



Master's thesis

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School of Transportation Sciences Master of Transportation Sciences

Estimating value of Time using discrete choice model for individuals in Kigali, Rwanda

Thesis presented in fulfillment of the requirements for the degree of Master of Transportation Sciences, specialization

Prof. dr. ir. Tom BELLEMANS

CO-SUPERVISOR:

dr. Muhammad ADNAN

2021 2022 |___



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PREFACE

The research presented in this thesis was conducted in the school of Transportation Sciences of Hasselt University, under the supervision of Prof. dr. Tom BELLEMANS and Prof. dr. Muhammad ADNAN, Between October 2021 and June 2022. I am grateful for completing this research successfully.

As a civil engineer, the value of time for individuals in Kigali, Rwanda has piqued my interest due to its importance in assessing transportation systems and infrastructure projects for a region like Kigali, which is experiencing significant growth in housing and development. The goal of this research is to estimate the value of time through individuals' mode choices and the factors that influence them, This has allowed me to answer the research questions that were identified, even though there are still gaps in the travel time valuations literature and resources in developing countries, including Kigali, and Rwanda.

With this research, I hope to contribute and provide a useful resource to future researchers who are estimating travel time valuations for a particular region, as well as other various parties involved in transport and infrastructure policies, planning, and economics in Kigali, thus I would like to expand it to a representation of Kigali's population for further analysis. Except for references to previous research, the research is entirely my own.

Ir. Murielle Jeannine Tuyizere June 2022

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I would like first to give praises and thanks to the almighty God for his strengths to me throughout this journey and to complete the research successfully. I can do everything through him who gives me strength.

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I am extremely grateful to my family for their love, prayers, encouragement, and continuing support to complete this research work. Also, I express my thanks to my sisters, cousins, and brothers-in-law for their support to make this research successful. I would like to say thanks to my friends and colleagues in Kigali, and many thanks to all participants that took part in completing the survey and enabled this research to be possible.

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ABSTRACT

Value-of-time (VOT) is a key factor in a wide range of transportation systems and infrastructure investment decisions by policymakers, planners, engineers, and economists. It is well known that discrete choice models can provide the value of travel time related to travelers' socioeconomic characteristics and individual mode choice. This study uses a methodological framework based on discrete choice modeling for the estimation of the VOT. The multinomial discrete choice model for mode choice has been estimated for intracity trips in Kigali, Rwanda. The stated preference survey/ method was used to collect the data for estimating the multinomial model and is administered to a random sample of 250 people. The mode choice is estimated for work and shopping trips. Values of time results for different types of time such as in-vehicle time, waiting time, and walking time (i.e. access/egress times) are computed. A work trip is estimated to have an in-vehicle time value of 17,100.9 rwfs/hr, a walking time value of 5,288.1 rwfs/hr, and a waiting time value of 727.1 rwfs/hr, whereas a shopping trip has values of 16,170.4 rwfs/hr; 3,703.8 rwfs/hr and 506.8 rwfs/hr respectively. According to the multinomial logit model results, work trips are estimated more appropriately than shopping trips.

Keywords: Value of time, Discrete choice model, multinomial logit model, stated preference data, Parameter estimation.

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ABBREVIATIONS

VOT: Value Of Time

DCMs: Discrete Choice Models

COK: City Of Kigali

IGC : International Growth Centre

RWFS (rwfs) : Rwandan Francs

GGGI: Global Green Growth Institute

IVT: In-Vehicle travel time

VTPI: Victoria Transport Policy Institute

MNL : Multinominal Logit Model

DCE: Discrete Choice Experiment

MLE: Maximum Likelihood Estimation

PT: Public Transport

RURA: Rwanda Rural Regulations Authority

GHGs: Greenhouse Gases

1. INTRODUCTION

1.0 Introduction

The value of time (VOT) is a key element in the appraisal of a wide range of policy and planning applications of transport projects. With the rapid growth of the economy and the increase in urbanization, the transportation system remains an essential component of every modern economy and everyday human life. Fosgerau (2019) argues that the economic attractiveness of different locations is strongly influenced by the travel time and cost of access to them. The monetary cost and the time spent on travel are the main elements of the inefficiency of travel. The value of travel time measures is one of the most critical parameters of transport planning in several countries and is an essential attribute of any transportation system. It is a significant factor that shapes travelers' decisions in the transportation market.

Value of travel time (VOT) can be defined as the price people are willing to pay to acquire an additional unit of time (Huq, 2007), It refers also to the cost of time spent on transport. value of travel time plays a key role in traveler's mode choice behavior and varies significantly with varying socioeconomic conditions (Athira & Munera,2014). VOT is determined by a number of factors and varies from country to country, industry to industry, and even person to person, where the characteristics of each travel are described by a number of variables (factors) that describe the individual and the mode, such as travel time, waiting time, travel cost, age, income, mode ownership, and so on.

The discrete choice model (DCM) is the most common method of estimating the value of time, describes how individuals choose between different alternatives, and Explain their mode choice behavior as the result of an individual's preferences while selecting the most preferred option. The model shows how strongly different factors influence the choice of travel mode and the linkages between the factors (Beser et al 1996). for example, Magelund (1997) studied how strongly income and work-related factors affect in the choice of travel mode and on the other hand have impact on estimation of value of time. In most of developing countries people who choose public transport are characterized by low income and in developed countries by parking conditions at their place of work.

A discrete choice model predicts an individual's decision (mode of transportation, route taken, etc.). DCMs are derived under random utility, its output is the utility value of each alternative (Chen&Li,2017).The logit model is the most popular practical DCM because of its simple structure and ease of estimation. The logit model is estimated using data that shows how individuals have chosen between different alternatives, These data may come from Stated Preference-data (SP) where individuals make hypothetical choices, from studies of travel behavior (RP data) with the actual choice's individuals made, or from a compilation of both RP and SP data (Ambarwati, 2017).

This research uses a discrete choice model to estimate the value of time and demonstrates its application in Kigali, Rwanda, taking into account the characteristics of each travel mode, their hypothetical traveler scenarios, and conducting the VOT analysis.

The rest of this research is structured as follows, a review of related literature and previous research is shown to analyze the range of VOT values available. An outline of the application technique, data gathering process, discrete choice model specification, and estimation follows this literature section. The results are presented in the next part, which will be followed by conclusions and limitations, and recommendations for future research.

1.1 Problem Statement

One of the main justifications for transport improvements is the amount of time and travel cost that traveler will save. Using a set of values of time, the economic benefits of a transport project can be quantified to compare them to the costs. The value of time is a key aspect of the cost of the time that a traveler spends on his/her journey and is the enormity of its potential impact on final transport planning and policy decisions (VTPI,2020).

Despite a large number of studies on urban travel mode choice, there are still gaps, particularly in developing countries, in the understanding of perceived and attitudinal barriers to sustainable modes and transport systems, as well as travelers' motivations for personal car use, and public transportation use, and their behavior in mode choice.

1.2 Research Questions

The study is being conducted to answer the following research questions :

- 1. What is the value of time for individual living in Kigali Rwanda?
- 2. what are the important determinants of mode choice decisions for individual living in Kigali Rwanda?

The answer to the research question aims to develop an understanding of the significance of VOT and the methods for estimating this value empirically, as well as the factors influencing the value of time.

1.3 Study area

Rwanda is a country situated in Central Africa, it's capital and biggest city is Kigali with a surface area of 730 km², it is in a rolling hills area with a series of valleys and ridges connected by steep slopes near the nation's geographic center. Since its independence from Belgian rule in 1962, the city has served as Rwanda's economic, cultural, and transportation center. Kigali is the direct point of entry for migrants and people from rural areas and beyond due to its central geographic location in the country and its location at the crossroads of north-south and east-west traffic routes leading to neighboring states.

Kigali City is divided into three districts: Gasabo, Kicukiro, and Nyarugenge. It is presently inhabited by approximately 1.2 million inhabitants with a population density of 1,552/km2. Kigali is 70% rural with a population that is relatively young- the youth make up about 60% and women make up slightly more the 50%, (City of Kigali,2021).



FIGURE 1 Location of the study area (Source : maps Rwanda,2022)

1.3.1 Transport in Kigali

Kigali is Rwanda's capital, and it is home to a variety of functions, including service companies, government offices, and ministries, hotels, residential, restaurants, schools and churches, banks, hospitals, industries, public transportation stations, conferences, and exhibitions, industries, sports, leisure and culture, shopping centers, etc. Due to these functions found in Kigali, transport remains important in its economic progress by improving the ease of doing business, facilitating investors, and designing mechanisms to assist the community.

Kigali's residents use transport modes to perform various activities in their daily lives. The several means of transport used to travel in Kigali include Taxi cabs, Buses, Motorbikes, Cars, and walking. Public transportation which is buses remains the most cost-effective and affordable mode of transportation for the majority of travelers however due to the lack of effectiveness, and accessibility of bus transport services, people prefer to use the motorbikes.

A motorbike can carry only two people at a time, a motorcycle driver and a passenger. Motorcycles, unlike public transport, can take a person from where he or she is to the final destination without having to go to a station or a specific stop; however, in some places, a walking time and waiting time is required because, whether they are in their parking spot or not, they are mostly found on main roads and not near homes, It is a good mode to use when there is traffic on the road (than buses and cars) and when you need to get somewhere quickly. Despite being more expensive than buses, motorcycles are fast, accessible, but Unsafe (the leading cause of road accidents in Kigali) and contribute to environmental pollution.

Modal share

The share of non-motorized modes is high compared to other modes, the walking share is around 52 %, the motorized modes have a share of 17% using public transport, 15% using cars, and 16 % motorbikes. Due to a large increase in the use of personal motor vehicles and the need for car dependency, the modal share of non-motorized modes is expected to decrease to 21% and increase for motorized modes to 19% public transportation use and 60% cars and motorcycles use by 2050, while GHG emissions, air pollution, and congestion from transportation modes are projected to rapidly increase (GGGI, 2020).

Transport cost

Bus public transportation is the most cost-effective mode of transportation in Kigali. The bus system can transport people in all districts of Kigali, though the distance and time to travel to the bus stop may be high. The fare can range from 150 rwfs (Rwandan francs) to around 800 rwfs, depending on the destination, RURA provides the fixed fares for buses at each location.

Motorbikes are still the most popular transport mode used by most people. They're quick, accessible, and cheap (but more expensive than the bus), motorbikes work on (almost) fixed fares based on distance, Fares range from 300-2,000 rwfs for the most parts of Kigali typically (300rwfs for the first 2km and 133 rwfs per additional km).

Taxi cabs work well in Kigali, but using taxi apps in Kigali requires a lot of patience because there is a certain amount of waiting time; many drivers are still not used to using the apps and may require assistance with directions however, there are taxi parking spots where you can find a taxi (this may require some walking and waiting time). Taxis cost 1500 rwfs for the first kilometer and 700 rwfs for each additional kilometer. This gives a range of 2500-10000 rwfs for taxi to travel in Kigali.

Kigali traffic is normally smooth and free of delays or congestion. During rush hours, which are between 7:30 and 8:00 a.m. and 5:30 and 7:00 p.m., traffic can become high as people are on their way to or from work, but there are various road networks for an alternate routes that can be used in such a situation, though they can also increase the in-vehicle travel time.

Kigali's transportation system has vastly improved in recent years than in most African cities, Good roads, effective traffic management, robust public transportation, and the introduction of ride-hailing apps make getting around much easier. With the considerable expansion and growth of housing and functions development in Kigali, it is necessary to assess the transport system which is an essential component of every modern economy.

Estimating the VOT through a discrete choice model in Kigali is also intended to bridge the gap in the value of time estimation resources and research, which in turn, supports future plans in the transport system, infrastructure, and the country's economic balance.

1.4 Structure of the report

The structure of this report is organized as follow :

- 1. Literature review : a thorough review of previous research concerning value of time , review of discrete choice analysis especially in relation to mode choice models and value of time estimated in different regions
- Methodology : detailing the specifics of how this research was carried out. This part include : (1) Stated preference survey : the relevant attributes and their values for selected modes of transportation, experimental design, questionnaire survey design, and data collection. (2) Model estimation: defining the utility function for MNL logit model and (3) value of time estimation.
- 3. Summary of the result and analysis
- 4. Conclusions and Limitations.
- 5. Recommendations

1.5 Assumptions and Limitations

This study is based on the following assumptions and limitations:

- The data from the survey is based on 250 respondents from the Kigali population.
- The hypothetical scenarios information set on which preferences will be made are those represented by the researcher in the survey only.
- The hypothetical scenarios presented by the research in the survey will be answered in a proper way and reflect the individual preference after analyzing each scenario .This means that the respondents are believed to attach utility weightings to each of the attributes in a choice situation (Abley, 2000).
- The attributes and levels included within the survey considered average minimum and maximum travel time and cost in different areas of Kigali therefore reflect the traveler situation in Kigali.
- Stated preference data will provide utility functions through individuals' responses about their preferences in a set of options . (Abley,2000)
- The questionnaire is prepared in basic English to maximize the understanding since English is first official language and not the local language.
- The data collection is done within the time constrain of the researcher (2 weeks) and uses an easy way in survey distribution
- All research questions would be answered through the methodology used in this research
- According to the DCMs model formulation assumptions, travelers are rational in their mode selection because they will select the travel scheme with the highest utility value (Chen and Li, 2017).

