

PROJECT ID:

ASSESSING THE POTENTIAL USE OF SHARED ELECTRIC BICYCLES FOR THE LAST  
MILE TRIPS. Case of Kigali, Rwanda

**DESSERTATION**

*Submitted by*

**Elidad TUYISENGE (Reg N° 221027786)**

*Under the Guidance of:*

**Classio Joao Mendiata**

**&**

**NKURUNZIZA Alphonse**

*Submitted in partial fulfillment of the requirements for the award of*

**MASTER OF SCIENCE DEGREE**

**IN**

**HIGHWAY ENGINEERING AND MANAGEMENT**

**AUGUST 2025**



**UNIVERSITY of  
RWANDA**

**COLLEGE OF SCIENCE AND TECHNOLOGY**

**SCHOOL OF ENGINEERING**

**P.O. Box: 3900 Kigali, Rwanda.**

**DEPARTMENT OF CIVIL ENVIRONMENTAL AND GEOMATICS**

**ENGINEERING (CEGE).**

## **DECLARATION**

I, **Elidad TUYISENGE**, with Reg. No **221027786**, from University of Rwanda College of Science and Technology, School of Engineering; Department of Civil, Environmental and Geomatics Engineering, following studies of Master of Science in Highway Engineering and Management Programme, hereby declare that this work is of my original and has never been submitted for any academic award in any other University or Institution or anyone else where he/she had the same purpose.

Students Names: **Elidad TUYISENGE**

Ref Number: **221027786**

Signature: .....

Date: **29<sup>th</sup> August 2025**

**CERTIFICATION**

This research proposal has been submitted with approval from the University supervisor (Main supervisor).

Main Supervisor Names: **Dr Classio Joao Mendiata,**

Department of Civil, Environmental and Geomatics Engineering

University of Rwanda College of science and Technology

P.O. BOX 3900, KIGALI

  
(Classio Joao Mendiata)

Signature: .....

Date: 31/08/2025

Main Supervisor Names: **Dr Alphonse NKURUNZIZA,**

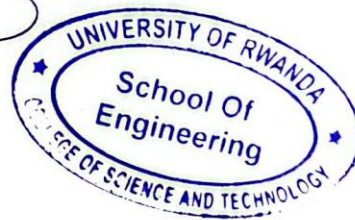
Department of Civil, Environmental and Geomatics Engineering

University of Rwanda College of science and Technology

P.O. BOX 3900, KIGALI

  
Signature: .....

Date: 31/08/2025



## ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to all those who contributed to the successful completion of this research project.

First and foremost, I extend my sincere appreciation to my supervisors, **Dr. Classio Joao Mendiata** and **Dr. NKURUNZIZA Alphonse**, for their invaluable guidance, constructive feedback, and unwavering support throughout the research process. Their expertise and encouragement were instrumental in shaping this study.

I am also grateful to the **University of Rwanda, College of Science and Technology (UR-CST)**, and the **Department of Civil, Environmental, and Geomatics Engineering (CEGE)** for providing the academic environment and resources necessary for this research.

Special thanks go to the respondents who participated in the surveys and interviews, as their insights and experiences were crucial to the findings of this study. I also acknowledge the contributions of my colleagues and friends who provided moral support and encouragement during the challenging phases of this work.

My heartfelt appreciation goes to my family for their endless love, patience, and motivation. Their belief in my abilities kept me focused and determined to achieve this milestone.

Finally, I thank all the individuals and organizations whose direct or indirect contributions made this research possible. This work would not have been successful without their collective support.

## **DEDICATION**

I dedicate this work to my beloved family, whose unwavering support, encouragement, and sacrifices have been my foundation throughout my academic journey. Their belief in my potential has motivated me to persevere and achieve this milestone.

I also dedicate this research to my friends and colleagues, whose friendship, constructive discussions, and shared experiences have enriched my studies and made this journey memorable.

Lastly, I extend my gratitude to all those who contributed directly or indirectly to the completion of this project, including respondents, mentors, and institutions. Your assistance has been invaluable in bringing this work to fruition.

## ABSTRACT

This study evaluates the potential of shared electric bicycles (e-bikes) for last-mile connectivity in Kigali, Rwanda, analyzing user preferences, current transport modes, and adoption barriers across different travel distances. Using a mixed-methods approach, including descriptive statistics and non-parametric tests (Mann-Whitney U), primary data was collected from 170 respondents representing diverse socio-demographic groups. The sample was predominantly young (55.3% aged 25–34), educated (94.7% with tertiary education), and employed (50%), reflecting Kigali's urban commuter profile.

Results indicate that walking (55.9%) remains the dominant mode for short distances (<1 km), while moto-taxis (28.2%) are costly yet widely used. Bicycle adoption is low (9.4%) but viable for medium distances (2–5 km). Non-parametric tests reveal significant predictors of e-bike willingness: for travel distance <1 km, occupation ( $p = 0.014$ ) and trip cost ( $p = 0.021$ ) are key; for 1–3 km, income ( $p = 0.028$ ) and trip purpose ( $p = 0.039$ ) matter most; Furthermore, a binary logistic regression model confirmed that increased distance from a public transport station is the strongest positive predictor of willingness to adopt e-bikes (OR = 1.57,  $p = .001$ ), while older age is a significant negative predictor (OR = 0.66,  $p < .001$ ). The model was statistically significant ( $\chi^2(5) = 25.92$ ,  $p < .001$ ) and a good fit for the data (H-L test  $p = .051$ ) and for 3–5 km, district of residence ( $p = 0.049$ ) and public transport use ( $p = 0.014$ ) are influential. Notably, no significant factors emerged for trips >5 km, underscoring e-bikes' limited appeal for longer distances. Younger respondents (18–34 years) and suburban residents showed higher willingness, while affordability and infrastructure gaps persisted as barriers.

The study concludes that e-bikes can effectively bridge last-mile gaps for 1–5 km trips, particularly in underserved suburban areas, but require targeted interventions: dedicated cycling lanes, integrated e bikes stations and parking at transit hubs, and subsidies for low-income users as critical enablers. This research provides evidence-based guidance for policymakers to promote e-bikes as a sustainable, cost-effective alternative to current modes, aiming to enhance urban mobility, and improve environmental outcomes.

**Key word:** Electric Bicycles, bicycle use markets, Last mile trips, Kigali

## Contents

DECLARATION .....	i
CERTIFICATION.....	<b>Error! Bookmark not defined.</b>
ACKNOWLEDGEMENTS.....	iii
DEDICATION .....	iv
ABSTRACT.....	v
LIST OF TABLES.....	viii
LIST OF FIGURES.....	ix
List of abbreviations.....	x
CHAPTER 1: GENERAL INTRODUCTION .....	1
<b>1.1. Back ground</b> .....	1
<b>1.2. Problem statement</b> .....	2
<b>1.3. Research motivation</b> .....	4
<b>1.4. Research objective.</b> .....	4
<b>1.5.1. Main research objective.</b> .....	4
<b>1.5.2. Specific research Objective.</b> .....	4
<b>1.5. Research questions,</b> .....	4
<b>1.6. Research matrix</b> .....	6
<b>1.7. Research scope</b> .....	7
<b>1.8. Organization of the Thesis</b> .....	7
<b>1.9. Study expected results</b> .....	7
CHAPTER 2: REVIEW OF LITERATURE.....	10
<b>2.1. The concept of Last-Mile connectivity</b> .....	10
<b>2.2. Electric Bicycles (E-Bikes) for Last-Mile connectivity</b> .....	11
<b>2.3. Shared Mobility Systems and Bike-Sharing Schemes</b> .....	12
<b>2.4. User behavior and preferences in adopting E-Bikes and shared mobility</b> .....	12
<b>2.5. Policy frameworks and incentives for promoting E-Bikes and shared mobility</b> .....	13
<b>2.6. The Rwandan context: electric mobility and Bike-sharing</b> .....	13
<b>2.7. Willingness of the use of electric bicycles on each travel distance for the last mile trips.</b> 15	
<b>2.8. Gaps in the Literature</b> .....	16

<b>2.9. Summary of the Literature Review</b> .....	16
<b>CHAPTER 3: METHODOLOGY</b> .....	17
<b>3.1. Case study description</b> .....	17
<b>3.2. Site Selection and description</b> .....	18
<b>3.3. Research Design</b> .....	18
<b>3.4. Determination of Sample size</b> .....	20
<b>3.5. Sampling technics</b> .....	21
<b>3.6. Data collection tools</b> .....	21
<b>3.6.1. Document review</b> .....	21
<b>3.6.2. Questionnaire survey</b> .....	21
<b>3.7. Data analysis</b> .....	22
<b>3.7.1. Goodness-of-Fit for Binary Logistic Regression</b> .....	22
<b>3.7.2. Non-Parametric test</b> .....	22
<b>3.8. Ethical considerations</b> .....	23
<b>3.9. Expected limitations</b> .....	23
<b>CHAPTER 4: DATA ANALYSIS AND INTERPRETATION</b> .....	24
<b>4.1. Characteristics of the respondent</b> .....	24
<b>4.2. Analysis of Current Modes of Transport for Last-Mile Trips</b> .....	24
<b>4.2.1. Social demographic characteristics</b> .....	24
<b>4.2.2. Travel distance with Transport Mode</b> .....	26
<b>4.2.3. Transport Mode by trip Purpose</b> .....	28
<b>4.2.4. Travel distance by trip Purpose</b> .....	28
<b>4.2.5. Travel distance by reason of transport mode choice</b> .....	29
<b>4.2.6. Travel distance with the expenditure</b> .....	30
<b>4.2.7. Travel distance and Residency location</b> .....	31
<b>4.2.8. Distribution of cost with various transport modes</b> .....	32
<b>4.3. Assessment of willingness to use electric bicycles for Last-Mile Trips</b> .....	34
<b>4.3.1. Binary logistic Regression analysis and Goodness-of-Fit</b> .....	37
<b>4.3.2. Non-parametric statistics analysis</b> .....	44
<b>4.4. DISCUSSION AND INTERPRETATION</b> .....	49
<b>4.4.1. Overview</b> .....	49
<b>4.4.2. Demographic insights and user characteristics</b> .....	49
<b>4.4.3. Current modal preferences and last-mile connectivity</b> .....	49
<b>4.4.4. User willingness and demographic influences on E-bike adoption</b> .....	49
<b>4.5. Policy Analysis for Promoting Electric Bicycles</b> .....	52
<b>CHAPTER 5. CONCLUSIONS AND RECOMMENDATION</b> .....	54

<b>5.1. Conclusions</b> .....	54
<b>5.2. Recommendations</b> .....	55
References .....	57

**LIST OF TABLES.**

Table 1: Research Matrix.....	6
Table 2: Sample Size Computation.....	21
Table 3: Socio-demographic characteristics and last-mile transport modes of respondents in Kigali..	25
Table 4: Frequency of Transport mode with Travel distance .....	27
Table 5: Travel distance with Travel purpose.....	29
Table 6: Travel distance by Reason of transport mode choice. ....	30
Table 7: Travel distance with Expenditures.....	31
Table 8: Travel distance by the location .....	32
Table 9: Distribution of transport costs by mode and distance from bus station .....	33
Table 10: Willingness to ride by travel distance.....	35
Table 11: Mean distance willing to ride electric bicycles by income level .....	36
Table 12: Average distance willing to travel by electric bicycle across and residential locations .....	37
Table 13: Goodness-of-Fit Statistics for the Binary Logistic Regression Model .....	40
Table 14: analysis with all combined distance.....	45
Table 15: Non-Parametric test statistics for travel distance less than 1km Vs the willingness to choose electric bikes. ....	46
Table 16: Non-Parametric test statistics for travel distance between 1-3km Vs the willingness to choose electric bikes .....	47
Table 17: Non-Parametric test statistics for travel distance between 3-5km Vs the willingness to choose electric bikes .....	48
Table 18: Non-Parametric test statistics for travel distance more than 5km Vs the willingness to choose electric bikes .....	48
Table 19: Willingness varies by travel distance.....	51

## LIST OF FIGURES

Figure 1: last mile problem [8] .....	10
Figure 2: Administrative maps kigali city.....	17
Figure 3: One station of electric bicycles in City center. Source: google photo.....	18
Figure 4: Transport mode with travel distance .....	27
Figure 5: Travel distance with travel purpose.....	29
Figure 6: Travel distance by choices of transport mode. ....	30
Figure 7: Travel distance by expenditures. ....	31
Figure 8: Travel distance and Residency .....	32
Figure 9: Distribution of transport costs by mode and distance from bus station.....	34
Figure 10: Mean distance willing to ride electric bicycle by age group .....	35
Figure 11: Mean distance willing to ride electric bicycle by income .....	37
Figure 12: Mean distance willing to travel by electric bicycle across location types.....	37

## **List of abbreviations**

MINENFRA: Ministry of infrastructure.

GoF: Government of Rwanda

CBD: Central Business District

RF: Random Forest model

SRS: Simple random sampling

SPSS: Statistical Package for the Social Sciences

NISR: National institute of Statistic of Rwanda.

UR-CST: University of Rwanda-College of Sciences and Technology (UR-CST

UN-Habitat: United Nation

WB: World Bank

## **CHAPTER 1: GENERAL INTRODUCTION**

### **1.1. Back ground**

Public transport systems carry travellers from one stop to another. However, to use public transport, individuals must first cover the distance from their starting point to the nearest stop. Similarly, after getting off at their destination stop, they must travel the remaining distance to their final destination. These segments at the beginning and end of a public transport journey are typically referred to as the first and last mile.(van Kuijk et al., 2022a). From a liveability and sustainability standpoint, the performance of public transport has been hampered by a persistent difficulty of limited connectivity to the first and last mile for Travelers. Satisfaction with public transport trips is strongly related to the travel experience in last mile trips. This implies that focusing on the complete door-to-door travel experience, rather than the quality of individual public transport modes, can attract more Public transport travelers. Consequently, this can impact the effectiveness and equity of transport systems [1]. Meeting the rising demand for transport is difficult in many cities, where an increasing number of vehicles has exacerbated traffic congestion and pollution. Many city residents continue to have limited mobility alternatives, particularly low-income people and those who live in locations without access to public transportation. Many inhabitants in city must walk to get around the city and even from the end bus station to their home [2]. Electric Bike sharing, as a form of shared transportation, has received increasing the attention to more country for sustainable environmental restoration and reduction of air pollution, as well as a promising solution to minimize the issues of traffic congestion. The basic premise of bike-sharing programs is sustainable transportation. Objectives associated with bike sharing programs include increased cycle usage and mobility options, an improved first/last mile connection to other travel modes, reduced transport congestion and energy consumption, reduced environmental impacts, and improved public health [3].

With addressing the implementation for the use of electric bike share, there is a need to conduct much research on addressing the issues to reach home implementation and assess the willingness of the users at each travel distance from the Public transport to the last destination. The present research aims to assess the potential use electric bike sharing system and assess how this should be integrated in the last miles trip assess by the users. Will also analyse the

provision of providing a comprehensive policy, business and academic guide that will indicate how bike-sharing schemes can be used in the future for the last miles trips.

The government of Rwanda (GoR) has committed to implementing sustainable transportation solutions. Building on the findings of an earlier e-mobility analysis, the city of Kigali was supported in the assessment of electric last-mile connectivity solutions. The assessment confirmed that electric bicycles can supplement public transport. Among the several business models examined, combining public transport with on-demand services could be an effective way to expand accessibility to underserved areas. The operators might provide semi-structured routes using electric bicycles, and users could reserve the service in advance [4].

Travel intervals for last-mile trips are critical in understanding user preferences and mode choice, as willingness to adopt electric bicycles (e-bikes) varies by distance. Studies indicate that for short distances (0–2 km), walking dominates, but e-bikes become competitive at 2–5 km due to their speed and reduced exertion compared to walking or crowded buses (W. Zhang et al., 2024). At intervals beyond 5 km, motorized modes are preferred, though e-bikes can bridge this gap if perceived as cost-effective and convenient [5]. Research in Kigali highlights that last-mile challenges peak at 3–4 km, where current options are either inefficient (walking) or expensive (motorcycles), creating an opportunity for e-bike integration [2]. Analyzing these intervals helps tailor policies to incentivize e-bike adoption where they offer the highest marginal utility, aligning with Rwanda’s sustainable mobility goals [4]

This research aims of analyzing the potential use of the existing shared electric bicycles for the last mile trips at each travel intervals to each traveller from the bus terminal to their home destination.

## **1.2. Problem statement**

The last mile of connection defines the portion of a transportation trip that connects a person's starting point, which is frequently their house or place of employment, to a public transit station or the final leg of the trip. In urban transportation systems, the last mile trip is the crucial connection that guarantees smooth transitions between modes of transportation or straight to a person's destination [6]. According to Kåresdotter et al., 2022 the first mile/last mile problem in public transport refers to the spatial accessibility of public transport and is the most important factor deciding whether a person will choose public transport. The problem in travellers transport refers to the disconnect between public transport and an individual’s origin or

destination. It is directly linked to whether public transport is considered accessible and thus whether individuals choose to use it. The most commonly used definition is that the last mile is the distance between the residence and public transport while the first mile refers to the distance between the work place/end destination and the public transport.

From a liveability and sustainability standpoint, the performance of public transport has been hampered by a persistent difficulty of limited connectivity of traveller to their home destinations. Satisfaction with public transport trips is strongly related to the travel experience in the end points destination. This implies that focusing on the complete door-to-door travel experience, rather than the quality of individual public transport modes, can attract more Public transport travellers. Consequently, this can impact the effectiveness and equity of transport systems [1].

The individuals living within a public transport network service area, considered as the area within the willingness to walk threshold distance. The willingness to walk for a certain distance varies by country and cities. The lack of connectivity within the transportation system has been shown to lead high expenses of using motorcycles and private car use and less use of other transportation modes, such walking.

