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THE DEVELOPMENT AND IMPLEMENTATION OF AN INNOVATIVE SMARTPHONE APPLICATION TO COLLECT ROUTE CHOICE PREFERENCE DATA

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ABSTRACT

Title:	The Development and Implementation of an Innovative Smartphone Application to Collect Route Choice Preference Data.
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Department:	Civil Engineering
University:	University of Pretoria
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The research presented in this thesis was motivated by two factors. Firstly, little route choice research has been undertaken in South Africa, especially in urban areas. This has resulted in significant gaps in our understanding of commuter route choice preferences and associated willingness-to-pay measures such as the value of travel time. Secondly, there are recognised limitations in the experimental methodologies used for route preference data collection, i.e., field data collected using revealed preference (RP) methods, and experimental data collected using stated preference (SP) methods. RP methods have high external validity, but the analyst has limited experimental control. SP methods have a high degree of analyst control of the experiment parameters, but the hypothetical nature of the route alternatives provides lower levels of external validity. The research presented in this thesis therefore had four objectives. Firstly, to provide a review of historical research and studies into mode choice and route choice modeling in South Africa and highlight any gaps in our understanding of commuter route choice preferences and the value of travel time. The findings confirmed that no route choice research has been undertaken in South African urban areas for the last two decades, and large gaps exist in our understanding of motorists' route choice preferences these areas. The findings confirmed the urgent need to undertake route choice research in South African urban settings, especially in the light of the governments user pays policy for urban road and public transport provision.

The second objective was to develop and demonstrate the proof-of-concept for an innovative, smartphone-based application with the acronym RAPP-UP (Route Choice Application – University of Pretoria), for collecting motorist route preference data in dense, congested urban road networks based on real-time traffic conditions at the time of the trip. The author of this thesis designed and prepared the specification for RAPP-UP, and an independent contractor was appointed to code the application and make it available on the Google Play Store® for survey participants to download. RAPP-UP was designed to achieve a better balance between external validity and analyst control. The third objective was to use RAPP-UP to collect route preference data from a sample of commuters in Gauteng Province, South Africa. The fourth objective was to estimate various types of discrete choice models

to quantify different forms of route preference utility and estimate the associated willingness-to-pay measures such as the commuter value of travel time.

RAPP-UP was designed for application in a self-validating survey context that included stated preference (SP) and revealed preference (RP) components. A degree of analyst control was introduced by allowing the analyst to factor the observed attribute levels before presentation to users in a pre-determined manner based on an unlabelled fractional factorial design. RAPP-UP's innovation was its ability to maximise external validity by generating two realistic alternative routes based on real-time road network travel data between a user specified origin and destination, thereby anchoring the experiment in a realistic and familiar setting. This innovation was enhanced by showing the route alternatives on a detailed road map background to provide orientation for the trip origin and destination locations, the routes themselves (highlighted on the road background), as well as the utility attribute levels for each route in a choice set format. After trading-off the attribute levels for each route, users were asked to choose their preferred route (SP component) and were then required to drive their chosen route (self-validating RP component). The GPS function in the smartphone was used to track the user to determine route adherence. An economic experiment was introduced by deducting the toll cost of a chosen tolled route from a user survey account that was allocated to each user at the commencement of the survey. The final survey account balance was paid to each user at the end of the survey. As each trip is one observation, the use of RAPP-UP was required over several days to obtain multiple observations from each user. RAPP-UP was designed to accommodate a detailed form of utility expression that contained a disaggregated form of travel time that specified the proportions of actual travel time (in minutes) in free-flow, slowed-down and stop-start travel conditions. The trip petrol cost (in Rands), toll cost (in Rands) and the probability of on-time arrival at the destination (in percent) were also included in the utility expression.

To illustrate proof-of-concept, a small sample of car commuters in the Gauteng Province of South Africa was recruited to participate in a route choice survey using RAPP-UP. The road network in the urban areas of Gauteng Province is dense and congested in the weekday peak periods, and the motorways are tolled. The route preference data of the sample of commuters provided the basis for the estimation of various forms of discrete route choice models. The models confirmed that the attribute coefficients for each category of travel time were significant, thereby corroborating international evidence. The congestion multipliers, i.e., the ratios of the travel time attribute coefficients for each trip time category, were within the ranges determined in international studies. The petrol cost, toll cost and probability of on-time arrival attribute coefficients were also significant. A toll road quality bonus representing the unobserved factors of utility was introduced as a dummy utility attribute for routes with tolled sections. The attribute coefficient had a negative sign, revealing that the survey participants associated a disutility for routes with tolled sections for the unobserved factors of utility.

All the objectives of the research were achieved. The research not only added to the body of literature on the topic of route choice behaviour in urban areas, but also provided insights into the practicalities of route choice data collection and model estimation.

DECLARATION

I, the undersigned hereby declare that:

- I understand what plagiarism is and am aware of the University's policy in this regard.
- The work contained I this thesis is my own original work.
- I did not refer to the work of current or previous students, lecture notes, handbooks or any other study material without proper referencing.
- Where other people's work has been used this has been properly acknowledged and referenced.
- I have not previously in its entirety or in part submitted this thesis at any university for a degree.

Disclaimer:

The work presented in this thesis is that of the student alone. Students were encouraged to take ownership of their projects and to develop and execute their experiments with limited guidance and assistance. The content of the research does not necessarily represent the views of the supervisor or any staff member of the University of Pretoria, Department of Civil Engineering. The supervisor did not read or edit the final report and is not responsible for any technical inaccuracies, statements or errors. The conclusions and recommendations given in the report are also not necessarily that of the supervisor, sponsors or companies involved in the research.

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ABBREVIATIONS

The abbreviations used in this thesis are as follows:

a) ASC – Alternative Specific Constant
b) BRT – Bus Rapid Transit
c) C-Logit the Commonality-Logit model
d) GC – Generalised costs
e) GT – Generalised time
f) GFIP - Gauteng Freeway Improvement Project, i.e., the Gauteng e-toll scheme
g) GPS – file format for use with various mapping platforms such as Google Maps® and OpenStreetMap®
h) IIA - Independence from Irrelevant Alternatives
i) IID - Independent and Identically Distributed (error terms)
j) JSON – JavaScript Object Notation text file format
k) KML – file format for use with Google Earth®
l) LCM – Latent Class Models
m) ML – Mixed Logit model
n) MNL - Multinomial Logit model
o) NGENE® - experimental design software
p) NLOGIT® – discrete choice modelling software
q) POTA – probability of on-time arrival
r) PS-Logit - Path Size Logit model
s) RAPP-UP - the Route Choice Application developed by the University of Pretoria
t) RP - Revealed preference
u) RPL – Random Parameters Logit model
v) SC - Stated choice
w) SP - Stated preference
x) VOR – Value of trip time reliability
y) VTT - value of travel time (usually in the context of non-work related VTT)
z) WTP – Willingness to Pay.

In this report the term *route* is used to describe a chosen road alignment between an origin and destination. The term *path* is used in some literature to describe the same thing, and hence *route* and *path* in the context of this research mean the same thing and are interchangeable.

Note that the NLOGIT® choice modeling software was used to estimate the various discrete choice models presented in this report. NGENE® was used to synthesise the designs for the stated preference experiments.

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1. INTRODUCTION

1.1 Background

Motorist route choice behaviour in the urban transport context in South Africa has been under-researched. This is unexpected given that the results of this research underpin the basis for urban transport investment decisions that, in most cases, have very high capital, maintenance and operating cost implications, and are enduring. While the transport choice research effort in South Africa has mostly focussed on mode choice simulation at the metropolitan level, there has been very little research aimed at route choice modelling. This has had unanticipated implications for at least one large urban toll project where commuter behaviour has not been what was expected, and the anticipated economic and financial feasibilities of the schemes have fallen short of expectations.

The last urban route choice research was undertaken in Gauteng in the early 2000's and is now outdated. Since that time, there have been significant advances in data collection methodology and the types of discrete choice models used for route choice simulation. The lack of research effort has left gaps in our understanding of motorist route choice behaviour in urban areas, and in the quantification of key microeconomic willingness-to-pay measures such as the non-work related value of travel time (VTT). Willingness-to-pay measures such as the VTT should directly influence transport policy, road infrastructure planning, traffic demand modelling and project economic appraisal. It is a key consideration in user-pays transport schemes such as toll roads. The user-pay principle for funding transport projects is government policy in South Africa as outlined in Sections 28 of the South African National Land Transport Act No. 5 of 2009 for public and private transport users (Government of South Africa, 2009).

In the urban context, the reliable prediction of traffic demand is becoming more important as traffic congestion levels increase, emphasising the need to efficiently allocate scarce resources for new and upgraded road infrastructure. Small and Verhoef (2007) state that the most critical part of planning transport infrastructure is predicting what will happen, especially how many people will use it and therefore what it will cost and what benefits it will provide. Furthermore Prato (2009) highlights that understanding motorists' route choice behaviour (and therefore the prediction of traffic demand on road networks) in urban areas is necessary for several reasons. Firstly, to support transport policy development, for example, to understand the demand implications of travel demand measures (TDM), user-pays schemes such as urban tolls, and congestion pricing schemes. Secondly, to provide inputs into the economic appraisal of new road and road improvement schemes through the estimation of demand as well as key non-market related input measures such as the value of travel time and the value of trip time reliability. And thirdly, to provide inputs into transportation demand models that are used in the planning and evaluation processes for demand prediction and for the calculation of the generalised time parameters that are used in the trip assignment sub-model. An example is the use of the value of travel time (VTT) for the conversion of monetary based trip costs into equivalent time units for the calculation of generalised time units used in the trip assignment process.

Two data collection methodologies are used to collect motorist route preference data, i.e., either revealed preference (RP) methods, or stated preference (SP) methods. Revealed preference methods are field data methods that observe or record the actual routes used by survey participants. Stated preference methods use hypothetical routes and trip attributes to generate route alternatives that the survey participant is required to choose from. However, the collection of motorist route choice preference data using either RP and/or SP methods is not straightforward. The strength of RP methods is that actual route choices are observed. But with RP these methods there are several weaknesses to be considered including the limited extent of analyst control over the survey parameters; the inability to gain insights into road schemes or policies that do not yet exist; and the absence of insights into the alternative routes that may be considered by motorists. The high number of potential alternative routes between an origin and destination on a dense urban road network is not an insignificant problem.

While SP methods provide high levels of analyst control of the experiment parameters, there are limitations associated with the validity and realism of the trip attributes when describing the hypothetical alternative routes. Also, survey participants may not act the same way in a hypothetical situation as in a real situation as there are not real trip time and cost implications for the trips in a hypothetical setting. This is termed “hypothetical bias,” which means that respondents in stated preference surveys tend to be willing to pay less than they would if there were real monetary consequences to their choice. An issue to keep in mind when using SP methods for route choice is the practical issue of the inclusion of route overlap in the choice sets. Route overlap is likely to occur to varying degrees in a dense urban road network. This issue of route similarity, i.e., the correlation between overlapping routes, also undermines the independent and irrelevant alternatives (IIA) constraint for the application of multinomial logit (MNL) models and requires the application of models that take account of route correlation.

More recently, SP surveys have been designed to include an RP component by incorporating the solicited trip time and cost attribute levels of an actual route from the survey participant (e.g., from a current or recently used route) into the choice set and pivoting the alternative route attribute levels off these actual levels. This requires the experimental design and pivoting process to be done ‘on the run’ in real time with pre-specified attribute level variations. This is easily achieved with either internet-based or face-to-face survey methods. This method does not however remove the risk of hypothetical bias in the responses.

The efficiency and cost of transport-related data collection has been substantially improved with the use traveller of smartphone devices and the development of applications for the collection of specific data types including origin-destination (O-D) studies, travel diary surveys, and revealed preference route choice surveys using the GPS tracking devices in smartphones. In addition, route guidance and trip information and planning platforms such as TomTom®, Google Maps® and Waze® have been available on mobile smartphones applications for several years. While the transport survey applications are typically developed as bespoke to researchers and transport authorities, there are platforms that provide templates that allow the development of applications for various types of surveys. The advantages of smartphone applications for transport data collection are the accuracy of the data and the level of detail that can be achieved. However, their use requires the widespread use of smartphones in the study setting, the ability by users to use and understand the use of the applications, and their willingness to participate. Ethics considerations are of high importance, especially the storage and security of collected data.

This discussion has highlighted two requirements, firstly, the need for the development of a route preference survey method that better balances the competing constraints of analyst control and external validity in the congested urban road environment incorporating the benefits of both RP and SP methods. Secondly, the collection of route preference data from a sample of motorists using this methodology and showing proof-of-concept by using the data to estimate different types of discrete choice models. Thirdly there is the opportunity to take advantage of the rapid technical development and abilities of smartphones and the data transmission speeds of 4G and 5G cell phone technology.

1.2 Objectives of the Research

The research presented in this thesis had four main objectives. The first objective was to undertake a review of the historical research and studies undertaken in South Africa for the estimation of the value of travel time, and specifically the non-work related value of travel time (VTT). The review considered the VTT estimates for public transport users and car users. The review placed the research conducted in this research in context, especially for car users, although the values for public transport users were also used to benchmark the values determined in this research. The review also identified the gaps that exist in our understanding of route choice behaviour and the route preferences of commuters. The failure of the largest urban toll scheme implemented in South Africa emphasised the urgent need to obtain a reliable and proven survey method for the collection of route choice preference data, the estimation of appropriate route choice models, and the derivation of robust estimates of VTT.

The second objective was the development of a low-cost smartphone application for the collection of route choice preference data from (commuting) motorists based on real-time travel conditions at their time of travel, including the generation of realistic alternative routes and their associated attribute levels. The application was required to accommodate both SP and RP components in the methodology. The SP component required the participant to choose between two route alternatives based on near real-time travel time and cost attributes in a choice set format. The RP component was introduced by embedding route choice consequences into the experiment with the participant having to physically drive their chosen route and be tracked while doing this to monitor route compliance. This approach emphasised the RP component as the participant experienced the travel time and cost implications associated with their preferred route. It should be noted that the route characteristics included the SP survey were focussed on the time and cost factors of utility. The impact of factors such as route safety, route familiarity and roadway condition were not considered.

Furthermore, the application accommodated an economic experiment to reinforce the financial implication of route choice. Survey participant accounts were established for each participant with a starting balance of R300.00. If participants chose a route with a tolled section, the toll cost was deducted from their survey account. At the end of the survey the balance of their survey account was paid to them. Thus, the survey participants were incentivised to carefully consider the route time and cost trade-offs when choosing their preferred route.

The third objective of the research was to demonstrate the efficacy of the application by undertaking a route choice survey on a small sample of Gauteng Province commuters in the Johannesburg - Pretoria region. The road network in this part of Gauteng Province is dense and has congested conditions during the weekday peak periods. The aim of this proof-of-concept survey was to ensure that the application could successfully be implemented on a small sample of commuters; to ensure the design of the application by 'stress-testing' it on a sample of commuters; and to collect route choice preference data for use in discrete choice models.

The fourth objective was to estimate different types of logit-based route choice models using the preference data from the sample of car commuters in Gauteng and derive estimates of the value of travel time. A variety of models were tested and evaluated including multinomial logit models (MNL); random parameter logit models (RPL) (also known as mixed logit models); and models that specifically take account of route overlap (i.e., route correlation) including the C-Logit and path-size (PS) logit. The RPL, C-Logit and PS-Logit models have never been applied in a route choice context in South Africa.

The research thus added to the academic body of knowledge into route choice data collection and behaviour simulation as follows:

a) It reviewed the history of choice modelling in general and route choice modelling specifically in South Africa, as well as the values of travel time derived from various studies.

b) It demonstrated a new, innovative, low-cost approach using a smartphone application for route choice data collection in a congested urban environment using real-time travel data and a combination of SP and RP methods.
c) It demonstrated the efficacy of the application by conducting a proof-of-concept route choice survey amongst a small sample of Gauteng Province commuters for their weekday morning trip to work.
d) It confirmed the statistical significance of discrete route choice models that have not been applied to route choice formulations before in South Africa including the RPL, C-Logit and PS-Logit models.
e) The results of the discrete choice models provided new and valuable insights into route choice behaviour for the small sample of commuters, enabling robust estimates of the value of travel time to be made.

Furthermore, the application was designed to accommodate a complex form of utility expression, with attributes that have not previously been tested in South Africa, such as the reliability of travel time and the trip travel times associated with different levels of congestion.

The development of the route choice application has enabled the expansion of research opportunities in motorist route choice behaviour in South Africa and internationally. It provides the opportunity to gain further insights into motorist behaviour in specific contexts such as urban tolls, congestion pricing and traffic demand management schemes. The outputs provide a deeper insight into the implications of transport policy; improved reliability of traffic demand modelling; and more accurate inputs into the economic appraisal of new and improved road schemes.

1.3 Scope and Requirement of the Research

The scope of the research was limited in the following respects:

a) The smartphone application limited the utility expression to a total of six time, cost and reliability attributes. The application has the flexibility to increase the number of route attributes to a total of eight, this number being constrained by the practical issue of space availability on a smartphone screen.
b) Only a linear-in-coefficient form of utility expression was tested for two route alternatives. The application had the flexibility to increase the number of route alternatives presented to users, however two route alternatives were considered adequate to demonstrate proof-of-concept.
c) The efficacy of the application was confirmed using a small sample of car commuters in Gauteng Province. While the small sample size was adequate to demonstrate proof-of-

concept, it was not adequate to investigate the heterogeneity in route choice behaviour, including income, route length, trip purpose and gender effects.

The research requirement was for a proof-of-concept for the new data collection methodology and its application in discrete route choice models. This required the execution of the route choice survey on a small sample of motorists in the Gauteng Province, mainly in the Johannesburg, Tshwane and Ekurhuleni metropolitan areas. The road network in this region is dense, consisting of tolled and un-tolled freeways, arterial roads and collector and distributor roads. While the traffic demand reduced during the COVID pandemic lockdown periods in 2020 and 2021, demand has since increased, and significant levels of congestion occur on the network during weekday morning and afternoon peak periods.

In summary, the requirements of this research were to:

a) Develop and implement a new smartphone-based route choice application that combines SP and RP methods using real-time traffic data in the alternative route generation process.
b) Use a proof-of-concept approach to validate the application of the application in an experimental setting using a sample of road users in the Gauteng region in South Africa to generate a combined SP and RP preference data set.
c) Use the preference data set to apply several discrete choice models for route choice simulation including models account for route overlap and correlation.
d) Use the discrete choice model outputs to estimate the non-work related value of travel time for the sample of survey participants.

1.4 Summary of the Methodology

The research methodology adopted is summarised in Figure 1. There were seven steps in the process with steps 2, 3 and 5 requiring external inputs, and specific interventions required between steps 1 and 2, 3 and 4 and 5 and 6. Each step is discussed briefly below.