2. LITERATURE REVIEW

2.0 Background

Several studies and practices of valuing travel time have been conducted in the last decayed. Becker (1965) used the formalized theory of time allocation, According to the time allocation model, an individual allocates his or her time and money to a variety of tasks in order to maximize utility when working under time and budget constraints. Beesley (1965) and Cesario (1976) estimated the value of time saved in commuting to work as a function of the wage rate. Raghava Chari and Khanna (1976) used home interview data in Ahmadabad and developed disaggregated models incorporating mode choice and trip frequency choice to calculate the value of travel time in rupees per hour.

Since the introduction of a time allocation model in the 1960s, other models have been implemented to estimate the value of travel time (VOT), Algers, 1994; Brownstone et al, 2002; Ahmed and Vaidyab, 2004; Hensher, 2006; Blayac, 2007; Tikoudis, 2008, Tseng and Verhoef, 2008; Tikoudis, 2008; Fezzi et al, 2012; Athira et al. (2016) employed multinomial logit model (a mathematical function, which predicts an individual's choice based on the utility or relative attractiveness), as a method for computation of value of travel-time measures. Fezzi et al (2012) also estimated the value of travel time specific for recreation trips by using a stated preference approach.

Kumar et al. (2004) developed multinomial logit models for the estimation of the VOT and the comfort levels for trip-makers traveling along rural bus routes in India using data collected through a stated preference survey however trip characteristics and socioeconomic characteristics of the respondents collected were not included in the final models.

This section presents a review of the relevant literature in the field of study in order to clarify a number of key concepts used in the current research, its objective is to present the state-of-theart in estimating the VOT in using stated preference survey and discrete choice model. Additionally, review of the values of time in different countries and their range obtained by other studies are also provided.

2.1 Value of time

VOT is a highly variable metric that varies by country, industry, and even individual travel decisions. This does not necessitate travelers being aware of any such number or value; however, the choices travelers make between routes and modes of transportation typically involve active trade-offs of travel time and comfort against monetary costs; as a result, such choices implicitly incorporate their underlying value of travel time. Most studies seeking to estimate VOT for passenger travel utilize discrete choice models (logit models) and use stated-preference data.

2.1.1 Evidence on Values of time

Several studies have estimated the estimation of travel time values and have provided the monetary valuations, some of the data set covers the evidence on valuations of time on different attributes such as walking time , waiting time , in vehicle time (IVT) , departure time shift, search time, congested travel time and headway, travel time reliability, etc. additional to this, values differ with the specific valuations of each studies relating to public transport values, Valuations by Mode Used and Mode Valued, Valuations by overall journey distance, RP and SP Valuations contexts, valuations by trip purpose etc . which shows that values of time may differ due to various factors , aim of the study, study area etc.

In the European-wide meta-analysis of values of travel time, the values were estimated (in € per minute in 2010 prices) using Abrantes and Wardman's (2011), and Shires and de Jong's (2009). studies and data based on the number of variables per alternative in the Stated Preference (SP) design along with the number of scenarios evaluated and the means of presenting the exercise; journey purpose; choice context; mode used and mode valued; region, etc. To the 349 studies and 3109 valuations of the monetary valuations and studies for each attribute data set (In-Vehicle Time, Congested Time, Free Flow Time Walk Time, Access Time, Wait Time, Interchange Waiting, Search Time, Headway, Departure Time Early, Departure Time Late, Time Departure Time for Both, Late Arrival, Schedule Delay and Early), IVT valuations dominate, accounting for more than half of the total and not below 40% in each data set, with 10% each for walk time and headway and around 5% each for combined reliability terms, combined wait times, combined departure time shifts, and access time.

Wardman, Chintakayala, Jong and Ferrer (2012) stated Noticeable features of the results from the RP valuations are almost always greater than their SP counterparts although we have to be mindful of possible confounding effects from variables such as journey purpose, distance and mode which it is a purpose of the meta-analysis to overcome. and In generally their study have obtained a good spread of values of time to support various analysis of a broad range of issues.

Public transport values of time

Quarmby's study (1967) was the first in the UK to assess walk and wait time values, he discovered walking and waiting times are worth between two and three times in-vehicle time. Daly and Zachary (1975) re-analyzed Quarmby's data and discovered that walk and wait time values were valued at 1.6 and 2.6 times the car-bus in vehicle time values, respectively. Walking and waiting time, according to Daly and Zachary (1977), are worth 0.9 and 3.5 times the time spent on public transportation, respectively. McKnight (1982) examined information from 17 studies spanning four nations on the links between walking, waiting, and vehicle time values, the mean walk time value was 1.85, but the mean wait time value was 2.4 of the ten disaggregate studies providing walk and wait time values covered in a review of international evidence (TRRL, 1980), walk time was valued close to twice in vehicle time on average, and wait time was valued around three times IVT.

Following the first British study (MVA et al., 1987), the focus shifted to stated preference (SP) data. Much of the subsequent SP-dominant British evidence is included in Wardman's meta-analysis (2001a). The average values of the walk and waiting time were determined to be 1.66

and 1.47 times in vehicle time, respectively. Steer Davies Gleave (1997, p23) found on a review of evidence from several countries that walking time is usually valued at between 1.8 and 2.4 times IVT. For simplicity, an average of 2.0 is advised, and waiting time is occasionally valued up to 4.5 times more than walking time A three-to-one ratio is recommended (Wardman,2004).

The first Dutch national study (Gunn and Rohr, 1996) calculated the values of walk time, interchange time, and service headway for public transportation customers. Walk time was rated at 1.0, 1.6, and 1.3 times in vehicle time for the three uses of commuting. For leisure journeys smaller than 50 km, Ramjerdi et al. (1997) estimated the in vehicle time value of headway to be 0.37, but only 0.21 for journeys longer than this, for business travel, the figures were 0.64 and 0.30 respectively. The more recent findings, both in the UK and abroad, present a challenge to the tradition of valuing walk and especially wait time at double the rate of in vehicle time (Cornet&Lugano,2018).

Transport modes and value of time Values

Although many studies have estimated values of time, there are two reasons why there is not a great deal of evidence of how the value of time vary with mode. studies which are concerned with valuation tend to focus on mode specific rather than various mode choice exercises to avoid the additional noise associated with choice data. in the latter context, it is often the case that mode choice models specify a common time parameter across modes and rely on a mode specific constant to discern quality differences (Wardman,2004).

The majority of the national value of time studies have estimated public transportation and car values. However, car values have tended to be estimated for both car users and public transportation users (MVA et al., 1987; Algers et al., 1996; Pursula and others, 2000). As a result, the valued effects of user type and mode are confounded, making the most comprehensive account of the value of time variation due to both user type and mode in a national sample. value of time study is provided in the first Dutch study (Gunn and Rohr, 1996) in a separate SP research, train users had a value of time when compared to the value of IVT for auto drivers in city traffic, Train users valued train time 6 percent more for commuting, 18 percent less for business, and little differently for leisure travel (Gunn et al., 1999), Although the results do not differentiate between user type and mode valued, they are consistent with the user type effect dominating the mode valued.

The Swedish (Algers et al., 1996) and the Norwegian (Ramjerdi et al., 1997) studies offered car and public transport users SP exercises relating to both their chosen mode and another way to look at in vehicle time value changes by mode. Wardman (1997) compared the values for different modes estimated in the same mode choice model using mode-specific parameters, car and train had a mean value of 3.84 pence per minute in the urban context for the 20 comparisons, compared to 4.25 for combinations of bus, and train. The evidence indicates, as expected, that user type effects outweigh mode valued effects, and that while train and car users have higher values, time spent in these modes is valued less than bus time. However, most studies fail to separate the effects of user type and mode valued.

2.1.2 Value of time in Europe

Several VOT studies have been done in Europe over the last decade, notably in the Netherlands (Gunn and Rohr 1996), Norway (Ramjerdi et al. 1997), Sweden (Alger et al. 1996), the United Kingdom (Gunn et al., 1996), and Switzerland (Gunn et al., 1996). (Axhausen et al., 2004). Wardman (1998) presents a meta-analysis of VOT based on 105 travel demand studies utilizing revealed-preference and/or stated-preference methodologies (Journal of Public Transportation, Vol. 10.2007).

Cirillo and Axhausen, (2006) conducted travel surveys in UK to estimate the value of travel time for Dwellers city in Germany, they discovered that travel time has an average value of around \$10/hour (estimated at 10-15 percent overall and up to 24 percent during non-working days).

In Sweden, the value of time was calculated using the data collected through two surveys carried out in 2007 and 2008 and the multinomial logit model to estimate the value of time (Eliasson and Börjesson, 2014) the results show that the value of time differs along several dimension, it is usually possible to consider differences in trip purpose, trip length, travel mode, and region. The 2008 survey comprised several modes: car, train, and bus for short and long-distance respectively, alongside the socioeconomic differences (children, employment status, etc.). They found that the trip length is essentially a proxy for travel cost and travel time, but it is practical to let the value of time depend on trip length since both travel cost and travel time change over time. The value of time calculated is as follows: for short distance commute: Car in Stockholm 12.1euro/hr, bus 5.3euro/hr, Train 7.2euro/hr, For short distance other purposes: car 7.8euro/hr, bus 3.8euro/hr, and train 7.3 euro/hr.

2.1.3 Value of time in Least -Developing countries

The value of time was investigated in a developing country context using conventional stated preference methodology. Surveys of residents' willingness to pay for travel time was conducted under various conditions in Bangladesh, Tanzania, and Ghana. According to the findings, the following are the average base travel time values for rural travelers in three countries: Bangladesh pays Taka 3.50 (US\$ 0.06) per hour, while Ghana pays per hour (US\$ 0.18), and Tanzania pays TZS 195 per hour (US\$ 0.18), representing 51 percent, 64 percent, and 49 percent area wage rates. Factors such as traveler gender, age, travel activity, load, comfort, road condition, and whether the traveler is paid for their time all had an impact on travel time values (VTPI,2020).

2.1.4 Value of Low-middle income countries

In low-income countries, Liu (2007) adds a stated preference component to revealed mode choices, asking 100 households in Shanghai to rank order their transportation choices, VOT has been estimated by examining actual mode choices in a nested logit framework VOT estimates averaged 64% of in-sample wage rates for in-vehicle time and 82% of wages for the out-of-vehicle time.

In San Jose, Costa Rica, Alpizar and Carlsson (2003) made several hypothetical choices between continuing to commute by car and switching to a public bus. The data from the model were used to calculate mean values of VOT, which were 40-50 percent of the sample's hourly wages, with a higher willingness-to-pay. According to count models based on the monetary cost of travel (bus fares, etc.), respondents valued travel time at 18-46 percent of the median hourly wage. (Kimuyu&Cook,2015).

2.1.5 Importance of Estimating the value of time

The value of time help in assessing transportation improvements , the economic benefits of a transportation project can be quantified using a set of time values and compared to the costs (forming the basis of cost-benefit analysis). for example, Lehtonen and Kulmala (2002) used VOT figures to estimate the travel time savings due to signal prioritization and real-time passenger information enhancements along two transit lines in the city of Helsinki, Finland. Grant-Muller et al. (2001) review the value of time state-of-the-art in the economic appraisal of transport projects, drawing on national practice in Western European countries.

There are numerous benefits to estimating the value of time, some of which are as follows:

- □ The value of time is used in cost/benefit analyses for transportation infrastructure investment.
- □ Value of time is used in transportation infrastructure investment.
- The value of time informs decision-makers about the benefits of a transportation project. The value that transportation users place on values of travel time influences their reaction to changes in the transportation network. For example, if the value of reduced travel time is high, the increase in demand or modal shift will be greater for a project that reduces travel time.
- Travel time values are critical in the design of transportation infrastructure. The Value of Time as a Highway Variable, Highway expansion projects are frequently justified on the basis of reducing traffic congestion and increasing traffic speeds, but they frequently do the opposite.
- □ In transportation models, the value of time is used to monetize travel time based on the transport mode characteristics and travelers socio-economic characteristics .
- Reducing travel time allows transportation users to spend the time saved more productively. Measuring travel time reduction has long been a critical component of the economic case
- □ VOT assists in determining the importance that people place on travel time for their journeys and provides input for assessing and comparing different modes of transportation.
- □ Value of time can be used to estimate travel demand ,It is used to value transit service quality improvements in terms frequency , waiting time , interchanges etc.
- □ Travel time is one of the most important parameters in transportation planning, and several countries and international organizations have established official values to ensure that transportation projects, programs, and policies are evaluated consistently (Mackie et al., 2014).