Walking is the most common mode of transport from the last mile to public transport in Western countries and the dominant mode of transport for distances up to 2 km in Sweden. Surveys and studies conducted in Swedish have consistently shown that individuals worldwide walk farther than the established rule of thumb of 400 m to a bus stop and 800 m to a train station, as well as longer distances to train stations than buses. Studies have also shown that willingness to walk varies between countries and demographics, trip characteristics, the built environment, and numerous other factors. Thus, it is unlikely that a new standard can be established, which could explain why 400 m and 800 m are still commonly used as rules of thumb. Research has shown that an increase in distance (or travel time) to a stop or station causes a reduction in individuals using public transport.(Kåresdotter et al., 2022)

The first- and last-mile problem is one of the biggest challenges of urban mobility systems and is often the main cause of other issues such as low public transport accessibility and forced car ownership in certain urban areas [7] . Despite the availability of public transport in Kigali, many residents face difficulties accessing their final destinations after alighting from buses. This issue is particularly pronounced in peripheral areas, where long walking distances or

expensive alternative transportation options are common. The lack of last-mile connectivity reduces the overall attractiveness and efficiency of public transport systems.

### 1.3. Research motivation

This study is motivated by the need to generate localized, evidence-based insights into the effective deployment of e-bikes for last-mile connectivity. By understanding user preferences, travel patterns, and determinants of adoption, policymakers and urban planners can better design targeted interventions ranging from infrastructure investments to pricing models that promote sustainable mobility and enhance urban accessibility for all residents. Ultimately, this study aims to bridge the knowledge gap in existing literature and inform the adoption of innovative, sustainable transport solutions tailored to Kigali and similar African urban settings.

### 1.4. Research objective.

This Study aims to get the perspectives of travelers in order to provide access to last-mile trips from the bus terminal in given travel intervals. To address the issue of individuals walking long distances, and use of motorcycles, this study will examine the willingness of various users and likelihood to shift the current mode of transport with the use of electric bicycles to reach the last miles. The study is structured around Four interrelated specific objectives:

#### 1.5.1. Main research objective.

The main objective of this study is **to assess which mode of transport people use to the last end miles trip**. At each travel distance interval, the current modes of transport in normal way without any circumstances will be assessed.

#### 1.5.2. Specific research Objective.

- To analyse at which distance people are willing to use electric bicycles to the last miles trips.
- To assess the likelihood of shifting from the current transport model to electric bicycles to the last miles.
- To provide the policy recommendation of promoting electric bicycles to the last miles trips.

### 1.5. Research questions,

Below tables show the research question for each objective:

Objectives	Research Question
------------	-------------------

<p>To assess which mode of transport people use to the last end miles trip. At each travel distance interval, the current modes of transport in normal way without any circumstances will be assessed</p>	<ul style="list-style-type: none"> <li>• What are the most commonly used modes of transport for last-mile trips at different travel intervals in the study area?</li> <li>• How do users perceive the convenience, cost, and efficiency of the current modes of transport for last-mile trips at various travel distances, and how do these perspectives vary by travel interval?</li> </ul>
<p>To analyse at which distance people are willing to use electric bicycles to the last miles trips.</p>	<ul style="list-style-type: none"> <li>• What socio-demographic factors influence the distance people are willing to use electric bicycles for last-mile trips within a specific travel interval?</li> </ul>
<p>To assess the likelihood of shifting from the current transport model to electric bicycles to the last miles</p>	<ul style="list-style-type: none"> <li>• What are the key factors that determine individuals' willingness to shift from their current mode of transport to electric bicycles for last-mile trips at different travel intervals?</li> </ul>
<p>To provide the policy recommendation to promote electric bicycles to the last miles trips.</p>	<ul style="list-style-type: none"> <li>• What are the strengths and weaknesses of the current policies in promoting the adoption of electric bicycles for last-mile trips between bus terminals and final destinations, and how can these policies be improved?</li> </ul>

## 1.6. Research matrix

This research matrix illustrates the relationship between research question and research objectives:

*Table 1: Research Matrix*

<b>Research Question</b>	<b>Research objectives</b>	<b>Reaserch method</b>	<b>Data sources</b>
What are the most commonly used modes of transport for last-mile trips at different travel intervals in the study area?	To assess which mode of transport people, use to the last end miles trip.	Descriptive statistics	Surveys using Questionnaire
How do users perceive the convenience, cost, and efficiency of the current modes of transport for last-mile trips at various travel distances, and how do these perspectives vary by travel interval?	To assess which mode of transport people, use to the last end miles trip.	Descriptive statistics	Users Surveys using Questionnaire
What socio-demographic factors influence the distance people are willing to use electric bicycles for last-mile trips within a specific travel interval?	To analyse at which distance people are willing to use electric bicycles to the last miles trips.	Binary Logistic regression analysis/ Non-Parametric Test	Interviews and surveys

<p>What are the strengths and weaknesses of the current policies in promoting the adoption of electric bicycles for last-mile trips between bus terminals and final destinations, and how can these policies be improved?</p>	<p>To provide the policy recommendation to promote electric bicycles to the last miles trips.</p>	<p>Descriptive statistics</p>	<p>Users Surveys using Questionnaire</p>
---	---	-------------------------------	--

### 1.7. Research scope

The study focuses on the use of shared electric bicycles for last-mile trips. It examines user preferences, travel behavior, and policy frameworks, with a particular emphasis on the integration of e-bikes into the existing public transport system.

### 1.8. Organization of the Thesis

The thesis is organized into five chapters. Chapter 1 introduces the research, including the background, problem statement, and objectives. Chapter 2 reviews the relevant literature on last-mile connectivity, electric bicycles, and shared mobility systems. Chapter 3 outlines the research methodology, including data collection and analysis techniques. Chapter 4 presents the data analysis and interpretation of findings. Chapter 5 summarizes the findings, provides conclusions, and offers recommendations for policy and practice.

### 1.9. Study expected results

The anticipated outcomes of this Study are aligned with the four objectives outlined for the research. This chapter presents an overview of what the expected results are for each objective and how these results will contribute to a deeper understanding of the existing shared electric bicycle market and its potential for future adoption.

### **Understanding the current modes of transport for the last mile trips**

The expected results for this objective involve identifying the current modes of transport used by people for their last mile trips within specific travel intervals at sampled terminal points. This was included gathering data on how people typically complete their journeys from bus terminals, public transport hubs, or key drop-off points to their final destinations. By assessing the current transportation choices, such as walking, moto-taxis, shared bicycles, or public buses, we will be able to determine the most common modes of travel. Through surveys and interviews, it was expected to gather information on the types of transport people rely on, the frequency of use, and the reasons behind their choices. In addition to mode preference, the study assessed factors influencing these choices, such as cost, travel time and convenience. The expected outcome is a comprehensive understanding of user behavior and preferences, which will provide insight into the demand for alternative modes of transport, particularly electric bicycles, for completing last mile trips.

### **Analyzing willingness to use Electric Bicycles for Last Mile Trips**

For this objective, it was expected to determine how far individuals are willing to travel using an electric bicycle during the final segment of their journey. The research focus on understanding the distance intervals where people would prefer to switch to an electric bicycle from other transport modes. This will be assessed based on the specific socio demographic characteristics and distances outlined, which was broken down into categories. It is expected to gain insights into the users' preferences regarding the convenience and practicality of using electric bicycles for travel intervals.

### **Assessing the likelihood of shifting from current transport mode to Electric Bicycles**

In terms of the likelihood of shifting from existing transport models to shared electric bicycles, the focus is based on the attitudes and willingness of commuters to adopt electric bicycles. Through a combination of surveys and focus group discussions, it is expected to find that while many commuters may express interest in shifting to electric bicycles, concerns such as the availability of charging stations, safety, and the initial investment in infrastructure may pose challenges to widespread adoption. Furthermore, we expect that factors such as weather, availability of bike lanes, and the presence of a strong policy framework will play a crucial role in influencing whether commuters are willing to make this shift. Ultimately, this objective will

highlight the potential barriers and opportunities for promoting electric bicycles as a viable transport alternative.

### **Policy analysis to promote Electric Bicycles for Last Mile Trips**

It is expected that the research will uncover key policy gaps and opportunities for integrating shared electric bicycles into the City transport. The expected results will analyze how the existing infrastructure, such as bus terminals and transport hubs, can be enhanced to accommodate shared electric bicycle stations. Improved last-mile connectivity makes public transport more accessible to people from all walks of life, especially those in rural, sub urban or peripheral areas who may not have easy access to bus services. This can help reduce social inequalities by providing more people with reliable and affordable transport option. The collaboration between public and private sectors in suburban area to integrate **e-bikes** for last-mile connectivity will offer numerous benefits, including improved environmental sustainability, social inclusion, economic efficiency, and overall urban mobility. By reducing traffic congestion, promoting healthier lifestyles, and providing affordable and efficient transportation options, e-bikes can transform how people travel from bus terminals to their final destinations, leading to more livable, sustainable suburban areas.

## CHAPTER 2: REVIEW OF LITERATURE

### 2.1. The concept of Last-Mile connectivity

The last mile connection defines the portion of a transportation trip that connects a person's starting point, which is frequently their house or place of employment, to a public transit station or the final leg of the trip from the public transport bus station to the final destination. In urban transportation systems is the crucial connection that guarantees smooth transitions between modes of transportation or straight to a person destination [6]. According to Kåresdotter et al., 2022 the first mile/last mile problem in public transport refers to the spatial accessibility of public transport and is the most important factor deciding whether a person will choose public transport. The first/last mile problem in passenger transport refers to the disconnect between public transport and an individual's origin or destination. It is directly linked to whether public transport is considered accessible and thus whether individuals choose to use it. The most commonly used definition is that the last mile is the distance between the residence and public transport while the first mile refers to the distance between the work place/end destination and the public transport.

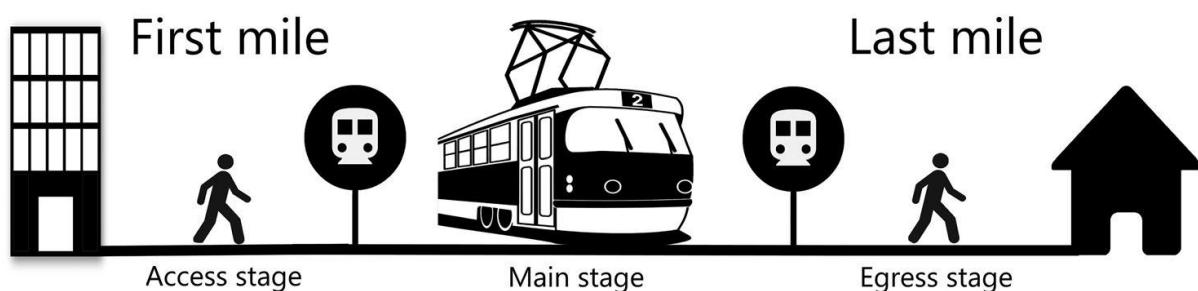


Figure 1: last mile problem [8]

The individuals living within a public transport network service area, considered as the area within the willingness to walk interval distance, following a road network, from a public transport stop or station can be considered to have access to public transport. The willingness to walk for a certain distance varies by country and cities. The lack of connectivity within the public transport has been shown to lead high expenses of using motorcycles and private car use and less use of other transportation modes, such walking.

Walking is the most common mode of travel from the last mile to public transport in Western countries and the dominant mode of travel for distances up to 2 km in Sweden. Using surveys, studies conducted in Swedish have consistently shown that individuals worldwide walk farther than the established rule of thumb of 400 m to a bus stop and 800 m to a train station, and also

walk longer distances to train stations than bus. Studies have also shown that willingness to walk varies between countries and demographics, trip characteristics, the built environment, and numerous other factors. Thus, it is unlikely that a new standard can be established, which could explain why 400 m and 800 m are still commonly used as rules of thumb. Research has shown that an increase in distance (or travel time) to a stop or station causes a reduction in individuals using public transport. (Kåresdotter et al., 2022)

## **2.2. Electric Bicycles (E-Bikes) for Last-Mile connectivity**

The integration of electric bicycles (e-bikes) into urban transport systems has increasingly attracted scholarly attention due to their potential to address critical urban mobility challenges, particularly for last-mile connectivity [9]. Research on sustainable urban mobility highlights that electric bicycles significantly reduce greenhouse gas emissions compared to conventional vehicles, promoting environmental sustainability [10] [11]. However, the acceptance and utilization of e-bikes depend substantially on user preferences and behavioural aspects. Li, Shen, and Jia (2021) explored user intentions to adopt shared electric bicycles, emphasizing that demographic factors such as age, income, and location critically influence user willingness and preference. Similarly, research from small and medium-sized cities in Belgium indicates that user preferences for bicycle sharing schemes are affected by weather, distance, rental costs, and socio-demographic factors [9].

Cargo e-bikes have also emerged as effective tools in urban logistics, particularly for the delivery of goods. They offer a viable solution to congestion and pollution problems associated with conventional delivery vehicles. Studies by [12] and [13] illustrate how e-cargo bikes effectively replace conventional vehicles in dense urban areas, significantly reducing operational costs and emissions.

The synergy between bicycles and public transport is further enhanced by integrating bicycles within public transport networks, significantly expanding their service areas [14]. The systematic literature review by Kosmidis and Müller-Eie (2024) confirms that successful integration depends on the quality and extent of cycling infrastructure, public transport network quality, and effective policy measures. [15]. Moreover, policy interventions and incentive programs significantly influence e-bike adoption. [16] highlight the importance of economic incentives, demonstrating that targeted financial support significantly increases the accessibility of e-bikes for various demographics, especially lower-income groups.

### **2.3. Shared Mobility Systems and Bike-Sharing Schemes**

Shared mobility, particularly dockless bike-sharing, has been effective in enhancing intra-urban human mobility, as observed in Beijing [17]. Dockless bike-sharing systems effectively address last-mile connectivity, showing clear peak usage patterns aligned closely with public transit schedules, significantly improving transit accessibility and convenience.

Given the study area geographical hilly terrain and growing urban population the potential for e-bikes to address the last mile challenge is significant. E-bikes offer higher speeds and comfort compared to conventional bicycles, making them well-positioned to complement existing public transportation or even compete with established taxi service. The market for shared e-bikes in Kigali may be influenced by several factors. Economic and social activity, public transportation service quality, and the availability of bicycle infrastructure are key drivers of demand for free-floating e-bike-sharing systems. [18]

Additionally, age, current cycling behavior, and weekday/weekend travel patterns are important factors determining user preferences for shared modes in the first and last mile. [19]. In in study area perspective view, it is crucial to consider these factors when assessing the existing market for shared e-bikes. To effectively implement a shared e-bike system for last mile trips in Kigali, several aspects need to be addressed. First, a station clustering method could be employed to optimize bicycle distribution and predict demand. [20].

### **2.4. User behavior and preferences in adopting E-Bikes and shared mobility**

In Kigali, understanding user behavior and preferences is crucial for successfully implementing such a system. User preferences for shared e-bikes are likely to be influenced by factors such as age, current cycling behavior, and travel patterns. Younger individuals (<26 years) may show a higher preference for e-bikes, especially for suburban destinations. [21]

Additionally, gender, bicycle availability, and travel frequency could significantly impact mode choices for first/last mile trips. It's important to note that access distance dramatically affects mode choices when shared bicycles are available. [22] The implementation for shared e-bike system requires careful consideration of user demographics and travel patterns. Factors such as age, gender, and access distance should be prioritized when planning the system distribution and infrastructure.