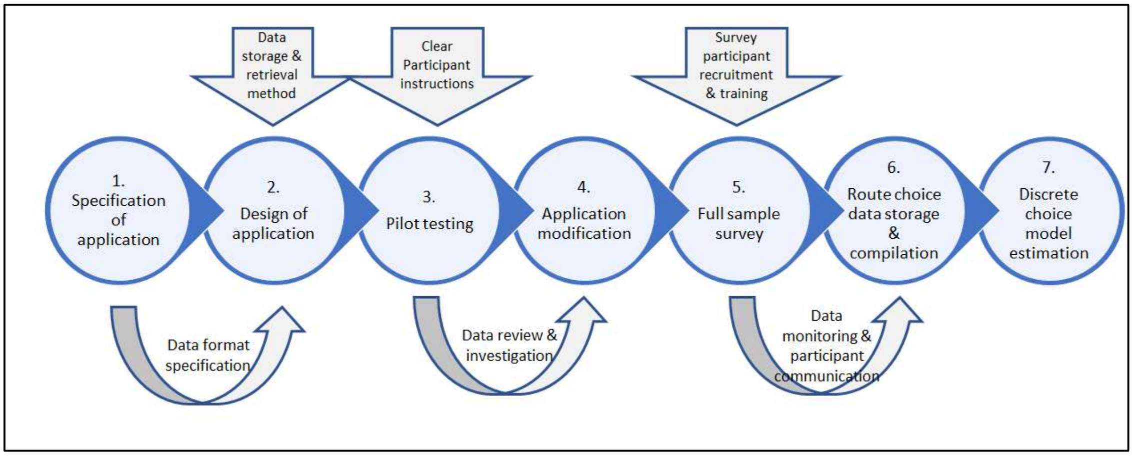


Figure 1: Research Methodology Flow Chart

Step 1 - Specification of the Application: The application concept was defined in this step. The concept was to collect preference data for route choice model estimation using real-time traffic data and a complex form of utility expression by means of a smartphone application. It required a detailed literature review of the use of smartphone applications for transport data collection, and specifically route choice SP and RP data collection. No evidence could be found of smartphone application-based SP methods for route choice. Mazen et al., (2019) developed a smartphone-based application to undertake SP surveys for mode choice. This app generated a random experimental design using context-aware SP profiles using user specific socioeconomic characteristics and past travel data along with relevant web data for alternative mode scenario generation. The generated choice tasks were automatically validated to reduce the number of dominant or inferior alternatives in real-time, then validated using Monte-Carlo simulations offline.

The specification of the route choice application required the formulation of four key issues. Firstly, whether it was feasible and practical to develop the application using real-time traffic data, Secondly, what the technical requirements were for the development, and thirdly the detailed specification of the application. Finally, the form and content of the utility expression was required. Particular focus was paid to two issues, firstly, the use of existing transport and traffic platforms such as TomTom®, Google Maps®, Waze® and Mapbox® to generate routes and route attribute levels. Secondly the route data format, transmission, cloud-based storage and retrieval requirements of what were anticipated to be large quantities of route data.

Step 2 - Design of the Application: The design stage comprised the design and coding of the application. Application performance monitoring (APM's) were designed and coded to use TomTom® traffic data to generate alternative routes, identify route travel times (categorized by free-flow, slowed-down and stop-start times and route lengths. APM's are software applications that enable monitoring of software and telemetry data. Traffic and route data can be monitored and downloaded from service providers such as TomTom for use in mobile applications. The route and traffic data is provided in specific formats as prescribed by the International Standards Organisation (ISO). The design of the application also required the specification of the background roadmap showing the highlighted route alternatives; the format of the route attribute levels in a clear and understandable format in a choice set format; and the provision of route guidance for the chosen route alternative. The route tracking feature was undertaken using the GPS devices in modern smartphones. The application was designed for use with recent model Android smartphones and was downloadable from the Android Play Store.

Step 3 – Application Pilot Testing: On completion, the application was pilot tested by a small group of University of Pretoria students. The pilot testing revealed that the application worked as required. However, modifications were needed to make the presentation of the route attributes clearer; the transmission of the route data more efficient (especially the feature to download the data from a smartphone in the case; the use of a remote database (MongoDb®) to store the considerable amount of route data in the cloud, and more easily retrieve the data. Ethics approval for undertaking the survey was obtained from the University of Pretoria Ethics Committee.

Step 4 – Application Modification: The modifications were made to the application screen presentation for better clarity. The data transmission process was modified as well as the data downloading process. The downloading process required the scripting of short command files that are executed in the Windows Command Prompt.

Step 5 – Full Survey: The sample of car commuters was recruited for participation in the full survey. A total of 50 participants were recruited, with 48 of these eventually taking part in the survey. The criteria for survey participation were owning their own car and using it for regular commuting to work in the Johannesburg – Pretoria area, ownership of a recent model Android smartphone, and willingness to do a total of eight trips to work on different days using the application. The participants were required to sign an informed consent form and complete a short socio-demographic questionnaire. Participants were provided with a questionnaire information brochure that explained the reasons for the survey, the process for downloading the application from the Google Play Store®, how their survey account balance operated, and the use of the application itself (participants were encouraged to trial use the application). During the survey the data transmitted from the smartphones was checked daily to ensure its integrity.

Step 6 – Route Choice Data Transmission and Storage. The route data was transmitted to the remote database from the individual smartphones by means of the GSM cellular network. During the full survey this database was monitored daily to ensure the integrity of the data. Data was also downloaded daily to analyse and transform into the format for input into the choice modelling software, NLOGIT®. The data was downloaded from the database in JSON format (Java Script Object Notational) which is a text file format. These files were easily converted to CSV (comma separated variable) file format that can be read into Microsoft Excel. Some external data manipulation was required, in particular the calculation of the extent of the route overlap. In addition, the route co-ordinate data can be read into a GIS file converter to plot the route in either Google Maps® or Google Earth®.

Step 7 – Discrete Choice Model Estimation. Once downloaded from the remote database, the route data and choice sets were downloaded, and the data prepared in NLOGIT® format. The various route choice models were estimated, and the outputs interpreted.

1.5 Structure of the Thesis

The remainder of this thesis consists of the following chapters and annexures:

a) Chapter 2 presents a background to the value of travel time in South Africa.
b) Chapter 3 discusses the data collection framework for route choice surveys.
c) Chapter 4 investigates the generation of routes on congested urban road networks.
d) Chapter 5introduces RAPP-UP, and innovative smartphone based route choice application for collecting SP and RP data .
e) Chapter 6 describes the technical RAPP-UP specification.
f) Chapters 7 discusses the generation of choice set attribute levels for route alternatives.
g) Chapter 8 presents the forms of discrete choice models for modelling route choice.
h) Chapter 9 describes the characteristics of the sample of car commuters who took part in the RAPP-UP survey .
i) Chapters 10 provides the results of the various discrete choice models that were estimated with the preference data collected using RAPP-UP.
j) Chapter 11 discusses the conclusions and recommendations of the route choice research undertaken using the data collected by RAPP-UP.
k) Annexure A contains the survey participant questionnaire.
l) Annexure B contains the survey participant instruction form.
m) Annexure C contains the RAPP-UP technical specification.

2. THE SUBJECTIVE VALUE OF TRAVEL TIME

2.1 Introduction

The value of travel time is perhaps the most important microeconomic parameter used in the transportation planning and appraisal process. This chapter provides a background to the theory of the value of time and presents values of time that have been derived in the South African urban commuter context. The context of the research presented in this thesis is route choice preference data collection and simulation in urban areas. This chapter also provides a review of the historical context of route choice data collection and simulation, starting with a literature review of route choice modelling in South Africa.

2.2 The Theory of Time Allocation

The theory of the allocation of time has been of interest since the early 20th century. Jara-Diaz and Rosales-Salas (2017) provide a detailed historical overview of the development of the theory. In the early part of the 20th century, time use studies were politically oriented, with Soviet studies focussed on the central planning of their economy, resting on the view that the value of an item was dependent on the time required for its production. American time use studies concentrated on home economics and the analysis of domestic labour (i.e., non-work related time allocation). The economic theory of the valuation of time was determined in the 1960's. In that period western time use studies started to focus on the informal economy and time allocation for leisure activities.

Becker's (1965) theory of the allocation of time that attached a value to time was a landmark. He postulated that individual satisfaction did not come from goods consumed directly, but from the "final commodity" itself whose value was derived from the market goods (i.e., input raw materials) and the time to prepare the commodity (Mackie, et al., 2001). Introducing time as a component of individual utility required the introduction of time input constraints in addition to the raw material input constraints. Becker argued that these two constraints were essentially one constraint to the individual as time could be converted to money by assigning less time to consumption and more time to work. The concept of the value of time was thus based on the opportunity cost of assigning saved time for any activity but work, and thus time was valued by the wage rate. In Becker's time allocation theory, the individual is balancing (leisure) time spent in consumption with the money value of work, therefore leisure had to be valued at the wage rate. This activity indifference approach to time valuation (i.e., all time should be valued at the wage rate) was the flaw in Becker's theory. In reality, some activities are assigned more time than wanted by individuals, i.e., there are some activities an individual would like to shorten but cannot as it is an intermediate activity undertaken not for its own sake, but as a necessary input to other activities. This includes the time spent travelling, especially for specific purposes such as commuting to work.

DeSerpa introduced a second landmark theory of time allocation in 1971 (DeSerpa, 1971). He included a set of minimum time requirement for each activity in an analytical form and postulated a utility function that depended on all goods and all time periods, including work and travel. The constraints he introduced established that consumption of a specific good required a minimum assignment of time. He defined the value of time as the marginal utility of (total) time and the marginal utility of income, and specifically attached a value for travel time savings. DeSerpa's economic theory of time allocation specifically recognised that not all activities could be adjusted until equality with the value of work, and the value of travel time (and especially in urban transport) was not wage-rate related, but rather from an individual's perception of time - cost trade-offs. A reduction in travel time potentially matters to the individual because of less travel, more of other (pleasurable) activities, changes in consumption patterns, and a change in activity schedule. If the sum of these effects is positive, then the individual is willing-to-pay to reduce travel time (Mackie, et al., 2001).

In the latter part of the 20th century, the focus of studies into time allocation changed to the domestic economy (i.e., unpaid work), gender equity, valuing non-market production, monitoring trends and the trade-off between domestic labour and leisure activities (Robinson, et al., 1989). The development of individual preference data collection methods (especially stated preference methods) and modelling techniques (especially discrete choice models instead of conjoint based models) were substantially improved in this time. In the 21st century these topics have continued to receive attention, but with more focus on policy-oriented issues such as work-leisure balance, the social impact of digital technologies, and more environmentally sustainable ways of living.

Jara-Diaz and Rosales-Salas (2017) propose the framework shown in **Figure 2** for the allocation of time use that they derived from time allocation literature. The perspectives gained from the literature were classified as historical, disciplinary and analytical. The types of analyses that have been performed are conceptual and/or theoretical; data collection and analysis; descriptive data (descriptive statistics are used to describe the basic features of data and provide summaries about the sample and the quantified measures); and modelling. The modelling analyses have focussed on paid work; unpaid work; leisure; and tertiary activities that include transport and sleep. Overall time use is a combination of these.

Thus, the value of travel time is a component of the tertiary activities in the overall time allocation spectrum. Reviews of transport time allocation have focussed on different aspects of travel demand and behaviour (for a large number of commercial and academic applications); on revealed and stated preferences methods for the collection of mode and route choice preference data; and the value of travel time and associated heterogeneity e.g., Wardman & Ibanez (2012) and household activity travel decisions for use in activity based transport simulation approaches e.g., Timmermans and Zhang (2009). In the context of the research into the VTT presented in this report, an analytical approach using discrete choice models has been used to estimate the value of travel time. A key feature of this approach the disaggregation of the overall VTT based on the total trip time into estimates for free flow, slowed-down and stop-start time travel conditions. This trip time distinction provided insights into the variation of VTT within the overall constrained utility maximisation process.

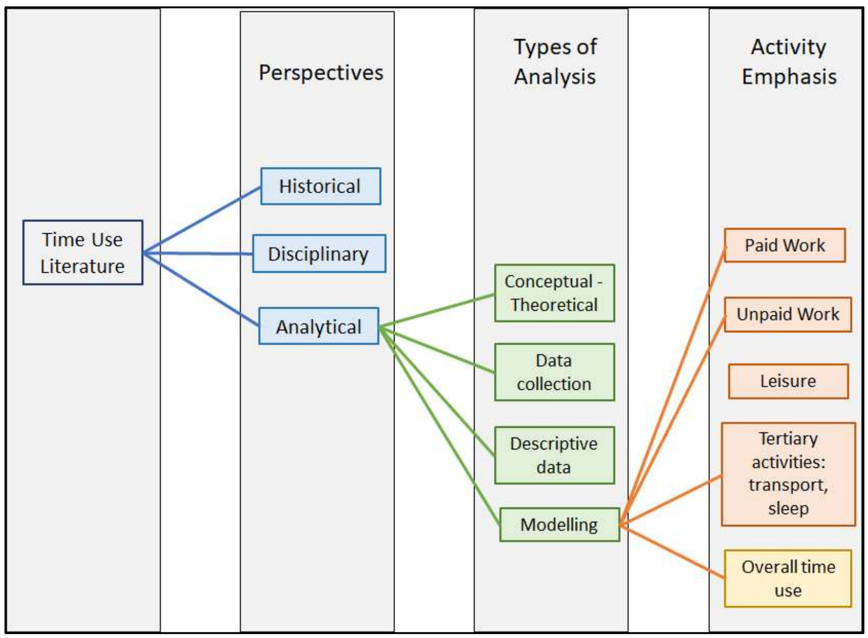


Figure 2: Time Use Literature Classification (after Jara-Diaz and Rosales-Salas *(2017)***)**

The

2.3 The Subjective Value of Travel Time (VTT)

The subjective or behavioural VTT is mostly derived from discrete choice models used for mode or route choice simulation. It represents the traveller's willingness-to-pay a monetary amount to reduce travel time (either in-vehicle, waiting, or walking) by one unit, e.g., an hour or minute. It represents the marginal rate of substitution between cost and time for a given level of utility. VTT is thus determined as the ratio of the trip time and trip cost utility attribute coefficients and represents what DeSerpa (1971) called the "value of saving time in an activity". DeSerpa emphasised that there is no reason whatsoever to expect that this willingness-to-pay for a reduction in travel time to be equal to the marginal wage rate. He emphasised that an individual's willingness to pay for travel time savings will exist if several effects are present, i.e., a reduction in travel time; the need to travel less; more of other (pleasurable) activities; changes in consumption patterns; and a change in activity schedule.

There are two VTT derivations, each with specific applications i.e., the perceived (or subjective) VTT used for modelling and forecasting, and the social (or equity) VTT used in project appraisal. The subjective VTT is derived from discrete choice models and is used in transport demand and forecasting models. The social VTT is used in the economic appraisal of transport schemes to determine the monetary values of time savings. The social VTT is premised on the fact that there is no reason that the value an individual is willing to pay for reduced travel times is equal to the value that society as a whole attaches to the reassignment of time of that individual (Mackie et al., 2001). Using the subjective VTT in an appraisal may lead to biased outcomes in favour of the higher income groups in society, especially in societies where there are high-income disparities such as South Africa. Mackie et al. (2001) point out that there are many examples of the subjective VTT being used in economic appraisals. In South Africa there are examples of where this mistake has been made (Gauteng Province of South Africa, 2002). In other instances, significant road infrastructure projects such as the Gauteng Free Improvement Project (South Africa National Roads Agency Ltd, 2010) used VTT values based on World Bank appraisal guidelines (World Bank, 2005) for non-work purposes estimated as 30% of the average household income. Hensher and Goodwin (2004) highlighted the risks of using average VTT values, especially in the case of countries with high levels of income disparity such as South Africa.

Travel times savings can make up a considerable proportion of total overall transport scheme benefits including in South Africa as highlighted in the UK by Mackie et al. (2001) and in South Africa by Hayes and Venter (2017). **Table 1** shows the proportion of travel time benefits to total scheme benefits for several large road and public transport projects in Gauteng Province, South Africa, and the project benefit cost ratio (BCR). The highest portion was 66% for the Gautrain Rapid Rail project, followed by the 2014 Rea Vaya BRT appraisal. The value of 29% for the Gauteng Freeway Improvement Project (GFIP) is well below the upper range of 80% for road projects in the UK suggested by Mackie et al. (2001).

The variation in proportions of time savings benefits occurred for three main reasons. Firstly, there was no consistency and transparency in the VTT used in the economic appraisals. The VTT used were either based on values derived from a proportion of the wage rate (GFIP Project), or from discrete choice models using SP data (Gautrain Rapid Rail System) or from unknown sources (both Rea Vaya BRT appraisals). For all the projects no account was taken of VTT heterogeneity amongst the target markets, for example resulting from income variation. Secondly the project target market themselves were different, for example the GFIP project vehicle market includes private, business and freight markets, while the target market for the Gautrain Rapid Rail and BRT projects was largely commuters. Thirdly, there was no consistency in the methodologies employed in the appraisal process. For example, accident cost savings were included in the GFIP and the BRT appraisals but not in the Gautrain appraisal.

Table 1: Proportion of Travel Time Saving Benefits for Gauteng Transport Projects

Gauteng Transport Initiative	Travel Time Savings as a Proportion of Total Economic Benefits (%)	Scheme Benefit Cost Ratio (BCR)
Gautrain Rapid Rail System 2002 (Gauteng Province, 2002)	66%	1.82 with travel time savings and 1.20 without. No wider economic benefits included
Gauteng Freeway Improvement Project (GFIP) E-Toll System (South African National Roads Agency Ltd, 2010)	29%	8.4 assuming a toll rate of R0.50 per km
Johannesburg Rea Vaya BRT System (Phase 1a + 1b) (City of Johannesburg, 2012)	32%	0.85 without wider economic benefits, 1.20 with wider economic benefits
Johannesburg Rea Vaya BRT System (Phase 1a) (EMBARQ, 2014)	37%	1.20 without wider economic benefits

Several countries have official, standardised values of travel time for application in transport appraisals, such as the United Kingdom (Batley et al., 2019, Wardman et al., 2016). The 2019 UK study highlighted that research into VTT regularly reveals new insights, for example that the work-related VTT derived from the employer's willingness-to-pay for travel time savings resulted in significantly different to those used previously, especially when trip distance was considered. The Wardman investigation in 2016 provides a comparison of the official values of time for several European countries against those estimated using a meta-model derived from meta-data. The values are segmented by trip purpose and by mode.

Of importance in the context of the route choice research presented in this report are the meta-analyses of subjective VTT in the UK by Abrantes and Wardman (2011) and in Europe by Wardman et al. (2016). These analyses highlighted the growing trend in VTT investigations to distinguish between congested and free-flow time VTT for car users. In 2016 in the UK, 4% of all valuation estimates (i.e., 68 out of 1,862 estimates) distinguished between free flow and congested travel time. In Europe the equivalent proportion was 7.5% (i.e., 94 out 1,247 estimates). This travel time distinction is investigated in more detail by Wardman and Ibanez (2012) when assessing motorist's valuations of travel time with traffic conditions. This investigation specifically investigated the concept of the congestion multiplier, i.e., the ratio of uncongested and congested utility attribute coefficient ratios, which is an important VTT consideration in this report.

2.4 Choice Modelling and VTT in the South African Urban Transport Context

Values of travel time are derived from mode and route choice models. Mode choice modelling has been performed by transport planners in South Africa since the 1970's, when the first multi-modal transportation models were developed in cities like Johannesburg (Stanway et al., 1980) and Cape Town (Behrens & Kane, 2002). These disaggregated models were based on the four-step modelling process, with simplified binary logit-based public versus private transport choice models based on generalised costs with assumptions made regarding the relative importance (i.e., weighting) of inter-zonal trip time and cost. Choice between the available public modes was performed using the all-or-nothing public transport assignment method, and vehicle route choice assignment was done using incremental assignment methods. The Masstran Study undertaken in 1990 to evaluate the feasibility of a rail-based underground mass transit system in Johannesburg (South African Department of Transport, 1991) used a simplified multi-modal choice model. It was the first model in South Africa to use the newly introduced EMME/2 transportation modelling platform. The generalised cost of a trip was estimated as the weighted average of the travel time and out-of-pocket costs and the mode shares estimated using a binary multinomial logit (MNL) model. The VTT was based on a proportion of the average wage rate.