2.1.6 Factors influencing Value of time

Traveler's travel time as well as factors like availability of travel modes and financial ability to pay, heavily influence traveler's decisions. The value of travel time varies greatly depending on a variety of factors such as the individual traveler characteristics (education, income, profession, car ownership etc.), mode characteristics, traveler's perception (parking fees, transport policies, tolls, fuel prices), environmental conditions.

- The traveler's Characteristics (e.g., income), It is generally thought that higher income groups value travel time at a higher price than lower-income groups. It is recommended that different income rates be used as the basis for calculating time value differences.
- Trip purpose: There is consensus that people traveling to work are willing to pay more. They value their time more for work trips than other trips. This includes also trip destinations like local/intracity and intercity trips.
- Congestion: reductions in travel time during peak periods, which are most likely to be congested, are likely to be valued more highly than reductions in travel time during off-peak periods for the travelers under congested conditions.
- The mode of transportation (e.g., bus, car, or walk)., the characteristics of modes and Levels of service (differences in comfort and other services) differ with the types of mode. It is generally accepted that time spent walking and waiting for a vehicle exposure to adverse weather has a higher value to the rider than time spent riding in the vehicle.
- The season, week, or day of the year (e.g., going home at the end of the day versus going to work in the morning).

There are different modes for estimating the value of time, despite the discrete choice model that has been seen to be the most effective method to estimate the value of time, the other methods are also used in the analysis and in measuring the value of time:

(1) route choice: where a route choice analysis, is compared with a faster and more expensive route option for a single travel mode, The difference in cost is assumed equal to the value of the difference in time,

(2) speed choice: attempt to supplement the results of route choice analysis based on the economic utility-maximizing assumption of individual's speeds that minimize the total trip costs including travel time as one component of the trip cost, vehicle operating costs and accident costs. Assuming that all costs are perceived by drivers and that the least cost speed is selected, the perceived time costs can then be determined (Athira,2016),

(3) Dwelling choice: this form of analysis, measures the value of time by comparing housing value against the time it takes to reach the work, but it can be used in collaboration with other estimating methods.

(4) Wage rate for the value of on-the-clock travel time, assume that there is a consensus that a driver's wage rate is the right measure of the value of his or her time when highway travel is part of the person's work. Thus, the average labor cost for truck drivers is an appropriate way to estimate value of time for truck traffic (Athira,2016).

Various other researchers used the multinomial logit model (Athira et al.,2016; Ahmeda and Vaidyab, 2004; Blayac, 2007; Hensher, 2006; Tikoudis, 2008 and Tseng and Verhoef, 2008) and mixed logit model (Algers, 1994; Brownstone et al, 2002; Fezzi et al, 2012; Tikoudis, 2008; and Tseng and Verhoef, 2008) for estimating the value of time. Richardson (2002) demonstrated the use of adaptive stated-preference surveys to estimate the value of time, the alternatives cost, and travel time coefficients that are needed to estimate the value of time can be delivered from discrete choice models. The discrete choice model is chosen as the model for estimating the value of time in this study and analysis of VOT for different income categories is determined.

2.2 Discrete Choice Model

Models developed for the estimation of VOT are often methodologically very similar, one of the methodologies includes the discrete choice model that has played an important role in transportation modeling for the last 25 years, DCMs are choice models delivered from the random utility theory of consumer behavior. Early applications of discrete choice consider alternative modes such as car, bus, and train which are assumed to differ in travel time and cost (Hensher, 1986). DCMs are mainly used to provide a detailed representation of the complex aspects of transportation demand and cost benefits analysis based on strong theoretical explanations (Athira,2016).

The choice of travel modes is no longer limited to single ways such as cars, buses, metro, etc. Due to the difference in travel time, speed, comfort, and travel cost, each travel mode are dominant in different travel situation and motives. In the influential factors associated with mode choice there comes the individual socio-economic attributes,(Bhat and Srinivasan,2005 believe that households with higher income have a preference for auto mode, Yang and Li,2013 found that females prefer to choose the bus over male) and travel attitudes such as travel cost and travel time (Liu & Weiguang,2019). Academics, economists, and policymakers utilize Choice Modelling to determine customer preferences. It is often recognized as the most scientifically sound way of studying and comprehending how people make decisions.

Why choice models?

We are constantly faced with decisions. Among discrete choice issues in travel behavior literature, travel mode selection has garnered the greatest attention. Choice modeling is founded on basic economic concepts, and it assumes that people make decisions by weighing the utility they receive from each alternative and selecting the one with the highest utility. According to Random Utility Theory, people perceive options differently and weigh them differently; as a result, when confronted with an identical set of information, people make different decisions. The majority of mode selection models are based on random utility.

DCMs employ a utility function to represent the attributes of the various modes and the travelers; the utility function is typically a weighted sum of the modal and personal attributes considered (such as travel time and reliability, travel cost, service frequency, and socio-economic characteristics, etc.). The logit model is the most basic and often used practical DCM (Train, 2009). According to the logit model, the likelihood that an individual will choose a particular option

is determined by its utility about the usefulness of all other options. However, this does not preclude the individual from selecting an alternative because he or she is unable to notice certain elements that influence the individual's decision. This is why the random term is required, it is given by:

 $V_{nj}=\sum_{k} (\beta_{jk}*) X_{njk} + \sum_{t} (\beta_{jt} * S_{nt})$ Where:

 x_{njk} : the k^{th} attributes of alternative j that observed by individual n,

 S_{nt} : attribute of the individual n

 β_{jk} , β_{jt} : parameter coefficients to be estimated

When there are more than two options in the choice set, the Multinomial logit model (MNL) is used. The Binary Logit Model (BL) is a variant of the MNL in which individuals are given only two options, the "choice" experimental design is based on stated preference surveys and is adjusted to the project's specific objectives, restrictions, and variables.

2.2.1 Stated preference survey

By displaying "experiments," stated preference (SP) surveys help quantify how people might behave in a new situation. Respondents are asked to choose between various options, policies, products, or services that have both desirable and undesirable characteristics in these experiments. SP surveys are used in a variety of transportation studies.

Common areas where SP surveys excel include (1) mode choice studies used to predict the share or an absolute number of trips made by mode, they are useful for ascertaining the potential market share for new travel options, particularly transit before they are built. (2) Value of time and reliability studies are used to understand the monetary value travelers place on travel time or on saving time. These surveys are typically used to optimize toll fee structures and are a necessary part of any traffic and revenue study financed through bonds and they are used to understand future vehicle purchasing decisions. SP is also Useful to understand how new options (e.g., electric and automated vehicles) influence purchasing behavior and adoption rates of emerging and potentially disruptive technologies(Ortúzar 2000).

SP Survey contains two main parts, the first one is the selection of Attributes and Levels. Irrelevant information can negatively affect your results, careful background research (and even focus groups) are often required to reveal what is important and how best to describe it. The second is the Experimental Design which dictates what combinations of attributes and levels are shown in each experiment. This enables statistical estimation for utilities of any attribute independent of others. The experimental designs are generated by software such as design macros in SAS code, SPSS, Gene, etc. It is important to check the correlations between attribute combinations generated in a design (over 0.20 can be problematic because the correlation interferes with estimating coefficients) (Orme and Brian, 2012).

2.2.2 Discrete Choice model Estimation

Biogen (biogeme.epfl.ch) is specifically created for estimating discrete choice models and for estimating the maximum likelihood of random utility models. whereas Stata and Nlogit are general statistical packages. Model Estimation (BIOGEME) is a freeware package designed for the development of research in the context of discrete choice models in general, and Generalized Extreme Value models in particular (McFadden, 1978). Biogeme is capable of estimating MNL models with both linear and non-linear utility functions and with random coefficients, with Biogeme the documentation is comprehensive and has helpful examples. Since Biogeme requires an initial time investment, it is necessary to use an alternative software package to set up the data in the format required by Biogeme such as CSV files, etc. (Bierlaire,2009).

2.2.3 Factors influencing Mode choice

Individual travel mode choice is influenced by the attractiveness of various transport modes, as well as the socioeconomic and demographic characteristics of the trip maker. The efficiency of a transportation system is affected by travel behavior for mode choice determination. Each country's analysis of travel behavior may differ depending on methodology, data collected, attribute variables, and units of analysis.

1. socio-economic determinants

These are the determinants such as age, gender, income, employment status, and vehicle ownership, it is likely known that females prefer to use public transport mode than males. Most analyses identify income and automobile ownership as primary determinants for explaining international differences in mode choice (Dargay and Gately, 1999; Ingram and Liu, 1999; Schafer and Victor, 2000). Both variables are closely related: rising income levels make owning and maintaining a car more feasible.

2. Mode availability and characteristics

Mode Availability

A transport mode must be available to the traveler. Availability may not be able to always be clearly defined, (Witchayaphong,2020) found auto availability to be one of the determinants of mode choice, where availability is assessed as the number of automobiles per licensed driver in the household. Auto ownership and availability are known to have strong correlations with income. Various modal split studies suggest that the decision of whether or not to use a car for the trip to work is directly related to the decision of how many cars to own in the household. (Winston, 1985) suggest that the number of cars owned by households should be endogenous to the model structure. also, the availability of transport modes in a region affects the individual behavior.

Mode characteristics

The level of service given by the mode is usually measured by mode characteristics. For motorized (bus and car) modes, the following characteristics often used are In-vehicle time, Walk egress time, and Parking cost. For car modes, transport cost and the fuel cost (usually used as

the marginal cost for the trip that varies by the distance traveled). For transit modes, other characteristics that are often part of the mode choice model include: Walk access time, Initial wait time, Transfer wait time, Transfer travel time (e.g. walking between stops), and Number of transfers for motorized modes, characteristics are usually limited to time and or distance. Travelers' speeds for non-motorized modes may vary much more than for motorized modes. A small amount of research has been done on cycling modes, but it appears that bicyclists prefer paths with specialized bicycle facilities, fewer turns, less automotive traffic, and fewer traffic controls (Adnan et Al, 2018).

a. Travel Time and Costs

The two most widely studied factors of travel-mode choice are time and cost, this distinction was made on the notion that time spent traveling in various ways could be valued differently. Quarmby (2009) separated travel time into two variables, recognizing that the amount of time spent out of the vehicle on a journey may be greater for bus passengers than for car passengers. According to Frank et al. (2008), transit riders are more sensitive to travel time than to transit fares, and riders value waiting times more than in-vehicle time.

Travel time for various modes was identified as a significant predictor of mode choice (Cervero, 2002; Frank et al., 2008). Cervero (2002) demonstrated that taking public transportation takes longer than driving a car, which reduces the likelihood of taking PT.

The cost difference between modes of transportation is also said to influence mode selection decisions (Paulley et al., 2006; Redman et al., 2013; Pnevmatikou et al., 2015). For example, Redman et al. (2013) concluded that PT could attract car users by lowering travel costs, implying that offering promotional low-cost PT fares could help people free from car use. (Braff and Mackkay,1982) discovered that parking fees are a crucial variable, the effect of operating costs on mode choice was lowered by separating the parking-cost component.

b. Comfort, Convenience, and Safety

Comfort, convenience, safety, reliability, and dependability have also been incorporated into mode-choice models. Ackoff (2009) measured comfort and convenience and included these two variables with measures of travel time and travel cost in a mode-choice model. "Comfort" and convenience were not well defined, so there is a strong likelihood that these concepts were not uniformly interpreted. Stopher (2007,2008) recognized that data variables such as comfort, convenience, and safety may add considerably to the explanatory and predictive power of disaggregate mode-choice model.

c. Number of modes

Studies that looked at three or more modes analyzed the two modes at a time in the beginning. Recent research has gone beyond the binary choice to consider options in more than two modalities (Dissanayake,2007) Many analysts, however, are still limited to two modes. Rarely are criteria for evaluating a specific number of modes provided, Policy considerations, or researcher convenience. An alternative criterion for determining the number of modes to be used in the analysis would be the number of modes available to the consumer or in a particular region. In most studies that investigate mode availability, the analyst decides whether or not a particular mode is available by setting an arbitrary distance or time limit for access to the mode. Alternatively, accessibility could be determined by the respondent.

3. Geographic Location

Traveler characteristics such as geographic location have been found to be highly important predictors of alternate modes of transportation. The availability of transportation modes is typically found to be greater in urban cities than in rural areas. Location and income are frequently linked; upper-class consumers have gravitated to cities' outskirts, while others prefer to be closer to the central business district (Guerra,2015).