## **2.5. Policy frameworks and incentives for promoting E-Bikes and shared mobility**

As observed in other cities, shared e-bikes can potentially contribute to last-mile connections of public transport trips, offering an environmentally friendly and efficient mode of transportation. Research has shown that shared bicycles, including e-bikes, can become the preferred mode when properly implemented. In China, for instance, more than 80% of public transport travellers opted for walking and shared bicycles as feeder modes after the introduction of bicycle-sharing systems [23]. However, it is important to note that user preferences may vary based on factors such as age, gender, and existing travel patterns. In Shenzhen, China, younger public transport users showed interest in adopting shared e-bikes but expressed concerns about pricing, while female users prioritized safety issues [24]

## **2.6. The Rwandan context: electric mobility and Bike-sharing**

Bike-sharing, often known as public bike share, makes bikes available to the general public for sharing purposes. In general, the bike-sharing user is able to borrow a bike at a station and return it at any station of the same program inside the city. (Ntamwiza & Bwire, 2023)

The program of bike share began in 1965 around the world and went through several stages of development. Today, it plays an important role in urban transportation. Bicycle sharing is more environmentally friendly than motorised sources of transportation. Furthermore, it is an effective solution for the research problems. (Ntamwiza & Bwire, 2023)

The city of Kigali has a tropical climate. The population is expected to grow to 3.8 million by 2035, up from approximately 1.2 million today. The city has a youth population of roughly 65%, with many of them being students. The city has implemented car-free days and zones (Kigali Car-Free Day, 2019). In 2019, the city of Kigali started bike-sharing to reduce traffic congestion and greenhouse gas emissions. It was divided into three composed districts. The only districts where bike-sharing is available are Gasabo and Nyarugenge. Only 9 of the 18 stations established are operational, including 5 stations in corridor Remera and 4 stations in the Central Business District. (Ntamwiza & Bwire, 2023)

The statistics indicate that bike-sharing usage has increased. In the first months of 2021, there were 3,543 bike-sharing trips. In the months of 2022, bike-sharing trips increased to 4,132. And among such journeys, model results suggested that dominant bike-sharing consumers are students. The dominant month in year 2021 is November with 1286 travels while in year 2022, the dominant month is January with 1491 trips. It was indicated that the available current station for bike sharing located in City center namely Marriott, NORSKEN, CBD corridor,

arena and serena. The Random Forest model has the accuracy of 84% in trips classification. It was indicated that bike-sharing program users at the Arena and Serena stations are students and they have significantly increased during the study period. MARRIOT and NORSKEN station riders are less likely to be students. The CBD corridor users of the bike-sharing program are likely to be students, whereas the Remera corridor users are non-students. The model's findings suggest that station location in line with land use is critical to the success of a bike share program.(Ntamwiza & Bwire, 2023)

The commonly used statistical model has been used to evaluate changes overtime on stations and corridors. Interestingly, based on Random Forest model (RF) which is accurate at 83.7%, the results indicate an exponential growth between Year 2021 and year 2022. Based on bike-sharing user increase, it is deduced that factors that contribute to bike-sharing variations are (1) fixed income of system users, (2) the Location of stations, (3) land use and location of education institutions. Most of the bike-sharing users shifted from public transport. This is due to the low performance of public transport operators and the high tariff of motor taxi transport. Bike-sharing was also found to cover short distances between households and public transportation or between transit stations and places of employment that may be too far to walk. It was found that the addition of bike lanes alongside new roadways has attracted a lot of sharing patronage. Finally, it is suggested that transport rules should recognize bike share riders as legitimate road users, and that drivers of motorized vehicles be educated on the need of sharing the road with cyclists.(Ntamwiza & Bwire, 2023)

Electric mobility is rapidly gaining attraction around the world as an energy efficient solution for transport of goods and people allowing for the use of renewable energy while avoiding tailpipe emissions. Introducing electric mobility will encourage a shift from imported oil products to domestically generated electricity. The introduction of e-vehicles should be paired with measures to facilitate a shift from personal motor vehicles to walking, cycling, and public transport. There are significant opportunities for the introduction of electric vehicle technology in shared transport services, including bike sharing and public transport. The development and the support of electric mobility is motivated by a number of ambitions at the national and international level, including Rwanda Vision 2050, Transition Rwanda, the Paris Agreement on Climate Change, the United Nations 2030 Agenda for Sustainable Development, and the Sustainable Development Goals [25]

Transport is part of Rwanda's Green City/Green Economy initiative, and bicycle policy is focused on improving road safety and reducing road congestion. Transport planners see that walking and cycling are cost-effective ways to reduce carbon emissions from the transport

sector. In 2021, the cabinet formally approved a policy to promote electric vehicles, particularly public transport and electric bicycles. Rwanda also has a commitment that every local authority must spend 33% of its transport capital expenditure on walking and cycling infrastructure, and may not spend more than 33% of its infrastructure budget on facilities for private cars [26]

### **2.7. Willingness of the use of electric bicycles on each travel distance for the last mile trips.**

The electric bicycles (e-bikes) for last-mile trips varies significantly across different travel distances, influenced by factors such as convenience, cost, and physical exertion. Studies indicate that for short distances (0–2 km), walking remains the dominant mode due to its perceived simplicity and zero cost, while e-bikes become increasingly competitive for intermediate distances (2–5 km) where walking becomes less practical (X. Zhang et al., 2024). E-bikes offer a balance of speed and reduced physical effort, making them attractive for commuters covering moderate distances, particularly in hilly or congested urban areas [27],

For longer last-mile trips (5+ km), motorized modes such as motorcycles or taxis are often preferred due to their speed, though e-bikes can still serve as a viable alternative if perceived as cost-effective and reliable [28] The assessment done in Kigali by the Government highlights that last-mile challenges peak at 3–4 km, of which the walking as an option of transport are inefficient and motorcycles are expensive, and support the use of e-bike for such distance. According to X. Zhang et al., 2024 the user willingness at this range of 3-4km depends on infrastructure, such as bike lanes and charging stations, as well as socio-demographic factors like income and age. Socio-demographic and environmental factors also shape the willingness across distances. Younger travellers and students are more likely to use e-bikes for medium distances, while older adults may prefer shorter trips or avoid cycling altogether due to safety concerns (van Kuijk et al., 2022b) Preferences are also influenced by weather, terrain, and the availability of safe parking; flat, well-connected routes promote greater e-bike riding (Adnan et al., 2019) . Customized incentives and infrastructure could increase adoption for trips up to 5 km in many cities, where the geography varies. In the end, knowing distance-specific willingness is essential for creating infrastructure and policies that are specifically targeted (Adnan et al., 2019) .Understanding distance-specific willingness is very important for designing targeted policies and infrastructure. By identifying optimal travel distances and addressing barriers like cost and safety, cities can integrate e-bikes into last-mile solutions effectively (Oeschger et al., 2020). This provides a scalable strategy for reducing dependency

on motorised transportation and walking as well as enhance urban mobility, which is in line with Rwanda's sustainability goals.

## **2.8. Gaps in the Literature**

From the literatures discussed, it was found that Kigali city has integrated were bike sharing of with Kigali city has implemented this system in 2019, and different users has exponentially increased years per years, however there is gap of how to link both public transport station with the list miles trips and analysis of potential use for electric bicycles to the last mile trips and for each travel distance using the existing electric bicycle sharing system. Currently the system is being implemented in the city center, and there is a need to expand the use of bike sharing system to solve the last and first mile's problems. The bike sharing station will be provided at each public bus stop station and near the public bus station taxi park.

## **2.9. Summary of the Literature Review**

Walking and motorcycle taxis are the dominant modes for last-mile trips, but these options are often impractical for longer distances or costly for low-income populations. Electric bicycles (e-bikes) emerge as a promising solution, offering a sustainable, cost-effective, and efficient alternative for short to medium distances (2–5 km). Studies show that e-bikes can bridge the last-mile gap by reducing reliance on motorized transport, lowering emissions, and improving accessibility, especially in hilly or congested areas.

Shared mobility systems, have gained traction globally for their ability to enhance urban mobility and integrate with public transport. In Kigali, bike-sharing programs have shown growth, particularly among students and in areas with supportive infrastructure. However, challenges like uneven bike distribution, safety concerns, and limited awareness hinder wider adoption. User preferences for e-bikes are influenced by factors like age, income, and travel patterns, with younger and middle-income groups showing higher willingness to adopt.

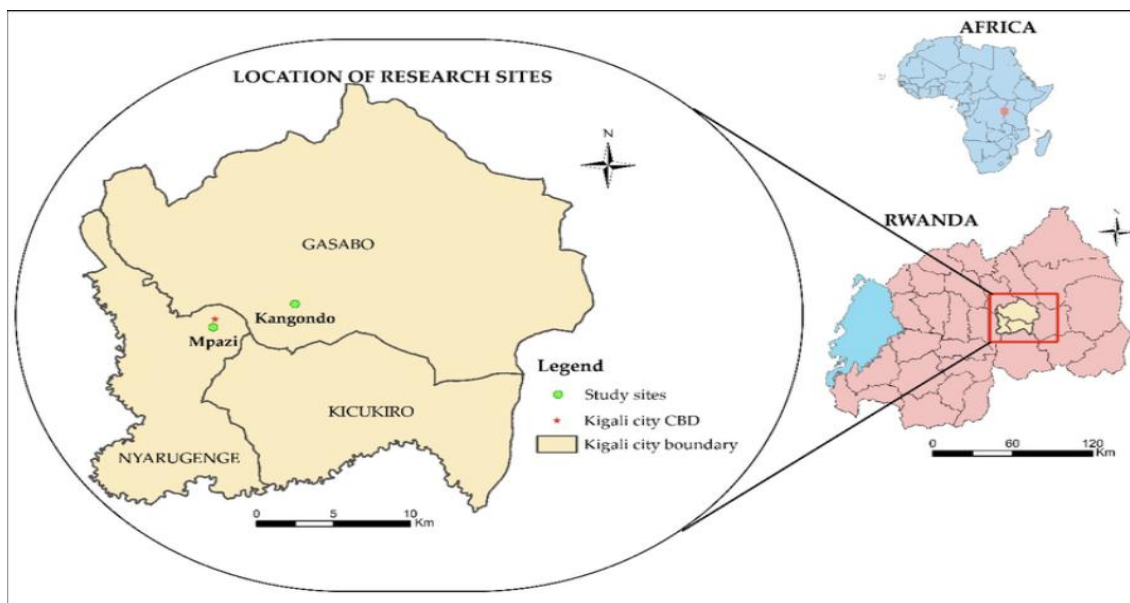
Policy frameworks and incentives play a crucial role in promoting e-bike use. Successful implementation requires dedicated cycling infrastructure, subsidies, public-private partnerships, and integration with existing transport networks. Rwanda's commitment to sustainable mobility, as seen in its Green City Initiative and electric vehicle policies, provides a strong foundation for scaling e-bike solutions. In summary, the literature underscores the potential of e-bikes to transform urban mobility, provided that infrastructure, policy, and user education are aligned to support their adoption.

## CHAPTER 3: METHODOLOGY

The chapter describes a research design, presents data collection instruments and a roadmap to solving the stated research questions.

### 3.1. Case study description

This study was undertaken in Kigali, a fast-rising city in terms of population and infrastructure that is key to the country's socioeconomic transformation and sustainable development goal. Resident population is around 1.2 million (National Institute of Statistics of Rwanda, 2022), and the area is approximately 730 square kilometres. Its population is expected to reach 3.8 million by 2035, showing intensive urbanisation and rising demand for efficient and sustainable transportation options. Kigali is divided into three administrative districts: Gasabo, Kicukiro, and Nyarugenge as per the figure below. The study sites comprised inner city, sub urban, perurban and rural zones.



*Figure 2: Administrative maps kigali city*

The city has a mountainous landscape and a tropical climate, which may influence travel mode preferences, particularly for active transportation options such as walking and cycling. However, the innovative green mobility policies, such as the 2021 national electric mobility policy and the deployment of car-free zones and days, indicate the dedication to sustainable urban transportation. Bike-sharing was formally inaugurated in Kigali in 2019, with 18 stations placed (of which only 9 was functioning), primarily in the Central Business District (CBD) and Remera corridor. According to recent bike-sharing usage data (Ntamwiza & Bwire, 2023),

students form a large portion of current users, particularly near the Arena and Serena stations, below is the figure for shared e bikes station in city center



*Figure 3: One station of electric bicycles in City center. Source: google photo.*

### **3.2.Site Selection and description**

Electric bicycles for passenger transportation are viewed as acceptable for short distances and low volumes of goods, particularly in metropolitan regions where access to conventional automobiles is limited. Given Rwanda's commitment to sustainability and technological innovation, there is a significant opportunity to address the last-mile problem by integrating electric bicycles (e-bikes) into the public transit system. This study examines the possible use of e-bikes for last-mile connectivity. Many inhabitants continue to have limited mobility alternatives, particularly low-income people and those who live in locations without access to public transportation. Many must walk to get around the city and even from the end bus station to their home [2]. The government of Rwanda has committed to implementing sustainable transportation solutions. Building on the findings of an earlier e-mobility analysis, and was supported in the assessment of electric last-mile connectivity solutions. The assessment confirmed that electric bicycles can supplement public transport. Among the several business models examined, combining public transport with on-demand services could be an effective way to expand accessibility to underserved areas. The operators might provide semi-structured routes using electric bicycles, and users could reserve the service in advance [4].

### **3.3.Research Design**

The descriptive approach was suitable for this study because it served as a data gathering instrument, allowing us to establish the traveller responses. This design was used to acquire

quantitative and qualitative data about the nature and characteristics of the respondents. The secondary data was conducted based on review of literature to cover existing studies on last-mile connectivity in urban areas, with a specific focus on developing countries and cities that have faced similar challenges. The review of literature examined the integration of sustainable transport modes like e-bikes in urban transport systems, the economic feasibility of such initiatives, and case studies of successful e-bike programs in other cities. This will provide valuable insights into best practices, challenges, and opportunities in implementing e-bikes for last-mile connectivity.

The data collection used a random sampling approach to collect primary data among the travellers in selected peripheral hub, inner city and rural areas. The survey was conducted to recognise the outcomes for each travel distance. Semi structured interview was conducted to selected number of passengers to allow their perspectives in travel distances in walking. Below is the method of data collection, data analysis for each objective

**Objective 1 To assess which mode of transport people use to the last end miles trip.**

- Using survey with Questionnaire and interviews where necessary.
- Analysis will be based on descriptive statistics.

**Objective 2.** To analyse at which distance people are willing to use electric bicycles to the last miles trips.

- Using survey method using Questionnaire and interviews on selected people.
- Analysis of data will be conducted using Non-parametric statistic test analysis/ Binary Logistic Regression analysis

**Objective 3:** To assess the likelihood of shifting from the current transport model to electric bicycles to the last miles for different travel intervals.

- Data will be collected using questionnaire
- Analysis of data will be conducted using Non-parametric statistic test analysis/ Binary Logistic Regression analysis

### 3.4.Determination of Sample size.

The Study used a combination of random and stratified sampling. These samplings were rendered possible by the fact that National Institute of Statistics- Rwanda has conducted a census on population size, Structure and distribution in 2022 in Rwanda. This census showed that the number of populations in City of Kigali is 1,218,071 peoples(National Institute of Statistics of Rwanda, 2022). This number allowed us to determine the sample size based on Cochran formula.

Evan Morris's sample size formula developed by William, G. Cochran and **Evan Morris** in 1980, Cochran's formula is used to calculate the sample size needed for estimating a proportion in a large population. The formula is:

*Equation 1: Sample size computation.*

$$n = \frac{NZ^2pq}{(E^2(N-1) + Z^2pq)}$$

Where:

n = sample size

Z= Z-value (e.g., 1.96 for a 95% confidence level)

p= estimated proportion of the population (Assuming the p= 0.5)

E= margin of error (desired level of precision)

N= The population size

$$\text{Therefore } n = \frac{1,218,071 * (1.96)^2 * 0.5 * (1-0.5)}{(0.07^2 * (1,218,071 - 1) + 1.96^2 * 0.5 * 0.5)} = 195.9677 \sim 196$$

**Since the sample size must be a whole number, we round up to 196.**

Therefore, a random sample of 196 in our target population was enough to give us the confidence levels we need.

Where the values are:

- Population size (N) = 1,218,071
- Z-value (Z) = 1.96 (for a 95% confidence level)
- Estimated proportion (p) = 0.5 (we use 0.5 for maximum variability and q=1-p)
- Margin of error (e) = 0.07 (7%)

## Sample size computation

Table 2: Sample Size Computation.

District	Population size per district	%	Sample size	Sample size distribution
Kicukiro	354,377	29%	196	57
Gasabo	610,416	50%		98
Nyarugenge	253,278	21%		41
<b>TOTAL</b>	<b>1,218,071</b>	<b>100%</b>		<b>196</b>

### 3.5. Sampling technics

A random sampling technic was applied in this study, the method refers to method where each individual in a population has an equal (or known) chance of being selected, allowing for statistical adjustments if needed. Simple random sampling (SRS) is particularly advantageous due to its straightforward implementation. It ensures fairness by granting every population member an equal opportunity for inclusion, thereby reducing selection bias. This method is crucial in studies assessing the potential use of electric bicycles (e-bikes), as an unbiased and representative sample enhances the validity of findings. Since SRS provides a sample that accurately reflects the population, researchers can confidently generalize results such as e-bike adoption rates or trip efficiency from the sample to the broader population [29]

### 3.6. Data collection tools

Data was collected and analysed using a variety of approaches. These include document reviews, questionnaires, observations.

#### 3.6.1. Document review.

The review focused on key policy and planning documents including the Rwanda National Transport Policy, Kigali City Master Plan, Green Transport Policy, and reports. International references from the World Bank and UN-Habitat were also consulted to benchmark global best practices in promoting electric mobility.

#### 3.6.2. Questionnaire survey

A structured questionnaire was used to collect data from Kigali residents on their awareness, usage, and attitudes toward electric bicycles. The survey covered topics such as willingness to adopt e-bikes, challenges faced, and policy preferences, and was distributed both online and in person to ensure broad participation.

### **3.7.Data analysis.**

The qualitative analysis conducted on this study was made in form of number as well as presentation was made in form of tables, charts and graphs representations and in form of text.

#### **3.7.1. Goodness-of-Fit for Binary Logistic Regression**

The use of descriptive statistics and binary logistic regression analysis was adopted which provide the analyse the impressions of travellers from the filled questionnaire for each respondent and by demographic data.

To ensure the robustness and validity of the binary logistic regression model, several goodness-of-fit statistics will be employed, the significance level (alpha) for all tests was set at  $p < 0.05$ . The analysis was conducted using SPSS Statistics software (Version 27).:

- 1. Omnibus Tests of Model Coefficients:** This Likelihood Ratio Chi-Square test was used to determine if the full model with all predictors provided a significantly better fit than a null model containing only the intercept.
- 2. Pseudo R-Squared Measures (Cox & Snell  $R^2$  and Nagelkerke  $R^2$ ):** These measures provide an approximation of the proportion of variance in the dependent variable explained by the model, analogous to the  $R^2$  statistic in linear regression.
- 3. Hosmer-Lemeshow Test:** This test evaluates whether the observed event rates match the expected event rates across deciles of predicted risk. A non-significant result ( $p > .05$ ) indicates that the model's predictions are well-calibrated and do not significantly deviate from the observed data.
- 4. Classification Table:** This was used to report the overall percentage of cases correctly classified by the model, comparing the predicted versus actual outcomes.

#### **3.7.2. Non-Parametric test**

The Non-Parametric test was adopted to analyse the willingness on each travel distance interval, the analysis was made on distance less than 1 km, 1-3km, 3-5Km, and More than 5km. this analysis test was adopted given that most of data was ordinal and normal data.

The qualitative analysis was carried out manually, and during data presentation, themes and concepts were analysed utilising several interviews to combine the material into a thorough description of what was going on in this study.

### **3.8.Ethical considerations.**

The use of an introductory letter from the schools of College of Sciences and Technology (UR-CST) authority, requesting for to whom it may concern for facilitation in data collection. The letter was sent to concerned authority to facilitate for data collection for this research. During this research, the respect of human dignity and secure information of consent from the respondents were considered and the information that acquired confidentiality and consider that are mainly use for this research only. The principles of academic integrity, which require the acknowledgement of the sources of collected data used in the survey were also considered.