In the late 1990's more sophisticated multi-modal choice models were introduced based on SP and RP survey methods. Both conjoint and discrete choice methods were used to estimate mode choice models from these data sets. The advantages of discrete choice models over conjoint analysis (Louviere et al., 2010) are well understood. In the early 2000's, the first regional transportation model to introduce discrete choice models was the Gauteng Province for the Gautrain Rapid Rail system model that simulated the binary choice between car and the Gautrain Rapid Rail (Brocklebank et al., 2001). The model was based on the Gauteng Province GTS2000 EMME model. Preference data from SP surveys were used for estimating the car and Gautrain trip utilities for both the general and airport passenger services. Commuting related values of travel time were estimated for each of these rail services that also segmented the market by income group. These values of travel time are discussed in the next section.

Since 2010, several four-step transportation models have been developed in the Gauteng Province by the Tshwane, Johannesburg and Ekurhuleni metropolitan authorities that have incorporated more sophisticated multi-modal choice models using discrete choice methods (Stacey, 2010), (Johannesburg, 2014). These models have been used to estimate the passenger demand for new bus rapid transit (BRT) systems that were planned and implemented at that time. Multinomial logit (MNL) models were used in Tshwane and Ekurhuleni and a random parameter logit (RPL) model (also known as the mixed logit model) was applied in Johannesburg. For all three of the models, commuter preference data from SP surveys were used to derive the modal utility equations based on a linear-in-parameters weighted average of attributes. An analysis of the SP experimental designs for these surveys was undertaken that demonstrated the designs all contained flaws that compromised the quality of the SP data sets (Hayes, 2021).

2.5 Historical Values of Travel Time in South Africa

Non-market related willingness to pay measures such as the subjective VTT are perhaps the most important parameters used in the transportation demand modelling and appraisal processes. For commuters this is termed the subjective commuter related VTT, and is non-wage related. This micro-economic measure is used in the formulation of transport policy such as public transport fare and toll road tariff strategies. The social VTT is used in the economic appraisals of transport schemes to quantify the non-work travel time savings benefits. As shown earlier, travel time savings make up to 40% of the overall scheme benefits in South Africa (Hayes & Venter, 2017) and up to 80% of total benefits for road schemes in the UK (Mackie et al., 2001).

The subjective VTT is also an input into transport demand models, specifically the trip assignment sub-models for public transport (or transit) assignment and vehicle assignment. These assignment models both require the quantification of trip cost in generalised time units and hence require the conversion of trip costs into equivalent time units. This is achieved by the conversion of monetary trip costs such as fares, petrol, parking, and tolls into equivalent time units using the subjective VTT. The willingness to pay for tolls based on travel time savings are thus a key input into urban toll and congestion pricing schemes.

Up until the early 1990's, the South African Central Economic Advisory Service provided estimates of the wage-related value of travel time. No estimates were provided for non-wage related VTT, including for commuters. The wage related VTT estimates were derived from average wage rates and were intended for use in the economic appraisal of transport schemes. In 1992, the estimates of wage related VTT were R24/hour for middle income workers (incomes between R9,500 to R38,000 per annum) and R69/hour for high income earners (incomes greater than R38,000 per annum) (van Zyl et al., 2001).

In the South African context, motorist and public transport commuter subjective VTT since the turn of the century have in all instances been derived from data collected from stated and/or revealed preference surveys and discrete choice or conjoint models. **Figure 3** presents the commuter VTT (normalised to 2017 Rand values using the average consumer price index during the period) that have been derived over the last 20 years for several projects and modes (Hayes & Venter, 2017). The VTT estimates were used in transportation demand models, mainly for the estimation of traveller mode choice between various public modes and the private (car) mode. None of the estimates for car users were derived from route choice experiments, only from mode choice experiments.

It is noticeable that the commuter VTT shows a decreasing value trend toward 2014 when the last significant stated preference surveys were done in Johannesburg. The reasons for this trend are unclear, but improved SP/RP survey methods and the use of discrete choice models in place of conjoint models may account for some of this. For car users across all income groups, the Ekurhuleni surveys in 2013 estimated a commuter VTT of R18/hour. These values are significantly lower than the estimates for high income motorists (R110/hour) and low-middle income motorists (R62/hour) in Gauteng in the year 2000.

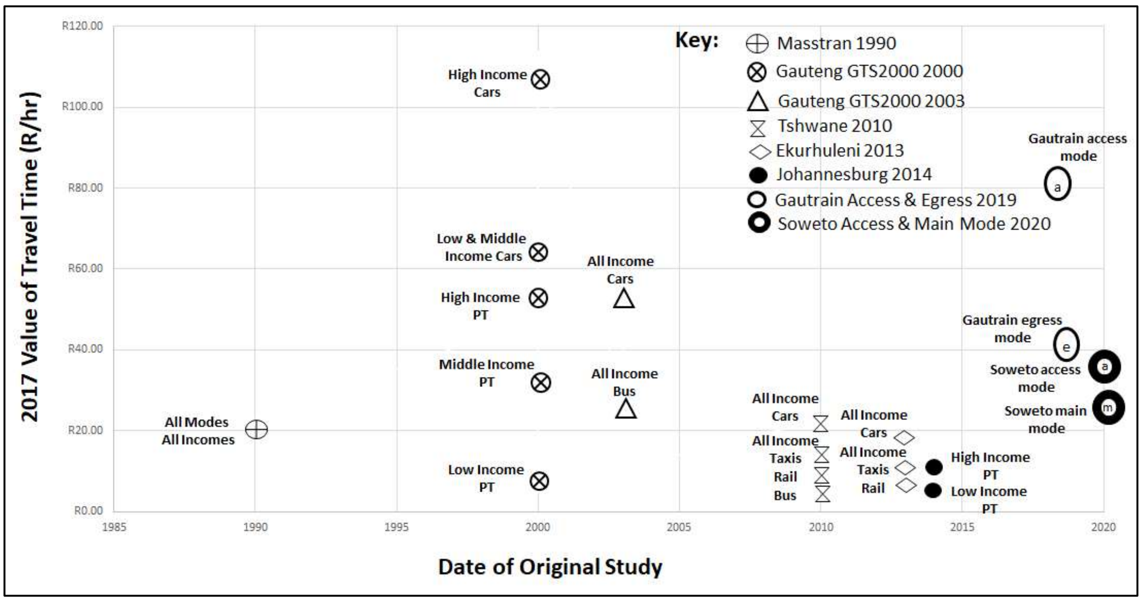


Figure 3: Historical Non-Work Related Values of Travel Time (VTT) in South Africa

The increases in wage rates are more likely to reflect increases in the VTT. However, there have been material differences in wage rate increases between low, middle and high income earners in the country, with low and middle income wage increases being lower than for high income earners. This has largely been due to the shortage of high-income skilled workers. The result has been high skill premiums raising wages at the top, leaving median wages stagnant (Mosomi & Wittenberg, 2020). Between 2000 and 2015 the overall real wage increase was 49.3%, or on average 2.3% per annum, while between 2000 and 2011 real median wages increased by 16.9%, or an average of 1.4% per annum, and have been on a downward trajectory since then. Normalising the VTT in terms of real income growth would thus indicate a widening inequality in values between low and high incomes.

Several important points are evident from **Figure 3**. Firstly, the range of values between studies and within some studies is significant. The reason for this source of heterogeneity is mostly attributable to the high income inequality in South Africa. The Gini index, used to measure income inequality in a country, was 63 for South Africa in 2014, the highest in the world (World Bank, 2022). Comparative countries such as Brazil, Indonesia and Colombia had values of 53.4, 38.2 and 51.3 respectively in

2019. Secondly, the studies since 2005 have revealed lower values of time than the earlier studies - generally lower than R20 per hour. These lower values reflect the improved quality of the methods to collect traveller preference data as well as improved discrete choice modelling methods. As a benchmark, the minimum legal hourly wage in South Africa in January 2017 was R16.36 per hour, and in 2022 was increased to R23.19 per hour (South African Government, 2022).

These lower values of travel time have profound implications for transport policy and the economic appraisal of transport initiatives in the South African urban context for both road projects (including urban road tolling and congestion pricing) and for the design and operation of urban public transport systems such as bus rapid transit (BRT). For example, the lower values raise questions about the high capital cost BRT systems that have been implemented in South Africa. Current taxi, bus and Metrorail public transport users are not willing to pay much for travel time savings but place a high importance on service accessibility, affordability, and reliability (Venter, 2018). So, implementing exclusive BRT bus lanes at a very high cost to save travel time may not be a sound policy. This approach is supported by an *ex-post* economic appraisal undertaken in 2012 for the Rea Vaya (Phases 1a and 1b) BRT system in Johannesburg that revealed benefit-cost ratios of less than 1.0 (Johannesburg, 2012). This outcome emphasised the need to re-evaluate the high capital cost model that has been implemented in several South African metros including Johannesburg, Pretoria, Ekurhuleni, Cape Town and Durban.

The Gautrain access and egress VTT are significantly higher than for the other modes. These higher values are as a result of the much higher income levels of Gautrain users (in 2019 over 50% of Gautrain users previously used their private cars for their commute), and significantly higher Gautrain fare levels compared to other public transport modes. The 2020 values from the Soweto surveys that included the access and main mode VTT are also higher than the values derived between 2010 and 2014. The access mode for Soweto public transport highlights the higher perceived value of travel time saving (by 34%) for a public transport trip access mode compared to the main mode.

To further explore the VTT for South African commuters, revised mode choice models were estimated with a consolidated stated preference data set from the Pretoria and Ekurhuleni Metropolitan areas in Gauteng Province. Mean VTT estimates from this large data set using multinomial logit (MNL) and random parameter (mixed) logit (RPL) models for all trip purposes in the weekday morning peak period were R13.89 /hour and R9.18 per hour for the MNL and RPL models respectively. RPL models provide a distribution associated with the mean value of R9.19/hour and depending on the mixing distributions used for the time and cost coefficients, the mean VTT value can be significantly different from the median value. These values were for low to middle income groups (i.e., for households earning less than R7,000 per month). The values confirm the lower VTT estimates derived between 2010 and 2014 shown in **Figure 3**.

This analysis highlighted that transport planners and economists in South Africa do not have a full understanding of commuting trip preferences, the related VTT and its heterogeneity across different modes used for commuting.

2.6 South African VTT Research since 2018: VTT is Not What We Thought It Was.

No recent urban route choice research has been undertaken in South Africa, and hence recent estimates of VTT have not been derived for car users in a route choice circumstance. This has left significant gaps in the understanding of route choice behaviour in the urban context, especially in the context of urban toll roads and/or congestion pricing. Without filling these gaps it is not possible to develop policies for the procurement of urban road schemes based on the user-pay principle. Equally it will not be possible to determine the demand and toll revenues of these schemes without significant risk, and subsequently undertake robust economic and financial appraisals of the schemes.

International research has meanwhile progressed rapidly, with the recognition that route utility is not simply the linear combination of the total trip time and cost components. For example, Hensher et al., (2016) highlighted that VTT can be materially affected when considered in the context of commuter transport budgets in urban cumulative toll systems. The research emphasised that toll affordability (or ability to pay) added a further layer of complexity to the estimation of VTT in these schemes. Additionally, while not within the scope of this research, factors such as real-time traffic information systems, road safety (or accident risk), driving comfort and route familiarity can also affect route choice behaviour (Harms, et al., 2021; Politis, et al., 2023). These factors are also in turn influenced by route conditions and geometric characteristics such as road surface quality, lane width and roadway lighting.

Research efforts into various forms of discrete choice models since 2018 in South Africa have highlighted that travellers can exhibit complex VTT behaviour. Research into the access and egress mode choices of Gautrain Rapid Rail passengers in Pretoria and Johannesburg showed that passengers have different perceptions of VTT for these parts of their train trip (Watts, 2022). The access VTT was R40/hour while the egress VTT was R80/hour. A possible explanation for this is that commuters are more concerned about arriving at their final destination on time (i.e., at work) on their station egress trip stage and less concerned about getting to the station on time in the access trip stage.

Research by the University of Pretoria into mode choice simulation for Soweto commuters in 2020 took into consideration the access mode component of public transport trips i.e., trips requiring the use of more than one mode or service. Nested logit models derived from SP/RP data amongst current public transport users (i.e., taxi, bus and BRT users) highlighted different VTT values for different stages of the commuting trip. For example, for middle and high-income earners (i.e., incomes more than R9,000 per month), the main mode VTT was R23.92 per hour, whilst for the access stage of the trip it was R35.46 per hour (Cheure et al., 2022) (to be published). This result is also shown in **Figure 3**.

Both these recent studies reveal the nuances in VTT that are not apparent from mode choice models that only consider the main travel mode when making a trip and emphasise the importance of the first and last mile considerations when planning public transport systems. They highlight that the commuter related VTT is not what we thought it was. The implications for transport demand models and economic appraisals of transport schemes are significant.

2.7 A Review of Route Choice Modelling in South Africa

Route choice SP and RP surveys in South Africa have largely been limited to three inter-urban freeway public private partnership (PPP) concession schemes that were undertaken during the 1990's and early 2000's by private concession companies, and the results are kept commercially in confidence. These PPP schemes require the concessionaires to design, finance, build/rehabilitate, maintain, operate and transfer the freeways over a 30 year period. The schemes are the N4 (east) freeway between Tshwane in South Africa and Maputo in Mozambique in 1997 (operated by TRAC Pty (Ltd)); the N3 freeway concession between Heidelberg (near Johannesburg) and Cedara (near Durban) in 1999 (operated by N3 Toll Concessions Pty (Ltd); and the N4 (west) freeway concession between Pretoria and the Botswana border signed in 2001 and operated by Bakwena Pty (Ltd). The N4 concessions carry a small proportion of urban commuter traffic on the freeway sections close to Pretoria. The three PPP concessions have been financially and operationally successful (Robert & Chan, 2015).

The last route choice preference survey in an urban setting based on SP and RP preferences methods was undertaken in South African in 2001. The was done by van Zyl et al. (2001) who undertook the initial investigations into the tolling of the Gauteng provincial freeways based on an express toll lane strategy. While this project was not implemented, it was the prelude to the Gauteng Freeway Improvement Project (GFIP) e-toll scheme that was implemented 10 years later in 2011, in which all the freeway lanes were tolled equally.

For the Gauteng freeway toll road investigation by van Zyl et al., both SP and RP surveys were conducted. For the SP survey component two hypothetical alternatives were defined in choice set format: a tolled freeway alternative without intersections, and an un-tolled arterial alternative with intersections. The SP trip utility was limited to 4 attributes, viz., toll fees, total trip time, stopped time at intersections and the type of roadway (2 lanes for arterials and 4 lanes for freeways). The trip fuel cost and trip time reliability were not included in the utility expression. The stopped time at intersections represented the introduction of stopped travel time in the utility expression. However, its interpretation is uncertain as stopped time at intersections may not be due to congestion but simply due to the method of control at an intersection. How this attribute was described to survey participants is also uncertain.

The RP survey was done on a face-to-face basis with a sample of tolled freeway users and parallel road users. The perceived values of two attributes on their current route were solicited from respondents, i.e., the current trip total travel time and toll cost, and the perceived values for the same attributes on the alternative route. The trip petrol cost was not included as an attribute. It was noted that respondents had difficulty estimating their perceived total trip time and toll costs for both their current and alternative routes. Multinomial logit models (MNL) were estimated with the SP and RP data sets.

Several findings were made from the study. Firstly, the values of travel time (VTT) estimated from RP data were higher than the values from the SP models. This is in-line with findings from international studies as shown by Lavasani et al. (2017), Shires and de Jong (2009), and Abrantes and Wardman (2011). Secondly, there was strong aversion from the SP responses to paying any toll on the freeways. The value of stopped time at intersections was up to 70% higher than travel time on the non-tolled routes (i.e., a congestion multiplier of 1.4). The VTT estimated from the SP and RP models was higher than the average hourly wage rate at the time. The range of VTT estimated was between R20 and R70/hour (in 2000 Rands) for commuters.

2.8 Lessons from the e-toll Gauteng Freeway Improvement Project (GFIP)

As highlighted earlier, South African research into urban route choice behaviour has lagged behind its international peers resulting in significant gaps in transport planners and economists understanding of route choice behaviour and VTT in the urban context. It was emphasised that this lack of insight created risks for the reliable forecasting of traffic demand and revenues for urban user-pay road schemes.

The project that best illustrated the urgent need to fill these research gaps is the Gauteng Freeway Improvement Project (GFIP). This freeway user-pay scheme was planned and operated as a state-owned toll scheme with open tolling infrastructure and systems in the urbanised Johannesburg / Pretoria regions of Gauteng Province. Tolls would be cumulative on the freeway system in two ways, firstly on a toll per kilometre basis, and secondly cumulative over time. A large proportion of traffic on the freeways during the weekday morning and afternoon peak periods is commuter traffic, with high levels of congestion experienced on parts of the freeway system during these periods.

Construction of the carriageway and interchange upgrades was completed in 2010 (in time for the 2010 FIFA World Cup held in South Africa) and the imposition of tolls was scheduled for early in 2011.

GFIP was implemented on 201 km of existing freeways after widening and upgrading the existing two-lane freeways in Gauteng Province to four lanes per direction as well as the upgrading of most of the interchanges on the freeway system. The estimated total capital cost was R19.6 bn (South African National Roads Agency Limited (SANRAL), 2010). The capital cost was financed by means of bonds issued by the South African National Roads Agency Ltd (SANRAL), that are guaranteed by the South African government. The project was the first area-wide implementation (and significant failure) of the South African Governments' policy of the 'user-pays principle' for the use of urban road-based transport infrastructure.

No route choice research was undertaken in the planning stage of the scheme, and there was hence no insight into motorist's willingness to pay tolls (or ability to pay tolls) for travel time savings using econometric methods when the scheme was devised, planned and implemented. Legal challenges by consumer advocacy and civil action groups to the imposition of tolls on the basis of inadequate consumer consultation resulted in the implementation of tolls on the freeways being delayed to December 2013.

From the onset, the GFIP e-toll system was met with strong resistance and negative sentiment from freeway users, and toll payment non-compliance has been consistent at levels of between 70% and 80%. The strong public resistance to the scheme led the Gauteng Province to appoint an independent advisory panel of experts to review the project in 2014. The review panel highlighted the lack of insight into route choice preferences and business and commuter related VTT as a weakness in the planning of the e-toll system (Gauteng Provincial Government Advisory Panel, 2014). In the context of this research the key issues raised by the review panel were:

- The use of an average VTT for all car commuters in the planning process was inherently risky, as there was likely to be significant heterogeneity in the commuter related VTT. This issue is highlighted as a significant risk for toll road projects by Hensher and Goodwin (2004).
- VTT was likely to vary according to the levels of congestion experienced by freeway users. For example, a motorist commuting in the off-peak direction on a freeway is likely to travel in mostly free-flow conditions. Even in the peak-direction, there is likely to be a mix of free-flow and congested travel conditions. Based on international experience the willingness-to-pay for travel time savings in free-flow conditions is lower than for congested conditions (Wardman, 1986; Wardman & Ibanez, 2012) and therefore it is unequitable to charge the same toll tariff for peak versus off-peak directions.

- A distinction needed to be made between commuters' willingness to pay for travel time savings based on vehicle operating costs (i.e., petrol costs) and their willingness-to-pay tolls for travel time savings. A meta-analysis of the European value of time by Wardman et al. (2016) revealed that the monetary units in which the valuation is expressed result in significantly different valuations. This finding was confirmed by Hensher and Rose in Australia (The Hensher Group, 2005).
- The consequence of motorists and especially commuters, paying cumulative tolls required investigation. Hensher (2016) found that when the commuters' bi-weekly toll budget was introduced as a utility affordability attribute, the ability to pay tolls reduced when toll affordability saturation levels were reached. At this point the VTT was significantly reduced.