4. Passenger's perception

These are the determinants such as transport policy, law, parking fees, tolls, fuel-efficient transport, quality service, etc. policies directly or indirectly affecting travel mode choice, It was shown that these policies resulted in a major reduction in single-occupant vehicle usage. Similar implications were taken in China to reduce car dependency and minimize transport-related emissions by Jain and Tiwari (Jain &Tiwari, 2016).

5. Trip Purpose

Choice models are typically created for certain trips. The rationale is that while considering different sorts of trips, consumers evaluate modes differently (e.g. work versus shopping), A person going to work is not the same person as a man going to the sea. Most disaggregate mode-choice models have focused on the commute to work. According to De Donnea, 1972, one reason for this is the choice rule's supposed rationality and information availability, mode choice assumes that people are likely to perform better in the case of the journey to work than for other trip purposes. The reason is that having a daily experience of this type of trip, the people concerned probably have a better knowledge of all the alternatives open to them than when they make infrequent types of trips, the work-trip data are the most abundant because policymakers gather and use work-trip data to plan the maximum capacity of transportation networks.

As a consequence of this focus on work trips, past mode-choice modeling efforts have tended to ignore how individual decision strategies may vary for other different types of trips (Abdel,2017).for instance, the fact that a person wishes to use the car for social activities and shopping activities during or after work hours may override other considerations, such as cost and time.

The other influences on on-road users' mode choice behavior include weather conditions (rain), Trip distance, etc. This study will focus on individual characteristics, trip purpose, travel time, and travel cost alternative mode characteristics.

2.2.4 Differences in mode choice between countries

A comparative case study was undertaken in the United States and Germany to evaluate the fundamental aspects relating to transportation mode choice. According to (Buehler, 2011), The key disparities in the characteristics between the two countries revealed that the United States was more car-dependent across the board. Furthermore, Germans living in lower-density regions

who were farther from public transportation were more likely to use their private vehicles than Germans living in higher-density areas who were closer to public transportation. Germans were more prone to walk, cycle, and public transportation, Germany's regulations such as rising costs of private ownership, promoted this behavior.

(Kunert and Lipps, 2005) conclude that socio-economic considerations may be less important in industrialized countries since the majority of households own a car. In wealthy countries, demographic factors such as household composition and life cycle, gender, and age may be more important drivers of mode choice, According to other studies, the very young, the elderly, and women take fewer and shorter travels than working males aged 18 to 65. (Axhausen et al., 2003; Giuliano and Dargay, 2005; Timmermans et al., 2003). or regions.

3. METHODOLOGY

3.0 Methodology Framework

A complete methodology is established based on the findings of the literature review related to the estimation of the value for individuals in Kigali, Rwanda. To answer the first research question, this research employs a stated preference survey conducted in Kigali, Rwanda, the data collected are used to estimate the value of time through the Multinominal logit model.

The second research question is answered based on the literature review and survey results, the determinants of mode choice decisions are analyzed with the critical reflection hypothesis that is observable in the selected transportation modes and their variation in trip motives.

The methodology framework used for this research comprises approaches that are presented below:

Literature review	•Review of the relevant literature (value of time , discrete choice model , stated preference survey etc.
	•Experimental design
Stated preferance survey	Suvey questionnaire design
Data analysis	•Review of socioeconomic Data
	·Data set up
MNI	 Model calbration using Pandas biogeme
Value of time estimation	•Value of time per each travel time category

3.1 Stated preference survey

One way of measuring the value of time is to use a Stated Preference (SP) survey. In SC experiments, respondents will be presented with a series of hypothetical choice situations consisting of several alternatives and asked to select the one that they most prefer. These alternatives are usually distinguished by several predefined attributes and levels. choice experiments are the most powerful and flexible method of SP surveys. Choice experiments that ask respondents to choose between two or more alternatives (e.g., bus, train) each described by one or more attributes (e.g., time, cost). An attribute is a characteristic of a service or product (e.g., price, time, brand, or color), The development of the SP survey will include the following parts :

- Trip characteristics (trip purpose and alternatives)
- Attributes and their levels,
- Experimental design
- Experimental design into hypotetical scenarios questions.

3.1.1 Trip Characteristics

Trip purpose

(Nadezda,2011) studied how strongly income and work-related factors affect the estimation of the value of time using discrete mode choice and on the other hand, have an impact on the choice of travel mode. Based on the literature, a Work activity trip is used as the basis for estimating the value of time in this research, but it will also distinguish between the value of time allocated for work and that allocated for a shopping trip, so two trip purposes, work, and shopping trips, are used to determine the mode choice behavior.

Alternatives

Alternatives indicate the types of the mode used to travel for an activity, as per the literature and the transport in Kigali the main transport modes used are bus, motorbike, car, taxicab, and walk which are analyzed in terms of alternative: alternative 1: Bus, alternative 2:Motorbike, alternative 3:car, alternative 4:taxicab, and alternative 5:Walk. Alternatives are defined by a set of attributes that are individually assessed by travelers in deciding on choosing an alternative. An alternative is specified by / consists of attributes and attributes' levels.

3.1.2 Selecting Attributes and their levels

The attributes and levels should be chosen so that respondents are presented with meaningful and realistic situations. A literature review and interviews are typically used to select attributes and levels. At this stage, issues can arise; for example, Mangham et al. (2009) highlight that accesses to relevant information can be difficult to establish attributes and attribute levels. In this study, the attributes are chosen based on the existing literature.

Attributes

The attributes have been identified as relevant to the research question, which means they will be used to describe each alternative in the choice tasks; however, those attributes may differ from one alternative to the next. We first considered the attributes that result in preference formation when selecting alternative attributes. For example, if the two modes of transportation are bus and car, decision-makers are likely to examine attributes such as frequency of service, waiting time, and walking time (time spent waiting at the station and time taken walking to the station) when evaluating the bus alternative; none of these attributes are associated with the car. Instead, decision-makers are more likely to consider car-related factors such as fuel cost, tolls, and parking fees.

In this study, the selected attributes are travel time and travel cost defined in terms of differences in Alternatives characteristics. "Bus" (alternative 1) has four attributes, i.e., "In-vehicle travel time", "Waiting time", "Walking time" and " travel /ticket Cost". Motorbike (alternative 2) has four

attributes. "On motorbike time", Waiting time, walking time, and travel cost. Taxicab (alternative 3) has 4 attributes as well In-vehicle time, Waiting time, walking time, and travel cost. Car (alternative 4) has 3 attributes in-vehicle time, travel cost, and parking cost, and walk alternative 5 has one attribute "travel time/walking time". Once the attributes are established, levels must be assigned to each of these attributes.

Levels

Levels are the values allocated to the attributes, determining attribute levels for those alternatives was not an easy task, alternative may incorporate a mix of common values. the levels of attributes may differ from alternative to alternative. Despite attributes being shared by alternatives, the levels decision-makers are associated with each alternative are likely to be different for example There is no need for the decision-maker to travel to the station or bus stop if they choose to travel by car, and hence they are likely to be able to leave home later than the bus choice, The levels of the attributes per each mode are selected based on the review of average travel time and travel cost per mode in Kigali. Time is evaluated in minutes and cost is evaluated in Rwandan francs (rwfs) (within the current (Bank of Kigali, May 2022) currency 1Euro = 1123.7213 rwfs), the four levels per each attribute have been selected to give a good approximation of the true underlying utility function. The attributes and levels are summarized in table 1 :

Attributes	Levels				
	Bus	Motorbike	Taxicab	Car	Walk
In vehicle time /On motorbike time(min)	<15 ,15- 30,30-45,>45	<15 ,15-30,30- 45,>45	<15 ,15-30,30- 45,>45	<15 ,15-30,30- 45,>45	x
Waiting time (min)	<10,10- 20,20-30,>30	<5,5-10,10- 15,>15	<5,5-10,10- 15,>15	x	х
Walking time (min)	<5,5-10,10- 15,>15	<5,5-10,10- 15,>15	<5,5-10,10- 15,>15	x	<30,30- 45,45- 60,>60
Travel Cost/ Rwfs	<300,300- 400,400- 500,>500	<500,500- 1000,1000- 1500,>1500	<2500,2500- 5000,5000- 7500,>7500	<500,500- 1000,1000- 1500,>1500 <300.300-	x
Parking cost (rwfs)	x	x	x	500,500- 1000,>1000	х

TABLE 1 Attributes and their levels.

3.1.3 Experimental design

Having identified the alternatives, attributes, and their levels, the next step is to design several choice sets that can be derived from alternatives with their attributes and levels, the number of possible alternatives is usually too large to have all respondents give their preference on all of

them. The goal of the experimental design is to choose the options and attribute combinations that force respondents to trade-off between the traits and so provide information about their preferences. For a given number of choice tasks, efficient experimental designs optimize the precision of estimated parameters of interest.

The process of drafting, testing, and optimizing the experiment questionnaire is involved in designing a stated or discrete choice experiment (DCE). There is statistical software that can be used in the design of SPSS, SAS code design macros, etc. The experimental design has created using the coding of design Marco to represent the possible combinations. This coding format assigns a unique number to each attribute level, beginning with 0, then 1, and proceeding to L–1 and the number of choices set given by (L-1)*M*A, where L is the number of levels, M the number of alternatives and A the number of attributes, SAS code is used to randomize the design using the linear statistical model experimental design.

Design Macros SAS Code experiment design

SAS code is used to allocate the attributes to design columns, the code has a rather stable syntax that is commonly used (design macros).it includes several basic procedures for designing experiments and analyzing experimental data and for data analysis, including proc plan, proc fact, proc optic, and the menu-driven SAS ADX for experiment design, and proc glm, proc Var comp, and proc mixed. The SAS code using the design macro provided several 32 choice scenarios per each alternative (the detailed code can be found in annex 1.) The experiment Window after the design Generated by SAS is shown in the figure below :

The SAS System					
Final Results	Set	x1	x2	x 3	x4
Design 4 Choice Sets 32	1	2	2	1	4
Alternatives 4 Parameters 12		3	4	2	1
Maximum Parameters 96 D-Efficiency 32.0000		1	3	3	3
Relative D-Eff 100.0000 D-Error 0.0313		4	1	4	2
	Final ResultsDesign4Choice Sets32Alternatives4Parameters12Maximum Parameters96D-Efficiency32.0000Relative D-Eff100.0000D-Error0.03131 / Choice Sets0.0313	Final ResultsDesign4Choice Sets32Alternatives4Parameters12Maximum Parameters96D-Efficiency32.0000Relative D-Eff100.0000D-Error0.03131 / Choice Sets0.0313	Final ResultsDesign4Choice Sets32Alternatives4Parameters12Maximum Parameters96D-Efficiency32.0000Relative D-Eff100.0000D-Error0.03131 / Choice Sets0.0313	Final ResultsSet x1 x2Design4Choice Sets32Alternatives4Parameters12Maximum Parameters96D-Efficiency32.0000Relative D-Eff100.0000D-Error0.03131 / Choice Sets0.0313	Final ResultsSet x1 x2 x3Design4Choice Sets32Alternatives4Parameters12Maximum Parameters96D-Efficiency32.0000Relative D-Eff100.0000D-Error0.03131 / Choice Sets0.0313

FIGURE 2 Experimental window in design macro.

After rearranging all the data with their index and set as generated by the design macro, the table below shows the combined choice sets per each alternative, the table below shows Choice set design example for bus Vs car alternatives:

TABLE 2 Generated choice sets.

	attribute	X1	X2	X3	X4
	In vehicle time	<15	15-30	30-45	>45
Set 1	Waiting time	20-30	10-20	>30	<10
bus	Walking time	10-15	<5	5-10	>15
	Travel Cost	400-500	>500	<300	300-400
	attribute	X1	X2	Х3	X4
Set 1	In vehicle time	<15	15-30	30-45	>45
Car	Travel cost	<500	>1500	500-100	00 1000-1500
	Parking cost	<300	500-100	0 >1000	300-500

The design macros code generated 32 choice sets per each mode , given 4 choices per scenario. The total of 128 scenarios are used to create the scenarios where the individual will choose their preferences.

3.1.4 Scenarios design

"Scenarios" are combinations of attributes and levels for each alternative. SP data represents choices in hypothetical situations; this may result in situations in which personal constraints are not taken into account at the time of choice; it is therefore recommended that the hypothetical scenarios be as realistic as possible.

The choice scenarios in all SP experiments are within-mode choices. Each scenario set consists of five alternatives, which were introduced as specific attributes that differ in terms of cost, invehicle time, waiting time, and walking time variability from the choice set design generated through design macros SAS code. The example of the scenarios design created is shown in table 3:

TABLE 3 Scenario design.