### **3.9.Expected limitations**

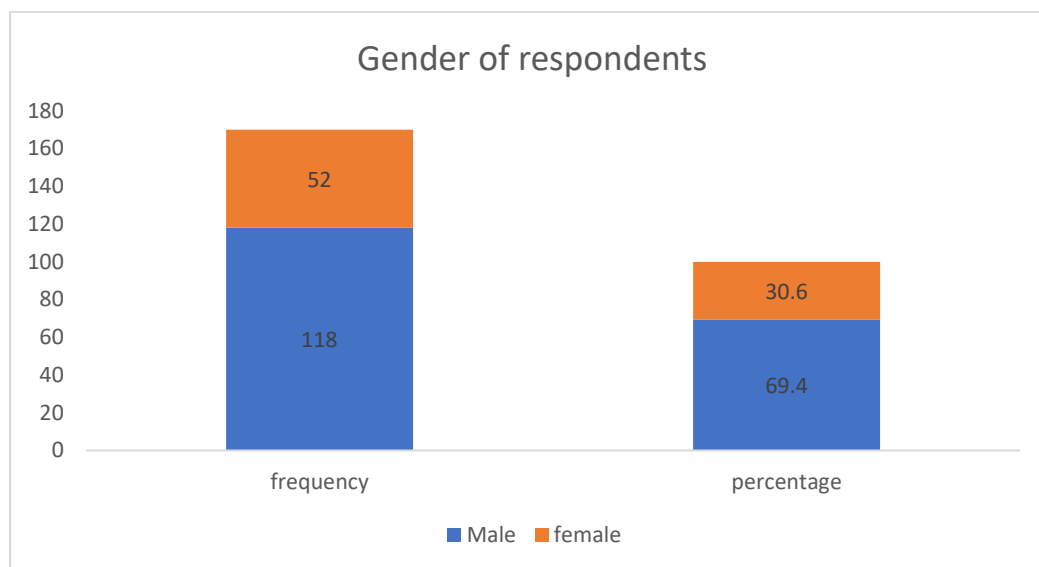
The limitation of the implementation of this research includes lack of cooperation of respondents for responding on questionnaire, where they were not confident for providing information easily, limitation on existing data on electric shared bicycles by public institutions, limitation also on the current working shared electrical bicycles sharing.

## CHAPTER 4: DATA ANALYSIS AND INTERPRETATION

This chapter represent the details of respondent’s views regarding connecting the last miles trips by the use of electric bicycles, and the current situation on electric bicycles system in Kigali city. The analysis was conducted by each objective of this research.

### 4.1.Characteristics of the respondent

The survey conducted has reached 170 respondents among 196 sampled which correspond to 87% of respondents. The figure below presents that 69.4% were males whereas 30.6 % respondent were females



### 4.2.Analysis of Current Modes of Transport for Last-Mile Trips

This section presents the findings on the current modes of transport used by commuters for last-mile trips in Kigali. The analysis will identify the most common transport modes and the factors influencing their use.

#### 4.2.1. Social demographic characteristics

Table below presents the demographic and socioeconomic profile of the study participants (N = 170), highlighting key characteristics relevant to last-mile transport behavior. The sample was predominantly male (69.4%), with the largest age group being 25–34 years (55.3%), followed by 35–44 years (22.9%). A significant proportion of respondents had attained tertiary education, with 76.5% holding a bachelor's degree and 18.2% a master's degree or higher. Half of the participants were employed (50.0%), while 20.0% were students. In terms of income, 36.5% reported earning more than 500,000 RWF monthly, while 14.7% indicated no income.

Respondents were primarily distributed across Kigali’s three districts, with the majority residing in Kicukiro (41.2%), followed by Nyarugenge (33.5%) and Gasabo (25.3%).

Regarding current transport practices for last-mile connectivity, walking was the most frequently reported mode (55.9%), indicating a continued reliance on active mobility options in urban Kigali. Moto-taxis were used by 28.2% of respondents, while bicycle use remained low (9.4%), despite the emerging policy interest in cycling infrastructure. Private car use (4.1%) and other modes (2.4%) were less common, suggesting that affordability and accessibility play a major role in mode choice for short-distance travel. These findings provide a baseline understanding of commuting patterns and can inform future interventions aimed at promoting equitable and sustainable last-mile transport alternatives such as electric bicycles.

Table 3: Socio-demographic characteristics and last-mile transport modes of respondents in Kigali

Demographic Characteristics		Frequency (n)	Percentage (%)
<b>N</b>		170	100.0
Gender	Female	52	30.6
	Male	118	69.4
Age	18-24	25	14.7
	25-34	94	55.3
	35-44	39	22.9
	45-44	4	2.4
	45-54	5	2.9
	55+	3	1.8
Education Level	No Education	1	0.6
	Primary School	1	0.6
	Secondary School	7	4.1
	Bachelor's Degree	130	76.5
	Master's Degree or Higher	31	18.2
Occupation/Employment	Unemployed	15	8.8
	Student	34	20.0
	Employee	85	50.0
	Business Owner	29	17.1
	Other	7	4.1

Monthly income level	Less than 50,000	11	6.5
	50,000 - 150,000	14	8.2
	150,000 - 300,000	24	14.1
	300,000 - 500,000	34	20.0
	More than 500,000	62	36.5
	None	25	14.7
District	Gasabo	43	25.3
	Kicukiro	70	41.2
	Nyarugenge	57	33.5
Mode of transport for last mile	Walking	95	55.9
	Bicycle	16	9.4
	Moto-taxi	48	28.2
	Private car	7	4.1
	Other	4	2.4

#### 4.2.2. Travel distance with Transport Mode

The Figure below provides a breakdown of different transport modes (Walking, Moto taxis, Bicycles, Private Car, and Other) based on the frequency of their use across four travel distance categories. Walking is the most frequent mode for distances less than 1 Km and remains significant for 1-3 Km. This suggests that walking is the preferred choice for very short trips. And As the distance increases beyond 3 Km, the frequency of walking drops, showing that walking is less practical for longer distances. Moto taxis are used across all distance categories but are most frequent for shorter distances, the presence of Moto Taxis all categories suggest that are flexible for various trip lengths.

Bicycles are rarely used for very short distances (<1 Km) but see increased usage for 1-3 Km and 3-5 Km. This indicates that bicycles are favoured for moderate distances where walking is less efficient. More than 5km the usage drops due to physical exertion or lack of infrastructure. Private cars are used across all distance categories, with the highest frequency for 1-3 Km and 3-5 Km. This suggests that cars are not the primary mode for last-mile trips. The use of Private car is relatively stable across distances, indicating they may be used for specific needs rather than daily short trips.

Table 4: Frequency of Transport mode with Travel distance

Frequency Mode of transport with Travel distance	Average Travel distance			
	Less Than 1 Km	1-3 km	3-5 km	More than 5 km
Walking	41	33	14	7
Moto taxis	15	16	10	4
Bicycles		4	10	2
Private Car	2	3	3	2
Other		1	2	1

Transport mode by Travel Distance

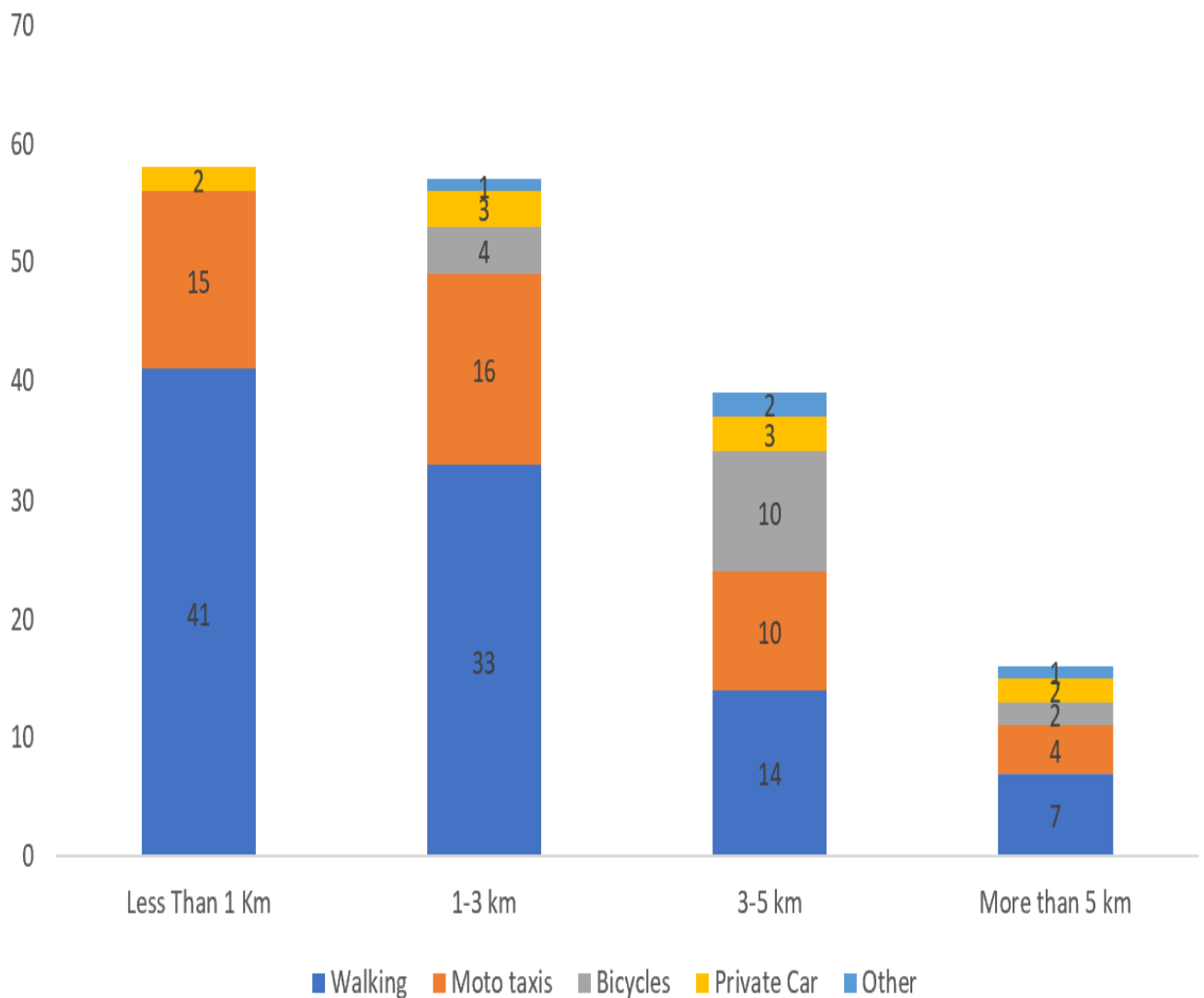


Figure 4: Transport mode with travel distance

### 4.2.3. Transport Mode by trip Purpose

The table and figure below represent the transport mode preferences based on trip purpose, the walking was preferred for leisure/social visits while the moto taxis was preferred more commonly on appointments, Bikes could replace moto taxis offering cheaper and greener alternative.

Table 5: Transport mode by trip purpose

Trip Purpose	Walking	Moto-Taxi	Bicycle	Private Car	Other
Work/Employment	26	31	3	7	1
Education	16	19	2	4	1
Shopping	12	14	2	3	1
Leisure/Social	8	9	1	2	0
Other	3	4	0	1	0

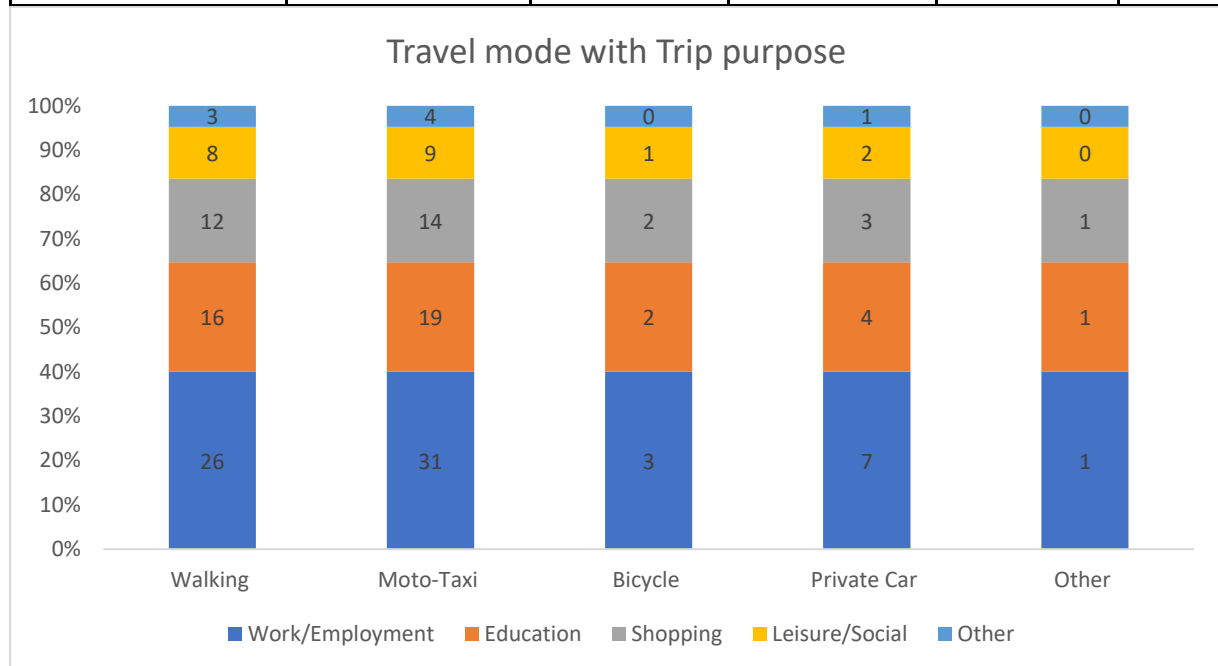


Figure 6: Trip purpose by Transport mode

### 4.2.4. Travel distance by trip Purpose

The table and figure below represents the relationship of travel distances by trip purpose, demonstrating that trips for work/employment are most common in the 1-3 km and 3-5 km ranges, with 31 and 16 instances respectively. Similarly, education-related travel is

concentrated within 3 km, with 13 visits being less than 1 km and 16 excursions falling within 1-3 km. Shopping and leisure/social visits are often brief, with the highest frequencies falling under the <1 km and 1-3 km categories. This concentration of short-distance commuting creates a significant opportunity for e-bikes to serve as a viable last-mile alternative.

*Table 5: Travel distance with Travel purpose.*

Trip Purpose	<1 km	1-3 km	3-5 km	>5 km
Work/Employment	10	31	16	10
Education	13	16	9	4
Shopping	16	10	5	2
Leisure/Social	8	7	4	1
Other	2	3	2	1



*Figure 5: Travel distance with travel purpose*

#### 4.2.5. Travel distance by reason of transport mode choice

The table below demonstrates that cost-effectiveness is the most important criterion for travellers over nearly all lengths, particularly for trips under 3 kilometres. Cost-effectiveness was indicated 30 times for travels under 1 Km, and 29 times for travels between 1 and 3 Km, vastly outnumbering any other reason. Convenience (14 citations for <1 km) and quickness (12 citations for 1-3 km) are key secondary reasons for shorter trips. This strong user preference for low-cost and convenient transportation options makes a compelling case for introducing and promoting electric bicycles, which excel in these specific areas.

Table 6: Travel distance by Reason of transport mode choice.

Frequency for Travel Distance	Availability	Comfort	speed	Convenience	Cost-effectiveness	Safety
Less than 1 km	3	2	8	14	30	2
1-3 km	3	6	12	6	29	1
3-5 km	8	6	6	6	12	
More than 5 km	2	1	3	3	6	1

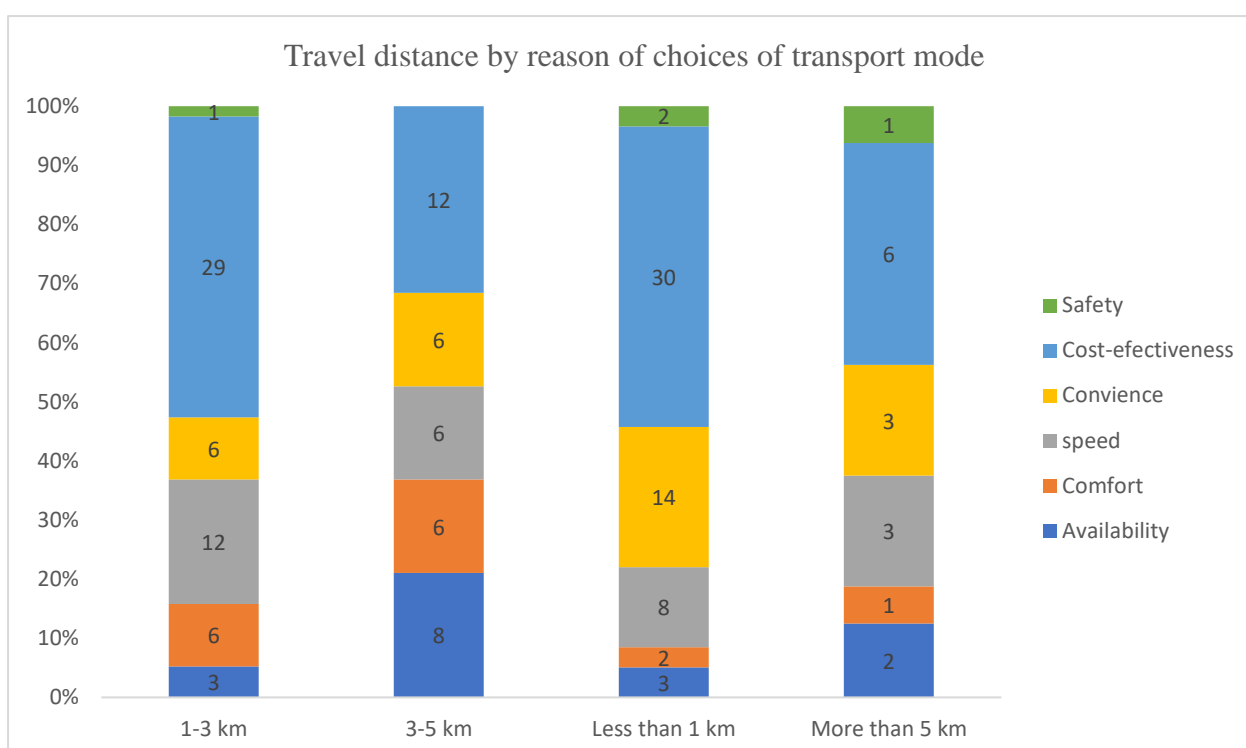


Figure 6: Travel distance by choices of transport mode.