Due to consistently high public resistance and a toll payment non-compliance level of approximately 80% in 2019 (Organisation Undoing Tax Abuse (OUTA), 2019), the GFIP e-toll project was scrapped by the South African National Treasury in late 2022. The toll road de-proclamation process was underway at the time of writing. The estimated credit losses and other receivables resulting from the GFIP e-toll project alone were R9.8bn on 31st March 2020. As the project sponsor, the South African National Roads Agency Ltd (SANRAL), has incurred significant financial and reputational damage, and the case for urban tolls and congestion pricing in South Africa has been put back many years (South African National Roads Agency Ltd, 2020). The South African Auditor-General's report in the SANRAL 2020 Annual report raises material concern that, due to the entities total debt of R14.85bn on 31 March 2020 which exceeds the entity's assets, it faces a severe short-term liquidity risk and "a material uncertainty exists that may cast significant doubt on the public entity's ability to continue as a going concern" (South African National Roads Agency Ltd, 2020). This uncertainty related to the collection of historical and future e-toll revenue, which now requires SANRAL to *"consider both the ability and the intention of customers to pay the consideration due".* This refers to both the willingness to pay and the ability to pay e-tolls, which was not investigated by SANRAL prior to the implementation of the GFIP e-toll system. SANRAL has been unwilling to disclose the commuter related VTT used in the GFIP traffic demand models for the weekday morning, midday and afternoon peak hours.

A similar urban freeway tolling system that was proposed by SANRAL for the Western Cape Province (Winelands N1/N2) was challenged in court by the City of Cape Town in 2016 and defeated on the basis that there was inadequate public consultation for the proposed tolling scheme (Polity, 2016). In this case SANRAL also did not undertake any route choice research to determine freeway and non-freeway user trip preferences and behaviour including willingness to pay tolls for travel time and cost savings.

Despite the failure of the GFIP scheme, there are still references made by various South African transport authorities for the implementation of urban tolls and congestion pricing. The South African Department of Transport Green Transport Paper (South African Department of Transport, 2017) mentions congestion pricing as *"an important part of a more comprehensive energy price rationalisation in the longer term"*. The Gautrain Management Agency (GMA) has publicly stated that revenues for the expansion of the Gautrain Rapid Rail System will be partly funded through motorist congestion charges (Engineering News, 2020). There is significant risk associated with the implementation of congestion pricing schemes given the lack of insight into the various non-work (and work) related VTT's and the failure of the GFIP e-toll scheme.

The lessons learned from the GFIP scheme have emphasised the significant gaps in our understanding of route choice behaviour in South African urban areas. Firstly, transport planners have no quantified insights into motorist route choice behaviour. Historical efforts to understand this behaviour are no longer valid and, in any event, had significant shortcomings. The route choice models estimated by van Zyl and Raza (2006) excluded trip petrol costs.

Secondly, the commuter related VTT is unknown, especially those derived from the disaggregated forms of travel time (i.e., free-flow versus congested travel times). More importantly there is no insight into the heterogeneity associated with an average value. The GFIP experience suggests that motorists are not willing-to-pay much for travel time savings, but this has never been quantified and there are likely to be other factors (e.g., the perceived lack of consultation on the GFIP project and general taxpayer frustration at perceived high levels of malfeasance in government project procurement and operation). This lack of insight into the willingness-to-pay tolls for travel time savings highlights the risk that the GFIP time savings benefits have been overstated in the scheme's economic appraisal.

Thirdly, South African transport planners have no insight into the other factors of utility that influence commuter route choice. An example is the value of travel time reliability that has been shown to be an important component on trip utility (de Jong & Bliemer, 2015; Batley et al., 2019). International evidence has shown that motorists have different values of travel time for different levels traffic congestion (Hensher & Rose, 2004; Wardman & Ibanez, 2012).

There are other route choice related issues that have received no attention in South Africa but are likely to have significant impacts on road planning, network modelling and economic appraisal. Empirical evidence provided in the UK by Batley et. al (2019) into the value of work-related travel time highlighted that the business-related VTT is not what it was thought to be. Economic theory suggests that the value of travel time savings is worth what the decision maker is willing-to-pay for it, so the business-related VTT should be based on what employers are willing to pay to save travel time. Based on extensive SP surveys undertaken amongst a sample of employers in the UK, the VTT's derived from the willingness to pay for travel time savings were significantly lower than the wage-based estimates for shorter trips (less than 32 km), about the same for trips up to about 100 km, and higher for trips longer than 100 km's.

2.9 Summary of Findings into Mode and Route Choice Modelling in South Africa

Based on the discussions in this chapter, several important findings were identified as follows:

a) The focus of choice modelling in the urban passenger transport context in South Africa has been on mode choice modelling. Over the last 10 years several mode choice models have been developed at the provincial and metropolitan level. Since the early 2000's there has been no research into urban route choice data collection and discrete choice modelling.
b) The surveys done for the mode choice models were all stated preference surveys. A review of these surveys found that all the experimental designs were flawed, with the discrete choice MNL models all displaying the characteristics of poor SP experimental designs, e.g., coefficients with the wrong signs, counter-intuitive coefficient magnitudes and implausible VTT.
c) The commuter related VTT is not what we thought it was. More recent studies by Hayes and Venter in South Africa (2017) indicate lower VTT values than earlier studies, with public transport user values generally less than R20/hour (except for Gautrain users for whom values are R40/hour and more). There is little insight into the heterogeneity associated with these lower values.
d) There is a large gap in the understanding of urban motorist route choice behaviour and trip preferences. There is also the associated uncertainty of urban road commuter willingness to pay for commuter related VTT, with no definitive values recently derived from the mode choice models. The heterogeneity associated with the VTT is also unknown. This is despite the implementation of a significant urban toll road initiative in Gauteng in 2011. The basis for the establishing the feasibility of a user-pay scheme is understanding the user's willingness to pay for travel time savings.
e) There is no insight into car trip utility attributes that have been highlighted as significant in international research and applications, especially the value of trip time reliability. Associated with this is the variation in VTT corresponding to different levels of congestion on urban roads that have been highlighted as significant in international studies. These are the VTT's associated with stop-start time, slowed-down time and free-flow time.

f) There has been no research into the effect of cumulative toll schemes on route choice behaviour in South Africa, i.e., the effect of distance-based tolls on linked toll roads; and tolls that accumulate over time, e.g., for a commuter this could be two tolled trips per day and 46 trips per month. This is exactly the case for the GFIP e-toll scheme, even though the scheme has a toll payment cap. Hensher et. al. (2016) showed that the affordability of cumulative tolls had a significant impact on motorists VTT. A toll budget constraint affects motorist willingness-to-pay for travel time savings and results in significant decreases in VTT, with motorists then either choosing different routes or changing travel mode.

2.10 The Complexity of Route Choice Modelling

Several authors have provided evidence that the route choice data collection and modelling process is more complex and dynamic than other travel related decisions such as travel mode choice (Ramos, Frejinger et al., 2012; Ben-Akiva, Polydoropoulou et al., 1994; Ben-Akiva, de Palma et al., 1991). This complexity has perhaps contributed to the limited research and insight into motorist route choice preferences in South African urban areas.

The complexity is created by the dynamic interaction of four factors. Firstly the drivers' personal preferences, learning trends and personality traits that defines their perceived route utility (Tawfik & Rakha, 2012). Secondly the trip purpose/s and required waypoints (for example a trip from home to work may require that a particular bridge be used or that an intermediate stop for a drop-off at school is necessary and hence may constrain the number of potential alternative routes). Thirdly the dynamic nature of traffic conditions on the road network (including time-of-day and day-of-week conditions) that may influence the route and departure time choice investigated by Prato et al. (2014). Finally the influence of advanced traffic information and route guidance systems (in-vehicle or smartphone-based) that provide minimum time and cost route options and reduce travel time uncertainty and may influence the preferred route (Mahmassani & Yu-Hsin, 1999; van Essen, et al., 2019).

Bekhor et. al. (2006) suggested that route choice modelling is a two-step process, i.e., firstly alternative routes are generated to form the choice sets, and secondly, the probability of a given route being chosen from a specified choice set is calculated. However, executing both steps is not straightforward. Prato (2009) suggests that there are two main challenges associated with route choice data collection and modelling. Firstly, the generation of alternative routes for the choice sets, and secondly, the estimation of discrete choice models, specifically to deal with the issue of route overlap and correlation.

To this, Dhakar and Srinivasan (2014) added more complexity by highlighting that there are large number of independent variables affecting driver route choice on dense urban road networks, including the number of left and right turns, the number of intersections, and the proportion of local roads, amongst others. Papinski et. al. (2009) also highlighted that behavioural factors of individual motorists also affect route choice, specifically the influence of route learning based on experience (i.e., habit), risk-taking behaviour (i.e., willingness to change routes) and the availability of traffic information.

Hess et. al., (2020) and Krcal et. al., (2019) added further layers of complexity to the collection of route preference data by either SP and/or RP methods by considering the needing to balance the external validity (or realism) of the route traffic data with the control of the independent trip variables, i.e., the attributes and attribute levels of the experiment. While SP methods enable high levels of control over the utility attributes and levels, the external validity of the alternative routes can only be presented in a hypothetical manner. While RP experiments provide high levels of external validity on the observed route, they lack the flexibility to vary the attribute levels. Some attributes may not even be observable with RP data such as the perceived travel time reliability of the route. With RP methods the generation of alternative routes is not straightforward because of the number of potential alternative routes and the difficulty associated with collecting the traffic data for those routes. These issues are discussed in detail in the next section.

3. THE DATA COLLECTION FRAMEWORK FOR ROUTE CHOICE SURVEYS

3.1 Introduction

Both RP and SP methods can be used to collect user preference data from travellers, and analysts are faced with choosing between these survey types, depending on the specific study objectives (including type of discrete choice model to be estimated), and the available resources (i.e., budget, technology, and timeframe). This chapter presents an analysis of these survey types in a route choice context.

3.2 The Control - Validity Framework for Choice Surveys

When selecting the appropriate survey type, an important consideration is the trade-off between the external validity of the survey (i.e., the degree to which the mode or route alternatives and their attributes and attribute levels reflect real-world conditions), and the degree of control over the survey attribute levels that the analyst has. The framework in **Figure 4** has been suggested by Bliemer (2020) to describe the location of the data types for RP and SP surveys and the trade-off between the survey external validity and the degree of control that the analyst has over the experimental design. The survey types are grouped into field data types that consist of revealed preference types, and experimental data that consist of the driver simulator and stated preference methodologies.

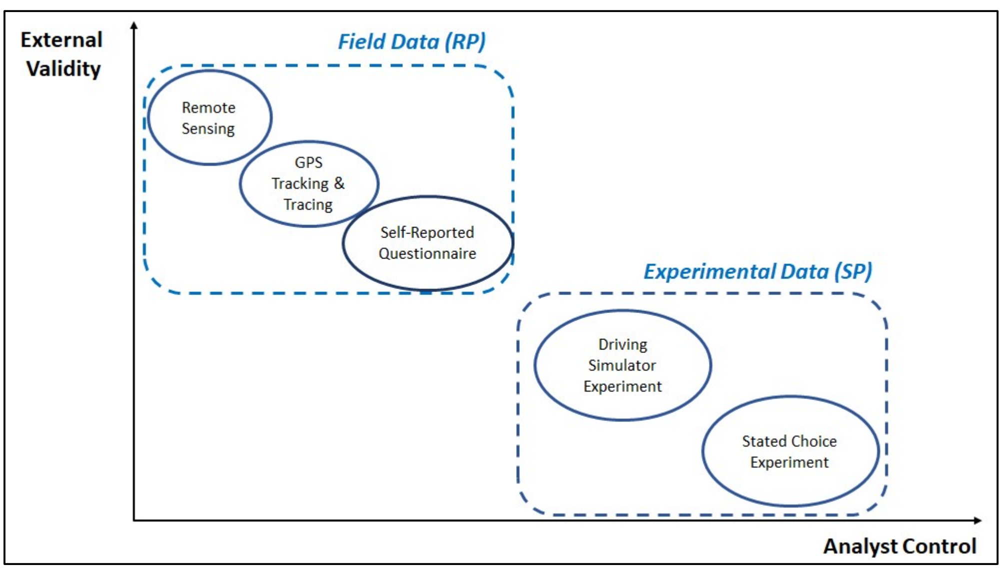


Figure 4*: External Validity / Control Framework and the Types of Data Collection Methods for Mode & Route Choice Simulation* (Bliemer, 2020)

Data collection complexity for RP route choice surveys is due to several factors, including the large number of possible alternative routes between origins and destinations; the potentially large number of observable and unobservable trip utility attributes affecting route choice; the dynamic nature and variability of traffic levels of service on congested networks including time-of-day and day-of-week effects; the availability of real-time traffic information to motorists that may affect route choice; and the high likelihood of alternative route overlap that violate the independent and irrelevant alternatives (IIA) constraint of standard multinomial logit models (MNL) (Prato, 2009).

3.3 The Evolution of SP and RP Methods

One of the advantages of SP over RP experiments is the level of control the analyst has over the definition of the attributes in the trip utility expression and the attribute levels used in the choice sets. More than this SP experimental designs have evolved and improved over time. The use of efficient designs over traditional orthogonal fractional factorial designs has improved the efficacy of SP surveys and the discrete choice models estimated from the data (Rose & Bliemer, 2009; Rose & Collins, 2015; Hayes, 2021). The application of efficient designs requires a prior knowledge of the utility attribute coefficients through previous local or international surveys and models. There are no applications of route choice SP surveys based on efficient designs in South Africa.

The historical limitations of RP data (prior to the wide availability of GPS devices and smartphones) to estimate discrete route choice models shifted the focus to improved SP methods of data collection. The outcome has been that the estimation of key non-market related willingness-to-pay measures such as the VTT and the value of trip time reliability (VOR) have mostly been done with data derived from SP surveys (Fayyaz, et al., 2021). Since the turn of the century route and mode choice SP surveys have mostly been done by means of computer aided personal interviews (CAPI) based on fractional orthogonal experimental designs, but more recently using efficient experimental designs. Multinomial logit (MNL) and random parameter logit models (RPL), also known as mixed logit models (ML), were commonly used to simulate route choice. Examples of these model types derived from SP data are found in Hensher (2001), and in Hensher and Rose (2005).

For route choice SP experiments the choice sets are based on hypothetical routes with pre-defined attributes and levels. This approach assumes the routes are unique with no overlap, which obviates the problem of route correlation that could occur in practice. SP surveys have also evolved to include an RP component. The external validity of hypothetical routes in SP surveys can be improved by using pivot experimental designs that calculate the alternative route attribute levels from the respondent's current (perceived) RP route attribute levels by pre-specified amounts (Choicemetrics, 2018). Thus the SP part of the experiment is pivoted from a RP trip, reducing the risk of hypothetical bias.

An alternative approach to combing RP and SP data in experiments was proposed by Train and Wilson (2009; 2008). The methodology, termed SP-off-RP, requires respondents to not only reveal their preferred mode or route and the typical levels of the attributes, but also to specify the limits of the levels, i.e., the observed range of attribute levels for each mode. The SP choice sets are derived from the RP attribute levels and the observed (RP) level range. MNL and ML models were estimated (assuming normal distributions for the attribute coefficients), with both models providing significant results, but the ML model providing a better goodness of fit as reflected by its lower log-likelihood value.

3.4 Recent Approaches to Collecting Combined SP and RP Data

Recently, driver simulation methods have been used to improve the external validity of route alternatives with combined SP and RP experiments. Driver simulation systems have long been used in road safety research but have been adapted for route choice research. These systems contain actual car dashboards, steering wheels and pedal controls linked to video screens to display the driving experience on the roadway, through intersections and with the effect of other traffic. Urban driving conditions can thus be realistically replicated and controlled with driving simulation systems. One such example is the Travel Choice Simulation Laboratory at the University of Sydney (TRACSLab, 2021). The TRACSLab simulator system is unique in that the driving simulators (10 in total at the Universities of Sydney and New South Wales) can be linked, enabling all driver participants to interact with one another on the virtual road network.

The TRACSLab simulators enable combined SP and RP route choice experiments to be performed iteratively (Fayyaz, Bliemer et al., 2021). The experiment requires participants to initially choose between two routes in an SP setting. An RP component is then introduced with the participants having to drive their chosen route using the simulator. This is not a "pure" RP method (i.e. the survey participants do not physically drive their chosen route in the field) – it is an "experimental" RP. This process can be iterated several times with varying route attribute levels to observe the change in driver choice behaviour. Route choice consequence can be introduced into the experiment through the introduction of a real toll cost for participants. This economic experiment is executed by providing a toll account to each participant with a starting balance. When a tolled route is chosen, the toll fee is debited from the account. At the end of the experiment, the participants are paid out their toll account balance.

The technological advantages of driving simulator systems are constrained by the high capital cost of implementation; limited sample sizes; and relatively short simulator driving times (up to 12 minutes to avoid driver simulator fatigue is reported by Fayyaz et. al (2021)). With breaks of three minutes between stated choice and simulator iterations, this allowed each participant to complete five iterations in about 90 minutes. The focus of the route choice research by Fayyaz et. al. (2021) using the driving simulators has focussed on the estimation of the value of travel time and the value of travel time reliability.

MyTrips (Rudloff & Straub, 2021) is a multi-modal mode and route choice survey instrument that uses RP trip data derived from participant trip diaries to estimate an SP survey off the observed RP data (SP-off-RP). Although not specifically designed for smartphone applications or the use of smartphone GPS systems, it uses modal or route trip data (derived from travel diaries) to generate alternative mode and routes superimposed on realistic map-based backgrounds presented to participants on-line. The usefulness of *MyTrips* is its ability to generate respondent specific multimodal public transport or route choice SP surveys based on the participant's observed RP trip data. The SP surveys are designed using D-efficient methods with an initial SP survey being used to generate the prior estimate of the attribute coefficients. The alternative trips are generated by a bespoke routing algorithm called Ariadne (Pranstetter, Straub et al., 2013), that uses several rules to eliminate unlikely alternative trips (e.g., alternative trip travel time cannot be longer than twice the RP route). The surveys are done online in five steps after recruitment of the sample:

i. Step 1: Introductory questionnaire to obtain participant socio-demographic and trip data.
ii. Step 2: Collection of RP trip data by means of on-line trip diaries.
iii. Step 3: Generation of alternative trips (for public transport surveys) or routes (for route choice surveys) and choice set calculation.
iv. Step 4: Main questionnaire to obtain detailed mobility preferences and an introduction to the survey methodology and the hypothetical nature of the scenario being tested.
v. Step 5: Generation of personalised SP-off-RP choice sets.

Latent class multinomial logit models were successfully developed for two multi-modal trip case studies. The first for the extension of the Vienna metro-rail system, and the second for replacement of existing bus services with the introduction of self-drive rural micro-transit vehicles (maximum 3 passengers).

