared, and R-squared predicted values of 93.47%, 93.00%, and 92.39%, indicating a relatively better fit for the Weibull regression model in capturing the variability of the data. The constant values for Gaussian regression and Weibull regression are 7.77 (with a standard error of 1.88, t-value of 4.13, and P-value of 0.000) and -0.1139 (with a standard error of 0.0208, t-Value of -5.46, and P-value of 0.0), respectively. It is confirmed that the constant term significantly differs between the two models. In the Gaussian model, six variables exhibited statistical significance, while for Weibull regression, nine variables demonstrated significance. The coefficients for the significant variables in each model are presented below.

In the Gaussian model, the coefficient for the variable ‘No Alighting’ is 0.492 (Standard error = 0.135, t-Value = 3.63, P-value = 0.000, VIF = 2.45), whereas in the Weibull model, the corresponding coefficient is 0.0801 (Standard error = 0.0318, t-value = 2.52, P-value = 0.013, VIF = 2.18). In the Gaussian model, the coefficient for the variable ‘No Boarding’ is 0.391 (Standard error = 0.137, t-Value = 2.85, P-value = 0.005, VIF = 2.25). In contrast, the Weibull model yields a coefficient of 0.0971 (Standard error = 0.0318, t-Value = 3.06, P-value = 0.003, VIF = 2.23). The interpretation revolves around the observed differences in coefficient values, both of which demonstrate a statistically significant impact.

In the Gaussian model, the coefficient for the variable ‘Boarding time’ is 0.4979 (Standard error = 0.0531, t-Value = 9.37, P-value = 0.000, VIF = 2.42). Conversely, the Weibull model presents a coefficient of 0.3463 (Standard error = 0.0358, t-Value = 9.68, P-value = 0.000, VIF = 2.48).

In the Gaussian model, the coefficient for the variable ‘Idle time’ is 0.3221 (Standard error = 0.092, t-Value = 3.5, P-value = 0.001, VIF = 2.3). Conversely, the Weibull model presents a coefficient of 0.0788 (Standard error = 0.033, t-Value = 2.39, P-value = 0.018, VIF = 2.32). The coefficient for the variable ‘Odd Penny’ in the Gaussian model is associated with a Standard error of 0.0869, a t-Value of 7.99, a P-value of 0.000, and a VIF of 3.38. In contrast, the Weibull model presents a coefficient of 0.32 with a Standard error of 0.0387, a t-Value of 8.26, a P-value of 0.000, and a VIF of 2.96.

The coefficient for the variable ‘Re-boarding’ in the Gaussian model yields a coefficient of 0.522 (Standard error = 0.137, t-Value = 3.8, P-value = 0.000, VIF = 1.41), while the Weibull model produces a coefficient of 0.0642 (Standard error = 0.03, t-Value = 2.14, P-value = 0.034, VIF = 1.16). Additional Weibull coefficients, which involve variables related to acceleration and stop location type, have been incorporated for a thorough examination and comparison of bus dwell time at stop.

In conclusion, there were differences in coefficients between the Gaussian and Weibull regression models across various predictors, suggesting variations in the impact of these predictors on the dependent variable. Statistical significance is evident for numerous coefficients in both models. The main takeaway about the flexibility of the Weibull regression over Gaussian is that Weibull regression provides greater flexibility in modeling because it does not assume that the errors (residuals) in the model follow a normal (Gaussian) distribution. Instead, Weibull regression can accommodate different shapes of error distributions, making it more useful and potentially more accurate for a wider range of data sets compared to models that assume a normal error distribution. This is particularly useful in scenarios where the data exhibit skewness or heavy tails that are not well-captured by a normal distribution. Which is consistence with study conducted by (Isukapati et al., 2017).

### 4.1.2 Gaussian regression

The outcomes achieved enable the researcher to affirm that the most influential predictors were identified, and a comparison with previous models has been conducted. In the upcoming section, the variables that significantly impact the bus dwell time at the stop in the context of Gaussian regression models will presented. From the results of this research six predictors were statistically significance.

- No-alighting passengers

The variable 'No-alighting passengers' measured in quantity and considered a component of dwell time, exhibited a statistically significant effect on bus dwell time at a stop. The coefficient of 0.492, determined through Gaussian regression modeling, indicates the strength of this impact. The significance is supported by a low p-value of 0.0. The number of riders disembarking from the bus at a specific stop was manually counted, employing methods such as a mobile video camera or manual tracking on paper for accurate observation.

The findings of this study are supported by research conducted by (Wang et al., 2016b),where the variable of alighting passengers demonstrated statistical significance with a p-value of 0.001 with corresponding coefficient for this significance was 0. 099. And another study (Dissertation, 2022) done his work on the investigation into dwell times at the high-passenger-volume station utilized real operational data using three factors related to passenger volume (boarding, alighting, and previous train loads) exhibited slight positive correlations with dwell times. The study's results align with a conclusion made in China(Kostyniuk & D'Souza, 2020). The possible reason might be a strong correlation between transit service performance, specifically the variability in dwell time, and the boarding and alighting practices of a diverse range of passenger groups which carry significant implications for the accurate estimation of dwell time. Moreover, passengers utilizing wheeled mobility devices experience significantly increased boarding and alighting times, particularly on low-floor buses. This is partly attributed to design limitations in equipment, such as the access ramp. The reason might be the incorporation of additional variables related to the use of mobility aids and other obstacles resulted in a substantial increase in the explained variance of the dwell time model, elevating it from 45.7% to 56.2%.

This study aligns with the findings of another researcher's work on the impact of various bus stop designs on bus operation time components in Singapore ( Liu et al., 2017b).The justification might be bus stop influenced by several factors, including the quantity of passengers boarding and alighting, the average time it takes for each passenger to board or alight, and a constant time element that encompasses the duration of door opening and closing.

- Number of boarding passengers

In this research, the variable 'No-boarding' exhibited a statistically significant effect on bus dwell time at a stop with a low p-value of 0.005. The coefficient of 0.391, determined through Gaussian regression modeling, indicates the strength of this impact with a higher reliability R-squared value is 92.96%, indicating that approximately 92.96% of the variance in the dependent variable was being explained by the independent variable(s).The findings of this study align with the work conducted in Australia (Tirachini, 2013a). Having two steps on the front door leads to a slower boarding process. However, the effect on alighting was not statistically significant. This is attributed to the considerably shorter duration of alighting compared to boarding. The possible explanation for this occurrence might be the increased complexity and time required for passengers to navigate multiple steps and friction created on each passenger during the boarding phase. in addition, formation of two lines of passengers to board a vehicle can have a negative impact on boarding times, compared to the case with low demand and one queue to board.

Other finding affirms the importance of boarding and alighting passenger volumes, as well as on-board passenger loading, in influencing dwell time at bus stops. The study also identifies additional factors impacting dwell time, including the type of vehicle (low- or high-floor), the time of day (peak, off-peak, inter-peak), and the station's location (city center, proximity to points of interest). These results underscore the multifaceted nature of dwell time, with various factors contributing to its variability(Cristoforo et al., 2020).

The regression models based on bus stop types produced statistically significant results within the acceptable margin of error (5% significance level), demonstrating high R2 values ranging from 73% to 95% for dwell time (DT). ANOVA tests further confirmed the statistical significance of F-statistics ($p < 0.05$). This study supported by the study conducted in USA (Arhin & Noel, 2015b). The reason might be the number of passengers alighting and boarding significantly contributed to the models, as indicated by the statistical significance of their coefficients. However, the study findings revealed that factors such as the number of approach lanes, the presence of parking, and bus pad length did not have a significant influence on dwell time. The possible explanation regarding this phenomenon might be, the non-significant influence of certain factors on dwell time may be due to their limited impact, effective design, uniformity across bus stops, local contextual factors of multiple elements influencing bus operations. Also, bus stops with different numbers of approach lanes, parking availability, and bus pad lengths might still share a common design that mitigates the potential impact of these specific variables.

Likewise, study in Australian researcher (Yang et al., 2019) states boarding and alighting behavior are consistently acknowledged as pivotal factors influencing dwell time. Notably, many researchers treat these factors as variables, emphasizing their significance in the complex dynamics of bus dwell time. This recognition underscores the ongoing efforts to develop comprehensive models that capture the nuanced interplay of various factors contributing to the overall understanding of bus dwell time.

- Bus stop Location

Bus stop location was not significantly impact on dwell time the study done in China (Wang et al., 2016c) bus dwell influence on the three types of bus stop locations, near-side, far-side, and mid-block. Consequently, a sensitivity analysis was carried out to examine how the placement of bus stops affects both bus dwell time and the time lost while serving the stop. The findings revealed statistically significant differences in measurements between near-side and far-side stops, as well as near-side and mid-block stops, during both peak and non-peak periods. However, the differences between far-side and mid-block stops were not found to be statistically significant. Moreover, the results suggested that near-side stops could lead to longer dwell time and increased time lost while serving the stop compared to the other two types of bus stops. The possible reason might be, in contrast to far-side and mid-block bus stops, a near-side bus stop experiences extended average delays for re-entering the traffic stream, bus stop failure time, and traffic signal delay. Specifically, at a near-side bus stop, the bus is required to wait until all other buses have completed serving their passengers and the traffic signal

turns green, allowing it to continue along the street. But The study's findings have significant implications for transportation authorities and operators, revealing that mean boarding and alighting times per passenger at bus bays consistently exceeded those at curb-side stops, registering an overall increase of 14% (0.2 seconds) (Liu et al., 2017).This discrepancy is primarily attributed to the additional maneuver required at bus bays, creating a gap between the bus and the curb. This maneuver prompts passengers to take extra steps onto the road during boarding and after alighting. Likewise, another research conducted in Australia (Tirachini, 2013a) a bus stop is positioned before a traffic light, drivers may opt to keep the door open, facilitating boarding while the traffic light is red. Furthermore, control strategies implemented at stops, such as bus holding to regulate headways or uphold adherence to a predetermined timetable, could contribute to an increase in dwell times.
Study ( Arhin & Noel, 2015a) investigated that predicting dwell time by bus stop type and time of the days concluded that dwell time is differ based on the bus stop location and time of the day. This research's test debate from the scholar. The justification might be the infrastructure and other local factors such as environment traffic rules would affect such time.

- Pavement method

The finding of this work related to 'Odd penny in the regression analysis is that coefficient is 0.6946, suggesting that, holding all other factors constant, the bus dwell time is expected to increase by 0.6946 seconds for every one-unit increase in odd penny fare time. This implies a positive association between odd penny fare time and bus dwell time. The high t-value (7.99) and low p-value (0.000) indicate that the effect of 'Odd penny' is highly statistically significant. The initial consideration for payment structure was 'Odd penny' and 'exact fare'. The findings show that 'exact fare time' was not found to be statistically significant in affecting dwell time. This suggests that variations in dwell time related to the exact fare time do not significantly contribute to delays in bus dwell time. Possible explanations for the non-significance include the idea that if passengers are well-prepared with the exact fare, the transaction process might be quick and not contribute significantly to delays. Another consideration is the consistency in exact fare times, if the variation in exact fare times is minimal across different instances, it may not have a visible impact on dwell time in the regression analysis. In contrast, 'Odd penny' transactions might introduce more variability or complexity. When discussing with previous work, it is important to highlight payment method having the most significant impact. Payment by cash results in approximately 2.3 times more delay compared to payment by card. The reason behind is handling cash transactions typically takes more time than electronic transactions. Counting change, verifying amounts, and processing cash transactions involve manual steps that contribute to delays(Ling KHOO, 2013).

There is inconsistency between the current study and a previous study in USA(Guenthner & Hamat, 1988) , where the latter found no significant differences between fare payment methods, could be attributed to various factors. Potential explanations for the discrepancy are changes in the transit system infrastructure or operational policies over time may impact the efficiency of fare payment methods. If there have been updates or modifications, they could influence the results. Passengers who pay the exact fare experience a decrease in dwell time, it could suggest that using exact change or electronic payment methods may expedite the boarding process compared to situations where passengers need to provide or receive change and support the current study(Fernandez, 2011).

- Idle time

In this work, the analysis of the ‘Idle time’ variable reveals a statistically significant and positive association with the bus dwell time at stop. The coefficient of 0.3221 indicates that a one-unit increase in ‘Idle time’ corresponds to a 0.3221 unit increase in the bus dwell time at stop. The large t-value of 3.5 signifies the significance of this relationship, suggesting that the observed association is unlikely to be due to random chance. Additionally, the low p-value of 0.001 further supports the statistical significance, indicating a minimal probability of observing such a strong relationship under the assumption of no effect. The VIF of 2.3 indicates a low level of multicollinearity among independent variables, reinforcing the reliability of the findings. Overall, these results affirm that ‘Idle time’ is a meaningful predictor of bus dwell time at stop in the regression model. The possible explanation on this regard might be, if fare disputes lead to delays in boarding or alighting passengers, it can contribute increased bus dwell time. Passengers taking longer to resolve payment issues or disputes with fare collection could extend the time the bus spends at a stop. The time spent waiting for passengers to fully enter the bus, ensuring that everyone is safely on board before departure, could contribute significantly to bus dwell time.

- Re- Boarding

In this study, the regression coefficient of re-boarding passengers is 0.522, indicating the expected change in the dependent variable (bus dwell time) for a one-unit increase in the independent variable (the number of passengers re-boarding), assuming all other factors remain constant. In summary, the positive regression coefficient for re-boarding passengers suggests that an increase in the number of passengers re-boarding is associated with a corresponding increase in bus dwell time. The statistical significance, as indicated by a t-value of 3.8 and a p-value of 0.000, supports the reliability of this relationship. Additionally, the low VIF of 1.41 suggests that multicollinearity is not a major concern in the regression model.

The positive regression coefficient for re-boarding passengers (0.522) suggests that an increase in the number of passengers re-boarding is associated with a corresponding increase in bus dwell time. The possible explanations for re-boarding passengers might contribute to a more complex boarding process compared to initial boarding, Passengers re-boarding may take longer to find available seats, resulting in extended dwell times, If more passengers are getting on and off the bus at the same stop, it can contribute to a longer dwell time, During bus near capacity and re-boarding passengers add to crowding, it may take more time for passengers to move to their seats or for the driver to manage the boarding process. The behavior of re-boarding passengers, such as hesitating to board or taking more time to find a seat, can contribute to increased dwell time, obstacles or narrow passages inside the bus, it may slow down the re-boarding process, Re-boarding passengers, especially those with mobility challenges, may require additional assistance or time, contributing to increased dwell time.

### 4.1.3 Weibull regression

The Weibull regression model analysis reveals important insights into the factors influencing bus dwell time. The root means square error (S) of 0.0756783 indicates a low average deviation between observed and predicted values, suggesting a good fit. The high R-squared (93.47%) and adjusted R-squared (93.00%) values highlight the model's strong explanatory power, even when considering the complexity introduced by additional predictors. Moving to the specific coefficients for various variables, such as No Alig. Weibull (Number of alighting), Alig.Weibull (Alighting time), Board.Weibull (Boarding time), Idle. Weibull (Idle time), No. Boa.Weibull (Numbers of Boarding), Odd.pen. Weibull (Odd penny Weibull), Re.boa.webull(Re-boarding passengers), Accel.Weibull (Acceleration time), Far side (Far side stop), each coefficient provides information on the expected increase in the hazard rate and, consequently, bus dwell time for a one-unit increase in the respective variable. These findings underscore the multifaceted nature of factors contributing to bus dwell time and emphasize the importance of considering each variable in optimizing bus schedules and improving overall transit efficiency.

A study conducted in South Korea (Kim, 2007b) the possible explanation for this consistency is that the empirical data model for dwell time distribution follows a Weibull distribution shape.

The study conducted in Beijing, China (Zhang & Bai,2021), in investigation into dwell times at various intermediate bus stations utilized probabilistic statistical methods. The possible concept in this regard, its flexibility allows it to capture various shapes of distributions, making it suitable for modeling diverse scenarios in dwell times.

In this study Weibull regression has to be the best fitted distribution for bus dwell time study which lack consistence the study conducted in Switzerland (Büchel & Corman, 2020).The possible reason might be log-normal distribution generally outperforms others for running times, while the gamma distribution is the second-best fit for dwell, running, and travel times, except when the Cauchy distribution is better under minimal spatial aggregation conditions.