#### 4.2.6. Travel distance with the expenditure.

The table and figure below illustrate the relationship between travel distance and expenditure among respondents, revealing that shorter distances (1-3 km and less than 1 km) are associated with higher frequencies of moderate expenditures (200-1000 RWF), while longer distances (more than 5 km) show lower expenditure frequencies, possibly due to alternative transport modes or cost-saving behaviours.

Table 7: Travel distance with Expenditures

Frequency of Travel distance with expenditure	200-500 RWF	500-1000 RWF	Less than 200 RWF	More than 1000 RWF	No Cost
1-3 km	17	22	2	7	9
3-5 km	8	16	4	9	2
Less than 1 km	14	20	4	8	11
More than 5 km	6	4	1	6	0

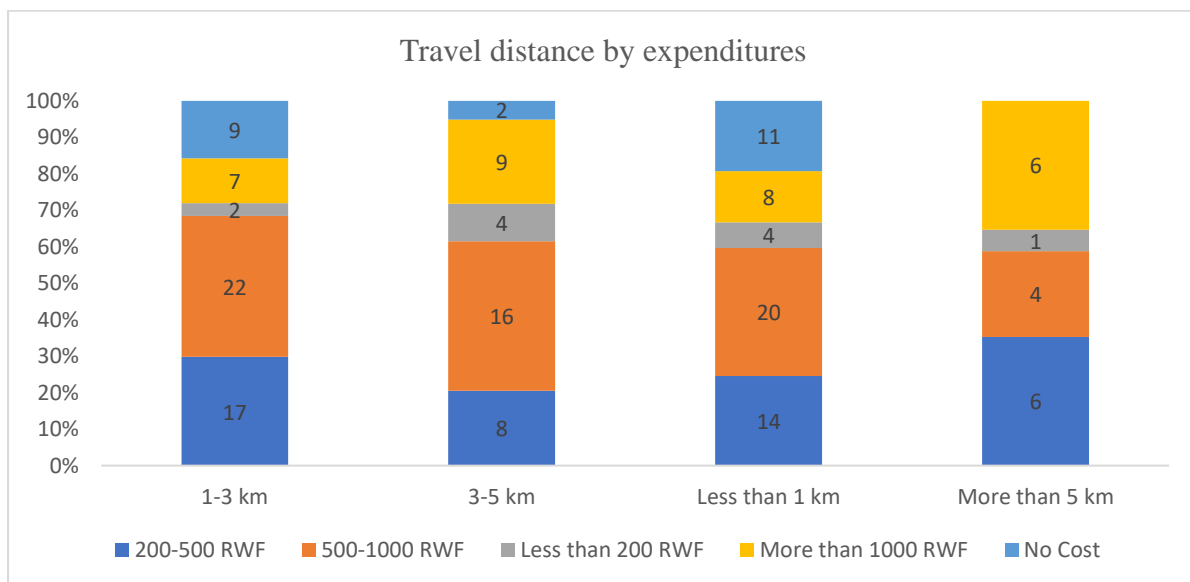


Figure 7: Travel distance by expenditures.

#### 4.2.7. Travel distance and Residency location

Table below illustrates the relationship between travel distance and residency location, demonstrating that suburban areas dominate travel across all distance categories, particularly 1-3 km and less than 1 km, whereas city centre trips are concentrated in shorter distances of less than 1 km. This shows a considerable need for last-mile connection in suburban and peri-urban areas, where electric bicycles could help fill gaps in public transport.

Table 8: Travel distance by the location

Frequency of neighbouring area	City Center (Downtown)	Per-urban area	Suburban Area	Rural Area	Other
1-3 km	11	3	37	6	
3-5 km	2	8	15	14	
Less than 1 km	22	1	26	9	
More than 5 km	2	2	5	6	1

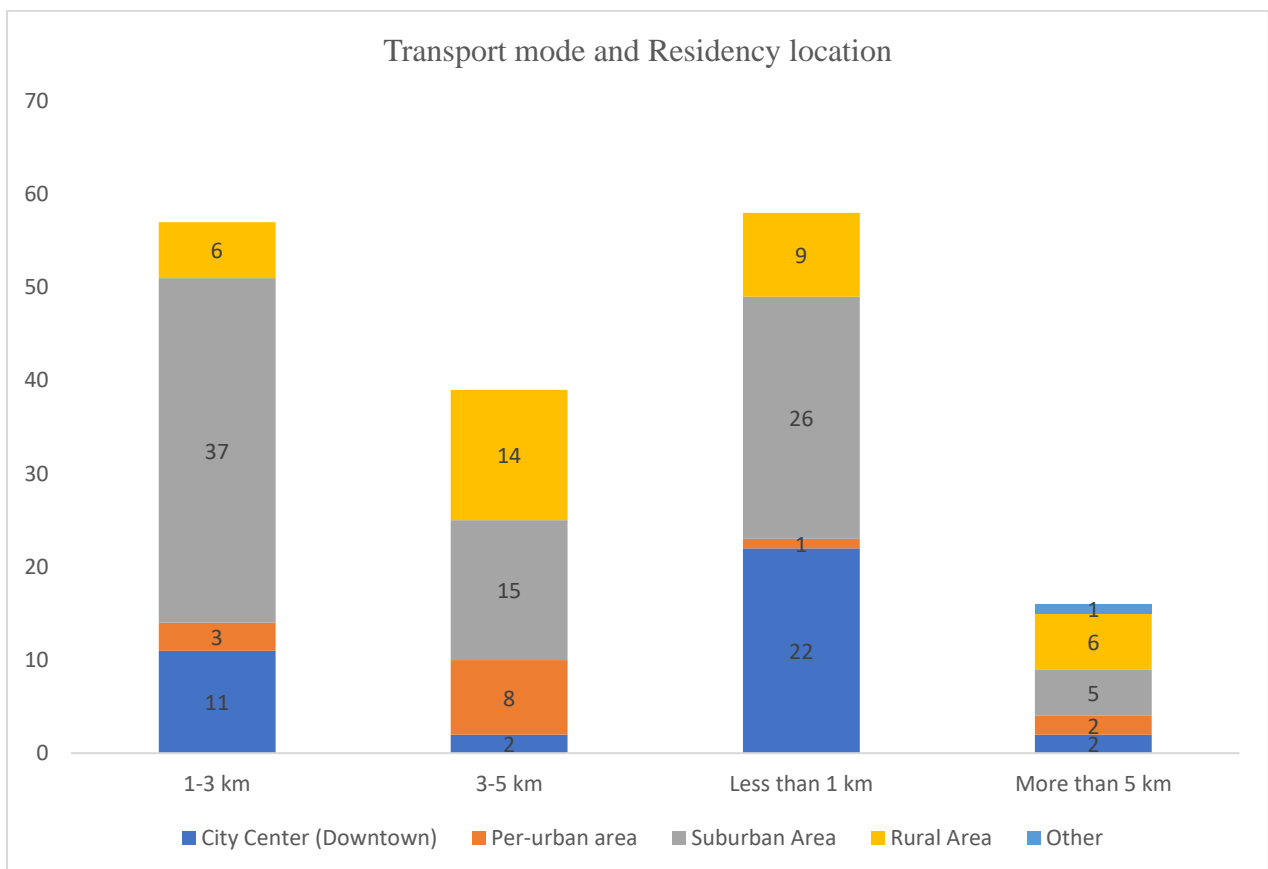


Figure 8: Travel distance and Residency

#### 4.2.8. Distribution of cost with various transport modes.

The table below discuss on travel mode choices across different distances and costs highlights important insights into current modal preferences and their implications for last-mile connectivity, particularly in relation to the potential adoption of e-bikes. From the table and figure below, walking dominates short trips under 1 km across all cost ranges, reflecting that people naturally choose walking when distances are minimal and cost is zero. However, as

distances increase (especially beyond 3 km), walking becomes less favourable, and reliance shifts to mototaxis. This pattern shows that for medium to longer last-mile trips (3–5 km and above), walking is not practical, and users are willing to pay more for faster alternatives. Mototaxis appear as the most common choice for trips above 1 km, especially in the 500–1000 Rwf range, indicating that many users are currently paying a relatively high cost for last-mile connections. This reliance on mototaxis suggests a gap that e-bikes could fill: providing a cheaper, flexible, and environmentally friendly alternative for distances where walking is inconvenient and motorized transport is costly. Bicycles show very low uptake in the current modal split, used sparingly at 1–5 km ranges, which are actually ideal distances for e-bikes. This low current use suggests either cultural, infrastructural, or accessibility barriers to traditional cycling. However, e-bikes—with assisted pedaling and lower physical effort—could overcome these barriers and make cycling more attractive, especially for 3–5 km last-mile trips, where walking is too far and mototaxis are relatively expensive.

Private cars appear minimally in the data, suggesting that car ownership is not a dominant factor in last-mile connectivity. This further reinforces that most last-mile users rely on either walking or paid modes (mototaxis), which opens a strong opportunity for e-bikes as an affordable intermediate option.

*Table 9: Distribution of transport costs by mode and distance from bus station*

<b>Travel mode Choise</b>	<b>Travel distances</b>	<b>no-cost</b>	<b>&lt;200</b>	<b>200_500</b>	<b>500_1000</b>	<b>&gt;1000</b>
Walking	<1km	9	5	1	1	1
	1_3km	6	7	6	1	0
	3_5km	2	4	7	1	2
	>5km	1	2	3	0	1
Mototaxis	<1km	2	1	3	5	5
	1_3km	0	1	6	7	2
	3_5km	1	0	2	6	16
	>5km	0	1	12	14	1
Bicycles	<1km	0	0	1	0	0
	1_3km	1	2	0	0	1
	3_5km	0	2	1	3	3

	>5km	0	0	0	1	1
Private Car	<1km	1	0	1	0	1
	1_3km	0	1	0	1	0
	3_5km	0	0	2	0	1
	>5km	0	0	1	1	1
Other	<1km	0	0	0	0	0
	1_3km	0	0	0	1	0
	3_5km	0	0	0	0	0
	>5km	0	0	0	0	0

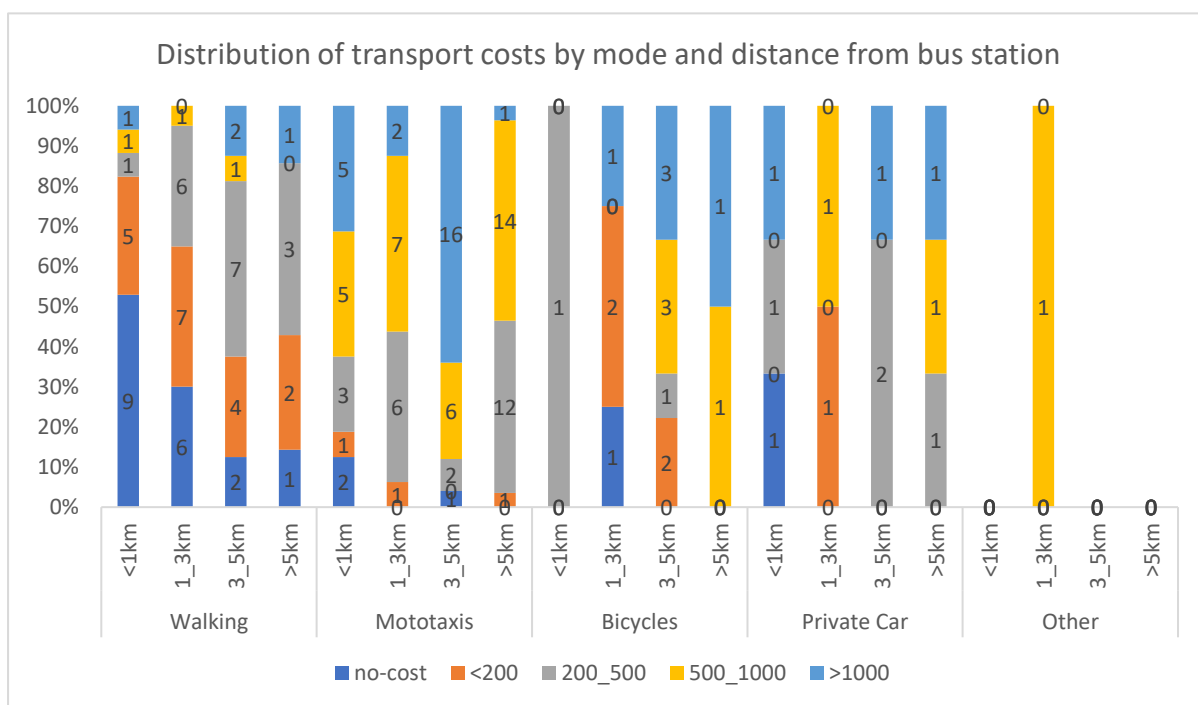


Figure 9: Distribution of transport costs by mode and distance from bus station

#### 4.3. Assessment of willingness to use electric bicycles for Last-Mile Trips

The data has been analyzed using the SPSS V27 in order to conduct the binary logistic regression and Non-Parametric test. The Binary logistic analysis was used to detail the analysis of demographic data to check the willingness for the total travel distance while the Non-parametric test was used to make analysis the willingness of the bicycle user for each travel distance. The choice of Non-parametric test is that the Logistic analysis model was failed for analysis consideration for each travel distance. The findings provide insights into the distance different where e-bikes are preferred over other transport modes. **Table below**

illustrates the correlation between the individuals are willing to spend riding an electric bicycle and the distance they are willing to travel. For most of all travel distance people aged 25-34 responded to be more willing to ride the e bike particularly for distance between 1-5 Km, this group is followed by people aged 35-44 group who are willing to ride, third group are peoples aged 18-24, below are the results in table and figure below

Table 10: Willingness to ride by travel distance.

Willing to ride by distance and age	18-24	25-34	35-44	45-44	45-54	55+
Less than 1 km	6	21	6	2	3	
1-2 km	5	27	18	1		1
2-5 km	11	24	11		2	1
More than 5 km	3	22	4	1		1

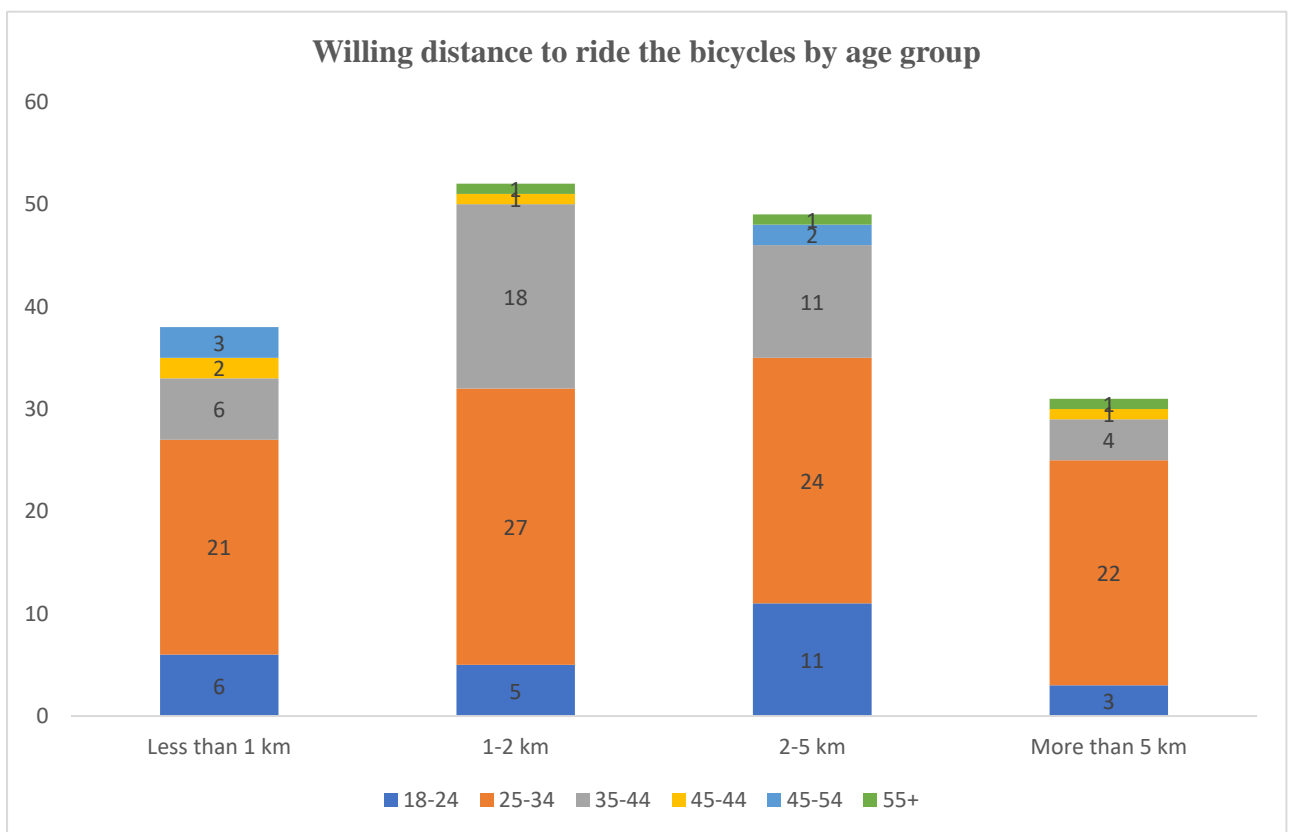


Figure 10: Mean distance willing to ride electric bicycle by age group

**Table below** reveals distinct variations in the mean distance that individuals are willing to travel by electric bicycle depending on their income level. Respondents with lower incomes (less than 50,000 RWF) are willing to travel longer distances, but their average for short

timeframes is relatively low. Middle-income earners (150,000–300,000 RWF) report the highest willingness at short distances, but this declines sharply indicating potential constraints or preferences for short, efficient travel.