3.5 RP Methods and the Advent of GPS Devices and Smartphones for Route Tracking

RP survey methods are essentially field-data methods where the actual behaviour and choice of participants is observed. For route choice surveys, RP methods originally focussed on self-administered travel diaries and self-reported questionnaires as a means to collect actual route paths and preference data. These methods rely on respondents recording their travel movements, including their routes descriptions on a daily basis over a period of time using either paper or electronic diaries. For route choice surveys, the main drawback of travel diary methods is the accuracy associated with the description of the routes used and the risk of trips not being recorded, i.e., non-reporting. These drawbacks, together with the high cost and efforts required to recruit and manage survey participants now limits their application. In 2016 the State University of New York's report into innovative methods for transport data collection (State University of New York (SUNY), 2016) indicated that travel diary methods were still used in in the state, but with increasing validation using transport smartphone applications for route tracking and trip information. In fact, as far back as 2001 efforts were made to replace travel diaries with GPS tracker devices that provided more accurate and complete data sets Wolf, Guensler et al., (2001). The use of smartphone-based travel diary applications is now more common, with examples provided by Berger and Platzer (2015) and by Allstrom, Kristoffersen et al., (2017).

The introduction of GPS specific tracking devices in the early 2000's considerably improved the ease with which to collect RP route choice and other travel behaviour data. These original devices were either attached to vehicles or had to be carried by fieldworkers or participants making the trip. The introduction of smartphones with embedded GPS devices has dramatically improved the ease with which to collect RP survey data especially because survey specific applications can be developed and used on these devices (Shen & Stopher, 2014; Wang, He et al., 2018). Smartphone GPS devices have overcome the original obstacles associated with GPS specific devices, i.e., being fixed to vehicles (and not individuals), the burden for survey participants to carry the mobile devices, and potentially forgetting to activate or carry them thereby increasing the risk of non-reported trips (Vlassenroot, Gillis et al., 2014). Furthermore, the ability to run bespoke survey applications on smartphones has significantly increased the potential for collecting additional multi-modal trip data by allowing specific trip questionnaires to be completed by respondents on their smartphones. The applications can passively record trip data by running in the background when the smartphone is switched on or can actively log trip data by means of a specific interface built as a front-end application.

GPS enabled smartphones have the ability to accurately measure a range of RP trip attributes such as trip travel times (including trip start and end times), route alignments, route lengths and speeds. Route topology can also be derived, e.g., the classification of roadways making up the routes. Out-of-pocket trip costs such as petrol and tolls can be derived from the observed paths, e.g., trip fuel costs can be estimated from trip distances assuming average fuel consumptions and the current price of fuel, and toll charges can be derived from plaza or gantry locations and their associated toll tariffs.

3.6 GPS and GSM Communication and Location Accuracy

A fundamental requirement of the research presented in this thesis is the ability to quickly determine survey participant locations; generate alternative routes and their attribute levels based on real-time traffic conditions and communicate these efficiently and clearly to participants; and then to track the participants using the GPS their devices in smartphones. It is only recently that this could be done with adequate accuracy and speed using smartphones. The early limitations of GPS devices and smartphone-based GPS devices were mainly related to the accuracy of location coordinates and the need to use map matching software to correct the traveller paths (Bierlaire, et al., 2010; Venter & Joubert, 2013). Smartphone tracking requires the use of Global Positioning System (GPS) satellite tracking to identify the location coordinates and time stamp of the smartphone signal, and GSM (Global System for Mobile Communication) technology using terrestrial cell phone towers to transmit the location data to a central data centre or a bespoke cloud-based remote database as shown in the following illustration.

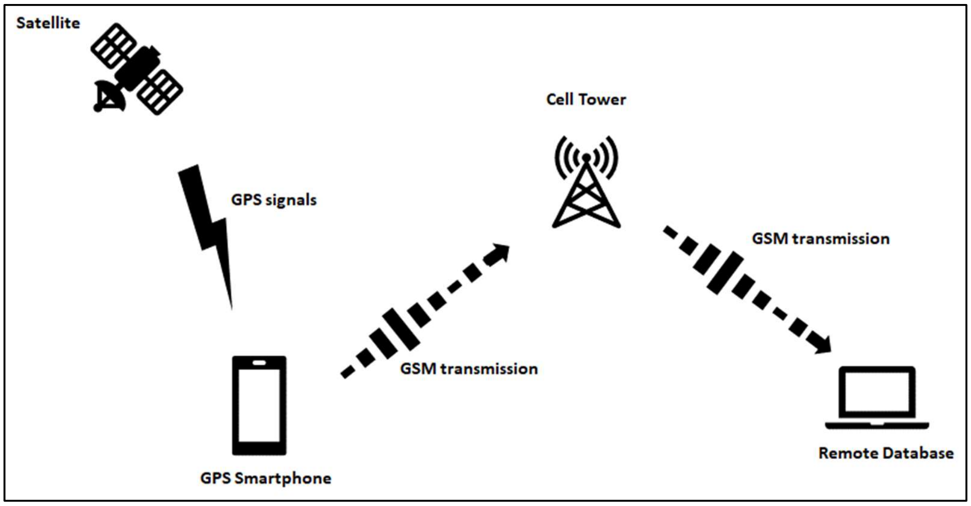


Figure 5: Illustration of GPS Satellite Communications with Smartphone and GSM Communication with Cell Tower and Remote Database

GSM location tracking via cell phone towers can be undertaken in combination with GPS satellite tracking when the GPS device in the smartphone is blocked by buildings, is under a bridge or in a tunnel. GSM tracking is not as accurate as GPS tracking. GPS locations are usually to within 5 meters accuracy, while GSM locations are within 30 meters accuracy in urban areas where there is a high density of closely spaced cell towers to perform the triangulation. To provide location and elevation locations, GPS requires access to at least three satellites to perform the location triangulation process and four satellites for the elevation location.

New smartphone technology, the introduction of 4G and 5G data transmission technology and the increasing number of orbiting satellites and cell phone towers in urban areas has significantly improved the speed of mobile communication and path tracking accuracy without the need for map-matching processes. The Institute of Navigation (ION) undertook a worldwide GNSS (Global Satellite Navigation System) exercise in 2015 with over 1,000 participants in 100 countries (Van Diggelan & Enge, 2015). The study determined that the global mean accuracy of smartphone GPS devices was 4.9 m in “open-sky” urban conditions. The study confirmed the ION “rule of thumb” figure of 5 m location accuracy. However, this accuracy deteriorated when the smartphones were in urban areas with high buildings, under bridges and within buildings. These conditions affect both GPS devices and smartphone GPS systems.

While a minimum of four satellites are required to accurately fix longitude, latitude and altitude, there are commonly many more than this observable from a location. The number of satellites available from a location can be determined using an application such as *GPSTest* that can be downloaded from the Google Play Store® or iPhone App Store®. While the number of observable satellites varies over a particular location, this application revealed that on average there are 16 satellites observable from the Johannesburg / Pretoria region at any one time. These are a combination of GPS (USA), Galileo (European), Glonass (Russian) and Beidou/BDS (Chinese) satellites in approximately equal numbers. Not all cell phones can receive signals from all these satellites. For example a Samsung A205F smartphone (2019 model) that has been used as part of this research located in Johannesburg can receive signals from GPS-A (advanced GPS), Glonass and BDS. The website https://www.gsmarena.com/ can be used to check the GPS capability of a particular smartphone model. This limitation was one of the reasons that survey participants were required to have a recent model Android smartphone.

Martin et. al. (2019) highlight that location and mobility tracking using smartphone-based GPS devices is becoming an important component of traffic data collection for Smart Cities to enable real-time traffic monitoring and management. For the derivation and analysis of traffic-related information the key data components are location identification (by means of location coordinates), path tracking (sequences of coordinates) and time stamping (time of coordinate generation).

An important consideration when using smartphone applications for transport surveys is the issue of participant data privacy. Ethics approval, informed participant consent, data anonymity and safeguarded data storage are all necessary requirements. Participation in transport surveys by smartphone users was investigated by Assemi et. al., (2018), highlighting the willingness to participate. The ease of use of smartphone survey applications was an important positive aspect for participants, but the perceived data privacy risk was a concern. However, this concern did not affect the participants willingness to participate in the survey when reassurance was given in regard to data safety and privacy.

3.7 Vehicle Tracking Technology for the Collection of RP Route Data

The rapid development of vehicle tracking technology, especially via GPS devices in smartphones, has made the collection of RP data easier. There are examples of the application of transport surveys using GPS devices and smartphone GPS devices for the collection of vehicle (Geyer, Ellis et al., 2019; Vaca & Meloni, 2013), pedestrian (Vlassenroot, Gillis et al., 2014; Alvarez & Leeson, 2015) and public transport passenger tracking surveys (Xiao, et al., 2012; Joseph, et al., 2020). Paths and path distances can be accurately determined using coordinate data; departure, arrival and total travel times can be accurately determined; and trip origins and destination locations identified within a few metres of accuracy. Trip costs such as petrol costs can be deduced with assumptions about average vehicle fuel consumption, and toll costs (if any) are also now available from platforms such as Google Maps®.

Transport survey smartphone applications (*apps*) are now commonly used to collect trip data. Most of these are passive data collection tools, i.e., they do not require any intervention by the participant other than to download the app onto their smartphone, and to activate it during their trip. While many of these apps are developed by researchers, platforms such as *Itinerum* provide app-based survey frameworks of various types of surveys that allow for customisation for specific project applications that collect data passively and actively (Patterson, Fitzsimmons et al.,

2019). These apps can be used in place of traditional household travel surveys, travel diary surveys, trip satisfaction surveys and origin-destination surveys. Survey participants are required to download the app onto their smartphones and activate the app before starting their trip. They may be required to input trip related data such as mode, fares, tolls, parking cost and trip purpose after they have finished their trip, amongst others. *Flocktracker* is another smartphone-based trip survey instrument developed by the Massachusetts Institute of Technology (MIT) (MIT , 2021).

3.8 Testing the Location Accuracy of Smartphone GPS Devices in Gauteng Province, South Africa

Extensive testing of route tracking for this research using a Samsung A205F smartphone showed that path tracking accuracy is now well within the requirements of the route determination without the need for correction with map matching (i.e., coordinate snapping). A key determinant of location identification is the smartphone pulse rate, i.e., the frequency at which signal pulses are sent from the phone to overhead satellites. A five second pulse frequency was used for this research and has been shown to provide high accuracy levels – within the accuracy limits of 5 m determined by the ION.

Examples of route plots for this research are shown in **Figure 6** and **Figure 7**. **Figure 6** shows the accuracy achievable for a path through the suburb of Rosebank, Johannesburg. Location errors vary with vehicle speed, with larger errors at higher speeds, i.e., when the distance between pulses increases. However higher speeds usually occur when there is less horizontal road curvature that reduces the magnitude of errors. Generally, error limits within 5 meters are achievable in the study area for this research.

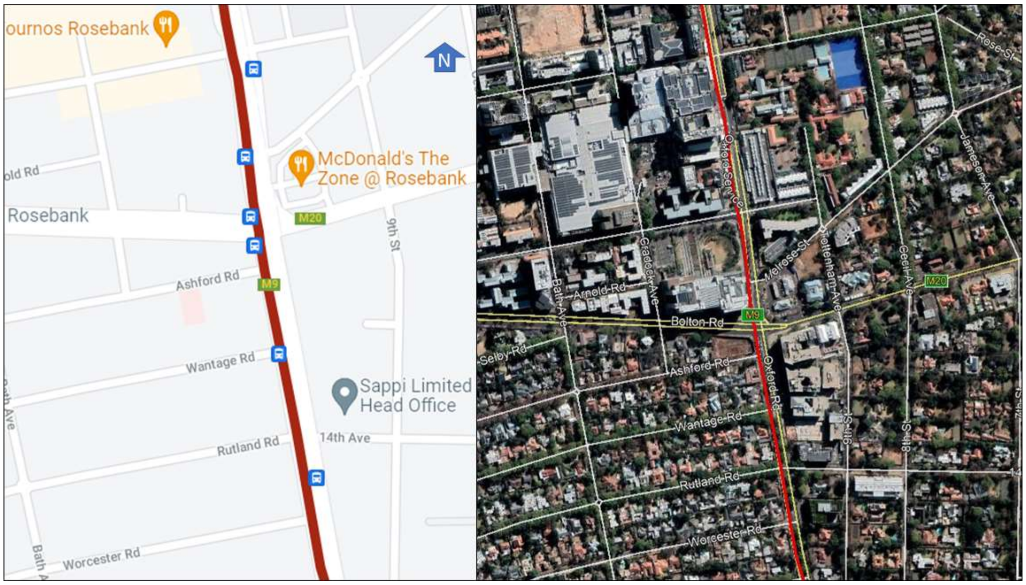


Figure 6: Route Plotting in Google Maps® and Google Earth® through Rosebank in Johannesburg

Figure 7 shows the path error through an intersection in Randburg, Johannesburg. The smartphone five second pulse locations are shown together with the estimated straight-line path between them. The maximum path error is estimated to be 5 m. This level of error does not materially affect the identification of the path or its total length.

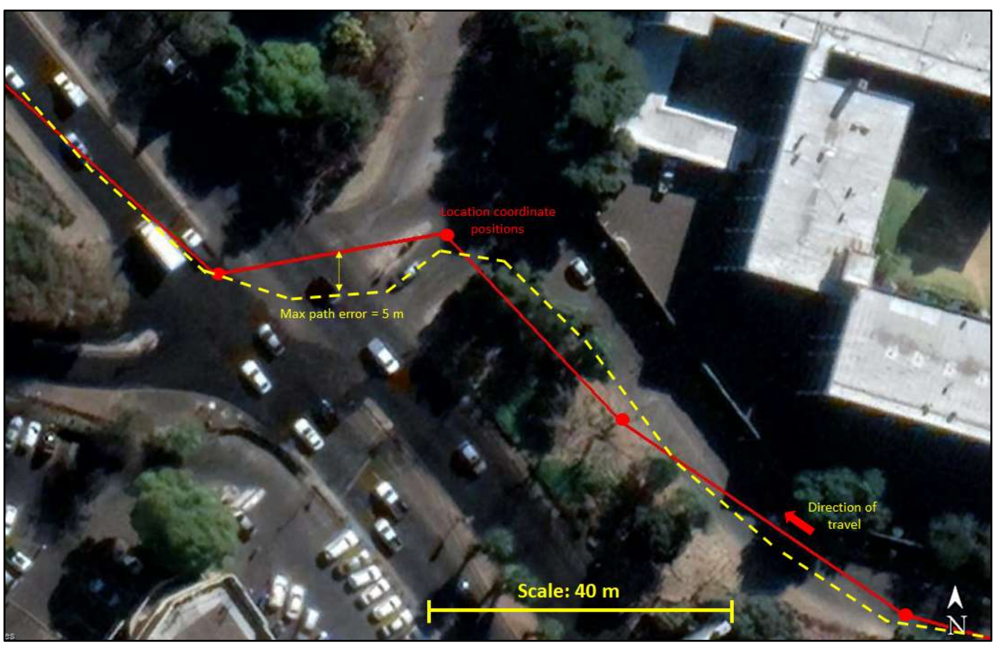


Figure 7: Path Error Illustration in Google Earth® through Randburg in Johannesburg

Figure 8 shows the path error on a high-speed peri-urban roadway in Centurion, Pretoria, with a gradual left turn horizontal curve and a speed limit of 100 kph. The distance between the five second smartphone pulses is about 130 m when travelling at the speed limit. The maximum alignment error is approximately 3 m.

Figure 8: Path Error Illustration on a Motorway in Centurion, Pretoria

4. GENERATING ROUTES ON CONGESTED URBAN ROAD NETWORKS

4.1 Introduction

Wang, He et. al., *(2018)* describe the nature of RP data derived from smartphone-based tracking devices as the contradiction of being data-rich but information-poor. This is because the revealed preference route only provides the revealed route alignment, origin & destination location, and route speeds and times. Petrol and toll costs (if any) must be inferred. The revealed route does not provide insights into personal preferences relating to travel time reliability, departure and arrival time flexibility and other attributes that constitute route utility. Most importantly the RP approach provides no insights into possible alternative routes.

The alternative products or services included in the set of alternatives is a key consideration in choice experiments. Implicit in the use of discrete choice models is the assumption that the analyst can correctly specify the relevant set of alternatives available to a specific individual, i.e., the 'choice set' of alternatives. In SP route choice experiments the specification of alternative routes is relatively straightforward as the routes can be hypothetical and the choice set is defined by the analyst through the experimental design.

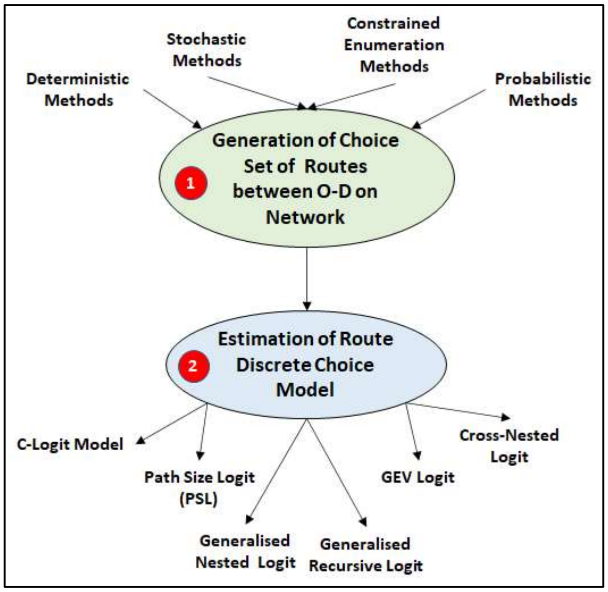
Most route choice models are derived from revealed choice behaviour (Prato & Bekhor, 2007) and are estimated by adding alternative paths to an observed one to constitute the choice set. In RP surveys the route choice set is unobserved, and its relevance and realism are unknown, requiring the analyst to make assumptions regarding its composition at the modelling stage. DeShazo, Cameron et al., (2009) argue that it is thus possible that the choice set specified by the analyst excludes relevant alternatives or includes irrelevant alternatives. The risks associated with misspecification of the choice set in RUM-based choice models can result in the estimation of biased parameters estimates and model forecasts (Lianhua, Adamowicz et al., 2015). Bliemer and Bovy (2008) showed that including irrelevant alternatives in the choice set could lead to unexpected choice probabilities, especially when accounting for route overlap using C-Logit or PS-Logit models.

Various approaches have been adopted to generate realistic alternative routes for inclusion in the choice set as described in the next section.

4.2 Approaches to Generating Alternative Paths for RP Route Choice Experiments

The two-step process for route choice model estimation is shown in **Figure 9**, together with the various methods that have been applied for the generation of the route choice set. The various route choice model types that can be applied are also shown.

GPS devices are widely used to accurately observe revealed route preferences. However, to estimate route choice models alternative routes must be identified and included in the route choice set. This is an important limitation of RP methods, as the estimation of realistic alternatives routes in a dense road network is a non-trivial task (Fayyaz et al., 2021). This problem has focussed research into methods for generating alternative routes to complement the observed RP route and generate the choice set of realistic routes.



Area-wide (macro) transportation demand models have been used to generate alternative least cost routes and compared to the observed RP routes derived from smartphone-based GPS data (Vacca & Meloni, 2013; Bekhor, et al., 2006). This deterministic approach requires the transport model to provide accurate trip path lengths, travel times and costs within the time period being simulated (e.g., the morning peak hour*)*.

Figure 9: Two-Step Route Choice Model Estimation Process Showing Route Generation Methods and Types of Models

Prato & Bekhor (2007) highlight several shortest-path methods to derive alternative paths from the digitised road network in the model but also identify two issues of concern. Firstly this approach relies ex-ante on the identification of the attributes that determine route choice behaviour, and secondly the accuracy of these attribute values derived from aggregated transportation models that typically simulate the average demand in the modelled period. There can be significant variation in demand and hence travel times around this mean demand value. For example, Sampson highlights the significant variations in monthly, daily and peak hour flows in South African urban areas (Sampson, 2017).