Set 1,X1	Attribute	tribute Bus Motorbike Taxi		Taxi	Car	Walk
	In vehicle time	8	8	8	8	Х
	Waiting time	25	13	8	х	Х
	Walking time	13	13	8	х	15
	Travel Cost	450	1250	3750	250	Х
	Parking cost	Х	Х	Х	150	х

3.2 Survey Questionnaire design

Several survey software products are available, this study used Qualtrics an integrated tool that allows to create surveys, publish them, and collect responses; it is an excellent tool for online surveys. By using Qualtrics, two major parts of the web-based survey questionnaire were created: the first part contains respondents' socioeconomic information, and the second part consists of a

set of various hypothetical choice scenarios, in which each respondent is given four different hypothetical scenarios to choose one alternative from a set of five alternatives for work and shopping activity, followed by questions about mode choice attributes selection criteria questions to understand more the individual choice behavior. the online survey was designed in a way that is easy for the respondents to operate on mobile devices and computer devices.

3.2.1 Questionnaire Survey Parts

Part 1 : Socioeconomic characteristics

Most analyses identify income and automobile ownership as primary determinants for explaining differences in mode choice, (Schafer and Victor, 2000) stated that females are more likely to take public transport than men, Socioeconomic conditions differ significantly across regions, resulting in differences in VOTs and mode choices. This part collected the socioeconomic characteristics of the respondents to analyze the determinants of mode choice and the value of time estimate.

The collected individual socioeconomic characteristic and their levels are shown in table 4.

Gender	Age	Occupation Levels	Education levels	Household Compositio n	Household monthly income (Rwfs)	mode ownershi p	Driving license
			Low : < Primary				
Male	18-24	Student,	T fiftary,	1	<100,000	Car	Yes
			Medium :				
		Unemploye	Primary-				
		d	Secondary,		100,000-		
Female	25-30			2	500,000	Motorbike	No
		Governmen	High :				
		t Employed	University-		500,000-		
	31-40		Masters	3_5	1,000,000	Taxicab	
		Private Company					
		Employed	Very High :		1,000,000-		
	41-50	Self	PHD	5_7	1,500,000	Others	
		Employed			1,500,000-		
	51-60			>7	2,000,000	None	
					>2,000,00		
	60+	Retired			0		
		Housewife					

TABLE 4 Socioeconomic characteristics levels.

Part 2: Hypothetical Scenarios Question

Out of the following alternatives, Select One which you would like to use for work, and one which you would like to use for shopping.



FIGURE 3 Hypothetical choice scenario example.

3.2.2 Randomization

Randomization was done to mitigate possible biases, for instance, the experiment design contain 128 scenarios which can be a difficult task for an individual to answer all the scenarios, randomization was implemented using the Qualtrics Choice tasks randomization question in the "Block Options" .blocking is partitioning the experimental design into blocks that contain a limited number of choice tasks for each respondent. Based on the content of each scenario, in terms of alternatives, attributes, and levels, we choose to randomize 4 hypothetical scenarios to each individual for the demonstration and leave the respondents time to analyze the various scenarios.

Using Qualtrics survey flow, Before the first-choice task, a Randomizer is used to define an embedded Data that takes the value groups (group 1, group 2, etc.) This Embedded Data is used to create branches that will allow displaying blocks of choice tasks conditionally on the value of the embedded Data.

	×	Randomizer Randomly	present	31 🕀	of the fol	owing element	is 🔽 Eve	enly Present E	Elements	Edit Count Add Below	Mov	re Dupli	cate Colla	apse Delet	e			
		+	ED Set	grou grou	dded Da	d				Add B	elow	Move	Duplicate	Add From C	ontacts	Option	s Delete	
+	~	Then Bran	ch lf: Is Equal to 1	Edit C	ondition					Мс	ove	Duplicate	Options	Collapse	Delete	e		
			+ Add a f	Show E	Block: Q	uestionnaiı	re 1 (9 Qu	estions)						Add	Below	Move	Duplicate	Delete

FIGURE 4 Randomized block design.

After the hypothetical scenarios, the respondents were asked to rank the attributes by their importance in their daily mode choice pattern and the questions to know which attribute they considered most while making their choices. A full version of the survey questionnaire in Qualtrics can be found in annex 2.

3.3 Data Collection

The data collection was done in Kigali, the current population of Kigali city is around 1.8 M Although the method for data collection is much easier and most convenient, it has a series of drawbacks and the most common ones are response turn-out and inability to follow-up with, etc. the survey was designed in English as the second language used by most of the population after the local language and the actual administration of questionnaires was made using emails and social media.

Sampling and Targeted Respondents

The targeted sample size of respondents is 250 responses due to the time constrain and the collecting data methodology (online), there is the need for a very high response rate to improve the actual representation of the residents of Kigali , Most of them prefer social media to email, but not all of them have internet access. To collect more data, the process was expanded to include social media platforms, and a pilot survey with 10 respondents was conducted.

The targeted population is the inhabitants of Kigali in its 3 districts, Aside from its geographical position (hilly), Kigali is densely populated and mostly occupied by Rwandans, there is no high observation of diversity from other countries. The population in Kigali is relatively young- the youth (age 15-34) make up about 60% and women make up slightly more the 50%. Rwanda's average annual household income is low (about \$400),(IGC,2015), based on its socio-demographic and economic characteristics, the response rate can be reduced and affected.

having various functionalities in Kigali such as education, shops, Hospitals, etc. The research shall target a population of 18-40 ages with their access to the social media and English knowledge, it will also target the population with smartphones and computer devices.

3.4 Data Analysis

(1) The analysis of socioeconomic characteristics part of the survey was done using SPSS and results from analysis options provided by Qualtrics (the results will be discussed in section 4).

(2) Data setup: to calibrate the discrete choice model using Biogeme version 3.2.8 to set up the data in a form required by Biogeme, the data collected will be analyzed and be made ready for pandas Biogeme, the data set up has been done by coding the data and save the file in CSV file : The code file name called: "MNL_model_murielle.csv" contain the following coding summary table (see table 7).

3.5 Discrete choice Model using Pandas Biogeme

This part provides an overview of the software for estimating the discrete choice model as described in the literature. Pandas biogeme (biogeme.epfl.ch) is the programming language that requires user-written code, it is specifically created for estimating discrete choice models and has the capacity of estimating MNL models with both linear and non-linear utility functions and with random coefficients. Biogeme has been used to calibrate a multinomial logit model with 5 alternatives, the utility function associated with alternative i is given by :

 $Vi = ASC_i + \beta_1 x i_1 + \beta_2 x i_2$, where :

i: an alternative

Vi : utility of alternative i

ASC_i : alternative specific constant of mode *i*

 β_1 , β_2 : beta coefficients to be estimated

xi : are the variables of the model associated with each alternative.

In order to estimate the coefficients of the model, the alternative specific constant ASC_i not all of them are identified it has the value of 1 if the associated alternative is available for the current observation, and 0 otherwise. The MNL biogeme command contain 5 main parts (the detailed code is found is found in Annex 3).:

(1) Import package, biogeme database: that describes to biogeme where the dependent variable can be found in the file and the package is defined.
(2) Beta: this section describes to BIOGEME 1.8 the list of coefficients that must be estimated. The syntax is:

```
#model ASC
ASC_Bus = Beta('ASC_Bus',0,-100,100,0)
ASC_Motorbike = Beta('ASC_Motorbike',0,-100,100,0)
ASC_Taxicab = Beta('ASC_Taxicab',0,-100,100,0)
ASC_Car = Beta('ASC_Car',0,-100,100,0)
ASC_Walk = Beta('ASC_Walk',0,-100,100,0)
```

#Travel time betas β , β _ttime = Beta('B_ttime',0,-100,100,0) β _wait_time = Beta('B_wait_time',0,-100,100,0) β _walk_time = Beta('B_walk_time',0,-100,100,0) #Travel cost betas

 β _travel_cost = Beta('B_travel_cost',0,-100,100,0)

β_parking_cost = Beta('B_parking_cost',0,-100,100,0)

- (3) Utilities: This is where the specification of the utility functions is described. The specification for one alternative must start at a new row, and may actually span several rows. For each of them, four entries are specified: [Utilities]
- 1: V_{Bus} av1: $ASC_Bus + \beta_ttime * Bus_ttime + \beta_wait_time * Bus_wait_time + \beta_waik_time * Bus_walk_time + \beta_travel_cost * Bus_travel_cost$
- 2: $V_{Motorbike}$ av2: ASC_Motorbike + β _ttime * Moto_ttime + β _wait_time
 - * Moto_wait_time + β _walk_time * Moto_walk_time + β _travel_cost
 - * Moto_travel_cost
- 3: $V_{Taxicab}$ av3: $ASC_Taxicab + \beta_ttime * Taxicab_ttime + \beta_wait_time$
 - * Taxicab_wait_time + β _walk_time * Taxicab_walk_time + β _travel_cost * Taxi cab travel cost
- 4: V_{Car} av4: $ASC_Car + \beta_ttime * Car_ttime + \beta_travel_cost * Car_travel_cost + <math>\beta_parking_cost * Car_parking_cost$

5: V_{Walk} av5 : ASC_Walk = β _ttime * Walk_ttime

- (4) Expressions: it describes to Biogeme how to compute attributes not directly available from the data and the file.
- (5) Model: it tells to Biogeme which assumptions must be used regarding the error term and which type of model must be estimated which is the multinomial logit model.
- (6) The other parts of the MNL code in biogeme are the file where the results will be saved and in pandas table.

3.5.1 Maximum likelihood (MLE) - Model overall Goodness of Fit

Maximum likelihood estimation is used to estimate the parameters in utility equations; V_Bus, V_Car, V_Motorbike, V_Taxi, and V_Walk. Maximum likelihood estimation is a method of determining the parameter values of a model in a way that maximizes the probability that the described procedure by the model matches the observed real data. The maximum likelihood method assumes that each time the observed choices are independent. This implies that the function of likelihood can be expressed as the product of single choice likelihood. it is a way to measure the goodness of fit for a model, MLE has been estimated in Pandas Biogeme.

The goodness fit measure how well the model fit, it can be calculated using the formula below however the panda's biogeme also provide its values.

$$\rho^{2}=1-L(\beta^{})/(L(0))$$
 and $\rho^{-2}=1-(L(\beta^{})-K)/(L(0))$.

The R-squared, also known as the coefficient of determination, is the percentage of variance in the dependent variable that can be explained by the independent variable. If the R-squared value is less than 0.3, this value is generally considered of very weak effect size, 0.3 < r < 0.5 is considered weak or low effect size, If 0.5 < r < 0.7 considered of moderate effect size, If R-squared value value > 0.7, this value is generally considered strong effect size, (Flinger and Notz,2013).

ρ2 increases when an additional variable is added to the model, the high value rho square represent that the model is better.

3.5.2 Individual Parameter testing

The individual parameter estimate can be valuated using the formula:

• t-statistics = $\frac{\widehat{\beta}_k}{\sigma_k}$ where ,

 $\widehat{\beta_k}$: the estimate of the kth parameter and

 σ_k : the standard error of the parameter estimate.

The parameter is considered significant if its t-statistics is larger than or equal to 2.0, which indicates that the level of significance is over 95%. (Abdel, 2017).

• P – value : is calculated as $p_k = 2(1 - \Phi(t_k))$ where Φ : the cumulative density of standard normal distribution. For a parameter to be significant , its p_value must be < than 0.05 (5%).

P-value and t statistics provide the same information to the model and are used to determine how significant each estimated parameter is to the model.

3.6 Value of time

The coefficient of the cost and the coefficient of the travel time estimated in the MNL capture the sensitivity of the travelers' utility toward changes in the travel time and the cost. As a result, their ratio can be used to capture the trade-off between travel time and travel cost, or the VOT.

The utility is in general unitless. To simplify notation, it is sometimes useful to express it in an imaginary unit of "utils " (Antoniou,2007). Assuming that the travel cost is measured in rwfs (Rwandan francs) and the travel time is measured in minutes, the units of the respective coefficients would then be utils/rwfs and utils/min, respectively. The ratio of the coefficient for the travel time over the coefficient for the travel cost will have units of rwfs/min (or rwfs/hr if multiplied by 60), which is the expected unit for a VOT measure (cost per hr):

 $VOT = \left(\frac{\beta time}{\beta cost}\right)^{\cdot}$, Coefficient of Travel Time/ Coefficient of Travel Cost

The travel time are categorized in in vehicle time, walking time and waiting time, the values of time per each category will be calculated as follow:

Value of In vehicle time = $\frac{\beta_{-}ttime}{\beta_{-}cost}$,

Value of walking time = $\frac{\beta_walk_time}{\beta_cost}$ and

Value of waiting time = $\frac{\beta_wait_time}{\beta_cost}$.

4. RESULTS AND ANALYSIS

4.1 Preliminary Data Analysis

4.1.1 Overview of Obtained Data-SP survey

The online questionnaire survey was distributed via social media using the link, the survey sample of respondents was random and resulted in a total number of 336 respondents among them 69.1 % finished the questionnaire survey at 100% and 30.9% did not finished the questionnaire. the survey lasted for two weeks 28th Feb- 6th March 2022(66% responses) and 7th -13 march 2022 (25% responses). The overall analysis is based on the participants who completed the survey, this gives a number of 234 respondents.