In contrast, higher-income individuals (more than 500,000 RWF) show a consistent increase in distance with time from 1.5 km to 5.8 km, indicating greater flexibility and perhaps greater access or familiarity with electric bicycle use. These results suggest that while economic factors influence the practical distance users are willing to cover, motivational and contextual factors may also shape overall adoption potential.

Table 11: Mean distance willing to ride electric bicycles by income level

Travel distance will to ride by income level	150,000 - 300,000	300,000 - 500,000	50,000 - 150,000	Less than 50,000	More than 500,000	None
1-2 km	5	15	4	1	21	6
2-5 km	6	7	7	5	16	8
Less than 1 km	10	6	2	3	10	7
More than 5 km	3	6	1	2	15	4

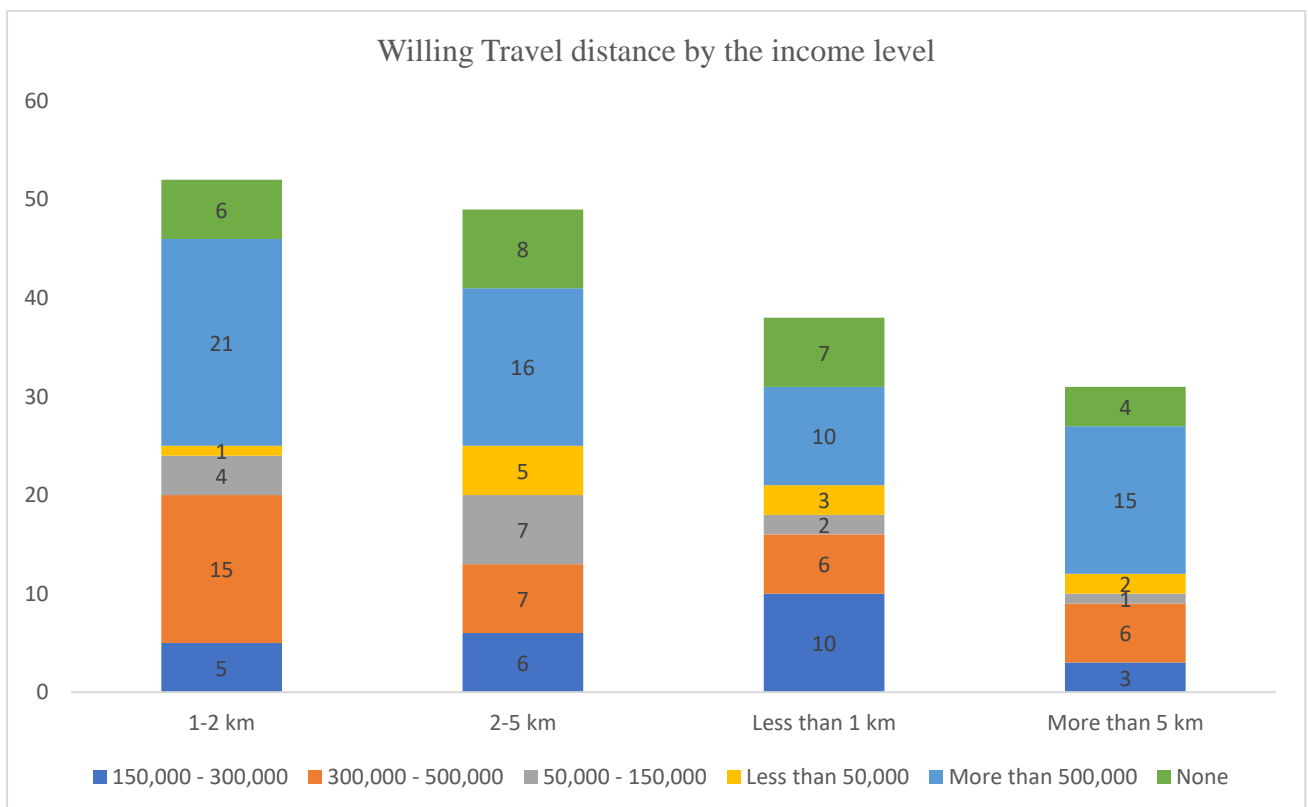


Figure 11: Mean distance willing to ride electric bicycle by income

Table 12: Average distance willing to travel by electric bicycle across and residential locations

	Less than 1 km	1-2 km	2-5 km	More than 5 km
City Center (Downtown)	9	8	13	7
Other				1
Perurban area	8	4		2
Rural Area	10	16	6	3
Suburban Area	11	24	30	18

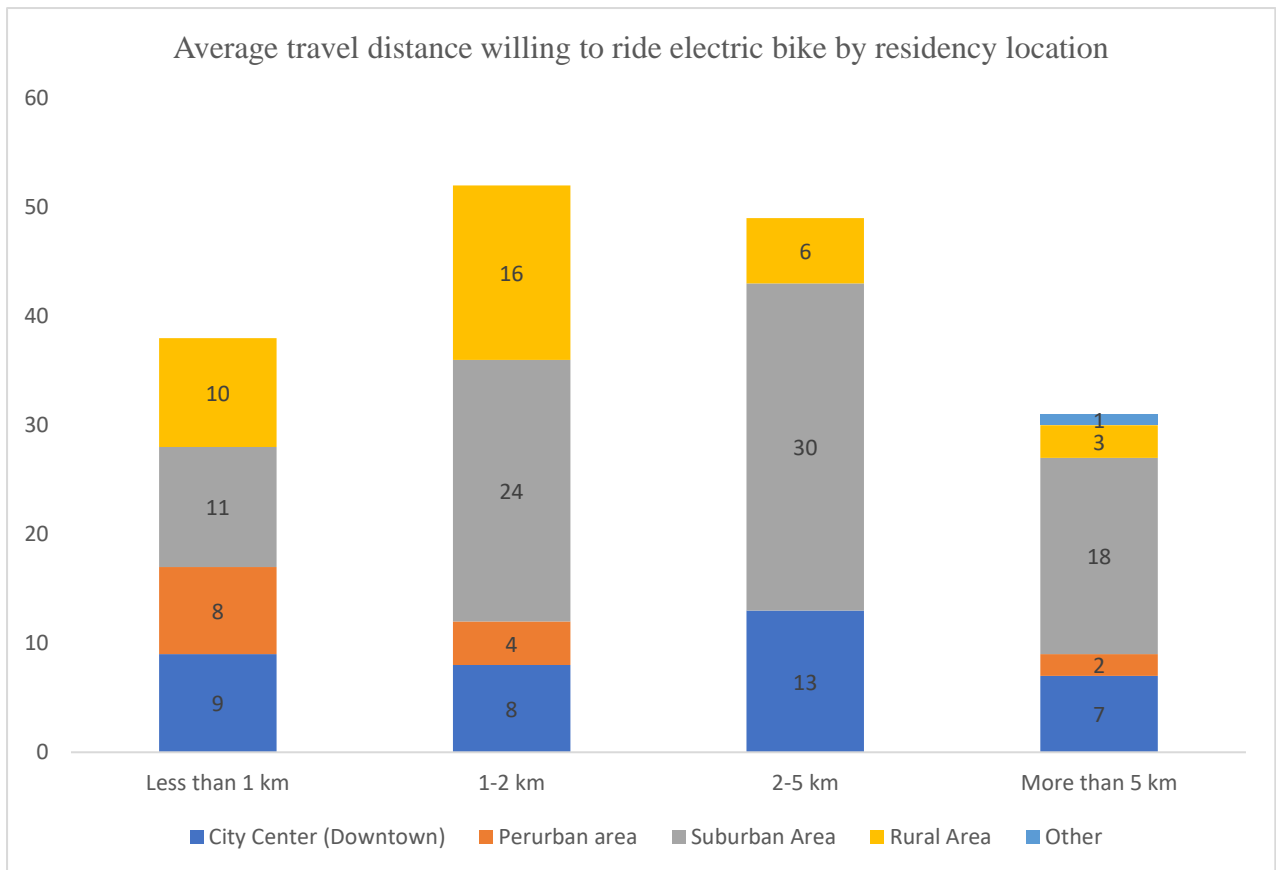


Figure 12: Mean distance willing to travel by electric bicycle across location types.

#### 4.3.1. Binary logistic Regression analysis and Goodness-of-Fit.

Binary logistic regression is a statistical method used to model the relationship between a dependent variable with two possible outcomes and independent variables that may be dichotomous, interval, or ratio in nature. Such variables are often described as discrete or qualitative and can represent specific events. Typically, dichotomous (dummy) variables are

coded as 1 for “yes” or “success” and 0 for “no” or “failure.” When coded this way, the mean of the variable reflects the proportion of cases with a value of 1, which can also be interpreted as the probability of the event occurring [30]. A binary logistic regression was performed to ascertain the effects of age group, gender, education level, occupation, and distance from home to the nearest bus station on the likelihood that participants would be willing to use electric bicycles.

Below formula were applies.

$$\text{a.k.a. Log Odds or Logit} \quad \log\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X \quad \text{Intercept}$$

Where **P** is the probability of having the outcome and **P / (1-P)** is the odds of the outcome. The analysis of assessing the willingness to use the electric bicycles for the last mile trips were conducted by analysis the number/People characters of reported traveler willing to shift from the current mode of transport to the use of electric bicycles. A binary logistic regression was performed to ascertain the effects of age group, gender, education level, occupation, and distance from home to the nearest bus station on the likelihood that participants would be willing to use electric bicycles. Below is the summary of tables of the obtained from the model Fit:

Case Processing Summary			
Unweighted Cases <sup>a</sup>		N	Percent
Selected Cases	Included in Analysis	170	100.0
	Missing Cases	0	.0
	Total	170	100.0
Unselected Cases		0	.0
Total		170	100.0
a. If weight is in effect, see classification table for the total number of cases.			
Dependent Variable Encoding			
Original Value	Internal Value		
0	0		
1	1		

Classification Table <sup>a,b</sup>				
Observed		Predicted		Percentage Correct
		willingness_to_Use_E_Bike	0	
Step 0	willingness_to_Use_E_Bike	0	68	.0
	Bike	1	102	100.0
Overall Percentage				60.0

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.405	.157	6.708	1	.010	1.500

Variables not in the Equation					
			Score	df	Sig.
Step 0	Variables	Age_group	10.756	1	.001
		Gender	1.005	1	.316
		highest_level_of_Education	.150	1	.698
		Occupation	.688	1	.407
		DistancefromHometoNearestBusStation	11.946	1	.001
Overall Statistics			24.143	5	.000

### I. Overall Model Significance and Goodness-of-Fit

The goodness-of-fit of the model assessment showed that the Omnibus Tests of Model Coefficients is highly significant ( $\chi^2(5) = 25.919$ ,  $*p* < .001$ ). This indicates that the model with the all five predictors (age, gender, education, occupation, and distance from home to the bus station) is statistically significantly better at predicting willingness to use e-bikes than a null model with no predictors. In essence, the set of variables, as a whole, meaningfully distinguishes between individuals who are willing and those who are not.

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	25.919	5	.000
	Block	25.919	5	.000
	Model	25.919	5	.000

The **Model Summary** below showed that the predictors accounted for a significant portion of the variance in willingness to use e-bikes (Cox & Snell  $R^2 = .141$ , Nagelkerke  $R^2 = .191$ ). The later indicate that the model explains approximately 14% to 19% of the variance in willingness to use e-bikes. While this leaves room for other unmeasured factors (such as safety perceptions, availability of bike lanes, or cultural attitudes), it represents a substantial and significant explanatory power for a model based on core demographics and a key spatial variable. This aligns with behavioral studies where human decision-making is influenced by a complex mix of factors beyond a few variables.

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	202.905 <sup>a</sup>	.141	.191
a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.			

The table below show the summary of **Goodness-of-Fit Statistics for Model**

*Table 13: Goodness-of-Fit Statistics for the Binary Logistic Regression Model*

Fit Statistic	Value	Interpretation
Omnibus Test ( $\chi^2$ )	$\chi^2(5) = 25.92, *p* < .001$	The model is statistically significant.
Cox & Snell $R^2$	0.141	
Nagelkerke $R^2$	0.191	The model explains ~19% of the variance.
Hosmer-Lemeshow Test	$\chi^2(8) = 15.44, *p* = .051$	The model is a good fit (*p* > .05).
Overall Classification Rate	70.6%	

## II. Analysis and Interpretation of Binary Logistic Regression Goodness-of-Fit

### 1. Goodness-of-Fit and Model Calibration.

The **Hosmer and Lemeshow Test** result is important ( $\chi^2(8) = 15.438$ ,  $*p* = .051$ ). A non-significant result ( $p > .05$ ) is desired, as it suggests the model's predictions do not significantly deviate from the observed data. A  $*p*$ -value of .051 is **right on the conventional threshold** and is universally considered acceptable, indicating a good fit. The accompanying contingency table shows a generally close alignment between observed and expected values across most deciles, further supporting the model's calibration. There is no evidence to suggest the model is a poor fit for the data.

**Contingency Table for Hosmer and Lemeshow Test**

		willingness_to_Use_E_Bike =		willingness_to_Use_E_Bike =		Total
		0		1		
		Observed	Expected	Observed	Expected	
Step 1	1	13	13.076	5	4.924	18
	2	13	10.503	4	6.497	17
	3	9	9.356	9	8.644	18
	4	5	7.984	12	9.016	17
	5	10	7.028	7	9.972	17
	6	6	6.032	11	10.968	17
	7	3	4.860	13	11.140	16
	8	3	4.253	14	12.747	17
	9	1	3.099	16	13.901	17
	10	5	1.808	11	14.192	16

The **Classification Table** shows the model correctly classified **70.6%** of cases, a substantial improvement over the **60.0%** accuracy of the null model (Step 0). This 10.6% improvement in predictive accuracy demonstrates the practical utility of the model. It is particularly effective at predicting individuals who *are* willing to use e-bikes (85.3% correct), which is the primary group of interest for policy implementation.

**Classification Table<sup>a</sup>**

	Observed	Predicted		Percentage Correct	
		willingness_to_Use_E_Bike	ke		
		0	1		
Step 1	willingness_to_Use_E_Bike	0	33	35	48.5
		1	15	87	85.3
	Overall Percentage				70.6

a. The cut value is .500

**Classification Table<sup>a,b</sup>**

	Observed	Predicted		Percentage Correct	
		willingness_to_Use_E_Bike	ke		
		0	1		
Step 0	willingness_to_Use_E_Bike	0	0	68	.0
		1	0	102	100.0
	Overall Percentage				60.0

a. Constant is included in the model.

b. The cut value is .500

## 2. Interpretation of Significant Predictors

The Variables in the Equation table below reveals the unique contribution of each predictor while controlling for the others. Two variables emerged as statistically significant ( $p < .05$ ):

**Variables in the Equation**

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step	Age_group	-.424	.129	10.707	1	.001	.655	.508	.844
1 <sup>a</sup>	Gender	-.473	.349	1.838	1	.175	.623	.315	1.234
	highest_level_of_Education	.026	.150	.031	1	.860	1.027	.765	1.378
	Occupation	-.134	.164	.665	1	.415	.875	.634	1.207

DistancefromHometoNearestBusStation	.452	.133	11.505	1	.001	1.572	1.210	2.041
Constant	1.342	1.000	1.802	1	.179	3.827		

a. Variable(s) entered on step 1: Age\_group, Gender, highest\_level\_of\_Education, Occupation, DistancefromHometoNearestBusStation.

- Distance from Home to Nearest Bus Station (B = 0.452, \*p\* = .001): This is the most powerful and significant finding of the model. The positive B-coefficient means that as the distance from a bus station increases, the likelihood of willingness to use an e-bike increases. The Exp(B) or Odds Ratio of 1.572 is the key interpretative value. It indicates that for every additional unit of distance (e.g., 1 kilometer), the odds of a person being willing to use an e-bike increase by 57.2% (calculated as  $(1.572 - 1) * 100\%$ ). This finding directly and powerfully addresses the core last-mile problem. It empirically proves that those who suffer most from the lack of connectivity (those living farther away) are the ones most likely to adopt a solution like e-bikes.
- Age Group (B = -0.424, \*p\* < .001): The negative B-coefficient signifies that as the age category increases, willingness to use e-bikes decreases. The Odds Ratio of 0.655 means that with each step up in age group (from 25-34 to 35-44), the odds of being willing to use an e-bike decrease by 34.5% (calculated as  $(1 - 0.655) * 100\%$ ). This strongly supports descriptive findings that younger demographics are the primary potential early adopters of this technology. The table above for variable equation explore how personal characteristics and transport-related factors affect the chances of using electric bicycles (e-bikes). One of the most important findings was that age had a clear impact. Younger people were more likely to use e-bikes than older people. In particular, people in age groups 3 (between 35 and 44) and 4 (between 45 and 54) were about 84% and 87% less likely to use e-bikes compared to the youngest group. This shows that as people get older, they are less likely to choose e-bikes. This may be because of differences in physical ability, habits, or how comfortable they are with new technology.

### 3. Interpretation of Non-Significant Predictors

From the variable equation table, gender, education level, and occupation were not significant predictors ( $p > 0.05$ ). This is a valuable finding in itself. It suggests that the willingness to adopt e-bikes for the last mile is not strongly dictated by gender, educational attainment, or job type when the influence of age and, most importantly, *geographic need* (distance to bus station) are considered. This implies the potential market for e-bikes cuts across these demographic lines, focusing instead on a specific spatial need and a younger age bracket.