In this study relation to age demographics, the boarding time for adults and seniors, passenger with child and their package cold effect on additional dwell time from qualitative study of this work. Which is consistent with done in Australia (Tirachini, 2013a). The possible reason for significant difference might be, senior passengers exhibit a slower speed during both boarding and alighting processes when compared to their younger counterparts, their physical limitations making it more challenging for them to navigate steps or move quickly, older individuals may have decreased balance and stability, requirements of additional assistance or more time to access seating or exit the vehicle, contributing to the overall slowdown in the process, age-related cognitive changes may also play a role, with seniors potentially taking more time to process information and make decisions during boarding and alighting. Study conducted in Malaysia (Ling KHOO, 2013) suggesting that crowding levels may impact dwell time duration. The mean dwell time for less crowded categories appears to be shorter when compared to more crowded categories. Crowded platforms tend to restrict passengers' maneuverability, as over-crowded boarding can impede smooth alighting activities Moreover, a higher number of passengers waiting at the platform increases the likelihood of congestion at bus stops, unavoidable prolonging dwell time.

Passengers readiness to alight before reaching their destination and examining the characteristics of passengers during the alighting process. The majority of passengers signal their intent to exit before the actual arrival at the stop. However, it's noteworthy that when passengers move toward the exit door before reaching the alighting door, the time taken for passengers to disembark tends to be longer. In general, passengers exhibited three common scenarios: moving to the door when the bus left one stop (128 passengers or 30.2%), moving to the bus door when the bus attempted to decelerate (160 passengers or 37.2%), and attempting to alight exactly at the stop (136 passengers or 32.1%). Despite the overall readiness of passengers during alighting, it is essential to acknowledge that 32.1% of passengers faced challenges embarking or disembarking when buses were at full capacity, highlighting the difficulties of maneuvering in and out of an overcrowded public bus transit system.

Among the 424 respondents, 338 (79.7%) of the passengers engaged in the practice of moving in and out of the bus door to create a free space for alighting passengers, while 86 (20.3%) did not partake in this movement to facilitate passenger disembarkation. This suggests that a majority of bus users, particularly those situated near the bus door, experienced these moves in and out scenarios. This observed pattern has a statistically significant impact on bus dwell time at stops, as evidenced in the accompanying figure. Consequently, it can be inferred that the actions of re-boarding passengers significantly contribute to the dwell time of the bus at stops.

The respondents' feedback on why buses did not stop near the right edge of the lane curve stone is indicated in 39 figure 40. Occupation of Space by other buses (28.5%) significant portion of respondents (121 individuals) identified the issue of buses not stopping near the right curve stone as being due to the occupation of space by other buses. This implies that congestion or competition for stopping space among buses may contribute to the problem.

Passengers obstructing the main traffic lane (45.3%): The majority of respondents (192 individuals) pointed out that passengers obstructed the main traffic lane, preventing buses from stopping at the designated location. This indicates that passenger behavior, possibly in terms of boarding or alighting, might be causing buses to deviate from the intended stopping point.

Other reasons (26.2%) substantial number of respondents (111 individuals) cited various other reasons for buses being unable to stop at the right curve stone. These might be including factors such as road conditions, vehicle issues, or other unforeseen circumstances that hinder buses from following the designated stopping pattern.

The conclusion drawn from the feedback emphasizes the critical nature of irregular passenger patterns and a lack of discipline. It underscores the need for spatial attention and law enforcement to address these issues. In other words, addressing the problems identified by the respondents requires a combination of better traffic management, enforcement of rules and regulations, and possibly improvements in infrastructure or facilities to facilitate smoother bus operations.

This study revealed that a significant majority of participants, comprising 270 individuals (63.7%), expressed a need for assistance, while 154 passengers (36.3%) indicated that they did not required any help to board and alighting. In the presented research, the data indicates that passengers seeking assistance have contributed to prolonged dwell times at stops, potentially affecting the overall operational efficiency of the bus service particularly during peak hours. This study is supported by the study conducted in (Tirachini, 2013b) presents the presence of two steps at the front door hinders the boarding process, with senior passengers requiring more time to board and alight compared to their younger counterparts. Additionally, a crowding effect is observed, as the presence of standing passengers inside the bus marginally decelerates both the boarding and alighting procedures. Passengers with disabilities or special needs**,** the design of the buses may impact passenger's ability to board or alight independently. If buses are not easily accessible, more passengers might express a need for assistance. Some passengers may prefer independence, while others may be more open to assistance**.**

Even though passengers may make efforts and spend time trying to get the exact amount of money needed to pay for their bus fare, they often find themselves without the correct change. This circumstance contributes to extended dwell times and warrants special attention.This is supported by the study conducted by (Hussain et al., 2023; Tirachini, 2013b).

Regarding bus step convenience both to board and alight, Alliance buses had significant frequency, as 291 passengers (68.6%) acknowledge the discomfort associated with entering and exiting these buses compared to Single Anbessa and Sheger buses. It suggests that steps of Alliance buses contribute to prolonged dwell times. This study is supported by the study (Tirachini, 2013b) confirmed that the presence of two steps at the front door slows down the boarding process another researcher agreed with if doors are not easily accessible or located in inconvenient positions, passengers may face difficulties entering or exiting the bus (Katz & Garrow, 2014) and (Dueker et al., 2013).

All of respondents acknowledge the presence of friction, in total of 424 (100%). Among them, 397 passengers (93.6%), friction was significantly increase dwell time during on their daily trips, while the remaining 27 passengers (6.4%) did not believe friction was cause of dwell time. This is supported with the research conducted in(Tirachini, 2013b). This might be the physical interaction between passengers and the elements of the boarding process, such as contact between passengers and the boarding ramp, seats, or other surfaces, overcrowded transit services lead to increased friction, hindering the smooth opening and closing of doors.

Furthermore, this study confirms, 347 passengers (81.8%), utilize baggage on their daily trips, while 77 passengers (18.2%) do not. Among those 242 passengers (57.1%) assert that their baggage increases dwell time and 182 passengers (42.9%) passengers was not affected by their baggage. Friction had significant effect on bus dwell time. Which is supported by the study conducted by (Watts et al., 2015).The possible explanation on this regard will be large luggage or assisting passengers with small children attributing this to passenger friction, which slow down the boarding process particularly near the bus door, and the difficulty for passengers to ascend high-floor doors this were identified as factors that can easily increase both alighting and boarding time. Passengers with smaller, more manageable luggage might find it easier to board and alight, while those with large or cumbersome items may experience more difficulties bus stop service time.

Passengers often plan their journeys based on schedules. If a bus consistently takes a long time at each stop, it may create uncertainty about the overall reliability of the bus service, leading passengers to choose more predictable modes of transportation.

332 (78.3%), changed their choice due to the significant effects of dwell time. while the remaining 92 passengers, or 21.7%, did not consider dwell time as a decision-making factor. This suggests that a majority of passengers in the study were influenced by the dwell time when making decisions during their daily trips, while a smaller percentage did not find dwell time to be a significant factor in their decision-making process. Passengers who changed their choice may be more time-sensitive, valuing efficiency and shorter dwell times. For them, minimizing waiting times at stops or stations might be a priority, influencing their decisions.

# CHAPTER 5 CONCLUSIONS AND RECCOMENDATIONS

## 5.1 Conclusions

There was no statistically significant difference between stop type and bus type when considering both variables together, as indicated by a p-value of 0.845, which exceeds the conventional significance threshold of 0.05. However, when examining the variables individually, there is a statistically significant difference between stop type and bus type concerning dwell time. Alliance buses had a higher dwell time than the other two buses (Anbessa and Sheger buses) (p-value = 0.0).

Passengers who carry luggage, elderly persons, and women with children significantly affect dwell creation at bus stops. Additionally, friction at the bus door has a significant effect on dwell time. Weibull regression exhibits a significantly lower RMSE (0.075) compared to Gaussian regression (3.93), indicating superior accuracy and a better fit for predicting bus dwell time.

In Gaussian regression, the number of alighting and boarding passengers, boarding time, idle times of odd pennies, and re-boarding passengers were statistically significant effects on bus dwell time at the stop, while the types of stop (Mid-block and Far side stop) and the time of day had no effect on dwell time. In Weibull regression, variables such as the number of alighting passengers, alighting time, boarding time, idle time, number of boarding passengers, odd penny idle time, re-boarding passengers, and acceleration time were statistically significant effects on bus dwell time. In contrast, the far side stop location and the time of day had no effect on dwell time.

The negative coefficients of the Weibull constant indicate that each independent variable is associated with the Weibull transformation of the respective variable. To comprehensively examine the distribution and behavior of dwell time data, various statistical tools, including Kolmogorov-Smirnov and Shapiro-Wilk tests, along with graphical instruments like histograms and scatter plots, were employed. Due to the complexity and random nature of dwell time, a probabilistic approach was found to be a better fit model over the deterministic model.

## 5.2 Recommendations

The effect of traffic signals in front of the bus stops and the probability of bus queue formation behind the bus stops needs further study. The study focused only on stop times; traveling time between stops will require future investigation. The availability and efficiency of exits that impact the speed at which passengers can alight need to be studied. Additionally, the socio-psychological aspects of dwell time, including passenger behavior, interaction patterns, and the impact of social dynamics, require further study. The critical nature of irregular passenger patterns and lack of discipline needs attention and law enforcement by transport agencies, as observed during the study. The Addis Ababa City Transport Bureau (AACTB) is encouraged to apply advanced machine learning techniques such as Automatic Vehicle Location (AVL), Automatic Fare Collection (AFC), and Automatic Passenger Counter (APC).

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# CHAPTER 7 APPENDIXS

## 7.1 Appendixes A: Bus trip per day and passenger density; Addis Ababa,2023

| ዴፖ | | ሳሚት | | | | |
|---|---|---|---|---|---|---|
| ኮድ | የመገናኛ ዴፖ መስመር | የአውቶቡስ ብዛት (ዕቅድ) | የተሰማራ አዉቶቡስ ብዛት | ነጠላ ምልልስ | የተሸፈነ ኪ/ሜ | የተሳፋሪ ብዛት |
| 1 | ከመገናኛ --49 | 4 | 5,913 | 44,698 | 276,104 | 966,979 |
| 2 | መገናኛ-- ከተቤ | 8 | 4,594 | 25,168 | 185,216 | 615,539 |
| 3 | ከመገናኛ --ካራ | 8 | 8,042 | 50,825 | 335,604 | 1,122,828 |
| 4 | መገናኛ-ጎሮ ሰፈራ | 4 | 6,785 | 28,863 | 335,707 | 1,061,814 |
| 5 | መገናኛ --አራብሳ | 6 | 21,182 | 179,823 | 926,365 | 4,746,690 |
| 6 | መገናኛ --አባዶ | 4 | 44,113 | 333,671 | 1,907,377 | 6,822,499 |
| 7 | መገናኛ --ጣፎ | 5 | 10,662 | 78,724 | 474,316 | 1,953,925 |
| 8 | ፈረንሳይ-ሜክስኮ | 4 | 5,118 | 42,651 | 219,277 | 815,781 |
| 9 | አባዶ --ፒያሳ | 5 | 4,773 | 39,140 | 220,053 | 768,369 |
| 10 | መገናኛ --ሜክሲኮ | 6 | 14,263 | 68,359 | 709,845 | 2,281,981 |
| ድምር | | 64 | 140,865 | 1,028,905 | 6,519,921 | 24,760,809 |
| ዴፖ | | ቃሊቲ | | | | |
| 11 | ሜክሲኮ-ጀሞ1 | 8 | 21,001 | 71,121 | 983,059 | 3,244,076 |
| 12 | ሳሪስ-ፒያሳ | 2 | 1,394 | 4,128 | 79,938 | 283,716 |
| ዴፖ | | ሸጎሌ | | | | |
| | አዲሱ ገበያ-ቁራ | | | | | |
| 14 | አዲሱ ገበያ-ቦሌ | 4 | 6,877 | 84,554 | 426,550 | 1,544,249 |
| 15 | ፒያሳ-ሳንሱሲ | 3 | 33,501 | 375,057 | 1,357,474 | 4,870,278 |
| 16 | አ/ተራ-ካሳንችስ | ,5 | 5,101 | 44,967 | 200,317 | 620,301 |
| 17 | ፒያሳ-ፈረንሳይ | 4 | 11,254 | 82,729 | 429,166 | 1,272,766 |
| 18 | መገናኛ-ፒያሳ | 4 | 16,921 | 140,348 | 890,983 | 2,801,229 |
| 19 | ፒያሳ-ቦሌ | 6 | 6,545 | 66,686 | 303,517 | 927,033 |
| 20 | ፈረንሳይ-ሜክስኮ | 5 | 9,224 | 84,991 | 490,879 | 1,428,995 |
| ዴፖ | | መካኒሳ | | | | |
| 21 | አለም ባንክ-ሜክሲኮ | 4 | 4,066 | 51,209 | 141,316 | 629,073 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 22 | አየርጤና -ሜክሲኮ | 8 | 17,345 | 170,783 | 635,495 | 2,617,984 |
| 23 | ሜክሲኮ-ካራ | 6 | 3,146 | 40,403 | 119,056 | 539,290 |

Source:Addis Ababa Transport office;2023

## 7.2 Appendix B: Questioner data

### 7.2.1 English version of questioner data

| |
|---|
| Q1.Sex? |
| Q2. How old are you? |
| Q3. Your level of education? |
| Q4. Do you prefer taking the bus for your daily commute? |
| Q5. Purpose you are using bus always? |
| Q6. How frequently do you take this bus route? |
| Q7. Before you reaching your alighting, time are you move to bus door to disembark? |
| Q8. If your answer is yes just answering the following? |
| Q9. Do you wait the bus exactly at bus stop? |
| Q10. Do you identify easily the destination of the coming bus and where it departs? |
| Q11.Do you think the buses were late at bus stop in the morning or in the afternoon? |
| Q12. How long you waiting at stop to get bus? |
| Q13. Do you go in and out of the bus to get off the passengers? |
| Q14. If your answer is yes do you think dwell is created due to this in and out scenarios? |
| Q15.Does the bus always stop near to curve stone to load and unload the passengers? |
| Q16. What is the reason the bus not stop near to the curve stone? |
| Q17. Do you have equal amount of coin with fare value? |
| Q18. If your answer is yes how often you have odd- penny in your hand to get fare? |
| Q19. If your answer is no how long you wait to get fare |
| Q20. Which fare structure is easily access for you to save your time? |
| Q21.Which places are you choose to ride? |
| Q22. Which place is needed long time to alighting and boarding? |
| Q23. Do you think buses have better standees space to a lighting and boards? |
| Q24.Which bus step is not good for you to board and alight? |
| Q25.Have you ever faced problems due to lateness of the bus at stop? |
| Q26. Do you need any assistance to board and alight bus steps? |
| Q27. Are you okay if the office of transport provides a single ticket for all public transport modes in a journey equal Tarif? |

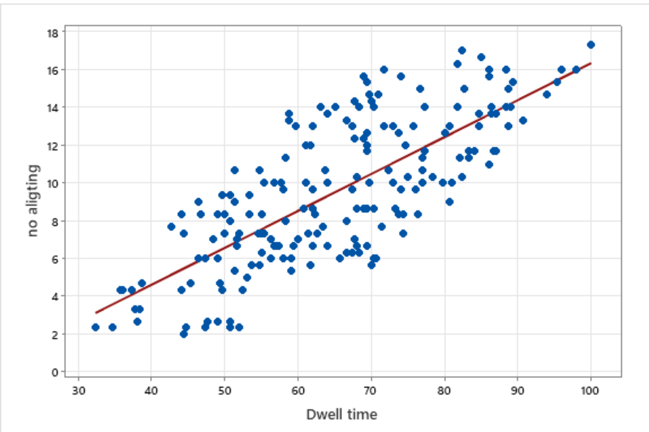
| |
|---|
| Q27. Are you okay if the office of transport provides a single ticket for all public transport modes in a journey equal Tarif? |
| Q28. Is there friction to board & alighting? |
| Q29.If your answer is yes do you think additional dwell time is created due to friction |
| Q30.Do you have luggage in your trip? |
| Q31. if your answer is yes do the luggage protect you from boarding and alighting |
| Q32. Does the time taken by the bus at stop affect your decisions for taking the bus? |

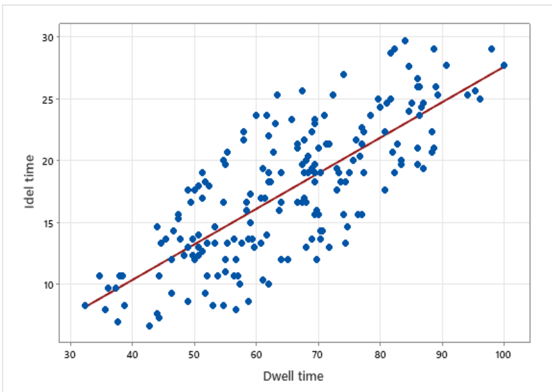
### 7.2.2 Research questions distributed to the respondent