The pilot survey was distributed to a random sample of 15 respondents in the form of an online questionnaire survey. Respondents were asked to complete a survey for testing purposes. After filling out the survey, the researcher interviewed them, asking for general feedback of the survey, how it is understandable, the time required to answer the questions, and understanding of the hypothetical scenarios. This approach reduced the number of errors that could occur in the survey and improved model estimation results after the survey, particularly in terms of scenario information and completion speed. Following the pilot survey and updates, the final survey was launched. According to the methodology, There were two sections into the questionnaire (see Annex 2 full completed survey sample).

1. Socioeconomic Characteristics

The socioeconomic characteristics part included 10 questions regarding the demographic and economic characteristics of the respondents .

Descriptive statistics

The data findings in Table 5 reflect individual socioeconomic characteristics. The genders are nearly balanced between male and female (54.9 percent and 45.1 percent) respectively. In terms of age, the majority are between 25-30 and 31-40 years old. This is due to the type of data collection (online survey), the fact that the majority of the population has a low income (access to the internet, smartphones, and computer devices), and the English language barrier, which can affect responses for those over 45 years old.

The respondents' education level is high between university and master's, but the majority have a university/bachelor's degree (although university and master's levels are combined). The household income reflects the average monthly income of the population, which is estimated at 400,000 rwfs as stated in section 1 of the study, with 52.2 %of the majority having a household size of 3-5 people. Most of the respondents (53.1%) do not own any mode of transportation, followed by those who own a car and those who own other modes of transportation such as bicycles, trucks, etc.

Characteristics	Levels	Frequency	Percentage	mean	SD
Gender	Male	134	54.9	1 15	0.50
	Female	110	45.1	1.45	0.50
	18-24 years	25	10.2		
	25-30 years	117	48.0		
Age	31-40 years	90	36.9	2.38	0.77
	41-50 years	9	3.7		
	51-60 years	3	1.2		
	1	16	6.6		
Fomily gize or	2	35	14.3		
Household size	3-5	128	52.5	3.05	0.93
	5-7	50	20.5		
	>7	15	6.1		
Education Status	Primary-Secondary	8	3.3		
	Technical courses	5	2.1	3 92	0 39
	University-Masters	229	94.2	0.52	0.00
	PHD	1	0.4		
	Student	24	9.9		
	Government Employed	60	24.7		
Employment status	Private company Employed	108	44.4	2.83	1.03
	Self Employed	40	16.5		
	Unemployed	9	3.7		
	Housewife	2	0.8		
	< 100,000	31	12.8		
Llouoobold	100,000-500,000	124	51.0		
monthly income	500,000-1,000,000	47	19.3	2 50	1 1/
(Rwfs)	1,000,000-1,500,000	25	10.3	2.30	1.14
(11110)	1,500,000-2,000,000	8	3.3		
	>2,000,000	8	3.3		
	Car	110	43.5		
Modo Ownorship	Motorbike	23	9.1		
	Taxi	8	3.2	1.00	0.00
	None	115	45.5		
	Others	3	1.2		
Driving License	Yes	129	53.1	1 /7	0 50
Driving Libense	No	114	46.9	1.41	0.00

TABLE 5 Socioeconomic characteristics - descriptive statistics.

2. Mode choice scenarios

The survey contained 128 hypothetical scenarios, and by randomly assigning 4 scenarios to each respondent, 32 scenario groups were created in the survey using a randomization method. Each respondent was asked to respond to four different hypothetical scenarios and choose an alternative preference for work and shopping trips. After these four scenarios, respondents were asked to rate the attributes based on their importance in influencing their alternative/mode choice.

Each respondent was presented with four scenarios, yielding a total of 936 observations. The scenarios included various modes of transportation (bus, motorcycle, car, taxicab, and walk), travel costs, and travel time. The in-vehicle travel times used in the SP experiments range between 60 and 100 minutes, the waiting time between 3 and 30 minutes, and the walking time between 8 and 25 minutes, with differences in the experimental design ranges reflecting the sensitivity of the real situation. Travel costs for the alternatives ranged between 150 and 10000 rwfs, while parking costs varied between 250 and 1500 rwfs. These travel times and costs represent realistic values for intracity trips in Kigali at various destinations to their workplace and shopping places.

1. Distribution of respondents and alternatives

Table 6 shows that the majority of respondents prefer bus mode and car mode (difference of 0.3 percent) for working activity, despite the economic characteristics of the majority of respondents (average household income equal to 300,000 rwfs). It also reflects the respondents' mode ownership (45.5 percent own no mode and 54.5 percent own a mode (43.5% own car mode). The majority prefers to shop by car, demonstrating respondents' preference for the dependability and comfort of car use in this activity.

Mode	Work Choice		Shopping choic	ce
	Frequency % F		Frequency	%
Bus	270	28.8	230	24.5
Motorbike	253	27.0	213	22.7
Taxi cab	52	5.6	57	6.1
Car	267	28.5	270	28.8
Walk	94	10.0	166	17.7
Mean	2.64		2.92	
SD	1.41		1.48	

TABLE 6 Distribution of respondents	s choices and alternatives
-------------------------------------	----------------------------

2. Mode choice influential variables

2.1 Mode attributes vs mode selection criteria

The respondents were asked to specify the transport mode attributes criteria while making their mode choice for work and shopping trips, The majority of respondents considered vehicle time (23.9 percent and 19.3 % for work and shopping trips, respectively), followed by travel cost (14.85 % and 10.7 % for work and shopping trips, respectively). We can conclude that all travel time and

travel cost mode-specific attributes are important in Kigali population mode choice.(see figure 5 below).





FIGURE 5 Alternative attributes vs alternative choice.

2.2 Car consideration and mode choice scenario

The respondents were asked to consider owning a car or not for both activities. According to the figure 6, 69 % of respondents would consider changing their choice if they don't own a car, and 48.6 % would continue to make the same choices while considering owning a car. The percentage of mode ownership as indicated in the descriptive statistics, the majority (45.5%) don't own a car, thus the mode ownership(owning a car or not) can lead to a change in mode choice behavior.(see figure 6 below).



FIGURE 6 Car consideration and alternative choice.



2.3 Travel time and travel cost

FIGURE 7 Travel time vs travel cost.

When comparing travel time and travel cost, the overall travel time is shown to be the most important criterion for choosing a mode of transportation for the majority of respondents, followed by travel cost. This demonstrates that respondents are willing to save their travel time over the cost of travel. Other people weighed in on all of the factors, particularly the waiting and walking times, as well as other factors such as traffic jams, travel distance, safety, peak hours, weather conditions, road types, emergency situation etc. (figure 7).

4.1.2 Data setup

As described in the methodology , calibrating the multinominal logit model in biogeme require coding of the data and Csv file format , the table 7 shows how the data from the survey were coded.

	count	mean	std	min	25%	50%	75%	max
User_ID	936	122.006	69.9358	1	61	123.5	182	241
Group	936	17.0652	9.28255	1	9	17	26	32
Gender	936	1.44979	0.49774	1	1	1	2	2
Age	936	2.37073	0.76861	1	2	2	3	5
Education_level	936	3.91453	0.39402	2	4	4	4	5
Household_size	936	3.03953	0.92357	1	3	3	4	5
Ocupation	936	3.56517	1.14417	1	3	4	4	7
Household_monthly_income	936	2.52885	1.17242	1	2	2	3	6
Mode_Ownership	936	2.98825	1.93501	1	1	2	5	5
Driving_Liscence	936	1.47222	0.4995	1	1	1	2	2
Bus_ttime	936	32.0278	19.1904	8	8	23	38	60
Bus_wait_time	936	21.0951	12.9764	5	8	15	25	40
Bus_walk_time	936	13.5481	10.1475	3	3	13	15	30
Bus_travel_cost	936	388.675	163.632	150	300	450	487.5	600
Moto_ttime	936	32.0278	19.1904	8	8	23	38	60
Moto_wait_time	936	15.5417	29.1387	3	3	8	13	330
Moto_walk_time	936	13.766	10.2195	3	8	13	30	30
Moto_travel_cost	936	1075.75	630.062	300	750	1250	1250	2000
Taxicab_ttime	936	32.0278	19.1904	8	8	23	38	60
Taxicab_wait_time	936	13.5897	10.1554	3	8	13	30	30
Taxicab_walk_time	936	13.5331	10.3364	3	3	8	30	30
Taxi_cab_travel_cost	936	5183.68	3072.62	375	1250	6250	7887.5	9500
Car_ttime	936	31.9797	19.1942	8	8	23	38	60
Car_travel_cost	936	1076.12	654.694	250	250	1250	2000	2000
Car_parking_cost	936	712.607	527.421	150	362.5	750	750	2000
Walk_ttime	936	48.688	27.2205	15	15	38	53	90
Work_Choice	936	2.63889	1.40813	1	1	2	4	5
Shopping_Choice	936	2.92415	1.4849	1	2	3	4	5

TABLE 7 Data setup for Biogeme

4.2 Model Estimation Results Using MNL

The Pandas biogeme software is used to calibrate the multinomial logit model of five alternatives based on the information gathered, as explained in Section 3 and the table 7 .The following equation provides the basic model for the utility function of work activity:

V_Bus = 0 + β _ttime * Bus_ttime + β _wait_time * Bus_wait_time + β _walk_time * Bus_walk_time + β _travel_cost * Bus_travel_cost

 $V_Motorbike = ASC_Motorbike + \beta_ttime * Moto_ttime + \beta_wait_time * Moto_wait_time + \beta_walk_time * Moto_walk_time + \beta_travel_cost * Moto_travel_cost$

 $V_{Taxicab} = ASC_{Taxicab} + \beta_{ttime} * Taxicab_{ttime} + \beta_{wait_time} * Taxicab_{wait_time} + \beta_{wait_time} * Taxicab_{wait_time} + \beta_{travel_cost} * Taxi_{cab_travel_cost}$

 $V_Car = ASC_Car + \beta_ttime * Car_ttime + \beta_travel_cost * Car_travel_cost + \beta_parking_cost * Car_parking_cost .$

V_Walk = ASC_Walk + β _ttime * Walk_ttime (3)

The basic specifications of each alternative (β _ttime, β _wait_time, β _walk_time, β _travel cost, β _parking_cost) the coefficients to be estimated, the actual choice have the value of 1 if the associated alternative is available and 0 otherwise. for the current observation Assume one utility constant ASC BUS = 0, the results are as follow:

4.2.1 Estimation report for work activity

1. Model fits results - The loglikelihood value

TABLE 8 Model fits results-work activity.

Model	Multinomial Logit
umber of estimated parameters:	9
Sample size:	936
Excluded observations:	0
Init log likelihood (L(0):	-4418.469
Final log likelihood (L(^_):	-1340.716
Likelihood ratio test for the init. Model:	6155.505
Rho-square for the init. Model (p^2 _2):	0.697
Rho-square-bar for the init. Mode(P ⁻² _2):	0.695
Akaike Information Criterion:	2699.432
Bayesian Information Criterion:	2743.006
Final gradient norm:	4.6224E-03
Nbr of threads:	1
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%

Relative projected gradient:	6.848874e-07
Relative change:	6.138786571088795e-11
Number of iterations:	23
Number of function evaluations:	54
Number of gradient evaluations:	16
Number of hessian evaluations:	16
Cause of termination:	Relative change = 6.14e-11 <= 1e-05
Optimization time:	0:00:00.505384

The higher a model's log-likelihood value, the better it fits a dataset. The log-likelihood value for a given model can range from negative infinity to positive infinity. The likelihood ratio, which describes the model's overall goodness of fit, has a high value of (6155.505) for N=936 (the number of observations used in the parameter estimation process). Perfect predictive accuracy is defined by the rho-squared value (q2), which ranges from 0 to 1. Henseler (2009), defines significant, moderate, and weak rho-squared values as 0.75, 0.50, and 0.25, respectively.

The rho-square value in this model indicates that the estimated variables have a moderate effect on the model. The data in Table 8 confirms that the dataset is a good fit for multinominal logit, allowing it to predict mode choice decisions reliably.

2. Estimated parameters

					Rob. Std	Rob. t-	Rob. p-
Name	Value	Std err	t-test	p-value	err	test	value
ASC_Car	0.121	0.156	0.775	0.438	0.158	0.764	0.445
ASC_Motorbike	0.00908	0.0931	0.0975	0.922	0.0962	0.0944	0.925
ASC_Taxicab	-1.15	0.223	-5.16	2.52e-07	0.222	-5.19	2.07e-07
ASC_Walk	0.0781	0.264	0.296	0.768	0.273	0.286	0.775
β_parking_cost	-0.000327	0.000142	-2.29	0.0218	0.000141	-2.31	0.0207
β_travel_cost	-0.000118	4.24e-05	-2.78	0.00542	4.88e-05	-2.42	0.0157
β_ttime	-0.0932	0.0175	-5.31	1.07e-07	0.0178	-5.24	1.59e-07
β_wait_time	-0.00143	0.00245	-0.582	0.561	0.00304	-0.468	0.64
β_walk_time	-0.0104	0.00506	-2.06	0.0398	0.00498	-2.09	0.037

TABLE 9 Estimated parameters -work activity.