#### 4.3.2. Non-parametric statistics analysis.

This method was explored to analyse the willingness of the respondent on each travel distance interval. Below is analysis on each travel interval

##### i. Analysis of willingness of shifting to electric bicycles by demographic analysis to all travel interval combined.

The analysis of assessing the willingness to use the electric bicycles for the last mile trips were conducted by analysis the number of reported traveler willing to shift from the current mode of transport to the use of electric bicycles. The analysis were combined for each travel distance interval to assess for every parameter for their level of significant. The table below represent the combined analysis of all travel distances and shows that several key factors influencing willingness to use e-bikes. The most statistically significant variables are Occupation ( $p = 0.000$ ), Monthly Income Level ( $p = 0.034$ ), and District of Residence ( $p = 0.041$ ). These results indicate that individuals' job types, income brackets, and residential locations play pivotal roles in their openness to adopting e-bikes. Gender also approaches significance ( $p = 0.053$ ), suggesting a potential trend that may warrant further investigation. Notably, variables like Age Group, Education Level, and Current Transport Mode do not show significant influence, implying that these factors are less critical in the broader context of e-bike adoption.

Table 14: analysis with all combined distance

**Test Statistics<sup>a</sup>**

	Age_group	Gender	highest_level_of_Education	Occupation	Monthlyincome_level	District_of_Residence	Residential_Area_Type	Distancefrom_HometoNear estBusStation (km)	Bus	currenttransportmode	minutes	Reason_of_trip_of_current_transport_choice	Cost_spending_per_trip	satisfaction	Frequency_of_ebike_use
Mann-Whitney U	2352.000	2342.000	2463.000	1569.500	2197.500	2235.500	2699.000	2616.500	2346.500	2643.000	2765.500	2475.000	2348.000	2739.500	2412.500
Wilcoxon W	3342.000	10343.000	3453.000	9570.500	3187.500	3225.500	3689.000	10617.500	10347.500	10644.000	10766.500	10476.000	3338.000	10740.500	3402.500
Z	-1.660	-1.938	-1.474	-4.602	-2.115	-2.048	-.292	-.581	-1.753	-.513	-.024	-1.125	-1.571	-.121	-1.307
Asymp. Sig. (2-tailed)	.097	.053	.140	<.001	.034	.041	.770	.562	.080	.608	.981	.261	.116	.904	.191

a. Grouping Variable: Willingness to Use E-Bike if Available

## ii. Willingness to adopt the electric bicycles for each travel interval

Below is the analysis conducted to each travel interval, with the willingness to shift to electric bicycles, during the analysis the following variables was considered: Age, Gender, Education level, Occupation, Level of Monthly income, District of residency, Residency area, Travel distance, Travel time, transport purpose, satisfaction with current mode, current mode of transport, use of public transport, Transport cost, Ebike use frequency:

### 1. For Distance trip less than 1km

The analysis of willingness for each travel distances was analysed using the Non-Parametric analysis. The table below presents the results of Mann-Whitney U tests, which were conducted to assess difference in various demographic and behavioural factors between groups based on their willingness to use e-bikes for travel distance less than. The key variables tested include age group, gender, education level, occupation, income, residential characteristics, current transport modes, trip reasons, cost, satisfaction, and e-bike usage frequency. The significance of these differences is indicated by the Asymp. Sig. (2-tailed) values, where a value below 0.05 suggests a statistically significant difference between groups.

Two variables showed statistically significant differences: Occupation ( $p = 0.014$ ) and Cost spending per trip ( $p = 0.021$ ). This implies that traveler willingness to use e-bikes is influenced by their occupation and how much they spend on their current transport mode. Other variables, such as age, gender, education, and residential area type, did not show significant differences ( $p > 0.05$ ), suggesting that these factors may not strongly influence e-bike adoption for last-mile trips in this sample.

The lack of significance for most variables, including satisfaction and frequency of e-bike use, indicates that willingness to adopt e-bikes may be driven by specific practical or economic factors (like occupation and cost) rather than broad demographic trends. Further analysis could explore these significant groups in more detail, such as identifying which occupations are more inclined toward e-bike use or how cost perceptions vary among users.

Table 15: Non-Parametric test statistics for travel distance less than 1km Vs the willingness to choose electric bikes.

Test Statistics <sup>a</sup>															
	Age_group	Gender	highest_Level_of_Education	Occupation	Monthlyincome_Level	District_of_Residence	Residential_Area_Type	Distancefrom_HometoNearestBusStation (km)	Bus	currenttransport mode	minutes	Reason_of_trip_of_current_transport_choice	Cost_spending_per_trip	satisfaction	Frequency_of_ebike_use
Mann-Whitney U	277.500	313.000	335.500	214.000	308.000	302.000	337.500	345.000	289.000	319.500	290.000	320.500	211.500	342.000	326.000
Wilcoxon W	397.500	1394.000	455.500	1295.000	428.000	422.000	457.500	465.000	1370.000	439.500	410.000	440.500	331.500	1423.000	1407.000
Z	-1.236	-.778	-.212	-2.456	-.640	-.767	-.140	.000	-1.119	-.519	-.982	-.444	-2.312	-.053	-.325
Asymp. Sig. (2-tailed)	.216	.436	.832	.014	.522	.443	.889	1.000	.263	.604	.326	.657	.021	.958	.745

a. Grouping Variable: willingness to Use E-Bike if Available

## 2. For Distance trip between 1km to 3km

The table below presents Mann-Whitney U test results comparing demographic, socioeconomic, and travel-related factors between groups based on their willingness to use e-bikes for (1–3 km). The findings reveal several statistically significant differences ( $p < 0.05$ ): Occupation ( $*p = 0.017*$ ), Monthly income level ( $*p = 0.028*$ ), and Reason for trip of current transport choice ( $*p = 0.039*$ ). Additionally, Frequency of e-bike use approaches significance ( $*p = 0.052*$ ). These results indicate that the traveller willingness to adopt e-bikes for medium-distance trips is influenced by their job type, income, trip purpose, and prior e-bike experience.

Notably, variables like age, gender, education, and residential area type showed no significant differences ( $p > 0.05$ ), implying these factors are less critical for e-bike adoption in this distance range. The lack of significance for Distance from Home to Nearest Bus Station ( $*p = 1.000*$ ) suggests that proximity to transit may not strongly influence e-bike willingness for 1–3 km trips, possibly because e-bikes are seen as independent solutions rather than transit connectors.

These findings highlight that strategies to promote e-bike use for medium-distance trips should target specific occupational and income groups, while also addressing trip-specific needs. The

near-significance of e-bike frequency use warrants further investigation, as familiarity with e-bikes could enhance adoption.

Table 16: Non-Parametric test statistics for travel distance between 1-3km Vs the willingness to choose electric bikes

	Test Statistics <sup>a</sup>														
	Age_group	Gender	highest_level_of_Education	Occupation	Monthlyincome_level	District_of_Residence	Residential_Area_Type	Distancefrom_HometoNear estBusStation (km)	Bus	currenttransportmode	minutes	Reason_of_trip_of_current_transport_choice	Cost_spending_per_trip	satisfaction	Frequency_of_ebike_use
Mann-Whitney U	234.500	195.000	218.000	153.500	154.000	213.000	227.500	258.000	241.000	226.000	242.000	165.000	197.500	254.500	165.000
Wilcoxon W	312.500	1141.000	296.000	1099.500	232.000	291.000	305.500	1204.000	319.000	304.000	1188.000	1111.000	275.500	332.500	243.000
Z	-.544	-1.604	-1.072	-2.380	-2.202	-.977	-.738	.000	-.396	-.739	-.355	-2.061	-1.305	-.076	-1.944
Asymp. Sig. (2-tailed)	.587	.109	.284	.017	.028	.329	.460	1.000	.692	.460	.722	.039	.192	.940	.052

a. Grouping Variable: Willingness to Use E-Bike if Available

### 3. For Distance trip between 3km to 5km

The table below represent the The Mann-Whitney U test results for 3–5 km trips reveal three statistically significant factors influencing willingness to use e-bikes: Occupation ( $p = 0.020$ ), District of Residence ( $p = 0.049$ ), and Bus usage ( $p = 0.014$ ). This suggests that job type, neighbourhood location, and reliance on buses play key roles in e-bike adoption for longer last-mile trips. The significance of Bus usage implies that individuals who frequently take buses may see e-bikes as a viable first-/last-mile connector, while District of Residence highlights regional variations in infrastructure or attitudes. Compared to the 1–3 km group (where Occupation, Income, and Trip Reason were significant), the 3–5 km results shift focus toward spatial and transit-related factors, possibly due to the longer distance making integration with public transport more relevant. The Monthly Income (significant for 1–3 km,  $*p = 0.028*$ ) loses significance for 3–5 km ( $p = 0.145$ ), suggesting cost sensitivity diminishes for longer trips—perhaps because other conveniences outweigh price concerns. Conversely, Frequency of E-Bike Use (near-significant at  $p = 0.052$  for 1–3 km) becomes insignificant ( $*p = 0.815*$ ), indicating prior e-bike experience matters less for longer distances.

Table 17: Non-Parametric test statistics for travel distance between 3-5km Vs the willingness to choose electric bikes

**Test Statistics<sup>a</sup>**

	Age_group	Gender	highest_level_of_Education	Occupation	Monthlyincome_level	District_of_Residence	Residential_Area_Type	DistancefromHometoNearestBusStation (km)	Bus	currenttransportmode	minutes	Reason_of_trip_of_current_transport_choice	Cost_spending_per_trip	satisfaction	Frequency_of_ebike_use
Mann-Whitney U	153.000	149.000	137.000	94.000	122.000	110.500	152.000	168.000	96.000	119.500	133.500	163.000	155.000	158.000	160.500
Wilcoxon W	258.000	449.000	242.000	394.000	227.000	215.500	452.000	468.000	396.000	419.500	433.500	288.000	455.000	263.000	460.500
Z	-.520	-.664	-1.480	-2.324	-1.456	-1.969	-.548	.000	-2.460	-1.562	-1.104	-.158	-.411	-.323	-.234
Asymp. Sig. (2-tailed)	.603	.507	.139	.020	.145	.049	.584	1.000	.014	.121	.270	.875	.681	.747	.815
Exact Sig. [2*(1-tailed Sig.)]	.665 <sup>b</sup>	.580 <sup>b</sup>	.361 <sup>b</sup>	.025 <sup>b</sup>	.171 <sup>b</sup>	.082 <sup>b</sup>	.643 <sup>b</sup>	1.000 <sup>b</sup>	.029 <sup>b</sup>	.144 <sup>b</sup>	.301 <sup>b</sup>	.893 <sup>b</sup>	.709 <sup>b</sup>	.777 <sup>b</sup>	.823 <sup>b</sup>

a. Grouping Variable: Willingness to Use E-Bike if Available

b. Not corrected for ties.

#### 4. For Distance More than 5km

For trips longer than 5 km (Table below), the Mann-Whitney U test results show no statistically significant variables ( $p > 0.05$ ) influencing willingness to use e-bikes, though Residential Area Type approaches marginal significance ( $p = 0.081$ ). This suggests that for such extended distances, e-bikes may not be perceived as a practical last-mile solution, regardless of demographic, economic, or travel-related factors. The lack of significance contrasts sharply with shorter trips (1–3 km and 3–5 km), where Occupation, Income, Bus Usage, and District of Residence played notable roles. The near-significance of Residential Area Type (e.g., urban vs. suburban) hints that infrastructure or density might weakly influence adoption, but the overall trend implies that e-bikes are less appealing for very long last-mile connectivity.

Table 18: Non-Parametric test statistics for travel distance more than 5km Vs the willingness to choose electric bikes

**Test Statistics<sup>a</sup>**

	Age_group	Gender	highest_level_of_Education	Occupation	Monthlyincome_level	District_of_Residence	Residential_Area_Type	DistancefromHometoNearestBusStation (km)	Bus	currenttransportmode	minutes	Reason_of_trip_of_current_transport_choice	Cost_spending_per_trip	satisfaction	Frequency_of_ebike_use
Mann-Whitney U	13.000	16.500	18.000	10.500	18.000	17.500	7.500	19.500	18.000	19.000	13.500	18.500	10.500	10.500	15.000
Wilcoxon W	19.000	22.500	109.000	101.500	109.000	108.500	13.500	110.500	24.000	110.000	19.500	24.500	101.500	101.500	21.000
Z	-.957	-.703	-.237	-1.276	-.209	-.296	-1.745	.000	-.237	-.071	-.855	-.140	-1.258	-1.259	-.625
Asymp. Sig. (2-tailed)	.339	.482	.813	.202	.835	.767	.081	1.000	.813	.943	.393	.888	.208	.208	.532
Exact Sig. [2*(1-tailed Sig.)]	.439 <sup>b</sup>	.704 <sup>b</sup>	.900 <sup>b</sup>	.239 <sup>b</sup>	.900 <sup>b</sup>	.800 <sup>b</sup>	.111 <sup>b</sup>	1.000 <sup>b</sup>	.900 <sup>b</sup>	1.000 <sup>b</sup>	.439 <sup>b</sup>	.900 <sup>b</sup>	.239 <sup>b</sup>	.239 <sup>b</sup>	.611 <sup>b</sup>

a. Grouping Variable: Willingness to Use E-Bike if Available

b. Not corrected for ties.

## **4.4.DISCUSSION AND INTERPRETATION**

### **4.4.1. Overview**

This chapter provides a detailed discussion and interpretation of the findings presented in Chapter 4 in relation to the existing literature on the use of shared electric bicycles (e-bikes). The interpretation focuses on demographic factors, transport mode preferences, travel distance, cost, accessibility, and willingness to use e-bikes while addressing the potential impact of e-bike integration within urban transport network.

### **4.4.2. Demographic insights and user characteristics**

The sample (N=170) was predominantly male (69.4%) with a majority aged 25-34 years (55.3%), highly educated (94.7% have at least a bachelor's degree), and mainly employed (50%). This reflects a younger, educated urban demographic with significant potential propensity to adopt new mobility technologies, consistent with prior findings that younger and educated populations tend to be early adopters of e-bike [31]

### **4.4.3. Current modal preferences and last-mile connectivity**

The table 3 confirm that walking (55.9%) remains the predominant current transport mode, particularly for distances under 1 km. it was practicality funds to decrease for trips exceeding 3 km, with its usage dropping from 33 to 7 for distances beyond 5 km. The Moto-taxis are the second most used mode (28.2%), offering flexible transport for varying trip lengths. Indeed, Table 9 demonstrates moto-taxis impose high costs especially noticeable for short distances where over 40% of riders pay more than 1000 RWF. This steep cost gradient underscores the premium nature of motorized last-mile travel and its financial burden on users. The table 4 and 9 illustrate that Bicycle usage for last-mile travel was limited (9.4%), but shows promising uptake for medium distances (3-5 km), where other non-motorized modes decline. This supports studies suggesting that traditional bicycles are chosen for moderate distances but physical exertion and lack of infrastructure constrain usage for longer trips [28].

### **4.4.4. User willingness and demographic influences on E-bike adoption**

The binary logistic regression model provides the most definitive evidence for the factors influencing e-bike adoption. The model's goodness-of-fit statistics (Hosmer-Lemeshow  $p = .051$ , Nagelkerke  $R^2 = .191$ ) confirm it is a robust and well-calibrated tool for understanding willingness. Its findings powerfully consolidate the results from the non-parametric analyses: geographic need, defined by distance from public transport, is the single strongest driver of willingness. For every additional kilometer a resident lives from a bus station, their odds of being willing to use an e-bike increase by 57% ( $p = .001$ ). This quantifies and confirms

the core last-mile problem and positions e-bikes precisely as its solution. Furthermore, the model corroborates the strong influence of age, with each increase in age category decreasing the odds of willingness by 34% ( $p < .001$ ), solidifying that younger demographics are the primary target market. Finally, the fact that gender, education, and occupation were not significant in the model ( $p > .05$ ) suggests that the potential for e-bike adoption is widespread across these demographics once the critical factors of geographic need and age are accounted for.

The results from the non-parametric analyses across different travel distances interval align closely with existing literature on e-bike adoption. For travel distance less than 1 km, the significant influence of occupation ( $p = 0.014$ ) and Cost per Trip ( $p = 0.021$ ) on e-bike willingness reflect the study conducted by Adnan et al. (2018) [9] and Fishman & Cherry (2016) [28], which highlight that economic and practical factors dominate short-distance mode choices. The lack of significance for demographic variables like age and gender supports the argument that short trips are primarily influenced by cost and convenience rather than broad socio-demographic trends [28]. This aligns with Kigali's current reliance on walking (55.9%) for short distances, as identified in the primary data, suggesting e-bikes could compete if priced competitively with moto-taxis, which are costly for short trips [2]

For 1–3 km trips, the significance of Occupation, Income ( $p = 0.028$ ), and Trip Reason ( $p = 0.039$ ) reflects literature emphasizing that middle-income groups and commuters with specific trip purposes (like work/education) are more likely to adopt e-bikes (X. Zhang et al., 2024) and [14]. The near-significance of Frequency of E-Bike Use ( $p = 0.052$ ) suggests familiarity with e-bikes may encourage adoption, corroborating findings from (Ntamwiza & Bwire, 2023) on Kigali's bike-sharing growth among students. The insignificance of proximity to bus stations ( $p = 1.000$ ) contrasts with studies from Beijing ([17]) but may indicate that e-bikes in Kigali are perceived as standalone solutions rather than transit feeders, a gap noted in the literature review (Kosmidis & Müller-Eie, 2024). [14]

For 3–5 km trips, the shift to spatial and transit-related factors District of Residence ( $p = 0.049$ ) and Bus Usage ( $p = 0.014$ ) supports the literature on e-bikes bridging gaps in public transport coverage (Kosmidis & Müller-Eie, 2024; Papaioannou et al., 2023) [14] and [13]. The decline in income significance ( $p = 0.145$ ) compared to shorter distances aligns with global trends where convenience outweighs cost for medium-distance trips [28]. The insignificance of e-bike frequency ( $p = 0.815$ ) contrasts with 1–3 km results, suggesting that for longer trips,

infrastructure (like bike lanes) and integration with buses matter more than prior experience, echoing recommendations from MININFRA (2021) [25] and Jennings (2023) [26].