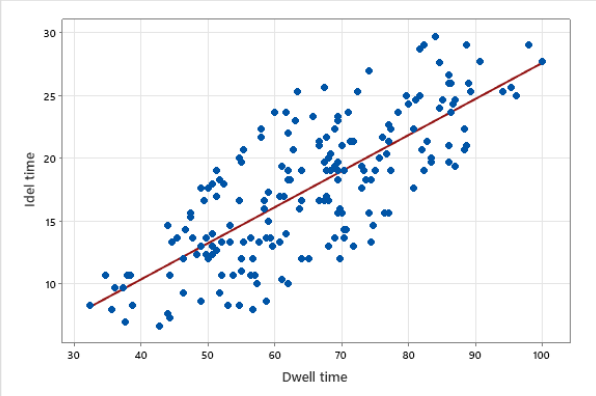
| |
|---|
| Q1. ጾታ? Gender? |
| Q2. ስንት አመትዎ ነው? How old are you? |
| Q3. የትምህርት ደረጃዎ? Your level of education? |
| Q4. Do you prefer taking the bus for your daily commute?? አውቶብስ ለጉዞወ ይጠቀማሉ? |
| Q5. ለምን ዓላማ መነሻ አውቶቡስ በብዛት የሚጠቀሙት? Purpose you are using bus always? |
| Q6. How frequently do you take this bus route? አውቶብስ መንገድ ምን ያህል ጊዜ ይጓዛሉ? |
| Q7. Before you reaching your alighting time, are you move to bus door to disembark? ከ አውቶብስ ከምወረድው ሲፈልጉ ቀድመው ወደ መድረሻ በሩ ይጠጋሉ? |
| Q8. if your answer is yes just answering the following? መልስዎ አዎ ከሆነ የሚከተሉትን ጥያቄ አብራሩ? |
| Q9.do you wait the bus exactly at bus stop? ለመሳፈር ትክክለኛ አውቶብስ መቆሚያ የተዘጋጀ ቦታ ላይ ቆመው ይጠብቃሉ? |
| Q10. do you identify easily the destination of the coming bus and where it departs? የአውቶቡስን መድረሻ እና መነሻ በቀላሉ ያውቃሉ? |
| Q11.Do you think the buses are late at bus stop in the morning or in the afternoon ወይንስ ከሰዓት አውቶብሶች የመሳፈሪያ ቦታ የሚደርሱት? |
| Q12. How long you waiting at stop to get bus? ፌርማታ ላይ አውቶብስ ለማግኘት ምን ያህል ጊዜ ይጠብቃሉ? |
| Q13. Do they go in and out of the bus to get off the passengers? የሚወርዱ ተሳፋሪወችን ለማስወጣት ከ አውቶብሱ ወተው ተመልሰው ገብተው ያውቃሉ? |
| Q14. if your answer is yes do you think dwell is created due to this in and out scenarios? መልስዎ አወ ከሆነ የጎዞ ሰዓት ጨምሮብኛል ገብተው ያስባሉ? |
| Q15.does the bus always stop near to curve stone to load and unload the passengers? አውቶብሱ ለመጫን እና ለማወረድ ወደ ተሳፋሪወችን መቆሚያ ተጠግቶ ይቆማል? |
| Q16. what is the reason the bus not stop near to the curve stone? መልስወ አይደለም ከሆነ ምክንያቱ ምንድነው? |
| Q17. Do you have equal amount of coin with fare value? ለመሳፈር ከታሪፍ ዋጋ ጋር እኩል የሆነ ሳንቲም አለዎት? |
| Q18. If your answer is yes how often you have odd- penny in your hand to get fare? መልስዎ አዎ ከሆነ፣ ትኬት ለማግኘት ምን ያህል ጊዜ በእጅዎ ላይ ሳንቲም አለ? |
| Q19. if your answer is no how long you wait to get fare መልስዎ አይደለም ከሆነ ለምን ያክል ጊዜ ትኬት ለማግኘት ይቆያሉ? |
| Q20. Which fare structure is easily access for you to save your time? የትኛው የትኬት አይነት ለርስዎ ጊዜወን |

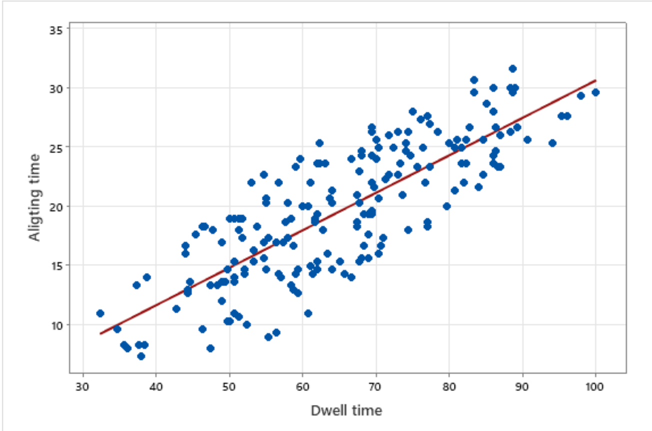
| |
|---|
| ይቆጥብልዎታል? |
| Q21.which places are you choose to ride? ለመሳፈር የሚመርጡት ቦታ የትኛው ነው? |
| Q22. which place is needed long time to alighting and boarding? የትኛው ቦታ ለመውረድ ጊዜ ይፈጅብወታል? |
| Q23. are buses have better standees space to a lighting and boards? አውቶብሶች የተሻለ የተሳፋሪ መቆሚያ እና መንቀሳቀሻ ቦታ አላቸው? |
| Q24.Which bus step is not good for you to board and alight? ከሚከተሉት የአውቶቢስ አይነቶች ደርጃ ለመውጣት እና ለመውረድ የትኛው ያስቼግርወታል? |
| Q25.Have you ever faced problems due to lateness of the bus at stop? በአውቶቡስ መዘግየት ምክንያት ችግሮች አጋጥመውዎት ያውቃሉ? |
| Q26. Do you need any assistance to board and alight bus steps? የአውቶቡስ ደረጃዎችን ለመውረድ እና ለመውጣት እገዛ ይፈልጋሉ? |
| Q27. Are you okey if the office of transport provides a single ticket for all public transport modes in a journey equal tarif? ለሁሉም የህዝብ ማመላለሻ አውቶብሶች ከመነሽ እስከ መድረሻ አንድ አይነት ዋጋ ቢሆን ይስማማሉ? |
| Q26. Is there friction to board &alighting? ከአውቶብስ ሲወርዱ እና ሲገቡ ግፊያ አለ? |
| Q28.Do you have luggage in your trip? አውቶብስ ጋ በሚሳፈሩበት ጊዜ ቦርሳ ይዘው ይገባሉ? |
| Q29.Does the time taken by the bus at stop affect your decisions for taking the bus? አውቶብሶች ፌርማታ ላይ የሚወስዱት ጊዜ አውቶብስን ለመምረጥ ተጸኖ አድርጎብወታል? |
| Q29.if your answer is yes do you think additional dwell time is created due to friction በግፊያ ምክንያት የአውቶብሱ የመድረሻ ጊዜ ይጨምራል ብለው ያስባሉ? |
| Q31. if your answer is yes do the luggage protect you from boarding and alighting ቦርሳዎ ለመውረድ እና ለመሳፈር ክልክልዎት ያቃል? |
| Q32. Does the time taken by the bus at stop affect your decisions for taking the bus? አውቶብሶች ፌርማታ ላይ የሚወስዱት ጊዜ አውቶብስ ለመምረጥ ተጸኖ አድርጎብወታል? |
| |

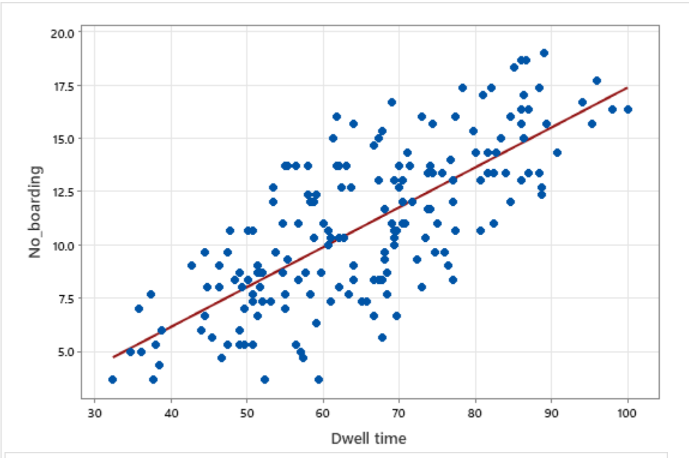
## 7.3 Appendix D: Assumption for the regression model