To address the demand accuracy obtained from transportation demand models, alternative route traffic data have been obtained from historical road network travel time data from sources such as Google Maps®, TomTom®, Waze® and MapBox®. These historical data sets have been used to determine shortest time paths for comparison with observed RP routes determined using GPS devices *(Tang & Cheng, 2016)*. An important advantage of this approach is that route overlaps can be quantified irrespective of the source of alternative route data. This allows the effect of route correlation to be allowed for in discrete choice models such as C-Logit and PS-Logit.

Prato and Bekhor *(2007)* identify three deterministic and a constrained enumeration methods for route choice set determination from either transportation models or historical network traffic data. These methods are appealing due to the efficiency of shortest-path algorithms. The deterministic methods are firstly, a link penalty approach that incrementally increases the link impedance (defined by a generalised cost function) of all links on the shortest route by fixed amounts, thereby identifying alternative shortest routes. Secondly, an iterative link elimination approach that removes the shortest routes in successive iterations. Thirdly, a stochastic simulation method that derives shortest route alternatives by drawing the link impedances from distributions defined by the analyst. Finally, a constrained enumerative method termed the branch and bound method constructs shortest routes by processing sequences of links according to a branching rule that accounts for behavioural constraints formulated to increase route likelihood and heterogeneity.

Frejinger, Bierlaire et al., *(2009)* proposed a corrected route sampling approach from the universal choice set of route alternatives for the estimation of the choice set. The sampling approach also requires the specification of a digitised road network, for example from a transportation model, and a route generation algorithm. The route sampling algorithm identifies the shortest route (based on the definition of link generalised costs). It then allocates weights to the links in the universal choice set of routes, based on the distance of the route from the shortest path route. The weights are used to generate link probabilities. A biased random walk process is then applied to the network and routes are generated using the link probabilities. Fosgerau, Frejinger et al., *(2013)* refined the unrestricted choice set approach using a recursive logit model. The path generation process is derived from link utilities using Bellman equations. The methodology was successfully applied to develop a path-size logit (PS-Logit) model to a road network with 3,077 nodes and 7,459 links.

An innovative approach to the generation of route choice sets for RP experiments was developed by Bierlaire & Kazagli (2016). This approach, called Mental Representation Item (MRI), removes the need for choice set generation. The MRI approach trades off complexity with realism based on the availability of data and the needs of the application. The novelty of the approach lies in its potential to break down the combinatorial complexity of the route choice models (i.e., choice set generation) by replacing the current (observed) route representation and associated correlation complexities, (which consists of a sequence of links on the network), with a simplified, aggregate and more abstract representation, viz. the MRI. The MRI behavioural approach argues that car commuters, when asked for their route (or path) to work, do not provide the description as a sequence of links, but rather as a series of geo-referenced landmarks. The landmarks could be roads, junctions, geographic features such as a shopping mall, an intersection, bridge, tunnel or a destination such as the city centre. So, the car commuter's behaviour is far more likely to be a sequence of geo-referenced landmarks than a detailed route (link by link) path description. These geo-referenced landmarks are the MRI's. Paths can then be built between the MRI's. The MRI approach therefore suggests starting at the aggregate strategic level using network based geo-referenced landmarks, working downwards to the disaggregate path level. Bierlaire & Kazagli (2016) successfully applied this approach with a cross nested and recursive logit model to a road network (defined with nodes and links) in the Canadian City of Quebec. The city is divided by a river and has two bridges, favouring it for the application of MRI method as the bridges are key waypoints for most trips.

Lastly, stochastic methods for generating route alternatives have also been developed by Bovy and Fiorenzo-Catalano (2007). This approach is meant for establishing choice sets prior to the choice modelling step. Based on its stochastic principle, a property of the route generation approach is that the size and composition of the generated choice sets are stochastic variables. The method can be applied to the generation of choice sets for multi-modal networks.

In summary, various methods can be used to generate the choice set of routes in an RP setting. The use of smartphone GPS tracking device can accurately determine the survey participants current (or observed) route and it's time and distance attributes. However, the generation of the alternative routes in the choice sets can be challenging. The process requires a digitised road network used with either a relevant transportation demand model or with historical link travel time and length data obtained from service providers such as Google Maps® or TomTom®. The restrictions with these approaches are that an appropriate transportation demand model may not be available. The use of the network and historical traffic data requires the use a route generation process be adopted, and several have been successfully developed. Historic traffic data may not always be appropriate for this purpose, especially if there have been changes in the road network itself associated with or independent of changes in traffic demand.

4.3 Using Route Guidance Platforms to Generate Alternative Routes and Route Attribute Levels

This section briefly summarises the route generation process used by in-vehicle and smartphone route guidance platforms. Motorist route guidance platforms such as Google Maps® and TomTom® generate alternative routes between a user specified origin and destination using real-time traffic data. The data is near real-time due to the delays in the collection and processing of the traffic data, and the presentation of the alternative routes to the motorist. Also, in congested conditions the traffic data can change relatively quickly, so a driver making a 30-minute trip only has near real-time data for part of the trip (i.e., at the point in time when the route is generated). Traffic data updates and re-routing is required when traffic conditions change.

For route guidance services the alternative routes are generated based on minimum travel times, but the platforms have the capability to include the route cost. This requires the user to subscribe to the guidance service and provided details of their motor vehicle including the engine size and current fuel price. This service is used mainly by owners of vehicle and truck fleets. Toll costs can also be determined for the route. Motorist can specify route preferences that influence the route generation process such as avoidance of certain road types and the need to pass waypoints on the trip.

The route generation process requires two sets of data, the road digitised road network (i.e., supply-side data) and the real-time traffic demand data (demand-side). The digitised road networks are obtained from platforms such as OpenStreetMap® and MapBox®. The digitised road network consists of road segments (or legs) defined by *a node* and *b node* coordinates (normally defined at intersections but also on roadways to define curvature or to disaggregated long sections of roadway). The road typology for each road segment is also defined (e.g., freeway, arterial; distributor), as well as the speed limit and number of lanes, amongst others.

Traffic data is continuously streamed (by means of cell phone tracking) from cell phone companies and guidance service providers on the road network. An extensive set of standardised traffic data is defined for each segment (or leg) on the road network including speeds and travel times. Free-flow (i.e., determined from the speed limit), slowed down and stop-start travel times can be quantified for each road segment. This data set can be accessed by application developers for commercial and research applications. The road network and traffic data are provided in a standard format that is discussed in the next section.

Figure 10 illustrates the basis on which the traffic conditions for a road segment (or leg) are generated. Note that the traffic data on a segment (e.g., the segment travel time and speed) is based on the (historical) previous 5 minutes travel time and speed prior to the route guidance request being made. If traffic data for the previous 5 minutes is not available, then either a longer period is used (e.g., 15 minutes) or use is made of historical traffic data for the segment that corresponds to the time period before in which the guidance request is made.

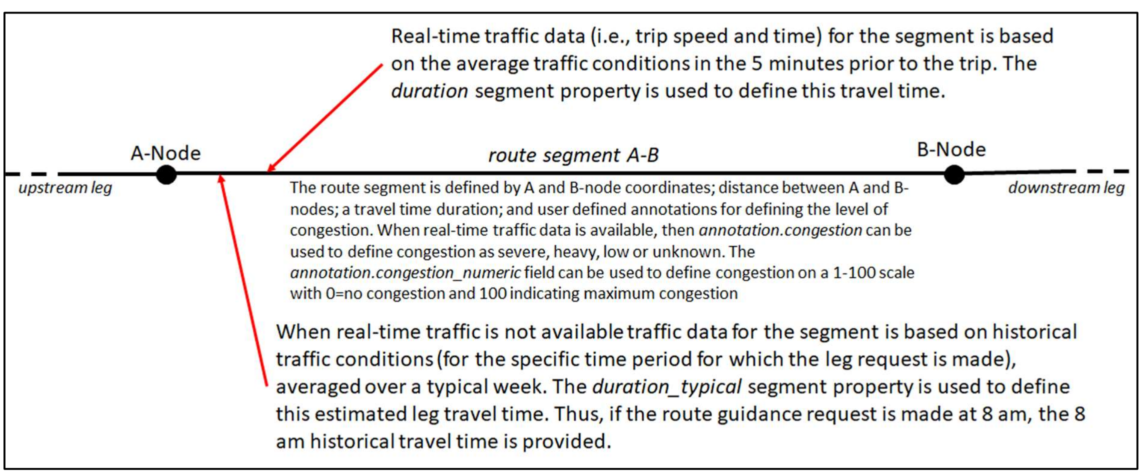


Figure 10: Definition of a Road Segment and Associated Traffic Data

The minimum time (optimal) route and a realistic alternative route/s are generated using a path building algorithm based on Dijkstra's tree building algorithm (Dijkstra, 1959), but modified to reduce the processing time and presentation to the user. A route is defined as a sequential set of road segments. The minimum time (optimal) route is generated first. Three criteria are then used to generate the alternative route, viz. the extent of *overlap* of the alternative and optimal route; secondly *local optimality* that considers the number of unnecessary detours on the alternative route; and thirdly the *stretch,* being defined as the ratio between the length of an alternative route and the length of the optimal route. These routes are then presented to the user graphically with route guidance instructions.

The following figure shows the optimal route and two alternative routes for a trip in Johannesburg during the weekday morning peak hour generated from Google Maps®. The optimal route is shown in blue, and the alternative routes in grey. The travel times and distances for each route are shown. Some points to note are as follows: there is some overlap between the optimal route and one alternative route; the range of travel times between the three routes is relatively narrow (i.e., 46 minutes minimum and 52 minutes maximum); the range of trave distances is also narrow (minimum 31.3 km and maximum 35.9 km); the routes are geographically separated; and the optimal route partly uses a tolled freeway but the toll cost is not shown. Users can specify their preferred route topology, e.g., not to use freeways. If these routes were presented in a choice set format the range of trip times, costs and distances would be relatively narrow. This feature is an important one and reflects the reality of travel on congested, dense urban road networks, i.e., while the alternative routes might be geographically spread, the range of attribute levels is narrow.

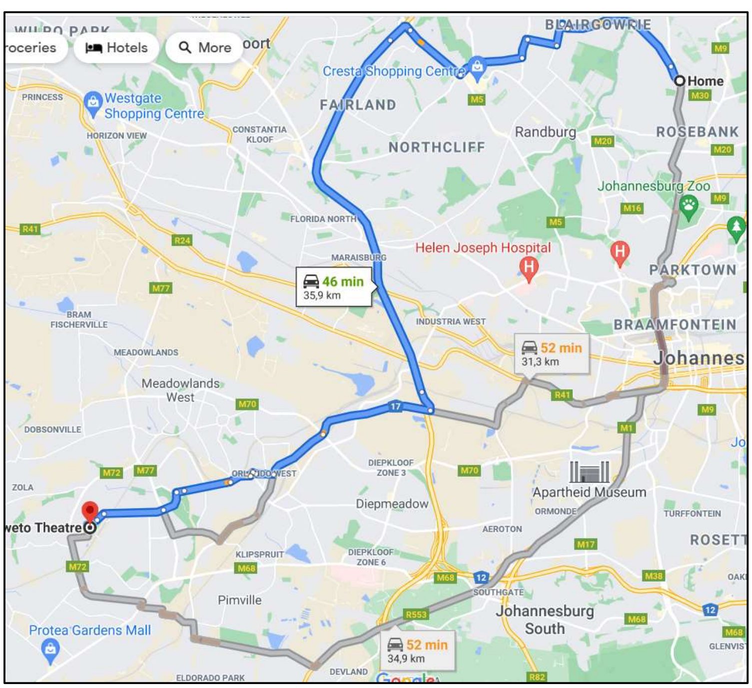


Figure 11: Optimal and Alternative Routes based on Minimum Travel Times (Google Maps®)

For a particular route, the route guidance driving aid also indicates sections along the route where traffic speeds are less than the speed limit (to varying degrees), indicating congested driving conditions or congestion due to an incident or obstruction in the roadway. An example of the congested sections of a route is shown in **Figure 12**. The route is shaded in different colours, each colour indicating different levels of service. Free-flow conditions on the route are shown in the blue shade (levels of service a and B); orange indicates slowed down conditions (levels of service C and D); and red and crimson indicate stop-start conditions (levels of service E and F). These level of service definitions are applied by segment, and when summed can be used to indicate the number of minutes in free-flow, slowed-down and stop-start time.

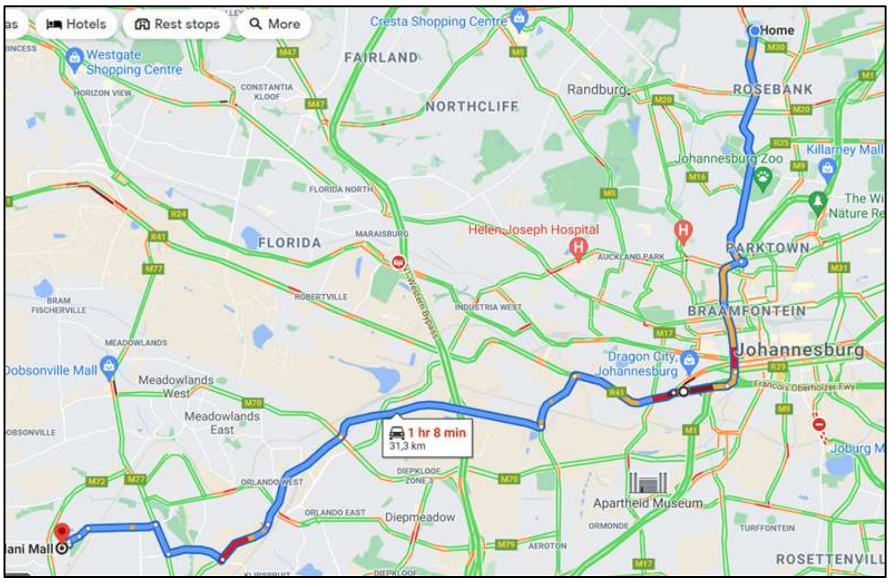


Figure 12: Example of Route with Congested Sections (Google Maps®)

5. INTRODUCTION TO RAPP-UP: AN INNOVATIVE SMARTPHONE BASED ROUTE CHOICE APPLICATION FOR COLLECTING SP AND RP DATA

5.1 Background to RAPP-UP

Given the challenge of balancing analyst control and external validity in route choice experiments, the focus of this research is on the development and application of a unique approach to route preference data collection using a smartphone application using a combination of SP and RP methods. The application has been given the acronym RAPP-UP (***R****oute choice* ***APP****lication* – ***U****niversity of* ***P****retoria*). To improve the external validity of the experiment the method is based on using near real-time traffic data to generate alternative routes, each with their unique real-time values of trip time, cost and trip time reliability. These route attributes and levels are presented to survey participants in a choice set format on their smartphone but supported with road map backgrounds showing each route.

A goal of this research was to develop a survey methodology that would place it in the upper right hand quadrant of the framework shown in **Figure 4**, and in so doing would require a combination of SP and RP methods using the strengths from each. The SP component provides more control of the experiment in the hand of the analyst by defining the utility equation attributes ex-ante and allowing some attributes levels to be varied according to a fractional factorial design. The RP component emphasises route choice consequences by physically driving the chosen route and experiencing a monetary impact if tolled freeways are chosen. RAPP-UP thus combines field and experimental data into a single survey methodology with more analyst control of the experimental design; the generation of realistic and accurate routes; the automation of survey data collection using a cloud-based database; and with a high level of external validity, i.e., with route attribute levels based on real-time traffic conditions.

The five-step process when using RAPP-UP is summarised in **Figure 13**. The two main inputs into the process are the TomTom® traffic data, and the game rules that have been established to calculate the attribute levels for some route attributes. The RAPP-UP outputs and data downloads to the remote database are completed after step 5, i.e., the transmission of the choice sets and tracked route data to the remote database. The SP component corresponds to step 4, and the RP component to step 5.

The game rule inputs are defined by the attributes and levels that are calculated from the TomTom® traffic data. For example, the attribute defining the probability of on-time arrival (*Pota*) is calculated from the routes free-flow, slowed-down and stop-start trip time components. The factoring of this value for input into the choice sets is also done independently from look-up tables built into the app.

It is important to note that all interaction with the survey participant is done on their smartphone. There is no requirement for any manual or paper-based intervention.

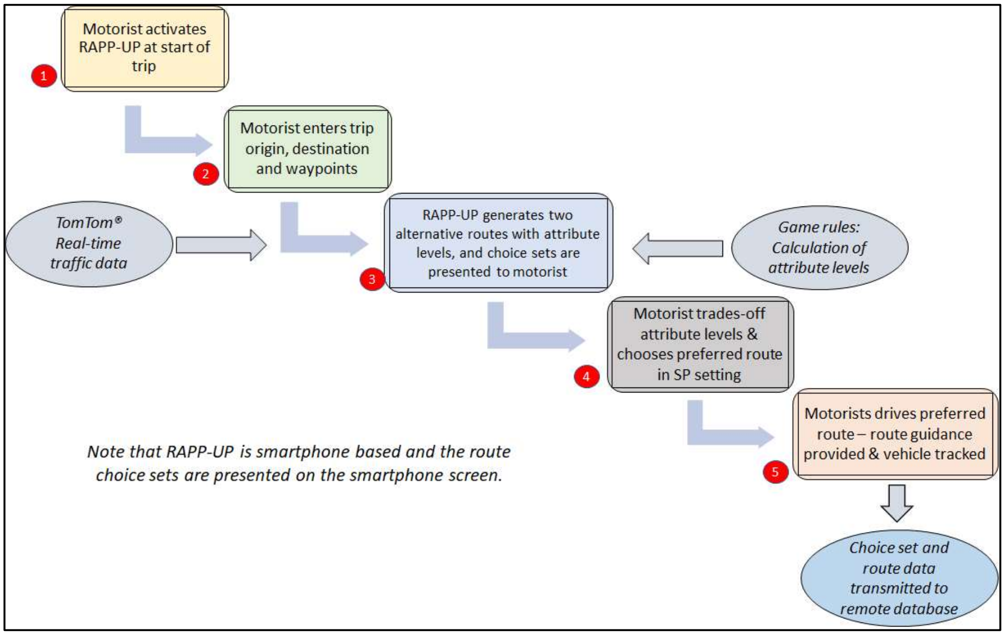


Figure 13: The RAPP-UP Five Step Implementation Process

5.2 Definition of Trip Utility

The design of RAPP-UP required the early definition of route trip utility. The details of the utility definition and the derivation of the attribute levels are discussed in subsequent chapters. A brief overview is provided here to provide the background of the development of RAPP-UP.

Trip utility for route choice experiments has most commonly been defined as a weighted linear combination of trip time, cost and trip time reliability attributes. Moreover in urban areas, trip time has been disaggregated into free-flow, slowed-down and stop-start time as demonstrated by Wardman (1986; 2016; 2012) and Hensher (2005; 2004; 2016) who have shown that motorists perception of VTT varies between these levels of congestion. Trip cost has most commonly been defined as the petrol cost (i.e., operating cost) of the trip, as well as toll and parking costs (if any). Trip time reliability has also been shown to be a significant portion of trip utility (Brownstone & Small, 2005; Carrion & Levinson, 2012).

Hence the definition of trip utility for RAPP-UP has been defined as the weighted linear combination of free-flow time; slowed-down time; stop-start time; petrol cost; toll cost; and trip time reliability.