The sign of parameters

The most basic test of estimation results is to look at the signs of the estimated parameters to see how a variable affects the model. It is clear from the results in table 9 that the travel time and travel cost coefficients/parameters estimates have the correct signs (negative signs). Are important to the model, for example, the cost parameter is typically expected to be negative, implying that as the cost increases, the utility or attractiveness of the alternative decreases. However, the alternative taxicab-specific constants have a negative sign, indicating a bias toward Taxi cab mode.

Parameter testing

The parameter is considered significant if its t-statistics is greater than or equal to 2.0, indicating that the level of significance is greater than 95%. A parameter estimate with t-statistics less than 2.0 is considered less significant, as is a parameter with a P-value less than 0.05 is considered as significant. Looking at the P-values in table 9, the results show that all of the β estimated coefficients are significant except for the β -wait time coefficient, which is 0.561 (this could be due to the sample size for the desired model effect, or some variations in hypothetical choice scenarios of specific mode attributes). The in vehicle time coefficient (β -ttime) is more significant than the other parameters.

In summary, the model estimation session was a success. The variables in the model have the proper sign for the main parameters : in vehicle time (β _ttime), waiting time (β _wait_time), walking time (β _walk_time), parking cost (β _parking _cost) and travel cost (β _travel_cost).

4.2.2 Estimation report for Shopping activity

1. Model fit

TABLE 10 Model fit results- Shopping activity

Modal	Multinomial logit
Number of estimated parameters:	9
Sample size:	936
Excluded observations:	0
Init log likelihood (L(0)):	-1490.496
Final log likelihood (L(^_)):	-1397.653
Likelihood ratio test for the init. Model:	185.6854
Rho-square for the init. Model (p^2 _2) :	0.0623
Rho-square-bar for the init. Model (P ⁻ 2_2):	0.0563
Akaike Information Criterion:	2813.307
Bayesian Information Criterion:	2856.881
Final gradient norm:	6.2952E-03
Nbr of threads:	1
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	2.604466e-06
Relative change:	5.206459344961334e-05
Number of iterations:	4

Number of function evaluations:	13
Number of gradient evaluations:	5
Number of hessian evaluations:	5
Cause of termination:	Relative gradient = 2.6e-06 <= 6.1e-06
Optimization time:	0:00:00.130744

2. Estimated parameters

						Rob. t-	Rob. p-
Name	Value	Std err	t-test	p-value	Rob. Std err	test	value
ASC_Bus	-0.223	0.163	-1.37	0.171	0.161	-1.38	0.167
ASC_Motorbike	-0.229	0.156	-1.47	0.143	0.155	-1.48	0.139
ASC_Taxicab	-1.08	0.233	-4.63	3.62E-06	0.228	-4.73	2.28E-06
ASC_Walk	0.146	0.223	0.654	5.13E-01	0.23	0.635	5.25E-01
B_parking_cost	-0.000223	0.00014	-1.59	0.112	0.000137	-1.62	0.105
B_travel_cost	-0.000133	4.17E-05	-3.18	0.00146	4.55E-05	-2.92	0.00352
B_ttime	-0.0601	0.012	-5	5.64E-07	0.0122	-4.91	9.01E-07
B_wait_time	-0.00334	0.00299	-1.12	0.263	0.00327	-1.02	0.307
B_walk_time	-0.00821	0.00522	-1.57	0.0116	0.00528	-1.56	0.12

Table 11 Estimated parameters -Shopping activity.

The model for work trips is estimated more appropriately than the shopping trips because the value of the loglikelihood estimated is higher for work trips.. Based on the Rho square results of the model (0.05), the variables have a very weak effect on the model (less than 0.3). This concluded that various studies consider the purpose of work trips in calibrating the model more than other trips, work trips are suitable for analyzing mode choice behavior and evaluating the value of time as well. This analysis shows why various studies consider work trips are suitable for analyzing mode choice behavior and evaluating the behavior and evaluating the value of time as well.

Although all of the estimated travel times and travel costs have correct signs (positive signs), the parking cost and walking time coefficients are insignificant because their P-value is greater than 0.05. This bias could be due to the sample size effect (which may not results in a better model) and variations in hypothetical choice scenarios and specific mode attributes; this demonstrates the influence of mode choice behavior on trip purpose.

For the mode attributes specific between modes, the Walk mode-specific constant with a positive sign indicates that it has less preference when traveling for shopping activity than other modes. the taxicab has a higher value than the bus and motorcycle, which may be related to other attributes such as comfort and reliability despite being expensive. Despite parameters having minor effect to the model and waiting time, parking cost coefficients being insignificant to the multinomial logit model, there are used to estimate the value of time simply because the estimated coefficients have the correct signs.

4.3 Value of Time estimation

The ratio between travel time and travel cost (equation (3) is defined as the value of travel time in the mode choice model, given the β time and β cost coefficients calculated from the multinominal model estimation. This can be used as an informal test to determine whether the model is reasonable.

The value of time calculated for different types of time (in-vehicle time, walking time, and waiting time) in Rwandan francs (rwfs) per hour (hr) is shown in table 14.

	Work purpose		Shopping	purpose
Travel time :	rwfs/min	rwfs/hr	rwfs/min	rwfs/hr
In vehicle time	285.0	17,100.9	269.5	16170.4
Walking time	88.1	5,288.1	61.7	3703.8
Waiting time	12.1	727.1	25.1	1506.8

TABLE 12 Value of time for work and shopping trips.

The table 14 shows :

The in-vehicle time value of 17,100 rwfs/hr (15.2 euro/hr) for work activity is greater than the in-vehicle time value of 16,170 rwfs/hr (14.3 euro/hr) for shopping activity by 930.5 rwfs/hr.

The walking time value is estimated to be 5,288 rwfs/hr (euro/hr) for work and 3,704 rwfs/hr (3.3 euro/hr) for shopping, with a difference of 1584 rwfs/hr.

Shopping activity has a higher waiting time value than work activity, with 1507 rwfs/hr (1.3 euro/hr) and 727.1 rwfs/hr (0.64 euro/hr) respectively, with a difference of 779rwfs/hr.

Work-related trips have a higher VOT, indicating that individuals in Kigali value their time more when traveling to work than when traveling to shop. Work trips are more likely to be indirectly driving forces (for example, the worker needs to arrive at work by a certain time, or needs to complete some activities within a certain time). In vehicle time and walking time are valued high for work trips than for shopping trips, whereas waiting time is high for shopping trips than for working trips. The estimated time values are associated with the observed mode choice behavior, but the in-vehicle value is higher than the walking and waiting time, and the findings in the literature show that the in-vehicle time value is generally lower than the walking and waiting time.

Discussion and comparison of VOT results with other studies

Given the value of in vehicle time for individuals is high than their waiting time value and waking time value compared to other studies in the literature ,studies have found the in-vehicle time to be valued lower that walking time and waiting time and suggested that the in vehicle time be valued double than walking time and waiting time but It has also stated in the literature that travel time valuations differ with the dataset ,study area , the aim of the studies etc.

the travel time valuations are split by data set type , there may be some uncertainty in the results of the survey and SP data set of the attributes . in the estimated multinomial logit model the in vehicle time coefficients is high compared to other coefficients and it has a high significant value as well , which has led to the high value of in vehicle time as the VOT is proportionally to the time and cost ,the high value of the coefficient indicate preference over other coefficients , as indicated in the results of the survey , the majority of the respondents considered the vehicle time while making their choices , for work and shopping activity (23.9% and 19%).the respondents mode ownership (54.5 owns a mode) is high compared to the respondents that owns no mode (among them 43.5% owns car mode) , the car attributes is the in vehicle time , travel cost and parking cost, a person owning a car , in making a choice individuals consider the car attributes . the SP data's provide data hypothetical scenarios that include existing and proposed scenarios , the respondents may tend to reflect their mode choice habit in their daily patten .

Other factors such as income, mode ownership, and specific modes (car, bus, or motorcycle) can be used in this research for further analysis of individual mode choice and individual characteristics. hence income has been identified as one of the factors influencing the value of time and mode choice in various studies, When selecting a mode, the individual tends to consider all of the attributes associated with it. While the overall travel time for a bus, motorcycle and taxi cab may include waiting time, walking time, and in-vehicle time, the observed attribute levels and mode choice results presumably reflect an individual preference for car mode in most scenarios, as well as the indirect high value of in-vehicle time.

The disparity in the results centrally to the studies in the literature , shows that values of time differ by country to county, region per region and individual per individual , the recent study done by Bertin & Ali, (2021) study, Although their aim was the implementation of real-time passenger information system through-improving public transport in Kigali , they conducted the stated preference survey in Kigali and multinomial logit model in their assessment , they also calculated the value of in vehicle time and waiting time expected after the implementation of real-time passenger for bus, the results shows the in-vehicle value of time higher than waiting time (87.87rwfs/ min value of in vehicle time and 42.78 rwfs/min) value of waiting time). This means the individuals in Kigali value the in vehicle time high than waiting and walking time .

5. CONCLUSIONS AND LIMITATIONS

5.1 Conclusion

Estimating the value of time using a discrete choice model and stated-preference surveys, as presented in its application in Kigali, yielded reasonable VOT estimates. supporting what is stated in the literature, the discrete choice model developed in the multinomial logit model is the convenient model for estimating the value of time and analyzing travel mode choice behavior also the multinomial logit model for work trips is estimated appropriately in calibrating the model and estimating the value of time than for shopping trips, which explains why various studies prefer to conduct similar studies using work trips as trip purposes.

The main goal of this research was to estimate the value of time for individuals in Kigali through the discrete choice model, the value of time estimated from the model reflects how individuals value their travel time in Kigali, revealing they value in-vehicle time higher than waiting time and walking time values, followed by walking time, which is valued higher than waiting time also for the individuals in Kigali time is high valuable when they are travelling to work than shopping.

There are values of time estimated in previous research of the least African developing countries (Ghana and Tanzania as described in the literature the value time), however considering the year the study of these respective countries have conducted and the lack of recent studies in developing and low-income countries, the research could not draw conclusions in their comparison. The comparison can be the observable fact that the value of vehicle time is valued higher than the values of waiting time and walking time, which is not the case in the literature for other developing countries.

The study incorporates socioeconomic characteristics data into the model specifications to evaluate the determinants of mode choice behavior, concluding that income and mode ownership determinants influenced mode choice behavior, and trip purposes determinants show changes in mode choices between work and shopping trips.

5.2 Limitations

Limitations describe the elements over which the researcher has no control; they will aid in determining the efficacy of the study's results. Some of the study's potential limitations are listed below :

- Comparative studies of the value of time estimation in Africa that is relevant to the study
- Time constraints: as part of the academic schedule/calendar and process to obtain a degree in transportation sciences, the researcher must work within a specific time frame to meet the expected deadlines, while also aligning with other courses. As a result, intensive research is limited, and the time frame for respondents to complete administered questionnaires is required for accurate results. A study conducted within a specific time frame frame provides a snapshot of the situation as it currently exists.

- In some cases, providing incentives and appreciation to respondents is required in a research study to motivate them to participate in the survey, give it time, and take the time to provide useful information.
- Language: Kigali, a city in Rwanda, uses Kinyarwanda as its local language. While conducting a study in a specific location requires relying on the most commonly used language for communication. Using a translated survey can also lead to information misinterpretation.
- Statistical software (Biogeme & SAS code): Using statistical software in data analysis may necessitate a thorough understanding of coding and data analysis.
- Online survey with Social Media Capacity: the study used social media in its data collection processes., the responses can be affected by age category, and network, some would think of insecurity and trust in social media as the majority of the collected responses used social media.

6. **RECOMENDATIONS**

Aside from being a master thesis project, it can also be used as a resource of relative information for practitioners, policymakers, and transport planners in Kigali, bridging the gap between the value of time consideration in providing sustainable transportation systems and the value of time consideration of-the-practice. The study provides an approach for further studies in Kigali. The data used in this research can also be used to conduct sensitivity analysis on the model and value of time estimation, as previous studies have suggested that including income levels in the model can provide a better understanding of the determinants of the value of time estimates.

Future research may fully consider estimating the value of time using discrete choice models. Explicit modeling of the correlation between each respondent's answers, as well as an increase in sample size, could improve estimation accuracy and the significance of the estimated coefficients.