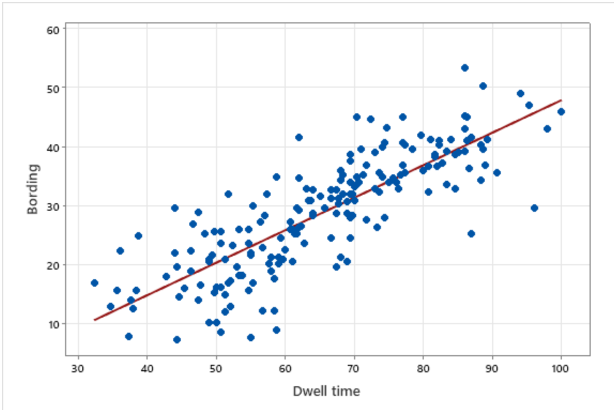


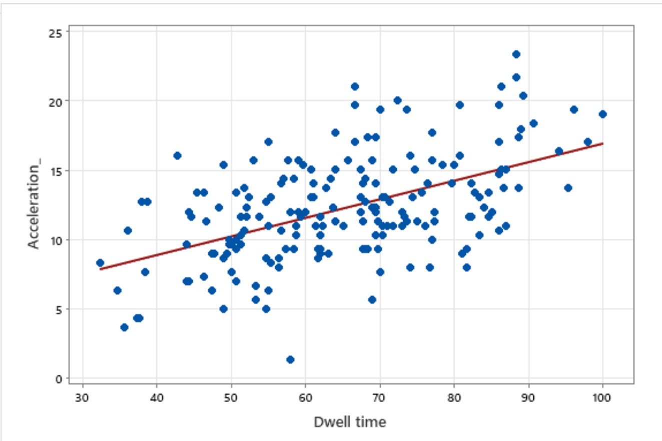



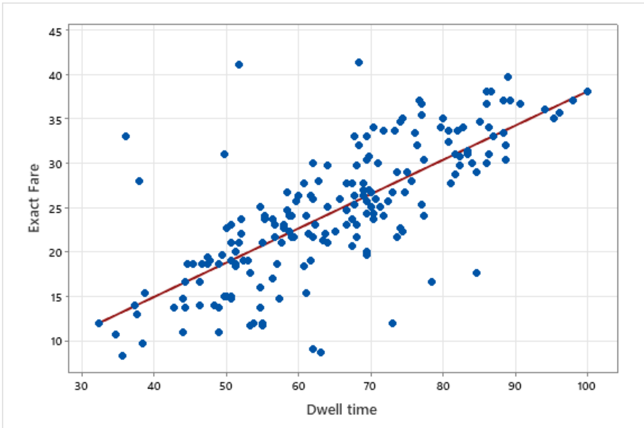

Idel time
Dwell time

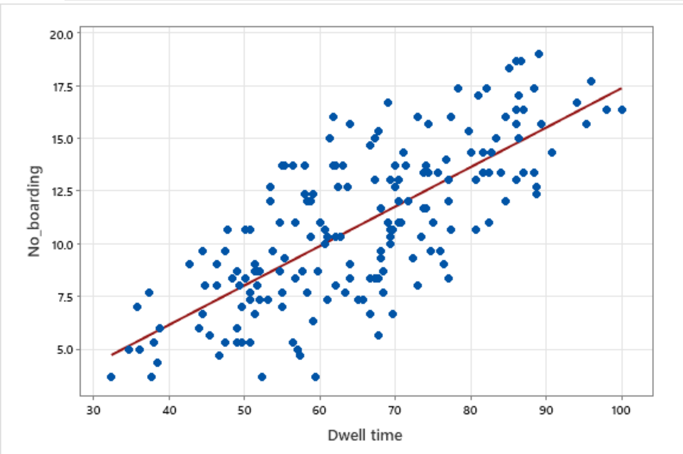

Aligting time
Dwell time

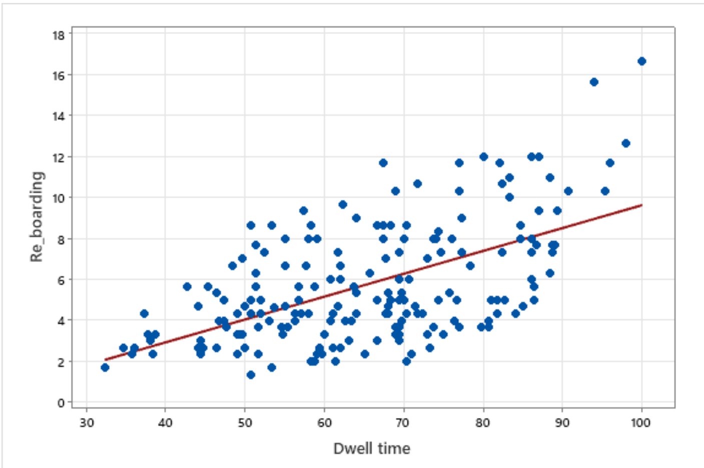

No_boarding
Dwell time

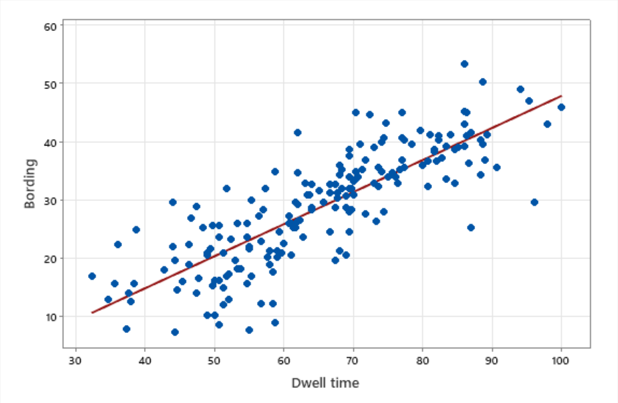

Bording
Dwell time

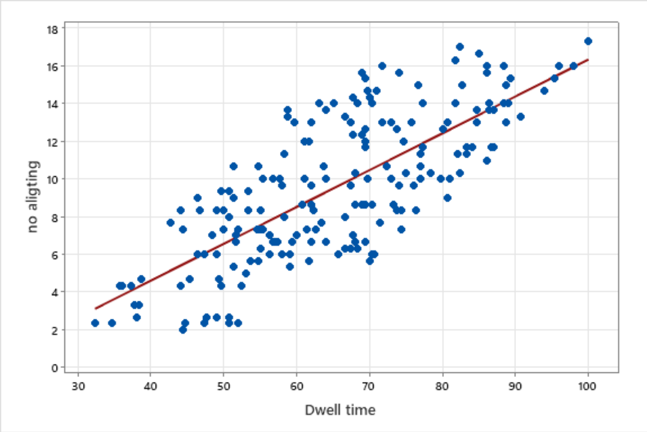

Acceleration_
Dwell time

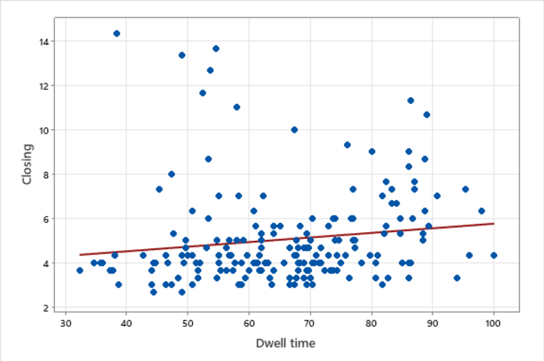

Exact Fare
Dwell time

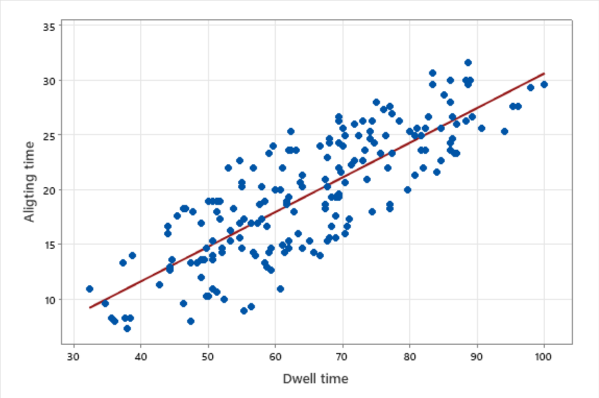

No_boarding
Dwell time

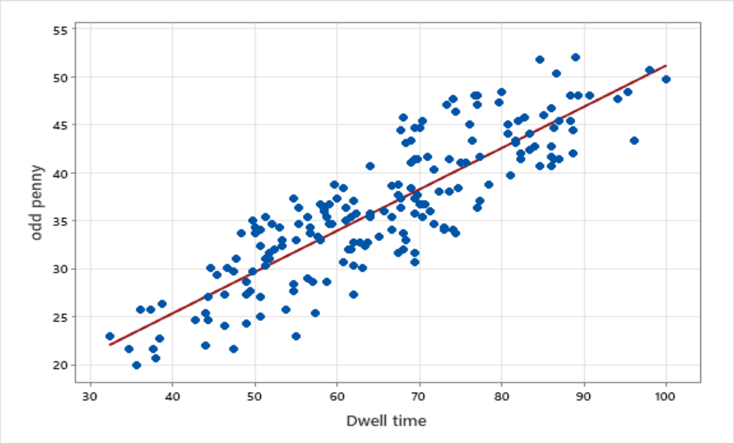

Re_boarding
Dwell time

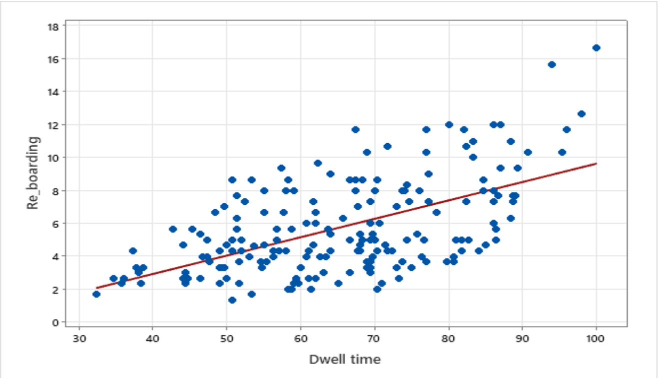

Bording
Dwell time

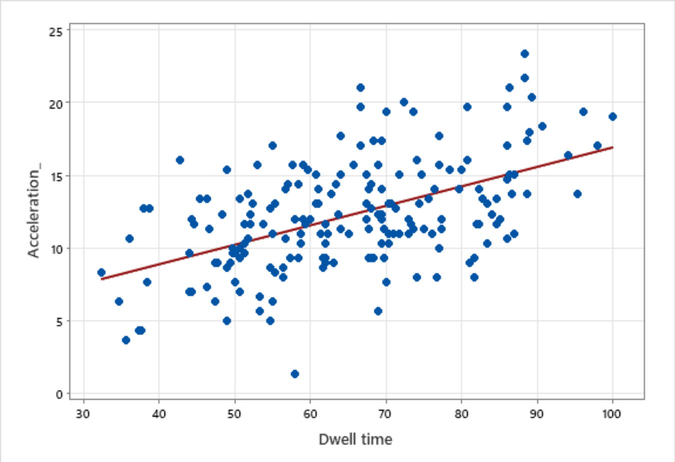

no aligting
Dwell time

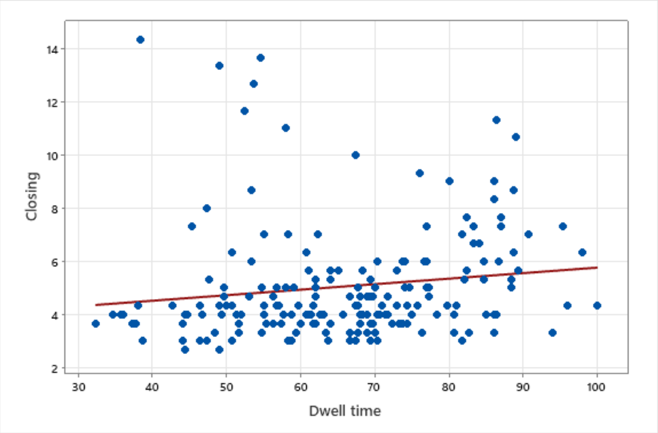

Closing
Dwell time


Aligting time
Dwell time


odd penny
Dwell time


Re_boarding
Dwell time


Acceleration_
Dwell time


Closing
Dwell time

### 7.3.1 Multi collinearity Assumption

| Pairwise Pearson Correlations | | | | |
|---|---|---|---|---|
| Sample 1 | Sample 2 | N | Correlation | 95% CI for ρ |
| Stop type | bus type | 192 | 0 | (-0.142, 0.142) |
| Pass.close main lane | bus type | 192 | 0 | (-0.142, 0.142) |
| Deceleration | bus type | 192 | 0.285 | (0.150, 0.410) |
| Door opening | bus type | 192 | 0.517 | (0.406, 0.614) |
| Number of alighting | bus type | 192 | 0.204 | (0.065, 0.336) |
| Alighting time | bus type | 192 | 0.38 | (0.252, 0.495) |
| No_boarding | bus type | 192 | 0.365 | (0.236, 0.482) |
| Boarding time | bus type | 192 | 0.251 | (0.113, 0.379) |
| Idle time | bus type | 192 | 0.253 | (0.115, 0.381) |
| Exact fare | bus type | 191 | 0.3 | (0.165, 0.424) |
| Odd penny | bus type | 192 | 0.341 | (0.209, 0.460) |
| Re_boarding | bus type | 192 | 0.441 | (0.319, 0.548) |
| Closing | bus type | 192 | 0.253 | (0.115, 0.381) |
| Acceleration_ | bus type | 192 | 0.106 | (-0.036, 0.244) |
| Pass.close main lane | Stop type | 192 | 0.033 | (-0.110, 0.173) |
| Deceleration | Stop type | 192 | 0.095 | (-0.047, 0.233) |
| Door opening | Stop type | 192 | -0.048 | (-0.189, 0.094) |
| Number of alighting | Stop type | 192 | 0.075 | (-0.068, 0.214) |
| Alighting time | Stop type | 192 | 0.098 | (-0.044, 0.237) |
| No_boarding | Stop type | 192 | 0.136 | (-0.006, 0.272) |
| Boarding time | Stop type | 192 | 0.133 | (-0.008, 0.270) |
| Idle time | Stop type | 192 | 0.119 | (-0.023, 0.256) |
| Exact fare | Stop type | 191 | 0.138 | (-0.004, 0.275) |
| Odd penny | Stop type | 192 | 0.079 | (-0.064, 0.218) |
| Re_boarding | Stop type | 192 | 0.222 | (0.083, 0.352) |
| Closing | Stop type | 192 | 0.022 | (-0.120, 0.163) |
| Acceleration_ | Stop type | 192 | -0.021 | (-0.162, 0.121) |
| Deceleration | Pass.close main lane | 192 | 0.023 | (-0.119, 0.164) |
| Door opening | Pass.close main lane | 192 | -0.045 | (-0.186, 0.097) |
| Number of alighting | Pass.close main lane | 192 | 0.108 | (-0.034, 0.246) |
| Alighting time | Pass.close main lane | 192 | 0.017 | (-0.125, 0.158) |
| No_boarding | Pass.close main lane | 192 | 0.062 | (-0.081, 0.201) |

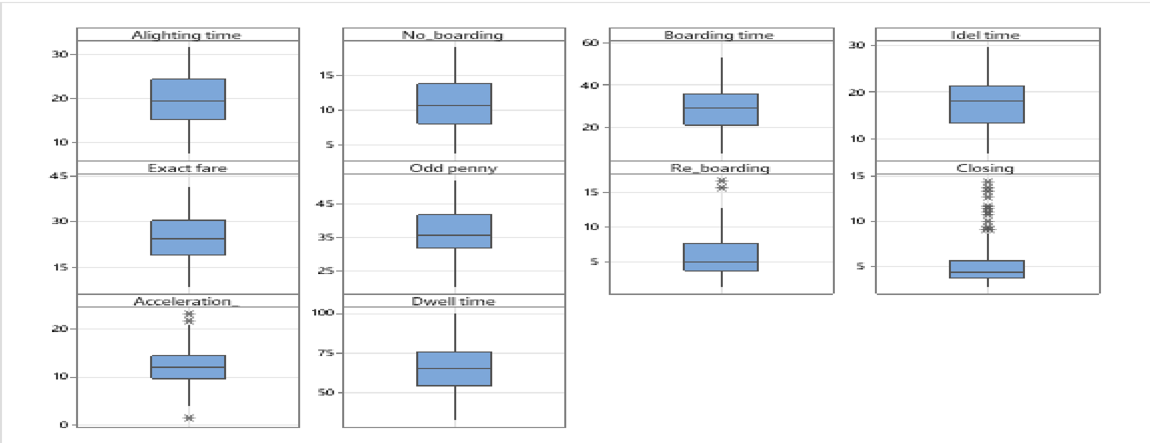
| | | | | |
|---|---|---|---|---|
| Boarding time | Pass.close main lane | 192 | 0.006 | (-0.135, 0.148) |
| Idle time | Pass.close main lane | 192 | -0.008 | (-0.149, 0.134) |
| Exact fare | Pass.close main lane | 191 | -0.065 | (-0.205, 0.077) |
| Odd penny | Pass.close main lane | 192 | 0.002 | (-0.140, 0.143) |
| Re_boarding | Pass.close main lane | 192 | -0.044 | (-0.184, 0.099) |
| Closing | Pass.close main lane | 192 | 0.095 | (-0.047, 0.234) |
| Acceleration_ | Pass.close main lane | 192 | -0.092 | (-0.231, 0.050) |
| Door opening | Deceleration | 192 | 0.419 | (0.295, 0.529) |
| Number of alighting | Deceleration | 192 | 0.476 | (0.358, 0.578) |
| Alighting time | Deceleration | 192 | 0.526 | (0.415, 0.621) |
| No_boarding | Deceleration | 192 | 0.496 | (0.381, 0.596) |
| Boarding time | Deceleration | 192 | 0.56 | (0.455, 0.650) |
| Idle time | Deceleration | 192 | 0.535 | (0.426, 0.629) |
| Exact fare | Deceleration | 191 | 0.44 | (0.318, 0.548) |
| Odd penny | Deceleration | 192 | 0.571 | (0.468, 0.660) |
| Re_boarding | Deceleration | 192 | 0.41 | (0.284, 0.521) |
| Closing | Deceleration | 192 | 0.187 | (0.047, 0.320) |
| Acceleration_ | Deceleration | 192 | 0.317 | (0.184, 0.439) |
| Number of alighting | Door opening | 192 | 0.326 | (0.193, 0.447) |
| Alighting time | Door opening | 192 | 0.4 | (0.274, 0.513) |
| No_boarding | Door opening | 192 | 0.387 | (0.259, 0.501) |
| Boarding time | Door opening | 192 | 0.268 | (0.131, 0.395) |
| | | | | |
| Idle time | Door opening | 192 | 0.344 | (0.213, 0.463) |
| Exact fare | Door opening | 191 | 0.327 | (0.194, 0.448) |
| Odd penny | Door opening | 192 | 0.423 | (0.300, 0.533) |
| Re_boarding | Door opening | 192 | 0.462 | (0.343, 0.567) |
| Closing | Door opening | 192 | 0.384 | (0.257, 0.499) |
| Acceleration_ | Door opening | 192 | 0.249 | (0.111, 0.377) |
| Alighting time | Number of alighting | 192 | 0.634 | (0.541, 0.712) |
| No_boarding | Number of alighting | 192 | 0.57 | (0.466, 0.659) |
| Boarding time | Number of alighting | 192 | 0.596 | (0.497, 0.681) |
| Idle time | Number of alighting | 192 | 0.597 | (0.497, 0.681) |
| Exact fare | Number of alighting | 191 | 0.587 | (0.486, 0.673) |
| Odd penny | Number of alighting | 192 | 0.665 | (0.578, 0.738) |

| | | | | |
|---|---|---|---|---|
| Re_boarding | Number of alighting | 192 | 0.346 | (0.215, 0.465) |
| Closing | Number of alighting | 192 | 0.064 | (-0.078, 0.204) |
| Acceleration_ | Number of alighting | 192 | 0.38 | (0.251, 0.495) |
| No_boarding | Alighting time | 192 | 0.632 | (0.538, 0.710) |
| Boarding time | Alighting time | 192 | 0.682 | (0.598, 0.751) |
| Idle time | Alighting time | 192 | 0.635 | (0.543, 0.713) |
| Exact fare | Alighting time | 191 | 0.582 | (0.480, 0.669) |
| Odd penny | Alighting time | 192 | 0.716 | (0.639, 0.778) |
| Re_boarding | Alighting time | 192 | 0.527 | (0.417, 0.622) |
| Closing | Alighting time | 192 | 0.151 | (0.009, 0.286) |
| Acceleration_ | Alighting time | 192 | 0.435 | (0.313, 0.543) |
| Boarding time | No_boarding | 192 | 0.558 | (0.452, 0.648) |
| Idle time | No_boarding | 192 | 0.608 | (0.510, 0.690) |
| Exact fare | No_boarding | 191 | 0.533 | (0.423, 0.628) |
| Odd penny | No_boarding | 192 | 0.685 | (0.602, 0.754) |
| Re_boarding | No_boarding | 192 | 0.451 | (0.331, 0.557) |
| Closing | No_boarding | 192 | 0.136 | (-0.006, 0.273) |
| Acceleration_ | No_boarding | 192 | 0.289 | (0.153, 0.414) |
| Idle time | Boarding time | 192 | 0.632 | (0.538, 0.710) |
| Exact fare | Boarding time | 191 | 0.566 | (0.461, 0.655) |
| Odd penny | Boarding time | 192 | 0.639 | (0.547, 0.716) |
| Re_boarding | Boarding time | 192 | 0.422 | (0.298, 0.532) |
| Closing | Boarding time | 192 | 0.027 | (-0.115, 0.168) |
| Acceleration_ | Boarding time | 192 | 0.436 | (0.314, 0.544) |
| Exact fare | Idle time | 191 | 0.568 | (0.464, 0.657) |
| Odd penny | Idle time | 192 | 0.675 | (0.590, 0.746) |
| Re_boarding | Idle time | 192 | 0.42 | (0.296, 0.530) |
| Closing | Idle time | 192 | 0.207 | (0.067, 0.338) |
| Acceleration_ | Idle time | 192 | 0.42 | (0.296, 0.530) |
| Odd penny | Exact fare | 191 | 0.82 | (0.768, 0.862) |
| Re_boarding | Exact fare | 191 | 0.442 | (0.320, 0.550) |
| Closing | Exact fare | 191 | 0.066 | (-0.077, 0.206) |
| Acceleration_ | Exact fare | 191 | 0.451 | (0.330, 0.557) |
| Re_boarding | Odd penny | 192 | 0.484 | (0.368, 0.586) |
| Closing | Odd penny | 192 | 0.145 | (0.004, 0.281) |