5.3 Combining SP and RP Data in RAPP-UP into a Self-Validating Method

The SP component of the experiment required the participants to choose from two alternative routes presented to them on their smartphones by RAPP-UP. Survey participants were required to trade-off the various trip time and cost attribute levels and select their preferred alternative. While this was the SP component of the survey it is important to highlight that the routes and their associated attribute levels were not hypothetical. The route attribute levels (times, costs, and trip time reliability) were based on real-time network operating conditions obtained from the TomTom® traffic data set used for route guidance as a driving aid.

The total trip time was disaggregated into free-flow, slowed-down and stop-start travel times categories. Hypothetical bias was addressed by introducing an RP component to the experiment - the participant was required to physically drive their chosen route and they were tracked to determine route compliance. An economic experiment was introduced to reduce the no-consequence drawback of SP experiments by means of a survey toll account. At the start of the experiment each participant was given a survey toll account with a positive balance of R300.00. Choosing a tolled route reduced the survey toll account balance by the toll fee amount. The balance of the survey toll account was paid out to participants at the end of the survey. Analyst control over the attribute levels has been implemented by introducing attribute factors for the toll cost and trip time reliability factors.

5.4 RAPP-UP Smartphone Application for Route Choice Surveys

The route choice experimental process adopted by RAPP-UP is shown in more detail in **Figure 14**. The figure highlights the key activities in the process required from the driver and the application. The driver initiated the survey process by activating RAPP-UP on their smartphone prior to starting their trip and entering their trip origin and destination locations as well as any waypoints if required. These locations can be determined with accuracy by typing in the suburb name and by manually adjusting the background map to the exact location. A green pin was inserted at the origin location and a red one at the destination location to provide orientation to the user. RAPP-UP then generated and displayed on-screen two alternative routes between the origin and destination (and through waypoints) based on real-time travel time data and presented the route attributes (i.e., the various travel times, costs and trip time reliability) in the form of choice sets to the survey participant. The route path coordinates, speeds, times, attributes levels and other route data were stored in the remote database.

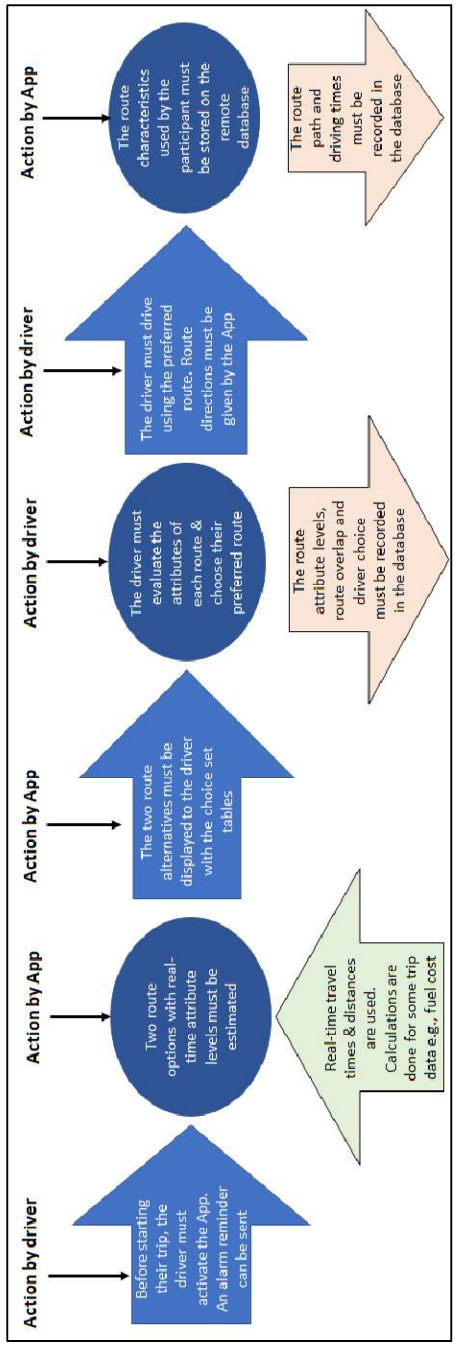


Figure 14: Motorist and App Activities in Smartphone-Based Route Choice Application RAPP-UP

The driver was then required to choose their preferred route and this choice was recorded in the remote database. The driver was required to drive their chosen route and the route was tracked. This route data was also recorded in the remote database, i.e., segment co-ordinates, segment lengths, time stamps and travel times. This data could then be used to plot the route and allow the analysis of the speeds, travel times, departure and arrival times and the time of arrival at the destination.

A key part of the RAPP-UP methodology was the transmission and storage of the route data on a remote cloud-based database. The RAPP-UP data collection, storage, processing, and analysis framework is shown in **Figure 15**. The process started with the data collection activity via the participants smartphone as per the flow chart in **Figure 14**. The route data was then downloaded from the smartphone to a secure, cloud-based remote database using the MongoDB® platform. MongoDB® is a cloud-based open-source document-oriented database. It is used to store large amounts of data and has data processing features. MongoDB® is not based on the table-like relational database structure but provides an altogether different mechanism for storage and retrieval of data, known as a NoSQL database, i.e., non-relational structure query language. The format of the data storage files is called BSON which is similar to the JSON format (Java Script Object Notation). The data was extracted from the database into JSON text format files (Java Script Object Notation) using executable command files in Windows. The JSON text files can be converted into CSV (comma separated variable) files that are editable in Microsoft Excel. After editing, the CSV route data files with longitude and latitude coordinates and other data can be converted to GPX and KML files formats for use with Google Maps®, Google Earth®, OpenStreetMap®, ArcGIS® and other GIS software for plotting and analysing spatial data. The conversion of the edited CSV files to GPX or KML formats was done with an online converter GPS Visualizer (https://www.gpsvisualizer.com/). The edited CSV files can be saved in Excel (.xlsx) format to undertake the analysis of the data and graph plotting. The route choice sets were prepared in the format required for the econometric software platform NLOGIT for discrete choice model estimation.

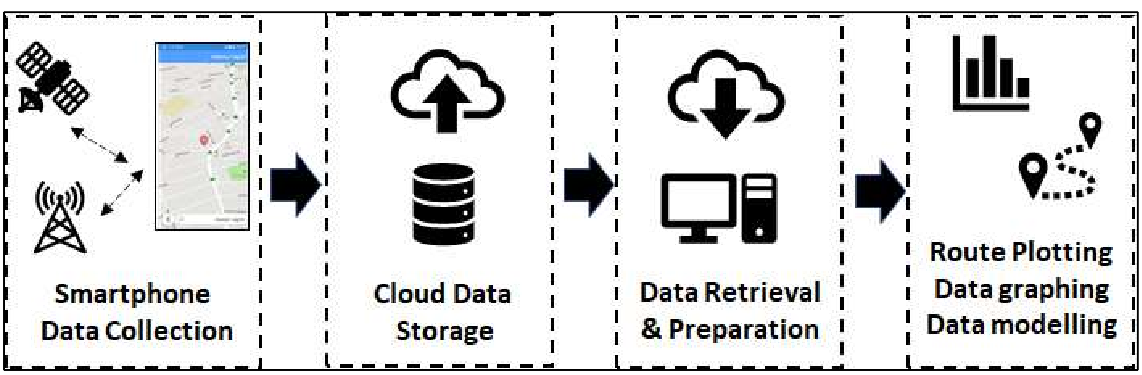


Figure 15: RAPP-UP Route Choice Survey Data Capturing, Storage and Analysis Process

Figure 16 shows the RAPP-UP screen with two alternative routes. RAPP-UP has a MapBox® road map background to assist users to identify their origin (O) location and destination (D). The network orientation can be changed by using two figures to drag the screen, and the north orientation restored by tapping twice on the screen. Zooming in and out the network is done in the same way. Two alternative routes between origin and destination were generated using the TomTom® route generation algorithm, i.e., an optimal minimum time route and an alternative route. The routes are not given names or numbers and are hence generic in nature and the experiment is classified as unlabeled. The methodology for the generation of these routes is discussed in the next chapter. In short, TomTom® propriety patented algorithms are used to generate an optimal route (based on the shortest travel time between origin and destination), and an alternative route based on several factors including route overlap, route lengths and the number of detours.

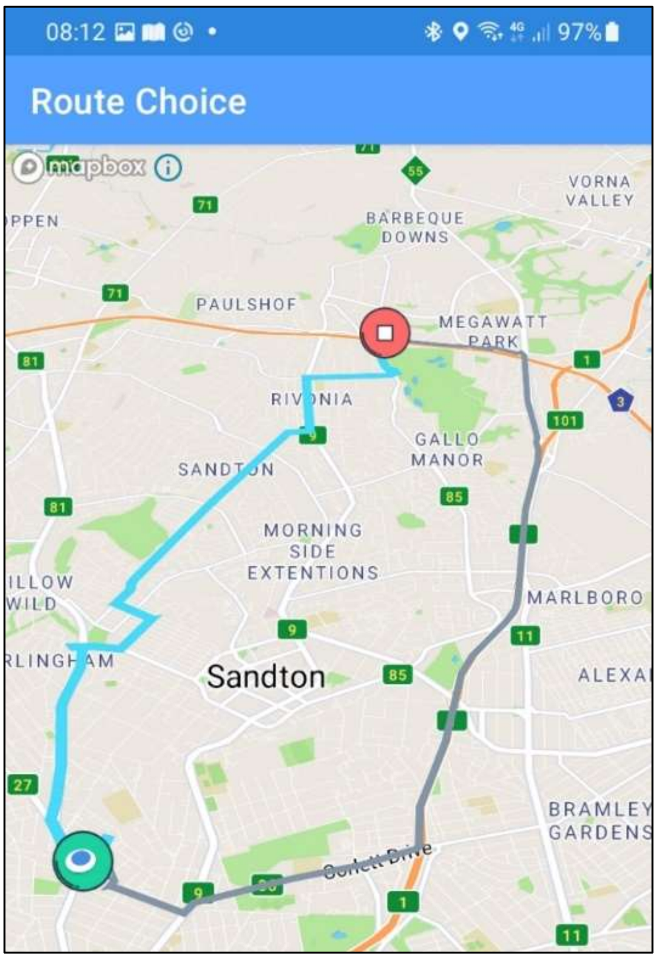
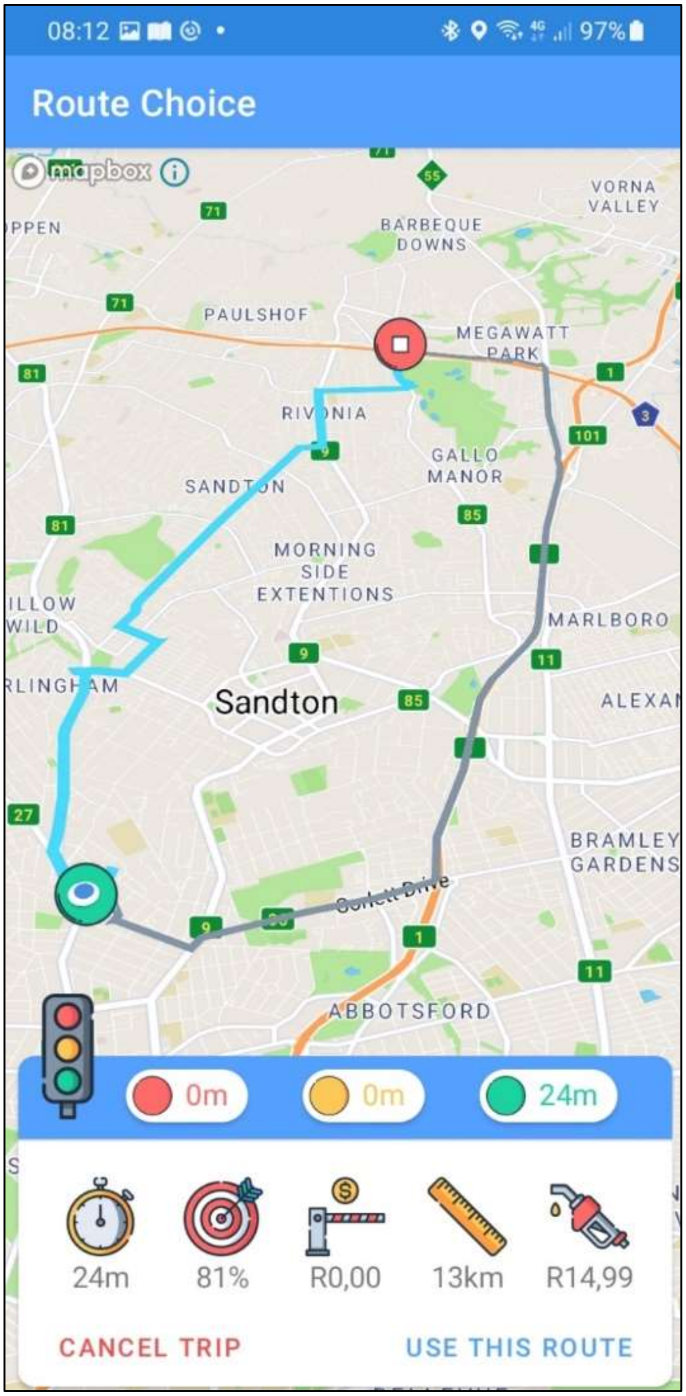


Figure 16 shows a RAPP-UP screenshot with two alternative routes between an origin in Rosebank in Johannesburg (green pin) and a destination in Sunninghill (red pin). One route outline is shown in light blue (western route) and the other in grey (eastern route). The map background is obtained from Mapbox (www.mapbox.com) and clearly orientates the driver by showing suburb names and roadways. Orientation is to the north. By using two fingers, the screen can be zoomed in and out and rotated in order to obtain more detail of the route alignments and the origin and destination suburbs.

Figure 17 shows the route attribute table, i.e., choice set for the western route that is highlighted as blue in colour.

Figure 16: Smartphone Screen Shot of RAPP-UP Road Background and Two Alternative Routes



Choice sets based on near real-time attribute levels for the travel times, costs and probability of on-time arrival at the destination are generated by RAPP-UP based on near real-time traffic data and presented to the participants on their smartphones in the form of choice tables using representative icons. An example of a choice set table for a route is shown in **Figure 17**. To clearly define the routes with their associated attributes and levels they are presented graphically on the map background. The traffic light icon represents the three trip time categories on the route, i.e., the green (free-flow), yellow (slowed-down time) and red (stop-start) times are shown as well as the total travel time (stop-watch icon). The target icon is the probability of arriving at the destination on time (in percent); the barrier icon is the toll fee for the route (in Rand); the ruler icon is the route length (in km); and the petrol nozzle icon is the petrol cost of the route (in Rands). Drivers then select their preferred route by tapping on the USE THIS ROUTE text.

Figure 17: Example of Route (Outline in Light Blue) with Choice Set Table Attributes and Levels

The RP component of the experiment requires drivers to physically drive on their preferred route between origin and destination. By driving their preferred route, the consequences of choice are embedded in the experiment. To further emphasise the consequence of route choice, an economic experiment was introduced. For this a toll account was established for each participant with a given, fixed balance at the start of the experiment. If a participant chose a tolled route for a trip, then the cost of the toll was deducted from their toll account. At the end of the survey, the toll account balance was paid to the participant in the form of an on-line shopping voucher.

When the survey participants travelled on their chosen route their path was tracked. Several data sets were generated for each trip and stored in the remote database. Firstly, the route coordinates for the alternative routes were stored. The route choice set tables were also stored together with the choice of preferred route. The coordinates of the tracked path of the driven route were also stored together with the associated time stamps. The extent of route overlap of the alternative routes was calculated and stored. This was measured by the length of overlap for each route.

5.5 Route Tracking between Trip Origin and Destination with RAPP-UP

Accurate location identification, route display and route tracking were important requirements for RAPP-UP. Location identification was important to accurately display the user's origin, destination, and any waypoint locations on a road map background. The ability to accurately display the routes on the map background to users was important to ensure route realism and accuracy and to provide accurate route guidance when making this trip. Plotting and analysing the actual routes driven by the participants after they have chosen their preferred route is important for several reasons. Firstly, it provides a record of the level of compliance between chosen and driven routes used and its associated driving distances and times for comparison against the route data presented in the choice sets. The time gap between the driver's selection of their preferred route and the traffic conditions actually experienced on the preferred route will cause travel time variation. It also provides a record of whether the driver adhered to the rules of the survey, i.e., to drive their chosen path. Drivers were informed beforehand that they would be tracked allowing their adherence to the survey rules to be monitored.

The location accuracy of the route tracking is important to ensure that the correct route alignment is used to quantify the actual trip times and distances. Route tracking accuracy has been seen as a potential problem for RP route surveys (Berger & Platzer, 2015; Tang & Cheng, 2016). When this occurs it is necessary to use route snapping software that "snaps" the route coordinates back onto the road centre line.

5.6 Route Tracking Accuracy for RAPP-UP

It was found that the RAPP-UP route tracking facility tracked the routes sufficiently accurately to avoid having to use snapping software. The following series of plots show a route that was tracked between Killarney and Randburg in Johannesburg between 07:29:08 and 07:51:46 on Friday 27th August 2021 and on 31 August 2021.

On 27th August the route length was 10.77 kms and 10.69 km on 31st August. The first series of figures shows the route on a Google Maps® road map background for both days. The second series of figures show the route plotted in Google Earth® with aerial photograph backgrounds. The figures are shown in different scales in order to provide insight into the accuracy of the paths. The Google Maps® plots were created by converting the route coordinates into a GPX file for Google Maps®, and a KMZ file for Google Earth®. There are numerous websites that provide file conversion services (e.g., CSV to GPX). The GPS Visualizer website was used for the conversion of CSV to KML and GPX formats in the figures shown.