A larger dataset is one of the requirements for such an analysis. Furthermore, the approach should be validated further by incorporating various data collection techniques, such as paper surveys. Because using the large overall sample size, realistic time and model fit values can be obtained.

Policymakers and transport planners should understand the value of time because the economic constraint that an individual face is a monetary constraint, travel time and travel cost is a major consideration in one's transportation choice. they should intend/strive to reduce the value of time spent on public transportation as the increase in car ownership and reliance on automobiles increase energy consumption and serious environmental consequences (Co2 emissions). In terms of energy conservation and environmental protection, public transportation (PT) outperforms automobiles. also understanding individuals' mode choice and behavioral responses to transportation and government actions will always be of interest to a broad range of society (Louviere, 2000).

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ANNEXES

ANNEX 1 Experimental design using SAS code-design macros

```
%LET PATH = C:\Users\jemur\Desktop\SAS;
 libname CASE "&PATH";
 /* create fractional factorial design with 4 attributes, 4 levels each */
 %MKTEX(4**4, n=2**4, seed=247)

proc print;
 run;
 /* Grouping of profiles in 8 set */
 /* Determine choice sets of alternatives */
 %choiceff(data=design, /* candidate set of alternatives */
           model=class(xl-x4 / sta), /* model with stdz orthogonal coding */
           nsets=32, /* number of choice sets */
           flags=4, /* 2 alternatives, generic candidates */
           seed=2035, /* random number seed */
           maxiter=100, /* maximum number of designs to make */
           options=relative, /* display relative D-efficiency */
           beta=zero) /* assumed beta vector, Ho: b=0 */

proc print data = best;
   var x1-x4;
   id set;
   by set;
 run:

data case.best;

   set best(rename=(x1 = A x2 = B x3 = C x4 = D));
 run;
 /* Number the profiles within each set according to increasing profile numbers */
Dproc sort data = case.best out= case.sort;
   by set index;
 run;

  data case.parking;

   set case.sort;
  by set index;
     drop _fl _f2;
 run;
```

```
/* Format variables and label variables */
value forma 1 = "<15 min"</pre>
                  2 = "15-30 min"
                  3 = "30-45 min"
                  4 = ">45 min ";
    value formb 1 = "<5 min"</pre>
                  2 = "5-10 min"
                  3 = "10 - 15 min"
                  4 = ">15 min ";
    value formc 1 = "<5 min"</pre>
                  2 = "5-10 min"
                  3 = "10-15 min"
                  4 = ">15 min ";
    value formd 1 = "<500 rfws"</pre>
                  2 = "500-1000 rfws"
                  3 = "1000-1500 rwfs"
                  4 = ">1500 rwfs";
```

```
run;
```

```
    data CASE.ChoiceDesign;

   set case.parking;
   format A formA. B formB. C formC. D formD.;
   label A = 'onmotorbiketime' B = 'waitingtime'
         C = 'walkingtime' D = 'travelcost';
 run;
 OPTIONS ORIENTATION = PORTRAIT;
 ODS RTF file = "&PATH\WZ_design_macro.txt";
 title "VoT using particular mode with macros";

proc print label;
   var A B C D;
   id set;
   by set;
 run;
 title;
 ODS RTF CLOSE;
```

```
/* Export the design to txt */

    PROC EXPORT DATA= CASE.ChoiceDesign

              OUTFILE= "&PATH\design macro.txt"
              DBMS=DLM REPLACE;
      DELIMITER='3B'x;
      PUTNAMES=YES;
 RUN;
```

ANNEX 2 Qualtrics questionnaire survey

VALUE OF TIME USING DISCRETE CHOICE MODEL

(This survey Should not take more than 10 min of your time)

My name is Murielle Jeannine T. and for my Master thesis at the University of Hasselt, We are conducting this survey to estimate the value of time through the individual choice of one alternative from a set of 5 alternatives use while traveling for Work and for Shopping.

The survey contains two parts :

The first part contains your Sociodemographic information,

The second part contains hypothetical scenarios that you may choose your preference alternative in a set of 5 alternatives characterized by the transport mode mainly used in Kigali (Bus, motorbike, Taxicab, car and walk) and influenced by Travel time (IN vehicle time, Waiting time, walking time) and Travel cost (Travel cost and Parking Cost).

YOUR FEEDBACK SHALL BE TREATED WITH MAXIMUM CONFIDENTIALITY.

Q0. Socio-demographic Characteristics (Personal information)

Q1. What is your gender ?

Male
 Female

Q2. What is your age ?

- 18-24 years
- 25-30 years
- 31-40 years
- 41-50 years
 41-50
 41-50 years
 41-50 years
- 51-60 years
- + 60 years

Q3. Please mention the name of district and sector where you live :

Kibagabaga, Gasabo district

Q4. Family size or Household size (Number of people in House)

01

02

3-5

- 0 5-7
- >7

Q5. What is your level of Education ?

- ⊖ < Primary
- O Primary-Secondary
- Technical courses
- Output Output

Q6. What is your Occupation ?

- O Student
- Government Employed
- Private company Employed
- Self Employed
- Unemployed
- Retired
- O Housewife

Q7. Household monthly income (Rwfs)

- <100,000
- 100,000-500,000
- 0 500,000-1,000,000
- 1,000,000-1,500,000
- 1,500,000-2,000,000
- >2,000,000

Q8. Mode Ownership: Which travel mode do you own or do your household own ?(mention also the number in the text box)

✓	Car, How many ? 1
	Motorbike , How many ?
	Taxicab, How many?
\square	None

Q9. Do you have a driving License ?



We are now going to present some hypothetical scenarios where certain details regarding each transport mode available in your area are provided: IN vehicle time, Waiting time, Walking time, Travel time, Travel cost, and Parking Cost. we will present you four pages of hypothetical scenarios which we would like to know your choice alternative in a set of 5 alternatives, these alternatives offer you choices to travel by Bus, Motorbike, Car, Taxicab, and Walk, Assuming you are traveling for work or shopping activities.

Before it, Please read the following information for your understating and answer to the question:



The 4 different scenarios are presented below:

Q171. Here is the first hypothetical scenario of your travel pattern.

Out of the following alternatives, Select One which you would like to use for work, and one which you would like to use for shopping.



Q172. Here is the Second hypothetical scenario of your travel pattern.

Out of the following alternatives, Select One which you would like to use for work, and one which you would like to use for shopping.



Q173. Here is the Third hypothetical scenario of your travel pattern.



Out of the following alternatives, Select One which you would like to use for work, and one which you would like to use for shopping.

Q174. Here is the fourth hypothetical scenario of your travel pattern.

Out of the following alternatives, Select One which you would like to use for work, and one which you would like to use for shopping.



Q175. What was the most variable you considered to make your choice for work?

In vehicle time
Onmotorbke time
Waiting time
Walking time
Travel cost

Parking cost

Q176. What was the most variable you considered to make your choice for Shopping ?



Q177. Imagine you have your own a car, would you still make the same choice to travel to your work or shopping ?



Q178. Imagine you don't have your own a car , would you still choose the same choice to travel to your work or shopping ?

YesNo

Q179. What is the criteria for you to choose your transport mode in your daily travel pattern ?

	Very important	Importatnt	Less important
Overall travel time (in vehicle time , walking time and waiting time)	0	۲	0
Travel cost (cost of ticket, cost of fuel, parking cost)	۲	0	0
Other, please specify On Motobike	0	۲	0
Embedded Data			
group: 19			
Location Data			
Location: (-2.0001068115	523 <u>4, 30)</u>		
Source: GeoIP Estimation			
Aaniema Kindu	Butembo Nord-Kivu Mt Musanze Rwanda Bukavu Muyin Sud-Kivu Burundi Rumonge	Bukoba Mus Kogera Mwanza Iga Geita Shinyang	simiy ga

ANNEX 3 Hypothetical Choice sets (128)

Group 1
































































ANNEX 4 Qualtrics block randomization

Show Block	: Information sheet (1 Question)	
Show Block	:: Socio-Economic Information (10 Questions)	
Show Block	:: Scenario information sheet (1 Question)	
Randomize Randomly	r present 🕒 31 🚱 of the following elements 💟 Evenly Present Elements Edit Count	
	Set Embedded Data:	
	group = 1	
	Add a New Field	
	Set Embedded Data:	
	group = 2	
	Auu a New Field	
	Set Embedded Data:	
	group = 3 Add a New Field	
	Set Embedded Data:	
	Add a New Field	
Then Brand If group	h If: Is Equal to 1 Edit Condition	
	Show Block: Questionnaire 1 (9 Questions)	
Then Brand	.h If: Is Equal to 2 Edit Condition	
	Show Block: Questionnaire 2 (9 Questions)	
Then Brancl	ı if:	
If group Is	Equal to 3 Edit Condition	
	Show Block: Questionnaire 3 (9 Questions)	
Then Brancl	n lf:	
	Equal to 4 Edit Condition	
If group is		
If group is	Shaw Plask Quarting ping 4/0 (uniting)	
If group Is	Show Block: Questionnaire 4 (9 Questions)	
lf group №	Show Block: Questionnaire 4 (9 Questions)	
If group is	Show Block: Questionnaire 4 (9 Questions)	
If group is Then Brancl If group is	Show Block: Questionnaire 4 (9 Questions)	
if group is	Show Block: Questionnaire 4 (9 Questions)	

ANNEX 5 Discrete choice model using Pandas Biogeme

```
#import the package
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
 import biogeme.models as models
from biogeme.expressions import Beta, log
import biogeme.version as ver
print(ver.getText())
biogeme 3.2.8 [2022-05-20]
Version entirely written in Python
Home page: http://biogeme.epfl.ch
Submit questions to https://groups.google.com/d/forum/biogeme
Michel Bierlaire, Transport and Mobility Laboratory, Ecole Polytechnique Fédérale de Lausanne (EPFL)
#code to read the file
df = pd.read_csv("MNL_model_murielle.csv")
#import database to biogeme
database=db.Database("choice_model_data",df)
from biogeme.expressions import Beta, DefineVariable
globals().update(database.variables)
df.describe()
 database.getSampleSize()
936
 #parameters of the model
 #model ASC
 ASC_Bus = Beta('ASC_Bus',0,-100,100,0)
 ASC_Motorbike = Beta('ASC_Motorbike',0,-100,100,0)
 ASC_Taxicab = Beta('ASC_Taxicab',0,-100,100,0)
 ASC_Car = Beta('ASC_Car',0,-100,100,0)
 ASC_Walk = Beta('ASC_Walk',0,-100,100,0)
 #Travel time betas
 B_ttime = Beta('B_ttime',0,-100,100,0)
 B_wait_time = Beta('B_wait_time',0,-100,100,0)
 B_walk_time = Beta('B_walk_time',0,-100,100,0)
 #Travel cost betas
 B_travel_cost = Beta('B_travel_cost',0,-100,100,0)
 B_parking_cost = Beta('B_parking_cost',0,-100,100,0)
```

##Define the representative utility functions V_Bus = 0 + B_ttime * Bus_ttime + B_wait_time * Bus_wait_time + B_walk_time * Bus_walk_time + B_travel_cost * Bus_travel_cost V_Motorbike = ASC_Motorbike + B_ttime * Moto_ttime + B_wait_time * Moto_wait_time + B_walk_time * Moto_walk_time + B_travel_cost * Moto_travel_cost V_Taxicab = ASC_Taxicab + B_ttime * Taxicab_ttime + B_wait_time * Taxicab_wait_time + B_walk_time * Taxicab_walk_time + B_travel_cost * Taxi_cab_travel_cost V_Car = ASC_Car + B_ttime * Car_ttime + B_travel_cost * Car_travel_cost + B_parking_cost * Car_parking_cost V_Walk = ASC_Walk + B_ttime * Walk_ttime

##Define the utility dictionary that associate the Choice with the utility function
V= {1:V_Bus, 2:V_Motorbike, 3:V_Taxicab, 4:V_Car, 5:V_Walk}

#Availability conditions with alternatives
av = {1:1,2:1,3:1,4:1,5:1}

#Choice model with biogeme function logprob = models.loglogit(V,av,Work_Choice)

#Create Biogeme object
biogeme = bio.BIOGEME(database,logprob,numberOfThreads=1)
biogeme.modelName = 'MNL-Choice_Model_Rw'

import biogeme.messaging as msg logger = msg.bioMessage() logger.setDebug()

```
results = biogeme.estimate()
```

```
#Print the estimated values
betas = results.getBetaValues()
for k,v in betas.items():
    print(f"{k:10}=\t{v:.3g}")
```

ASC_Car = 0.121 ASC_Motorbike= 0.00908 ASC_Taxicab= -1.15 ASC_Walk = 0.0781 B_parking_cost= -0.000327 B_travel_cost= -0.000118 B_ttime = -0.0932 B_wait_time= -0.0143 B_walk_time= -0.0104

#Results in a pandas table
pandasResults = results.getEstimatedParameters()
print(pandasResults)