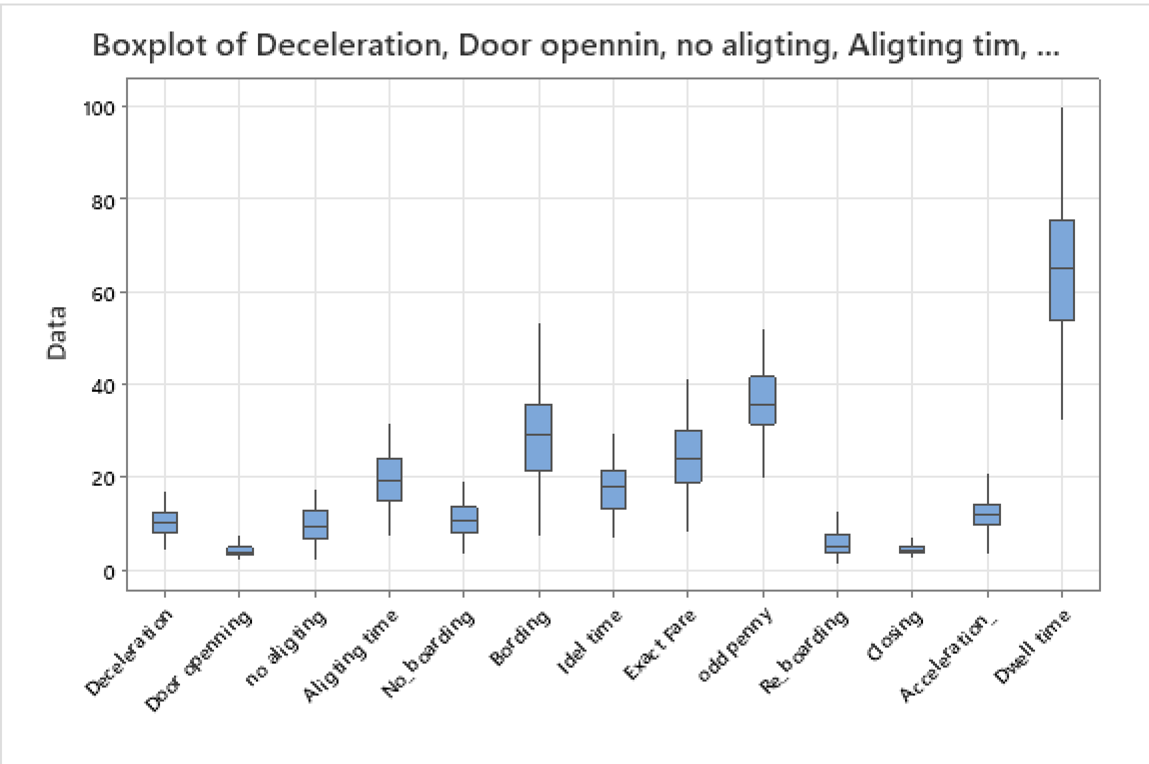
| | | | | |
|---|---|---|---|---|
| Acceleration_ | Odd penny | 192 | 0.462 | (0.343, 0.567) |
| Closing | Re_boarding | 192 | 0.283 | (0.148, 0.409) |
| Acceleration_ | Re_boarding | 192 | 0.312 | (0.179, 0.435) |
| Acceleration_ | Closing | 192 | -0.054 | (-0.194, 0.088) |

### 7.3.2 Assumptions of outliers

#### 7.3.2.1 Before removed extreme outliers of regressors

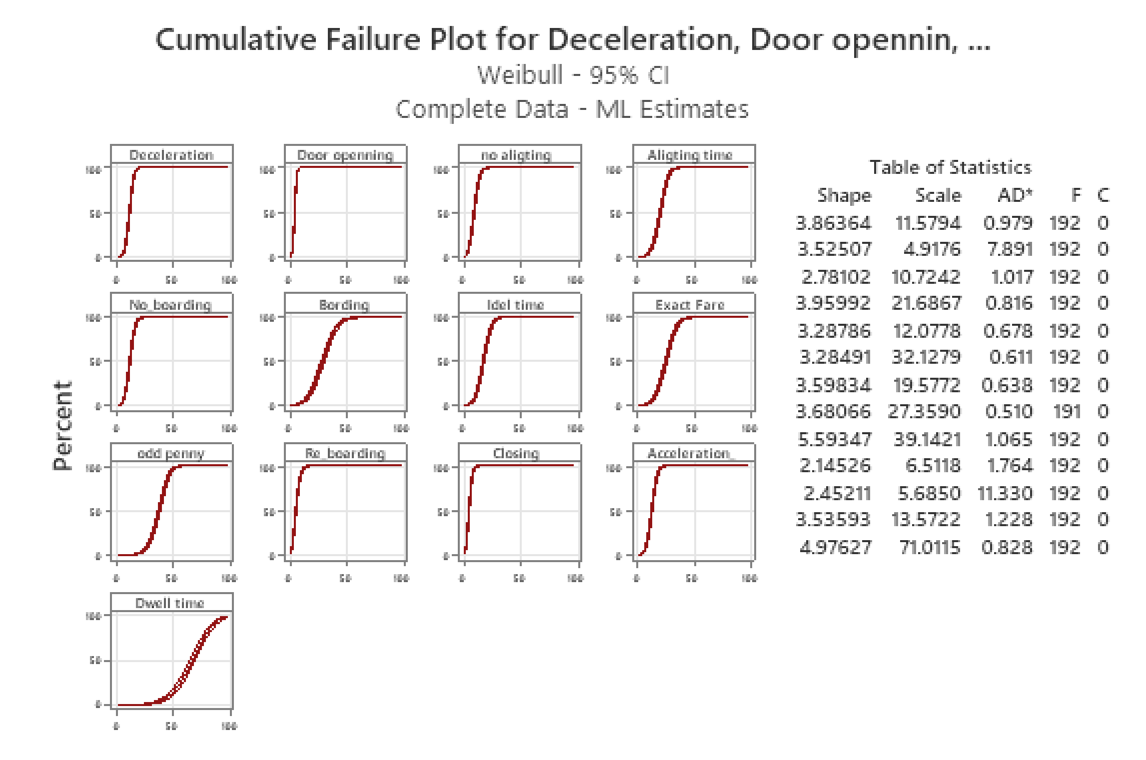


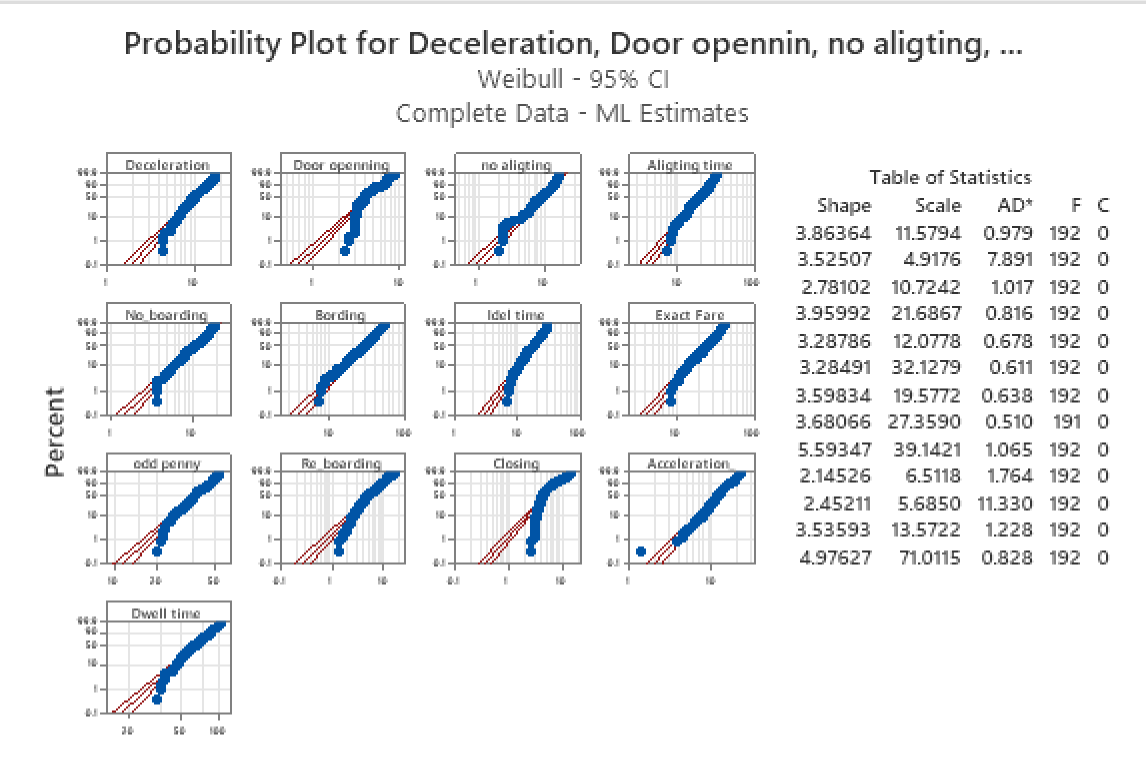

### 7.3.3 After removed extreme Outliers of regressors

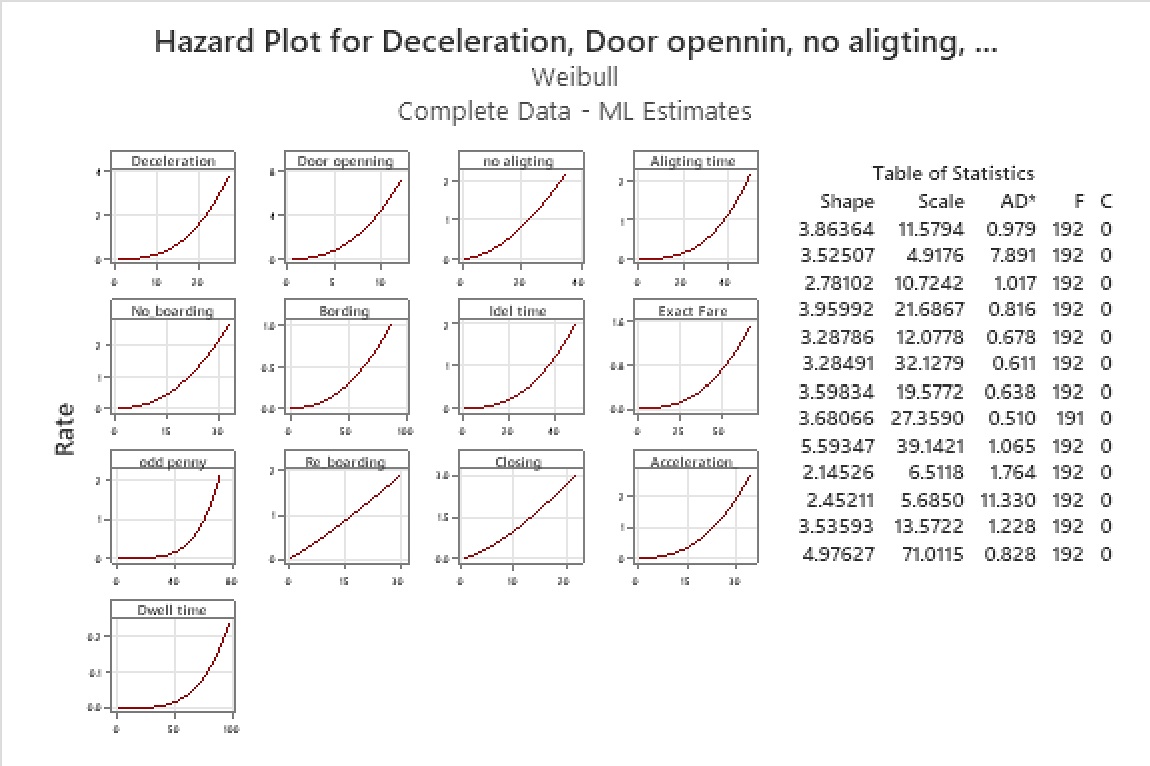


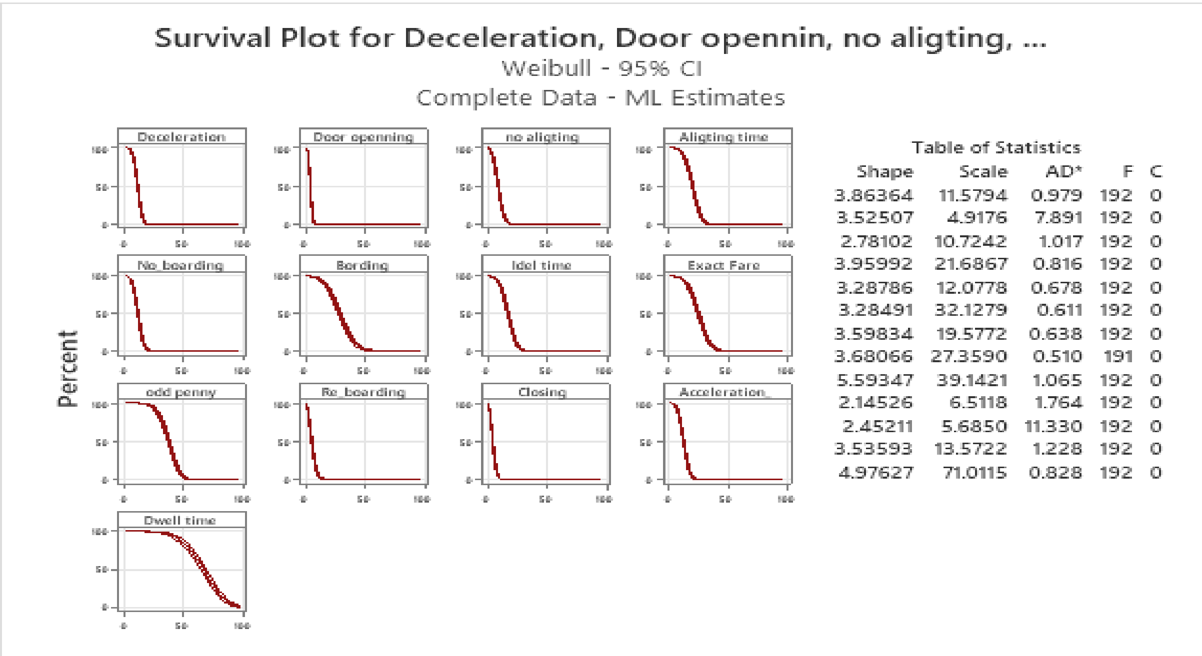
## 7.4 Appendix E: Weibull Distribution

### 7.4.1 Probability plot of dwell time variables,2023






### 7.4.2 Distribution overview plot for reliability study

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 0.979 |

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|

| | |
|---|---|
| Weibull | 7.891 |

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 1.017 |

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 0.816 |

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 0.678 |

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 0.611 |

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 0.638 |

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 0.510 |

Goodness-of-Fit

| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 1.065 |

Goodness-of-Fit

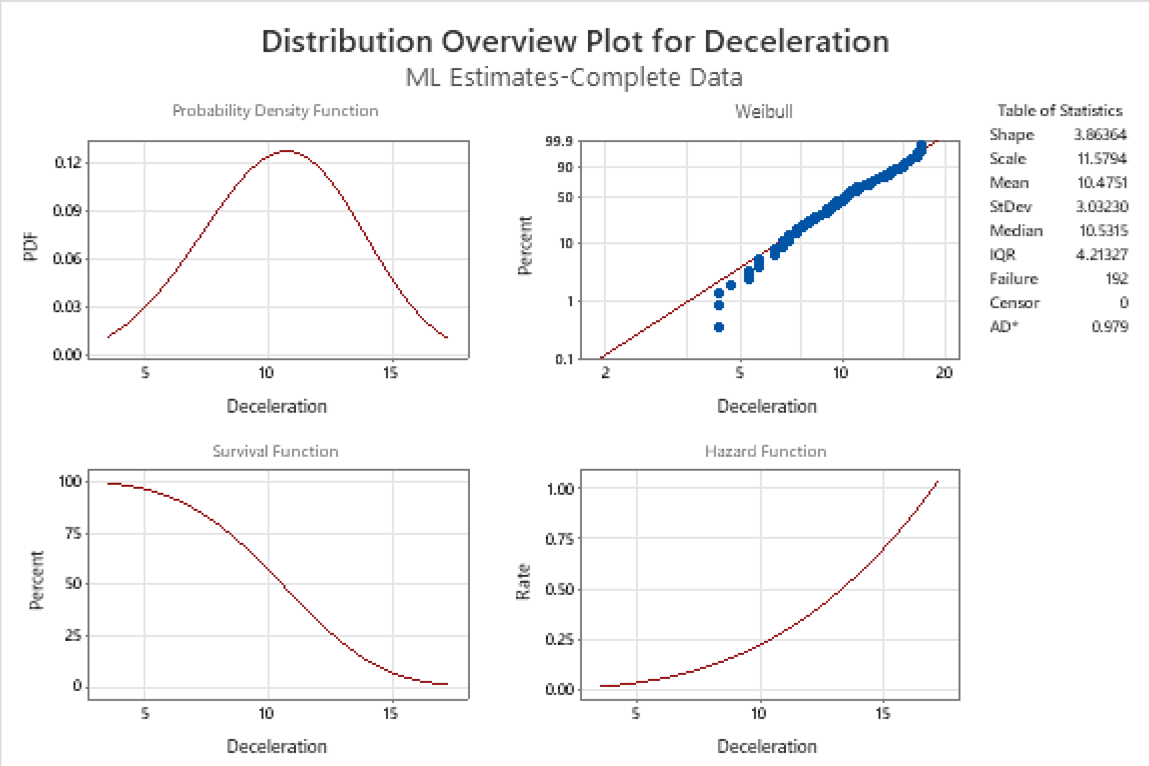
| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 1.764 |