For trips beyond 5 km, the lack of significant variables ( $p > 0.05$ ) except marginal Residential Area Type ( $p = 0.081$ ) validates literature asserting e-bikes' limited viability for long distances ([28] and; (W. Zhang et al., 2024)). This aligns with Kigali modal preferences, where motorized modes dominate for  $>5$  km trips due to fatigue and time constraints [27]. The near-significance of residential area hints at suburban demand, but the overall results reinforce that e-bikes are best targeted at 1–5 km trips, consistent with Rwanda's policy focus on short-to-medium-distance mobility (MININFRA, 2021) [25].

Table 8 and Figure 11 demonstrate spatial variations in travel distance and willingness to use e-bikes. Suburban areas dominate longer travel distances (2-5+ km), indicating a strong need for last-mile solutions in peri-urban and suburban zones where public transport access diminishes. Users in city centers tend to prefer shorter distances under 1 km.

Consistent with the research objective 2, people living farther from bus stations are almost 4 to 5 times more likely to use e-bikes. This underscores the natural fit of e-bikes as a solution to the last mile problem, providing efficient, flexible connections between fixed-route public transport nodes and dispersed residential areas [10].

For cost-effectiveness and user satisfaction by distance, walking is consistently the most cost-effective mode but satisfaction is highest with private cars, likely reflecting comfort and convenience despite higher costs. Given the cost of moto-taxis, e-bikes present a cost-effective and environmentally sustainable alternative, offering lower operating costs and emissions while maintaining better travel speed and flexibility compared to walking or conventional bicycles [5]. The willingness to adopt e-bikes by current moto-taxi users and walkers suggests modal shifts that could alleviate congestion and reduce air pollution.

To understand how willingness to use e-bikes varies by travel distance, the following table summarizes the significant factors for each interval:

*Table 19: Willingness varies by travel distance*

<b>Distance Interval</b>	<b>Significant Factors (<math>p &lt; 0.05</math>)</b>	<b>Near-Significant Factors (<math>p &lt; 0.10</math>)</b>	<b>Key Insights</b>

<1 km	Occupation (p = 0.014), Cost per Trip (p = 0.021)	Frequency of E-Bike Use (p = 0.052)	Economic and practical factors dominate for very short trips.
1–3 km	Occupation (p = 0.017), Income (p = 0.028), Trip Reason (p = 0.039)	Frequency of E-Bike Use (p = 0.052)	Income and trip purpose become important alongside occupation.
3–5 km	Occupation (p = 0.020), District (p = 0.049), Bus Usage (p = 0.014)	Residential Area Type (p = 0.081)	Spatial and transit-related factors gain prominence for medium-distance trips.
>5 km	None	Residential Area Type (p = 0.081)	E-bikes are less viable for long distances, with no clear demographic drivers.
All Distances (Combined)	Occupation (p = 0.000), Income (p = 0.034), District residency (p = 0.041)	Gender (p = 0.053)	Occupation is consistently significant across all distance

#### 4.5. Policy Analysis for Promoting Electric Bicycles

The preceding analyses revealed that electric bicycles are widely accepted and perceived as feasible for short and medium-range travel intervals. Furthermore, their potential to reduce environmental degradation, and the urban mobility burden on low-income populations underscores their relevance to Rwanda’s broader sustainable development goals. However, key challenges particularly around infrastructure, cost, awareness, and systemic integration must be addressed through robust policy frameworks.

The policy analysis highlights that **infrastructure availability**, including dedicated bike lanes and secure parking, is the most critical enabler for e-bike uptake. Over 50% of respondents identified these as key motivators, echoing international evidence that without safe infrastructure, even cost-effective sustainable mobility options fail to gain traction [15]. Further, the literature advocates for integrating bike-sharing stations at public transport hubs, a strategy strongly supported by the observed higher e-bike usage and willingness among those living farther from bus stations. Government incentives, affordability measures, and awareness

campaigns, though less emphasized by respondents, should complement infrastructural investments to foster a supportive environment for e-bike growth (Langford et al., 2013).

Overall, the research confirms the theoretical and empirical expectation that shared electric bicycles have significant potential to enhance last-mile connectivity in Kigali, especially for medium-distance trips in suburban areas and for younger, middle-income residents.

The findings emphasize a comprehensive policy approach combining:

- Investment in safe cycling infrastructure (dedicated bike lanes, parking)
- Integration of e-bike stations with existing public transport nodes
- Pricing strategies and subsidies to enhance affordability
- Public awareness and incentive programs to encourage adoption

## CHAPTER 5. CONCLUSIONS AND RECOMMENDATION

### 5.1. Conclusions

The Study revealed that walking remains the dominant transport mode for last-mile connectivity, representing 55.9% of trips, especially for distances less than 1 km. Moto-taxis are the second most popular mode used by 28.2% of respondents across various distance categories, offering flexibility but at high costs. Bicycle usage currently stands at 9.4%, but shows promise for medium distances for 2-5km, where walking becomes less practical and mototaxis are financial high, particularly in suburban and peri-urban areas where public transport access is limited.

A binary logistic regression model, identified the two most critical predictors of willingness. **Distance from home to the nearest bus station was the strongest positive predictor** ( $B = 0.45$ ,  $p = .001$ ). The odds ratio of 1.57 indicates that for every additional kilometer a respondent lived from a bus station, their odds of being willing to use an e-bike increased by 57.2%, the model is confirming that individuals' characteristics living further from the bus station are 4-5 times more likely to use e bikes. This finding empirically validates the study's core premise and unequivocally demonstrates that e-bikes are a potential solution to the last-mile connectivity problem. **Age group was a significant negative predictor** ( $B = -0.42$ ,  $p < .001$ ), with the odds of willingness decreasing by 34% for each increase in age category. The model also highlighted that younger demographics aged 18-34 years are the most willing adopters These findings from the multivariate model are consistent with and reinforce the patterns identified in the non-parametric tests for specific distance intervals.

The Non-parametric test analysis showing significantly reduced willingness by each separate travel distance, for travel distance less than 1 km, occupation and cost per trip emerged as significant predictors of e-bike adoption ( $p = 0.014$  and  $p = 0.021$ , respectively), suggesting that economic and practical factors dominate short-distance mode choices. However, demographic variables like age and gender were not significant, indicating that affordability and convenience are primary drivers for this distance range.

For travel distance between 1–3 km, occupation ( $p = 0.017$ ), income level ( $p = 0.028$ ), and trip purpose ( $p = 0.039$ ) significantly influenced willingness to use e-bikes. Middle-income groups and traveler traveling for work or education were more inclined to adopt e-bikes, aligning with global trends where e-bikes are favored for medium-distance trips due to their balance of speed and cost-effectiveness. The near-significance of prior e-bike use frequency ( $p = 0.052$ ) suggests that familiarity with e-bikes may further encourage adoption.

For travel distance between 3–5 km, District of residence ( $p = 0.049$ ) and bus usage ( $p = 0.014$ ) were significant, indicating that e-bikes are seen as viable connectors to public transport. Unlike shorter trips, income level lost significance ( $p = 0.145$ ), implying that convenience and integration with public transport outweigh cost concerns for longer distances.

For travel distance exceeding 5 km, no significant predictors of e-bike adoption were identified ( $p > 0.05$ ), except for a marginal influence of residential area type ( $p = 0.081$ ). This suggests that e-bikes are perceived as less practical for very long last-mile trips, where motorized modes remain preferred due to fatigue and time constraints.

Income levels showed nuanced effects in descriptive analysis, with middle to higher-income groups expressing higher willingness to use e-bikes for medium distances; however, affordability remains a concern for lower-income groups. The influence of residential location further indicates suburban and peri-urban residents have greater willingness to adopt e-bikes, reflecting their longer travel distances and less availability of public transit options.

The results reinforce e-bikes' potential to shift modal choices away from costly motorized options, yielding benefits in congestion mitigation and air quality improvement. Infrastructure, specifically the availability of safe, dedicated bike lanes and secure parking, has been identified as the most critical enabler for electric bicycle adoption, cited by over half of respondents. Lack of protective cycling infrastructure and charging facilities remain significant barriers. Policy incentives and public awareness campaigns, though less prominent in respondent priorities, form vital complementary interventions. The study highlights that enhancing infrastructure and integrating e-bike sharing stations at public transport hubs are fundamental strategies to support widespread adoption, consistent with international best practices. This research confirms the substantial potential for shared electric bicycles to enhance last-mile connectivity in Kigali, particularly among younger and middle-income users residing farther from bus stations and covering short to medium trip distances. To capitalize on this potential, a coordinated policy approach focusing on infrastructure development, affordability, and integration with existing public transport is essential. Addressing safety and accessibility barriers will further boost adoption and contribute to sustainable urban mobility objectives.

## **5.2. Recommendations**

From the conclusions, the following are proposed as recommendations to policymakers, urban planners, and potential private sector operators:

### **1. Targeted infrastructure development and planning:**

- **Prioritize dedicated cycling lanes:** The city should invest in connection network access especially along corridors connecting major bus terminals to suburban and peri-urban residential areas. This addresses the foremost safety concern and is the most critical enabler for adoption.
  - **Strategic Placement of E-Bike Stations:** E-bike sharing stations should be integrated near the key public transport hubs like bus terminals, taxi parks and high-demand generators like universities, business districts, markets.
- 2. Adopt Financial and business model incentives:**
- **Implement usage-based pricing** that reduces the cost depending on travel interval like <3 km. Consider also subscription models or integrated ticketing with public bus services to enhance affordability and attract regular commuters.
  - **Introduce Targeted Subsidies:** purchase incentives for low-to-middle-income groups and students, who have shown high willingness but may be sensitive to initial costs. This could be part of a broader green mobility incentive scheme.
- 3. Policy and Regulatory Frameworks:**
- **The Update the National Transport Policy or the City Master Plan** should be recognized and plan for e-bikes and micro-mobility as integral components of the public transport system,

## References

- [1] M. G. G. H. Y. S. E. Boarnet, "First/last mile transit access as an equity planning issue.," *Transport. Res. Part A: Policy Pract*, pp. 103, 296–310, 2017.
- [2] F. & U. P. Ndayisaba, *Transportation challenges in Kigali: The last-mile dilemma and its impact on urban mobility*, Kigali: Rwanda Urban Mobility Review, 2022.
- [3] S. J. d. Dieu, "BIKE SHARING SYSTEM IN CITY OF KIGALI," UR-CST, Kigali, 2020.
- [4] G. o. Rwanda., *Sustainable transportation solutions for Kigali: Electric last-mile connectivity assessment*, Kigali: Ministry of Infrastructure., 2023.
- [5] E. & C. Fishman, *Transport Reviews*, pp. 36(1), 92–113., 2016.
- [6] a. M. Z. G. S. D. Müller, "The Last Mile Problem: A Case for Integrating Transportation," *Journal of Urban Transportation*, pp. 45(2), 123-135., 2020.
- [7] B. C. P. C. Giulia Oeschgera, "Investigating the role of micromobility for first- and last-mile connections to Public Transport," *Journal of Cycling and Micromobility Research*, pp. 1-2, 2023.
- [8] Juveline, "Analysis Of Last Mile Transport Pilot Implementation Of The last mile delivery," <https://jethrojeff.com/>, 2025.
- [9] M. A. S. B. T. Y. A. & S. E. M. Adnan, "Last-mile travel and bicycle sharing system in small/medium-sized cities: User's preferences investigation using hybrid choice model," *Journal of Ambient Intelligence and Humanized computing.*, 2018.
- [10] C. R. W. J. X. & X. Y. Cherry, "Comparative environmental impacts of electric bikes in China.," *Transportation Research Part D: Transport and Environment*, 14(5), p. 281–290, 2009.
- [11] I. A. J. & C. T. T. P. 1. 1. Philips, " E-bikes and their capability to reduce car CO<sub>2</sub> emissions.," *Transport Policy*, pp. 116, 11–23, 2022.

- [12] F. C. I. S. K. & D. W. Arnold, "Simulation of B2C e-commerce distribution in Antwerp using cargo bikes and delivery points.," *European Transport Research Review*, p. 10, 2017.
- [13] E. I. C. & K. K. Papaioannou, "Last-Mile Logistics Network Design under E-Cargo Bikes.," *Future Transportation*, 3, p. 403–416, 2023.
- [14] I. & M.-E. D. Kosmidis, "The synergy of bicycles and public transport: a systematic literature review.," *Transport Reviews*, 44(1), p. 34–68, 2024.
- [15] L. M. P. J. P. & C. P. [9] Martinez, "Shared Mobility's Role in Sustainable Mobility: Past, Present, and Future.," *Annual Review of Environment and Resources*, ., pp. 49, 191–222, 2024.
- [16] C. M. J. C. C. R. & J. L. R. Bennett, "Using E-Bike Purchase Incentive Programs to Expand the Market – North American Trends and Recommended Practices.," *Transportation Research and Education Center, Portland State University.*, 2022.
- [17] X. W. J. P. S. R. X. Z. G. & F. Y. Xu, "Exploring intra-urban human mobility from dockless bike-sharing: A Beijing case study.," *International Journal of Applied Earth Observation and Geoinformation*, , p. 122, 2023.
- [18] H. D. K. W. A. H. B. Sergio Guidon, "Electric Bicycle-Sharing: A New Competitor in the Urban Transportation Market? An Empirical Analysis of Transaction Data," *Transportation Research Record: Journal of the Transportation Research Board*, 2019.
- [19] B. V. A. G. H. D. A. C. N. V. O. Roy J Van Kuijk, "Preferences for first and last mile shared mobility between stops and activity locations: A case study of local public transport users in Utrecht, the Netherlands," *Transport Research Part A: Policy and Practice*, 2022.
- [20] S. Z. Y. Q. C.-C. W. Jian-You Xu, "Demand Prediction of Shared Bicycles Based on Graph Convolutional Network-Gated Recurrent Unit-Attention Mechanism," *Mathematics*, 2023.
- [21] B. V. A. G. H. D. A. C. N. V. O. Roy J Van Kuijk, "Preferences for first and last mile shared mobility between stops and activity locations: A case study of local public

transport users in Utrecht, the Netherlands," *Transportation Research Part A: policy and Practice*, 2022.

- [22] T. W. X. C. Aihua Fan, "How Have Travelers Changed Mode Choices for First/Last Mile Trips after the Introduction of Bicycle-Sharing Systems: An Empirical Study in Beijing, China," *Journal of Advanced Transportation*, 2019.
- [23] T. W. X. C. Aihua Fan, "How Have Travelers Changed Mode Choices for First/Last Mile Trips after the Introduction of Bicycle-Sharing Systems: An Empirical Study in Beijing, China," *Journal of advanced Transportation*, 2019.
- [24] Z. T. S. L. X. W. J. Z. Jiangyue Wu, "Towards niche market for shared mobility: Identifying heterogeneity of potential early adopters to use shared electric bikes in a Chinese mega city," *Transport in urban Data Science and Technology*, 2023.
- [25] MININFRA, "National Transport Policy and Strategy for Rwanda," MININFRA, Kigali, 2021.
- [26] G. Jennings, "USAID Bicycles for growth Rwanda Bicycles Market system," USAID, Kigali, 2023.
- [27] J. Ndayisaba, "Electric bike share scheme to bring new experience in Kigali's transport...," *KT Press*, 2022, July 2.
- [28] E. & C. C. Fishman, "E-bikes in the mainstream: Reviewing a decade of research. Transport Reviews,," *transport reviews*, pp. 36(1), 72–91., 2016. .
- [29] G. Sharma, "Probability Sampling in Research Methodology," 2017.
- [30] J. P. Hoffmann, *Generalized Linear Model: An Applied Approach*. Boston: Pearson., Boston, 2004.
- [31] G. H. d. A. C. ., N. v. O. ., Roy J. van Kuijk \*, "Preferences for first and last mile shared mobility between stops," *elsevier*, p. 286, 2022.
- [32] J. Smith, *The rise of e-commerce and its impact on urban mobility*, 2022.

- [33] P. & M. A. Nkurunziza, Addressing the last-mile challenge in Kigali's public transportation system: The role of electric buses. Rwanda Urban Transport Review,, Kigali, 2023.
- [34] W. Bank, "Kigali's Sustainable Transport Future: The Role of Electric Buses in Overcoming the Last-Mile Problem. World Bank Group. <https://www.worldbank.org/en/publication/xxxxx>," Kigali, 2022.
- [35] J. & L. R. Smith, "Electric bicycles in urban logistics: A routing model for last-mile delivery.," *International Journal of Urban Transportation*,, pp. 22(3), 150-165, 2024.
- [36] J. & L. R. Smith, "Electric bicycles in urban logistics: A routing model for last-mile delivery," *International Journal of Urban Transportation*, pp. 22(3), 150-165., 2024.
- [37] S. A. T. B. A.-u.-H. Y. E. M. S. Muhammad Adnan, "Last-mile travel and bicycle sharing system in small/medium sized cities: user's preferences investigation using hybrid choice model," *Springer Nature Link*, pp. Volume 10, pages 4721–4731, (2019), 17 May 2018.
- [38] Y. e. a. Zhang, *Journal of Transport Geography*, p. 85, 2020.
- [39] C. I. K. K. Eleni Papaioannou, "Last-Mile Logistics Network Design under E-Cargo Bikes," *Future Transportation*, 2023.
- [40] T. W. X. C. Aihua Fan, "How Have Travelers Changed Mode Choices for First/Last Mile Trips after the Introduction of Bicycle-Sharing Systems: An Empirical Study in Beijing, China," *Journal of Advanced Transportation*, 2019.