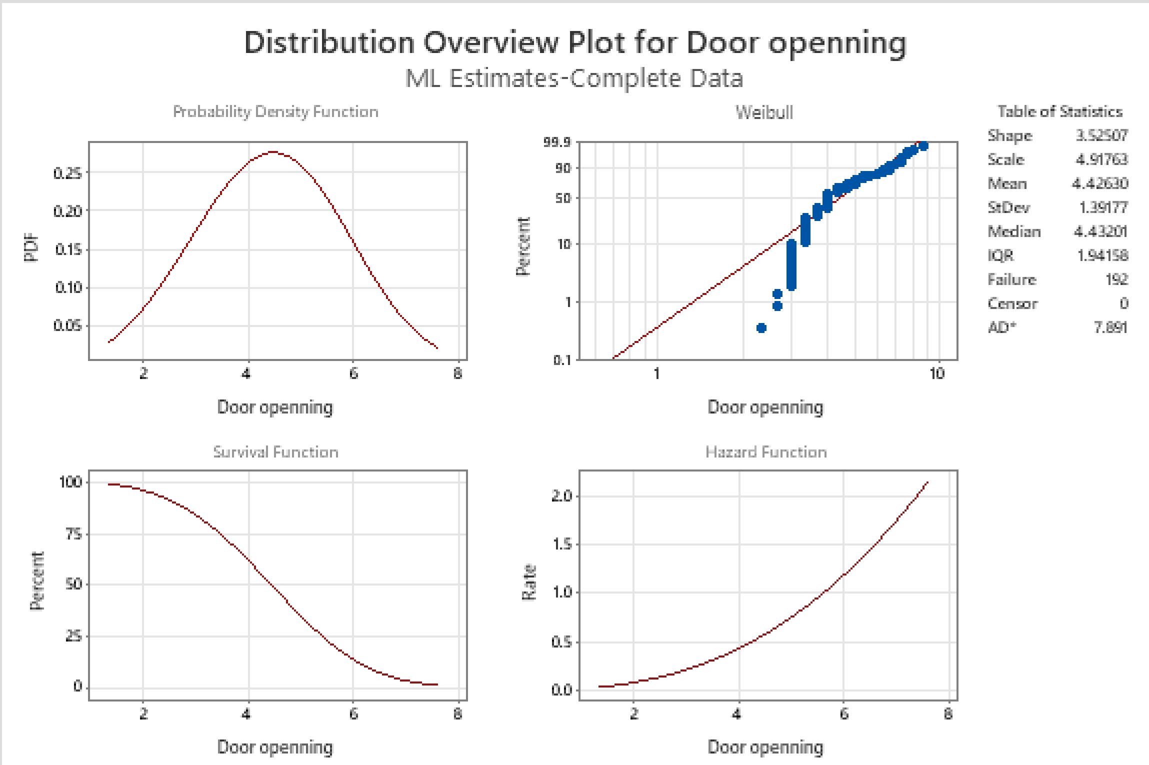
Goodness-of-Fit

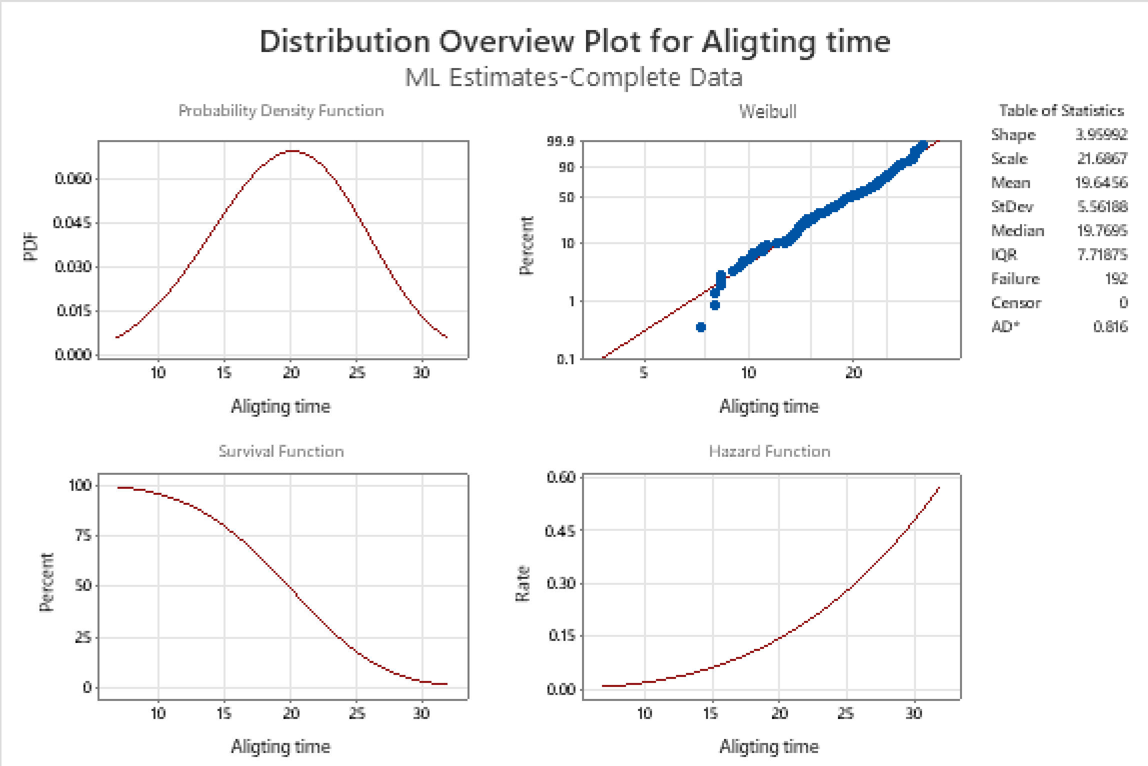
| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 11.330 |

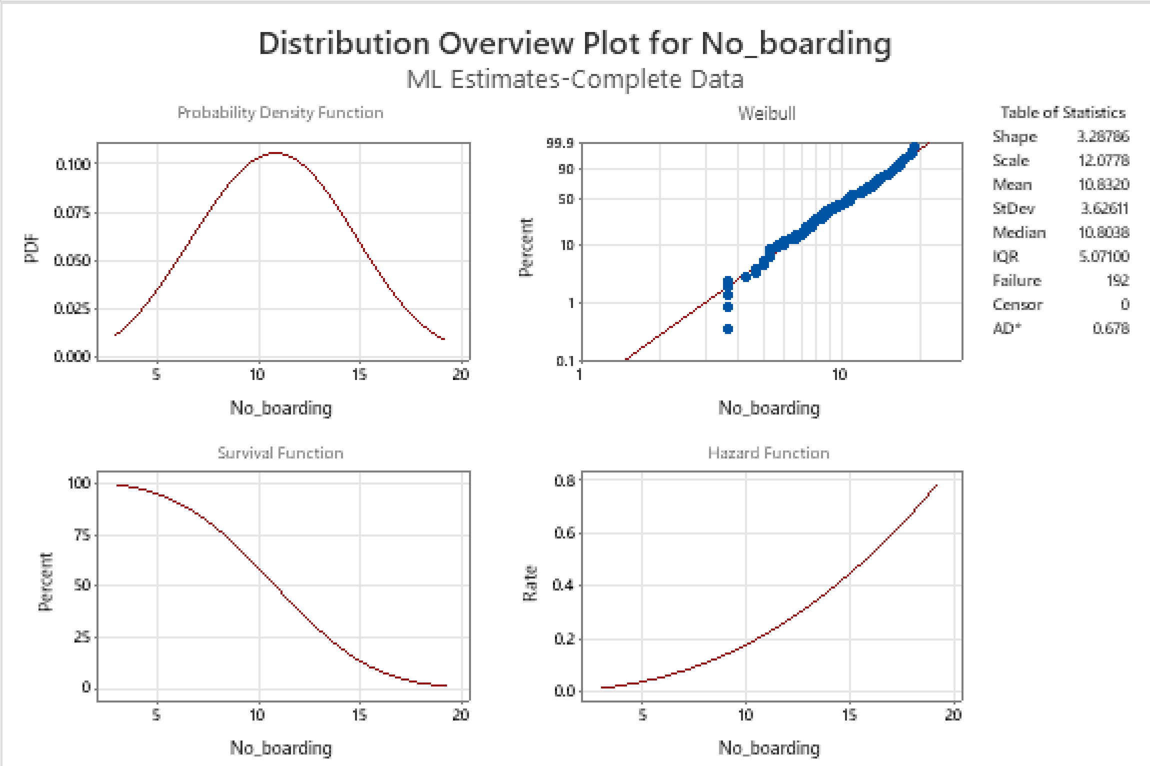
Goodness-of-Fit

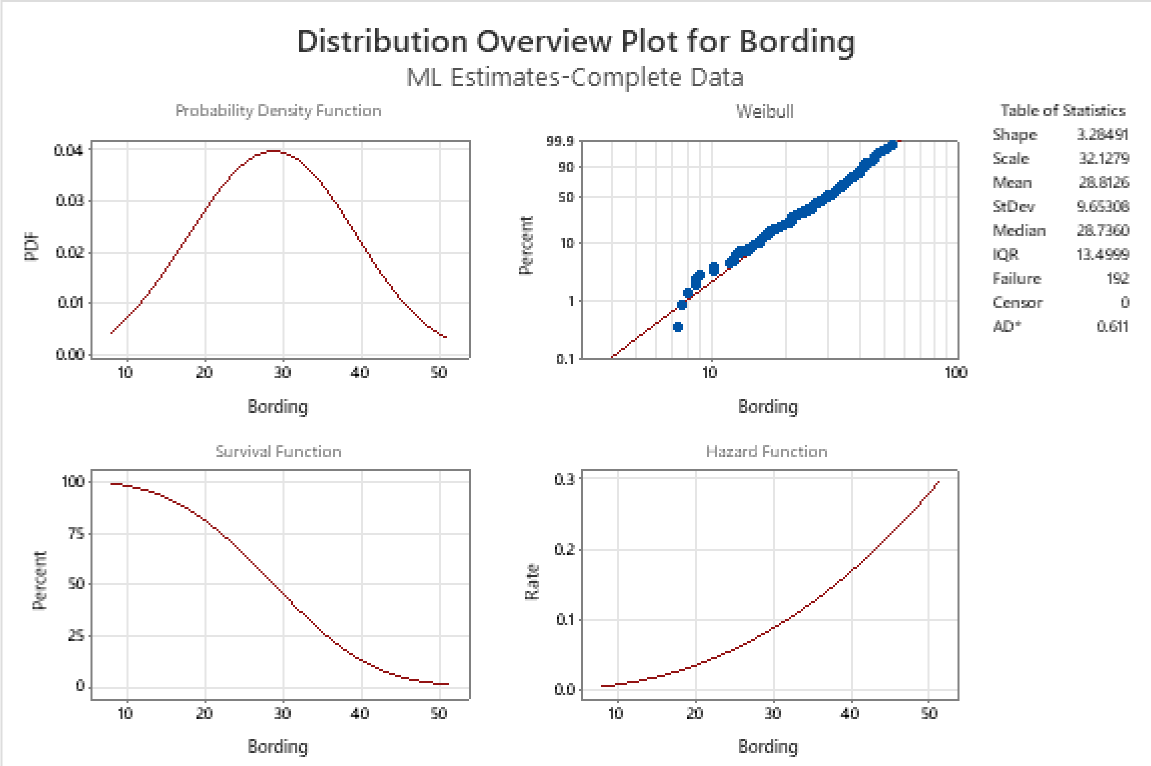
| Distribution | Anderson-Darling (adj) |
|---|---|
| Weibull | 1.228 |

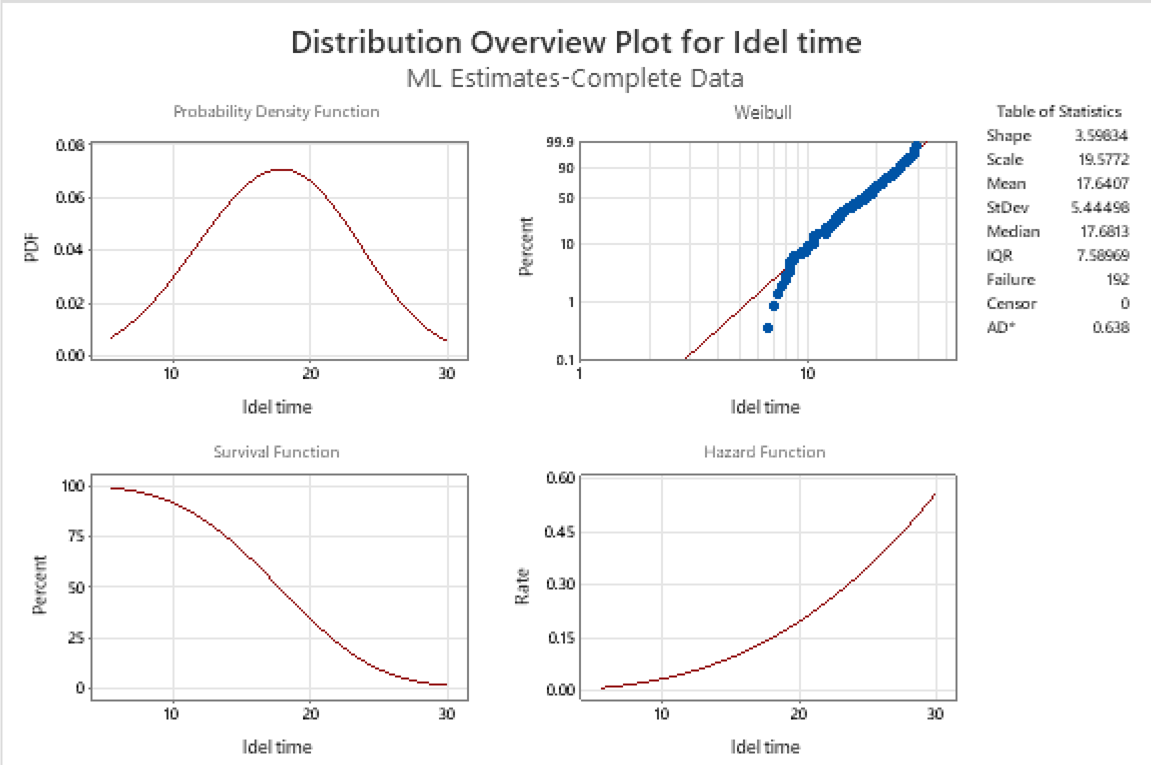

Distribution Overview Plot for Deceleration
ML Estimates-Complete Data
Probability Density Function
Weibull
Table of Statistics
Shape 3.86364
Scale 11.5794
Mean 10.4751
StDev 3.03230
Median 10.5315
IQR 4.21327
Failure 192
Censor 0
AD* 0.979
PDF
Percent
Deceleration
Survival Function
Hazard Function
Rate

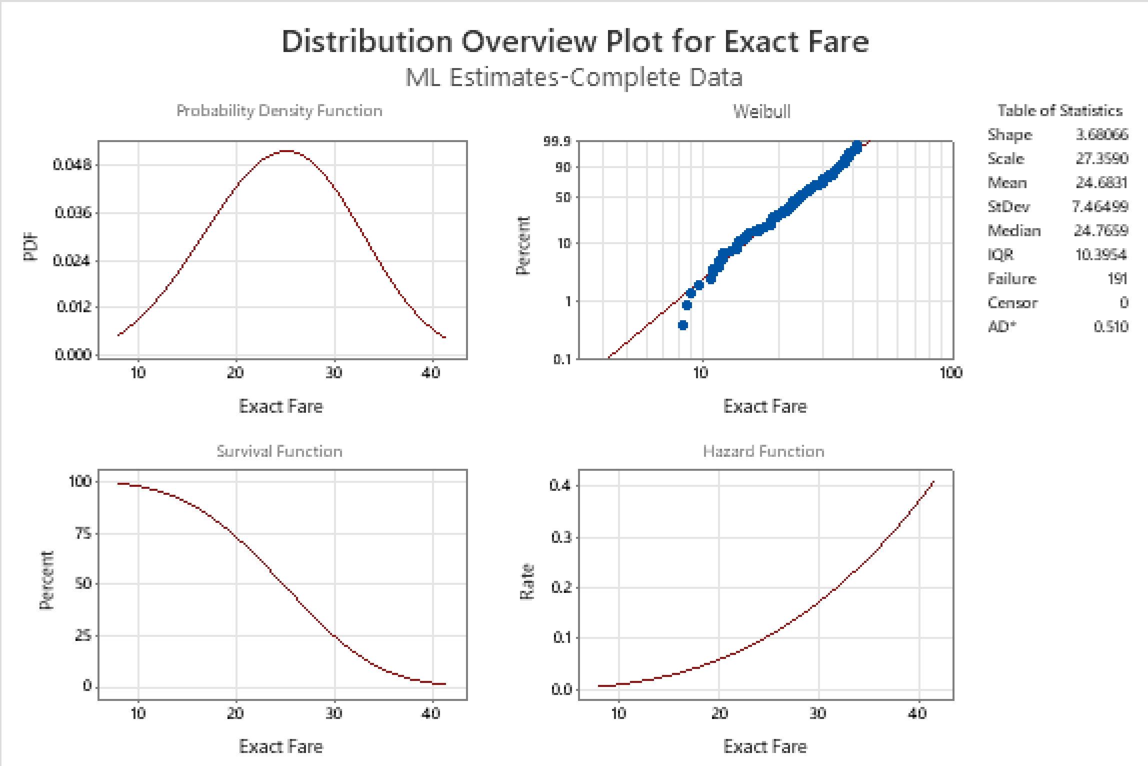

Distribution Overview Plot for Door openning
ML Estimates-Complete Data
Probability Density Function
Weibull
Table of Statistics
Shape 3.52507
Scale 4.91763
Mean 4.42630
StDev 1.39177
Median 4.43201
IQR 1.94158
Failure 192
Censor 0
AD* 7.891
PDF
Percent
Door openning
Survival Function
Hazard Function
Rate

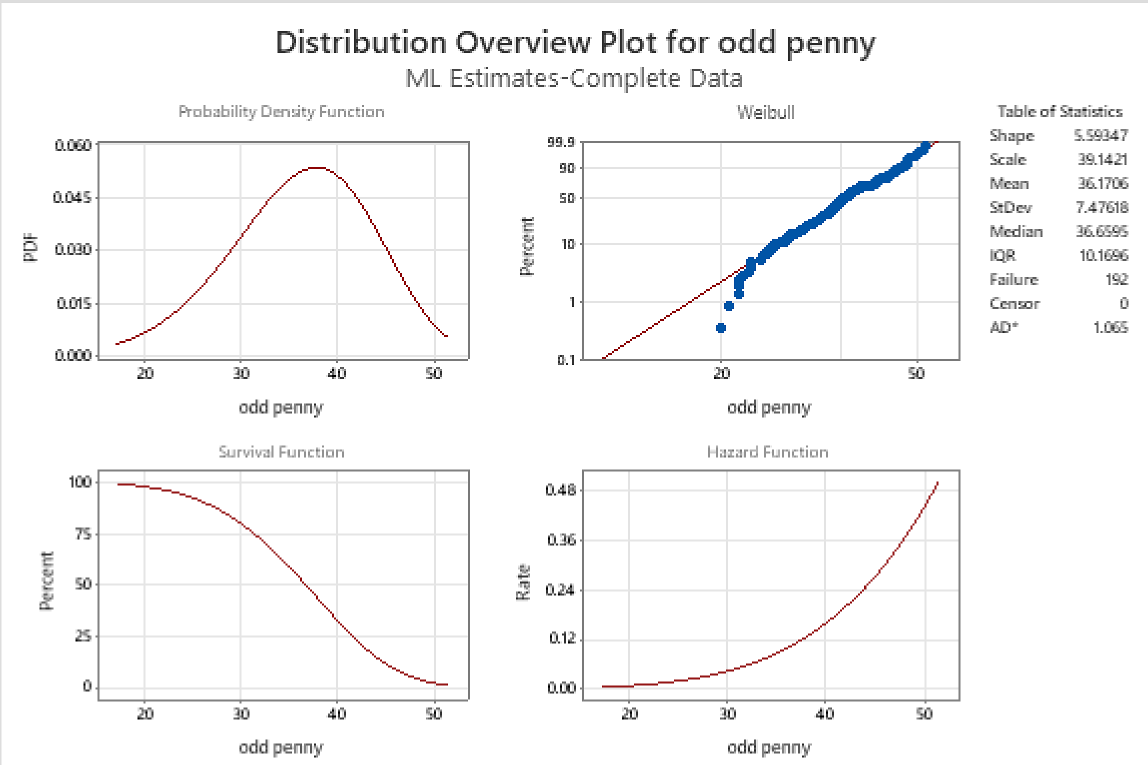

Distribution Overview Plot for Aligting time
ML Estimates-Complete Data
Probability Density Function
Weibull
Table of Statistics
Shape 3.95992
Scale 21.6867
Mean 19.6456
StDev 5.56188
Median 19.7695
IQR 7.71875
Failure 192
Censor 0
AD* 0.816
PDF
Percent
Aligting time
Survival Function
Hazard Function
Rate

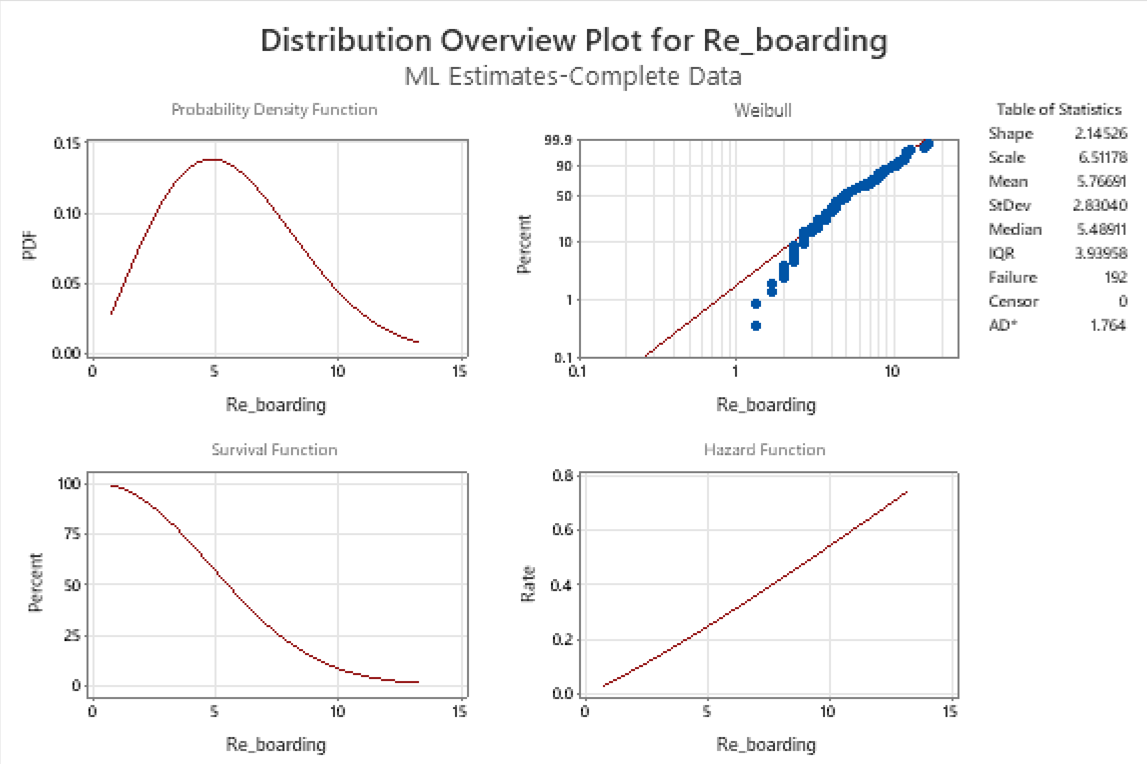

Distribution Overview Plot for No_boarding
ML Estimates-Complete Data
Probability Density Function
Weibull
Table of Statistics
Shape 3.28786
Scale 12.0778
Mean 10.8320
StDev 3.62611
Median 10.8038
IQR 5.07100
Failure 192
Censor 0
AD* 0.678
PDF
Percent
No_boarding
Survival Function
Hazard Function
Rate

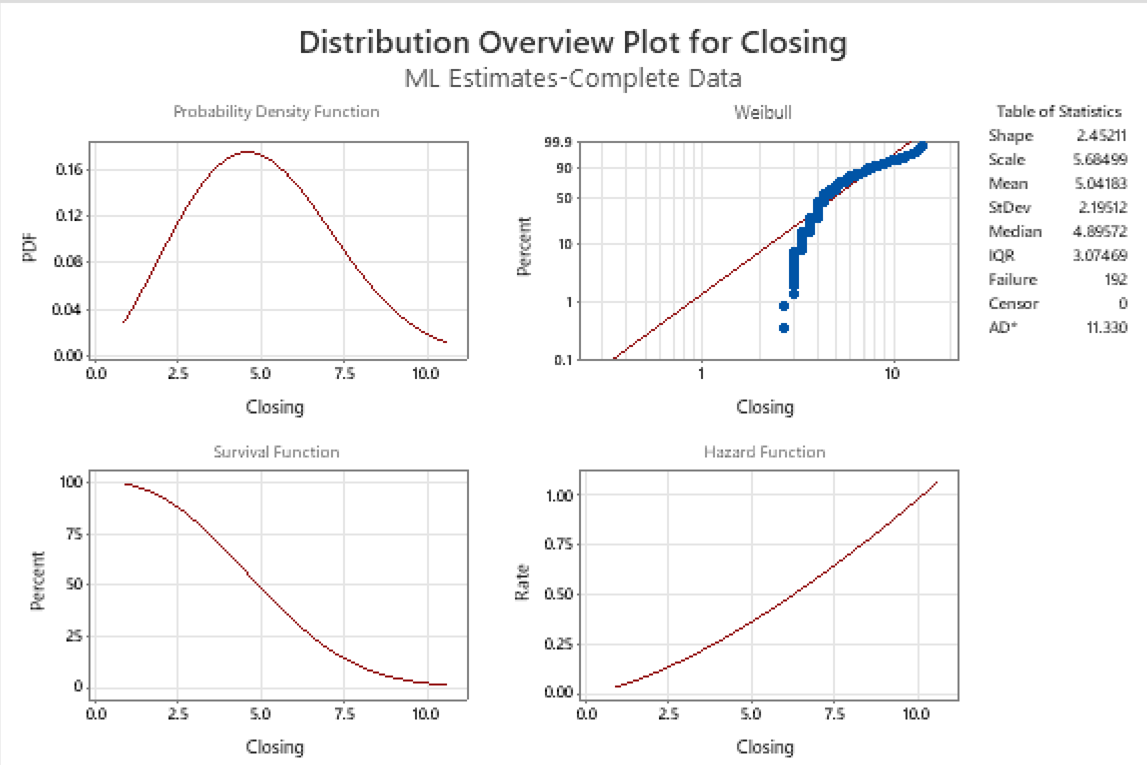

Distribution Overview Plot for Bording
ML Estimates-Complete Data
Probability Density Function
PDF
Bording
Weibull
Percent
Bording
Table of Statistics
Shape 3.28491
Scale 32.1279
Mean 28.8126
StDev 9.65308
Median 28.7360
IQR 13.4999
Failure 192
Censor 0
AD* 0.611
Survival Function
Percent
Bording
Hazard Function
Rate
Bording

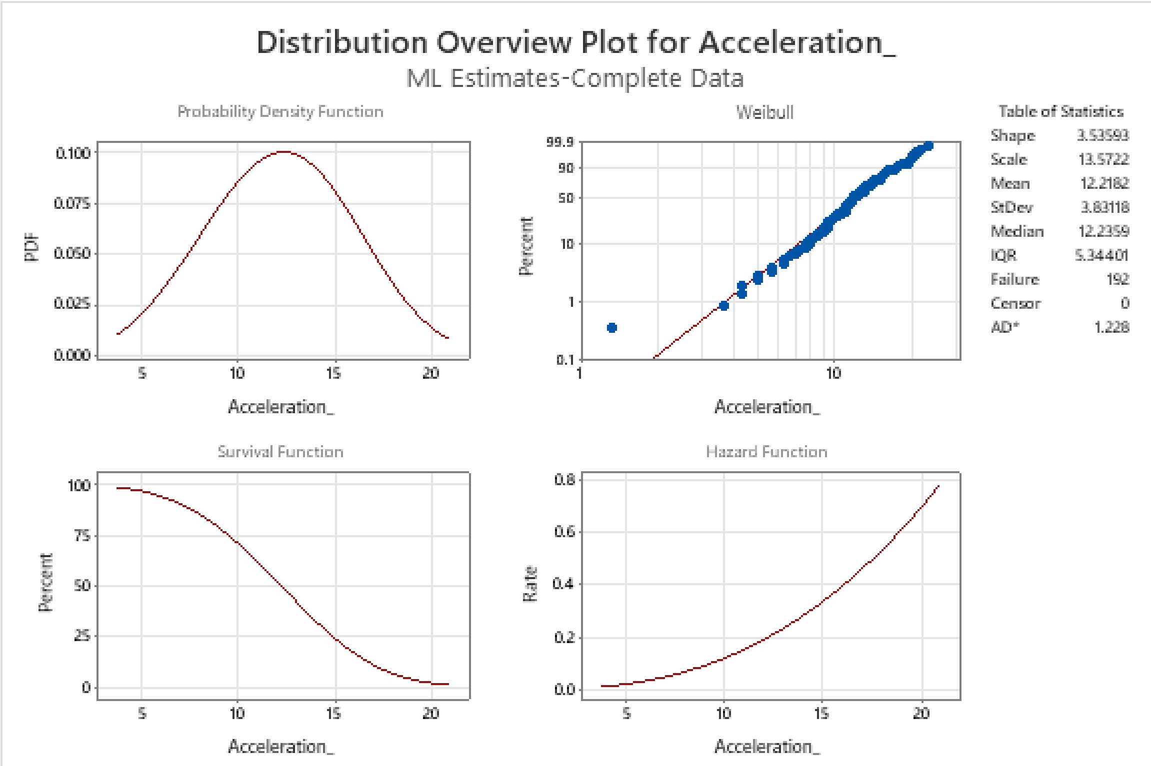

Distribution Overview Plot for Idel time
ML Estimates-Complete Data
Probability Density Function
PDF
Idel time
Weibull
Percent
Idel time
Table of Statistics
Shape 3.59834
Scale 19.5772
Mean 17.6407
StDev 5.44498
Median 17.6813
IQR 7.58969
Failure 192
Censor 0
AD* 0.638
Survival Function
Percent
Idel time
Hazard Function
Rate
Idel time


Distribution Overview Plot for Exact Fare
ML Estimates-Complete Data
Probability Density Function
Weibull
Table of Statistics
Shape 3.68066
Scale 27.3590
Mean 24.6831
StDev 7.46499
Median 24.7659
IQR 10.3954
Failure 191
Censor 0
AD* 0.510
PDF
Percent
Exact Fare
Survival Function
Hazard Function
Rate

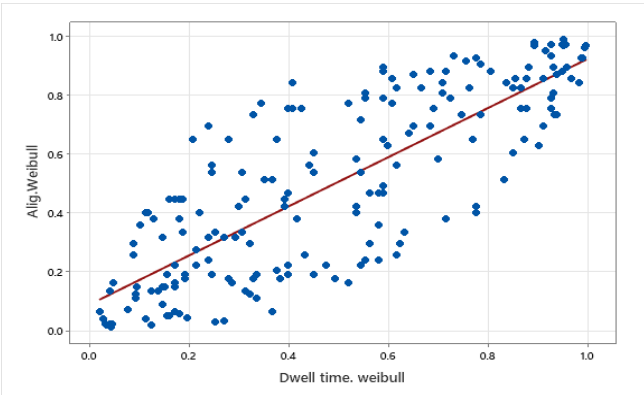

Distribution Overview Plot for odd penny
ML Estimates-Complete Data
Probability Density Function
Weibull
Table of Statistics
Shape 5.59347
Scale 39.1421
Mean 36.1706
StDev 7.47618
Median 36.6595
IQR 10.1696
Failure 192
Censor 0
AD* 1.065
PDF
Percent
odd penny
Survival Function
Hazard Function
Rate

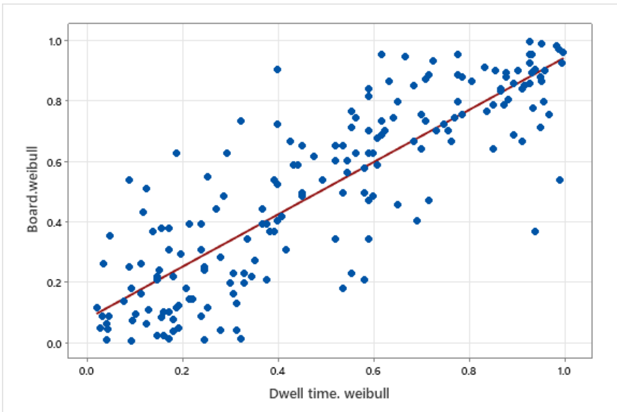

Distribution Overview Plot for Re_boarding
ML Estimates-Complete Data
Probability Density Function
PDF
Re_boarding
Weibull
Percent
Re_boarding
Table of Statistics
Shape 2.14526
Scale 6.51178
Mean 5.76691
StDev 2.83040
Median 5.48911
IQR 3.93958
Failure 192
Censor 0
AD* 1.764
Survival Function
Percent
Re_boarding
Hazard Function
Rate
Re_boarding

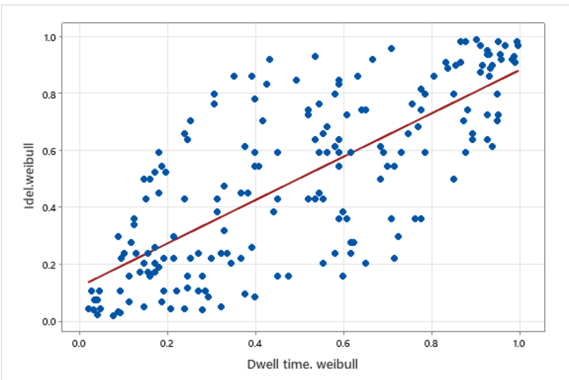

Distribution Overview Plot for Closing
ML Estimates-Complete Data
Probability Density Function
PDF
Closing
Weibull
Percent
Closing
Table of Statistics
Shape 2.45211
Scale 5.68499
Mean 5.04183
StDev 2.19512
Median 4.89572
IQR 3.07469
Failure 192
Censor 0
AD* 11.330
Survival Function
Percent
Closing
Hazard Function
Rate
Closing

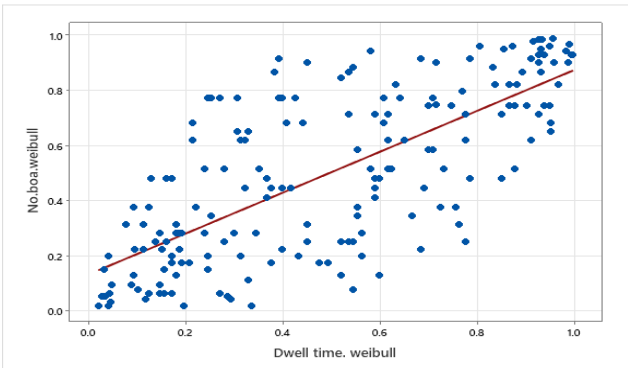


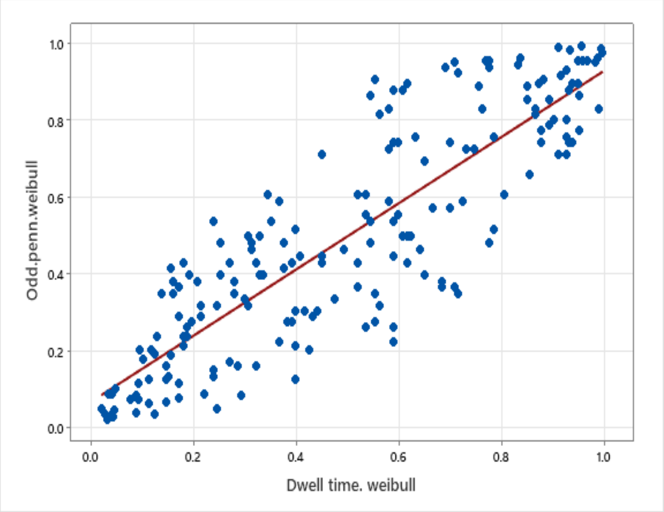

### 7.4.3 Scatterplot of Weibull

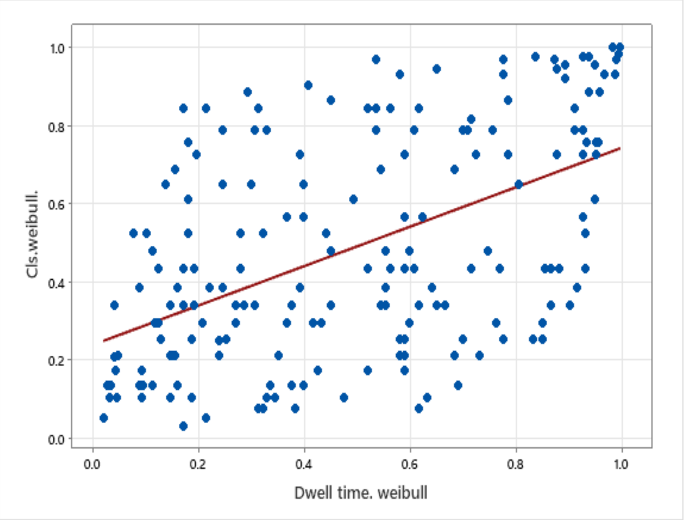


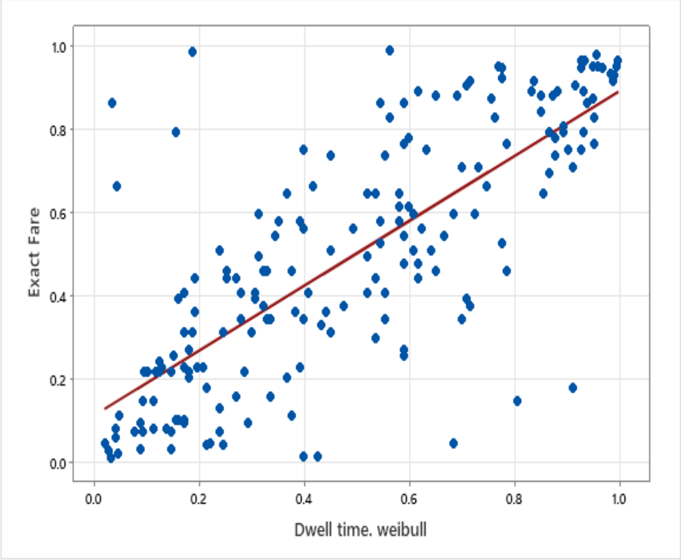



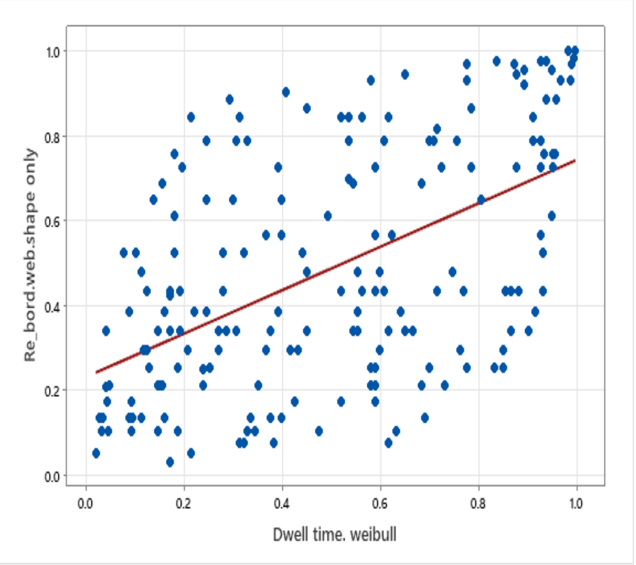



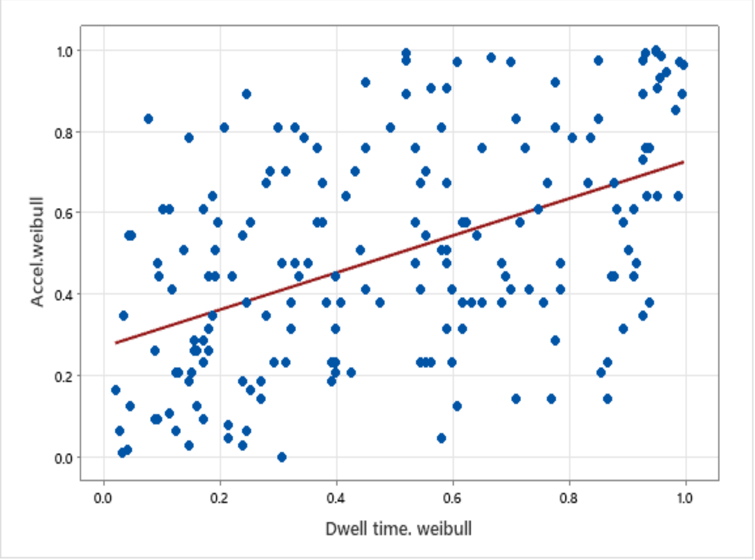



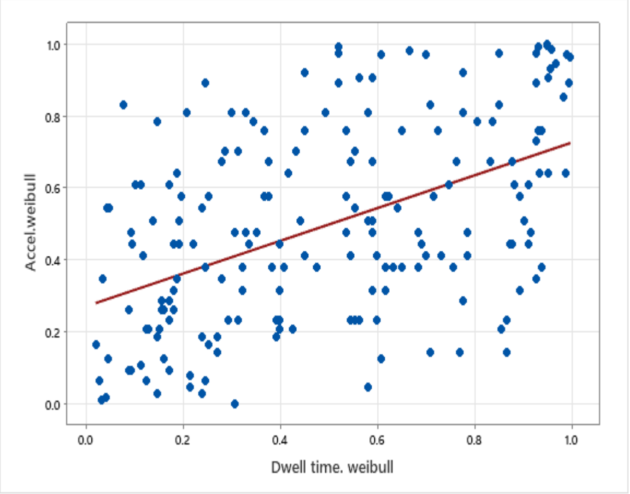

Odd.penn.weibull
Dwell time. weibull


Cls.weibull.
Dwell time. weibull


Exact Fare
Dwell time. weibull


Re_bord.web.shape only
Dwell time. weibull


Accel.weibull
Dwell time. weibull


Accel.weibull
Dwell time. weibull

### 7.4.4 Pairwise Pearson correlations

| Sample 1 | Sample 2 | N | Correlation | 95% CI for ρ |
|---|---|---|---|---|
| Dor.op. Weibull | Dce1.Weibull | 192 | 0.432 | (0.309, 0.540) |
| No alig. Weibull | Dce1.Weibull | 192 | 0.464 | (0.345, 0.568) |
| Alig.Weibull | Dce1.Weibull | 192 | 0.5 | (0.386, 0.599) |
| Board.Weibull | Dce1.Weibull | 192 | 0.548 | (0.440, 0.640) |
| Idle.Weibull | Dce1.Weibull | 192 | 0.514 | (0.401, 0.611) |
| No.Boa.Weibull | Dce1.Weibull | 192 | 0.5 | (0.386, 0.600) |
| Odd.pen.Weibull | Dce1.Weibull | 192 | 0.578 | (0.475, 0.665) |
| Cls.Weibull. | Dce1.Weibull | 192 | 0.354 | (0.224, 0.472) |
| Re.boa.webull | Dce1.Weibull | 192 | 0.284 | (0.149, 0.409) |
| Accel.Weibull | Dce1.Weibull | 192 | 0.282 | (0.146, 0.407) |
| Exact Fare | Dce1.Weibull | 192 | 0.45 | (0.329, 0.556) |
| No alig. Weibull | Dor.op. Weibull | 192 | 0.33 | (0.197, 0.450) |
| Alig.Weibull | Dor.op. Weibull | 192 | 0.415 | (0.290, 0.525) |
| Board.Weibull | Dor.op. Weibull | 192 | 0.268 | (0.132, 0.395) |
| Idle.Weibull | Dor.op. Weibull | 192 | 0.328 | (0.196, 0.449) |
| No. Boa.Weibull | Dor.op. Weibull | 192 | 0.384 | (0.257, 0.499) |
| Odd.pen.Weibull | Dor.op. Weibull | 192 | 0.429 | (0.306, 0.538) |
| Cls.Weibull. | Dor.op. Weibull | 192 | 0.476 | (0.359, 0.579) |
| Re.boa.webull | Dor.op. Weibull | 192 | 0.541 | (0.432, 0.634) |
| Accel.Weibull | Dor.op. Weibull | 192 | 0.244 | (0.106, 0.373) |
| Exact Fare | Dor.op. Weibull | 192 | 0.337 | (0.205, 0.456) |
| Alig.Weibull | No alig. Weibull | 192 | 0.626 | (0.531, 0.705) |
| Board.Weibull | No alig. Weibull | 192 | 0.611 | (0.514, 0.693) |
| Idle.Weibull | No alig. Weibull | 192 | 0.591 | (0.490, 0.676) |
| No.boa.Weibull | No alig. Weibull | 192 | 0.549 | (0.442, 0.641) |
| Odd.pen.Weibull | No Alig.Weibull | 192 | 0.662 | (0.574, 0.735) |
| Cls.Weibull. | No alig. Weibull | 192 | 0.305 | (0.170, 0.428) |
| Re.boa.webull | No alig.Weibull | 192 | 0.157 | (0.016, 0.292) |
| Accel.Weibull | No alig. Weibull | 192 | 0.358 | (0.228, 0.476) |
| Exact Fare | No alig. Weibull | 192 | 0.607 | (0.509, 0.690) |
| Board.Weibull | Alig.Weibull | 192 | 0.673 | (0.587, 0.744) |
| Idle.Weibull | Alig.Weibull | 192 | 0.634 | (0.541, 0.712) |
| No. Boa.Weibull | Alig.Weibull | 192 | 0.612 | (0.515, 0.693) |
| Odd.pen.Weibull | Alig.Weibull | 192 | 0.717 | (0.640, 0.779) |
| Cls.Weibull. | Alig.Weibull | 192 | 0.521 | (0.410, 0.617) |
| Re.boa.webull | Alig.Weibull | 192 | 0.265 | (0.128, 0.392) |
| Accel.Weibull | Alig.Weibull | 192 | 0.405 | (0.280, 0.517) |
| Exact Fare | Alig.Weibull | 192 | 0.602 | (0.504, 0.685) |
| Idle.Weibull | Board.Weibull | 192 | 0.629 | (0.535, 0.707) |
| No. Boa.Weibull | Board.Weibull | 192 | 0.563 | (0.458, 0.653) |
| Odd.penn. Weibull | Board.Weibull | 192 | 0.642 | (0.551, 0.718) |

| | | | | |
|---|---|---|---|---|
| Cls.Weibull. | Board.Weibull | 192 | 0.397 | (0.270, 0.510) |
| Re.boa.webull | Board.Weibull | 192 | 0.113 | (-0.029, 0.251) |
| Accel.Weibull | Board.Weibull | 192 | 0.406 | (0.280, 0.518) |
| Exact Fare | Board.Weibull | 192 | 0.581 | (0.478, 0.667) |
| No.boa.Weibull | Idle.Weibull | 192 | 0.607 | (0.510, 0.690) |
| Odd.penn. Weibull | Idle.Weibull | 192 | 0.658 | (0.570, 0.732) |
| Cls.Weibull. | Idle.Weibull | 192 | 0.369 | (0.240, 0.485) |
| Re.boa.webull | Idle.Weibull | 192 | 0.277 | (0.141, 0.403) |
| Accel.Weibull | Idle.Weibull | 192 | 0.425 | (0.301, 0.534) |
| Exact Fare | Idle.Weibull | 192 | 0.571 | (0.467, 0.659) |
| Odd.penn. Weibull | No.boa.Weibull | 192 | 0.669 | (0.582, 0.740) |
| Cls.Weibull. | No.boa.Weibull | 192 | 0.417 | (0.292, 0.527) |
| Re.boa.webull | No.boa.Weibull | 192 | 0.236 | (0.098, 0.366) |
| Accel.Weibull | No.boa.Weibull | 192 | 0.258 | (0.121, 0.385) |
| Exact Fare | No.boa.Weibull | 192 | 0.532 | (0.422, 0.626) |
| Cls.Weibull. | Odd.penn. Weibull | 192 | 0.447 | (0.326, 0.553) |
| Re.boa.webull | Odd.penn. Weibull | 192 | 0.278 | (0.142, 0.404) |
| Accel.Weibull | Odd.penn. Weibull | 192 | 0.43 | (0.307, 0.539) |
| Exact Fare | Odd.penn. Weibull | 192 | 0.845 | (0.799, 0.881) |
| Re.boa.webull | Cls.Weibull. | 192 | 0.434 | (0.311, 0.542) |
| Accel.Weibull | Cls.Weibull. | 192 | 0.287 | (0.151, 0.412) |
| Exact Fare | Cls.Weibull. | 192 | 0.402 | (0.276, 0.514) |
| Accel.Weibull | Re.boa.webull | 192 | 0.043 | (-0.100, 0.183) |
| Exact Fare | Re.boa.webull | 192 | 0.203 | (0.063, 0.335) |
| Exact Fare | Accel.Weibull | 192 | 0.414 | (0.290, 0.525) |