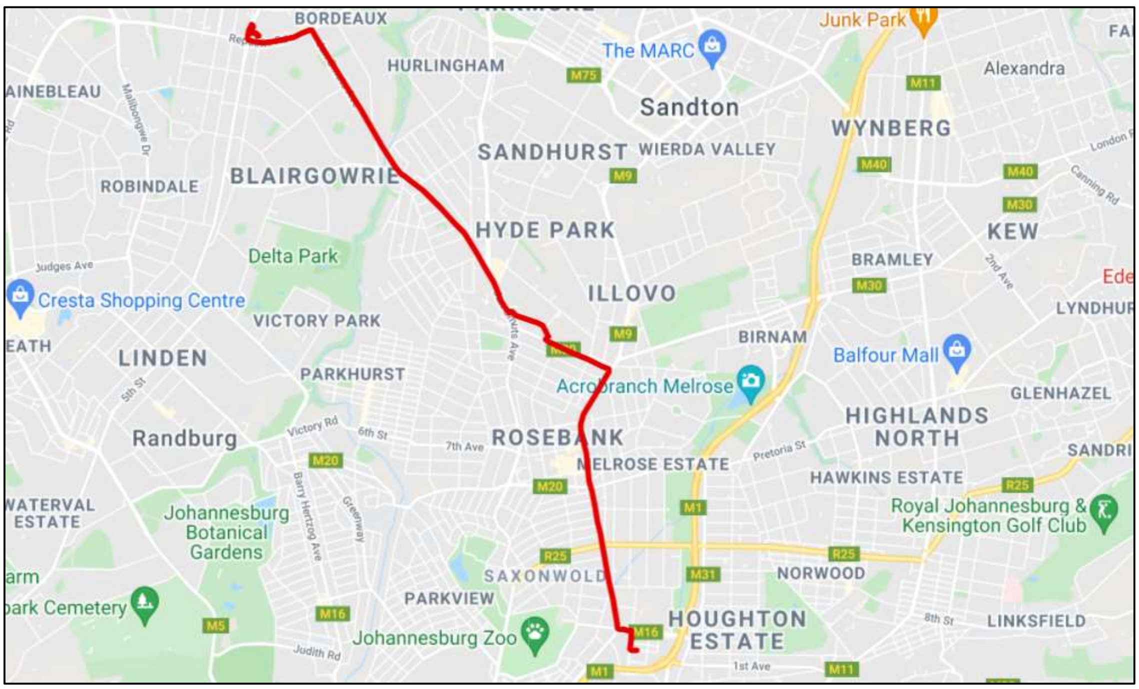


Figure 18: Route Plot 27 August 2021 Killarney (Origin) to Randburg (Destination), Johannesburg (Google Maps®)

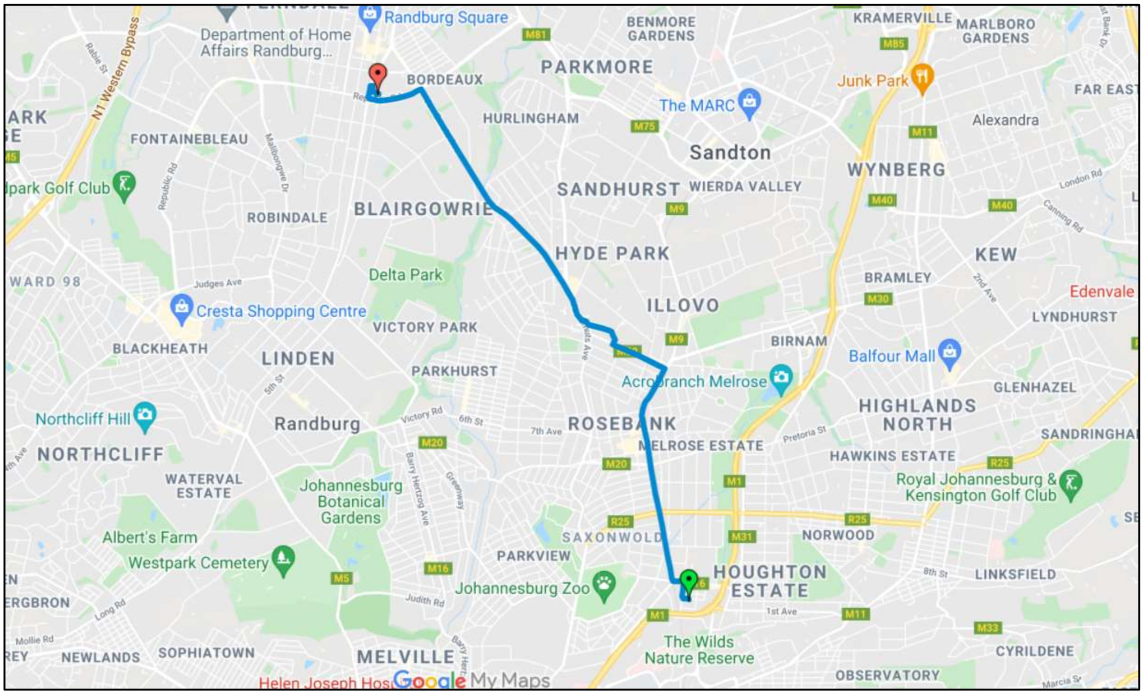


Figure 19: Route Plot 31 August 2021 Killarney (Origin) to Randburg (Destination), Johannesburg (Google Maps®)

Figure 20 shows a smaller scale plot of part of the route through Rosebank.

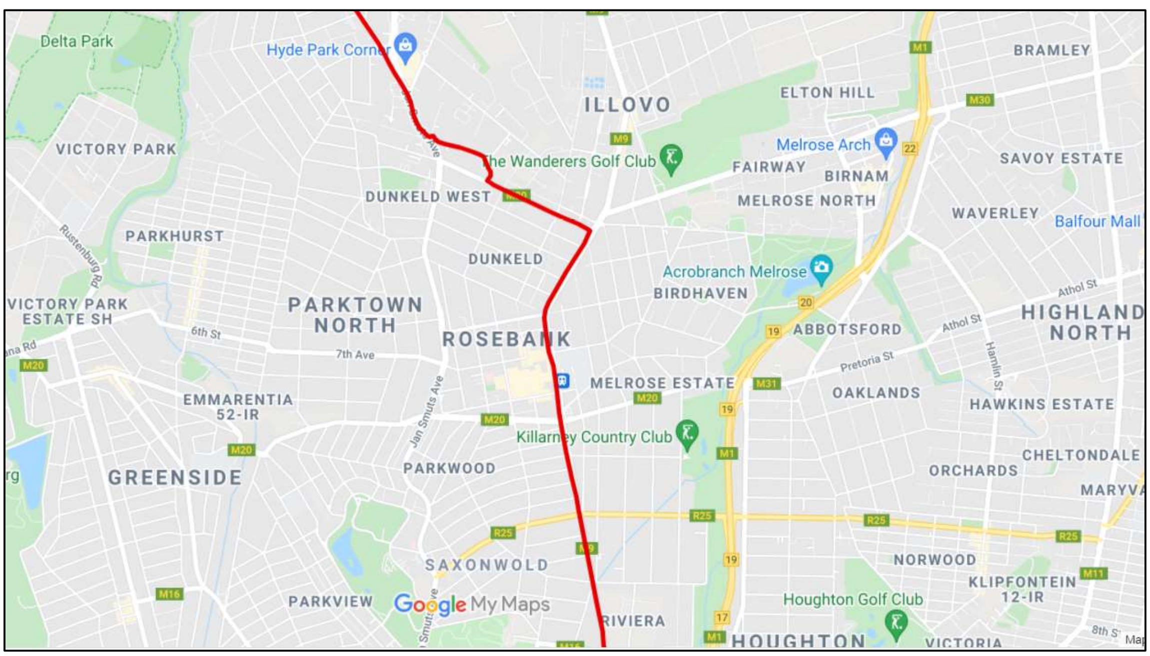


Figure 20: Smaller Scale Plot of Killarney (Origin) to Randburg (Destination) Route (27th August 2021) (Google Maps®)

Figure 21 and **Figure 22** show small-scale plots of part of the route on a map background. The route path lies on the roadways used for the trip.

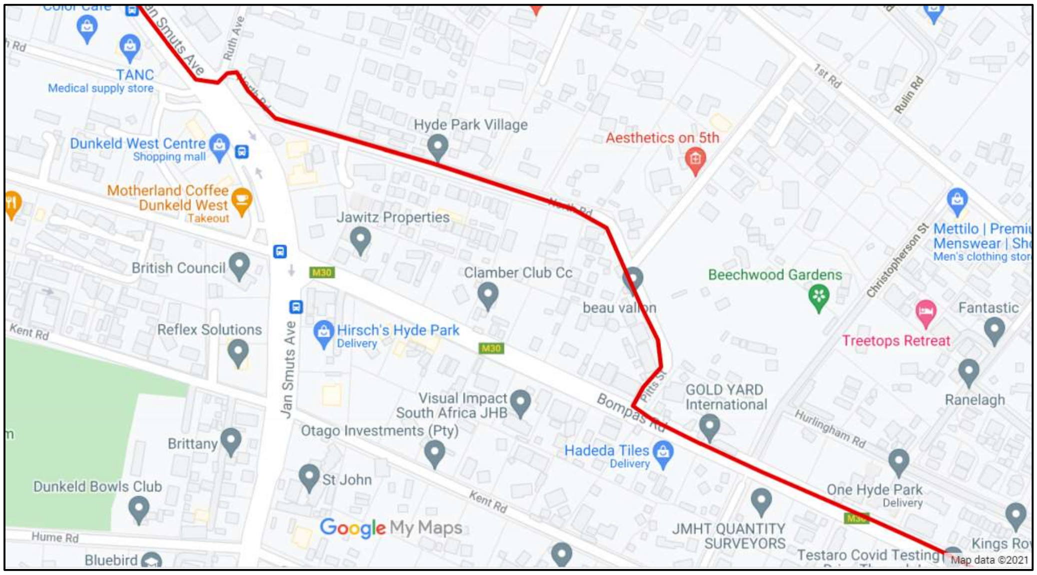


Figure 21: Small Scale Plot of Part of Killarney (Origin) to Randburg (Destination) Route (27 August 2021) (Google Maps®)

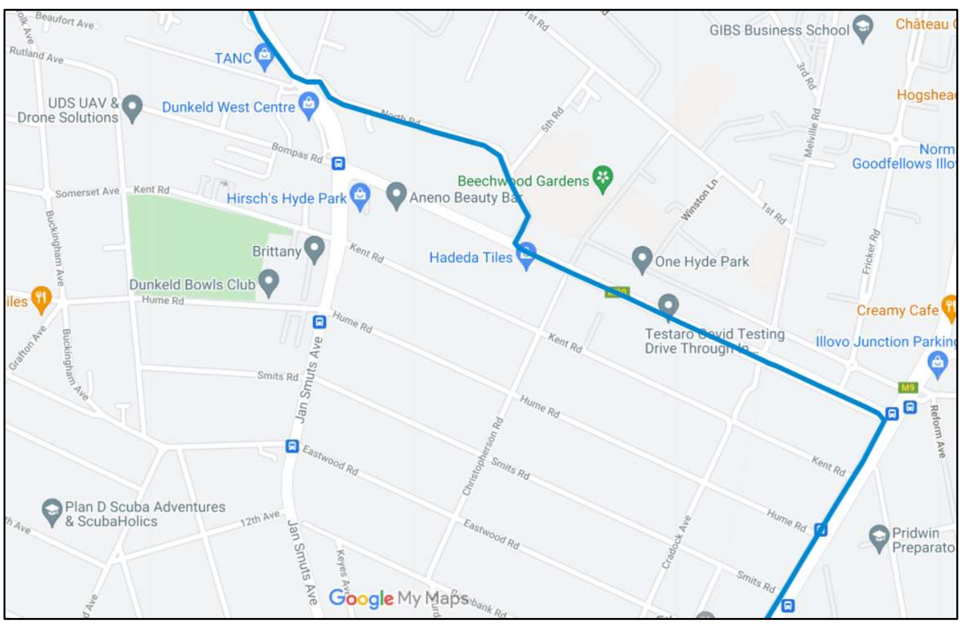


Figure 22: Small Scale Plot of Part of Killarney (Origin) to Randburg (Destination) Route (31 August 2021) (Google Maps®)

The following sequence of figures shows the same route with an aerial photograph background using a KML file with Google Earth®. **Figure 23** shows the full route from Killarney in the south to Randburg in the north via Rosebank and Hyde Park.

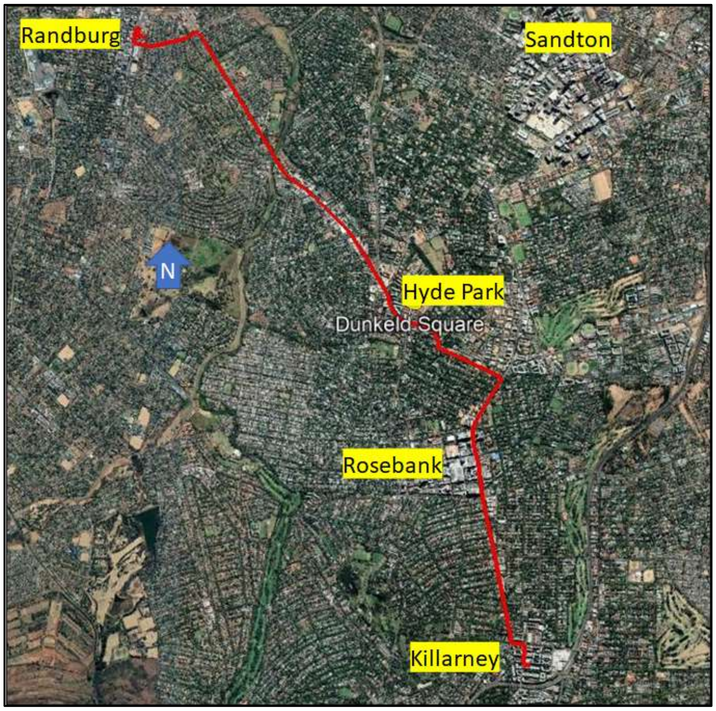


Figure 23: Plot of Killarney (Origin) to Randburg (Destination) Route 27th August 2021 (Google Earth®)

Figure 24 shows two smaller scale plots of parts of the route. In both figures it can be clearly seen that the plotted path lies on the roadway used for the trip.

Figure 24: Smaller Scale Plots of Killarney to Randburg Route (Google Earth®)

The following figures show further plots of the route on different sections. Once again it be seen that the path accuracy is adequate for accurate route plotting and analysis purposes.

Figure 25: Smaller Scale Plots of Killarney to Randburg Route 27th August (Google Earth®)

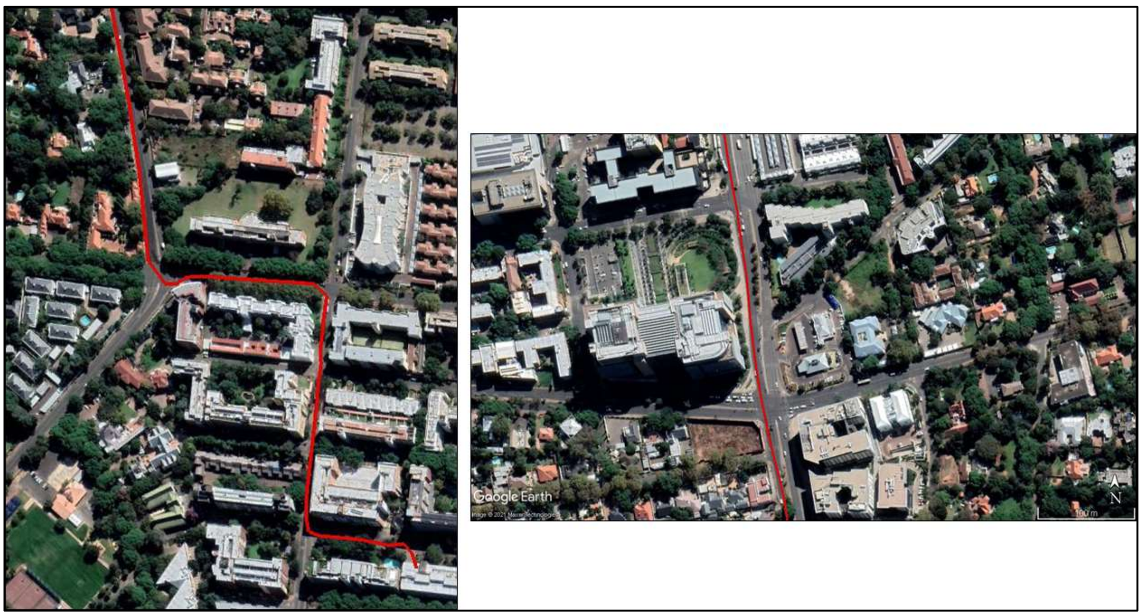


Figure 26: Smaller Scale Plots of Killarney to Randburg Route 31st August (Google Earth®)

The following figures show the travel speed and elevation profiles for the Killarney to Randburg route shown in the previous figures. The speed profile in **Figure 27** shows a widely fluctuating range of speeds during the trip on 27th August 2021. With a total travel time of 22 minutes and 38 seconds and a route length of 10.77 kms, the average travel speed was 29.4 kph. The maximum speed was approximately 85 kph, speeds of less than 10 kph occurred a total of 15 times.

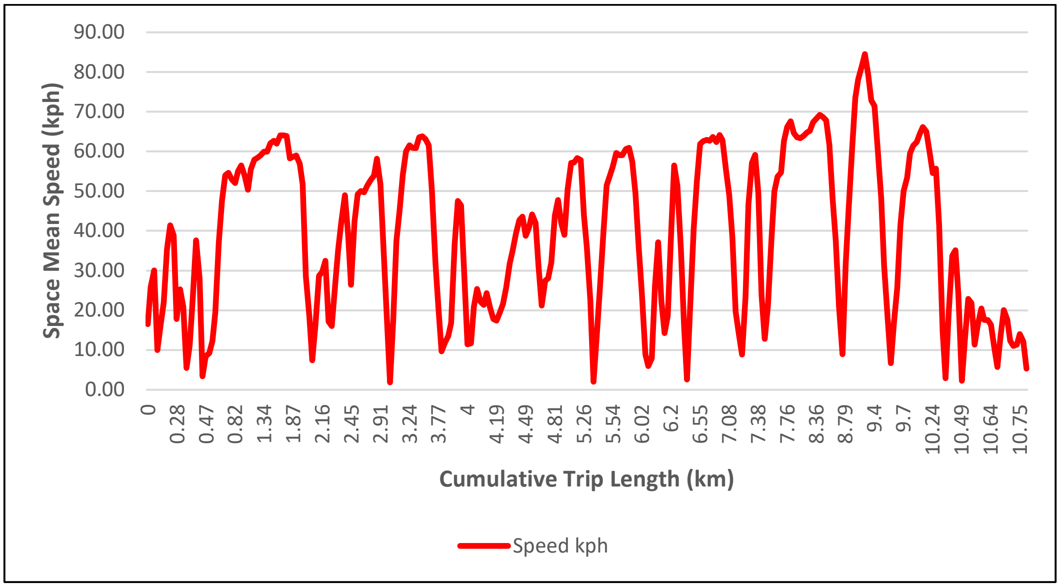


Figure 27: Speed Profile for Killarney to Randburg Trip (27th August 2021) (kph)

The speed profile for another trip on 31 August 2021 is shown below in **Figure 28**. The overall average speed was 31.4 kph, with a total driving time of 20 minutes and 24 seconds and a total trip length of 10.69 km. The maximum speed was 80 kph and the speeds dropped below 10 kph on 10 occasions during the trip.

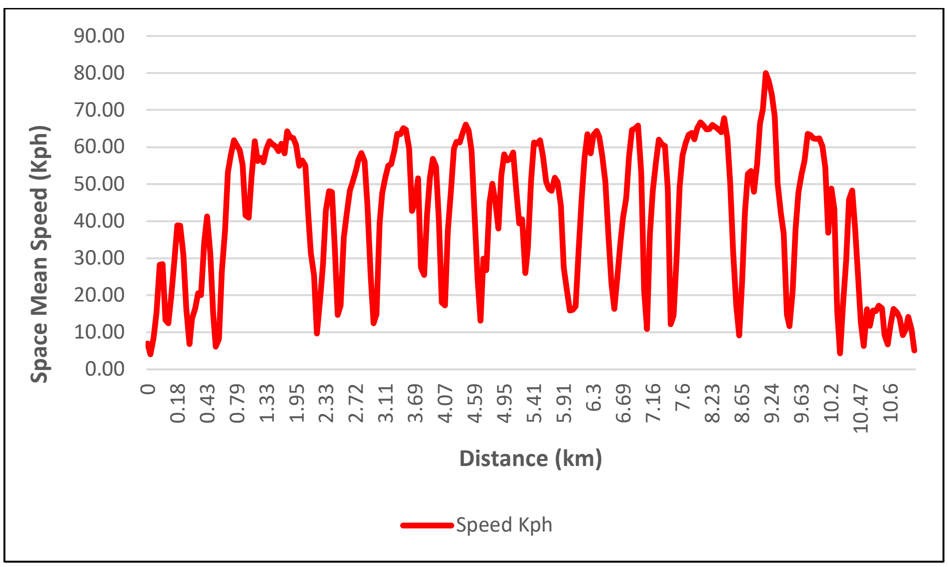


Figure 28: Speed Profile for Killarney to Randburg Trip (31st August 2021) (kph)

The altitude of the trip made on 27th August 2021 is shown in **Figure 29**. There was an overall loss of altitude on the trip, from about 1,723 metres above sea level to 1,626 meters above sea level. The minimum altitude was 1,550 m.

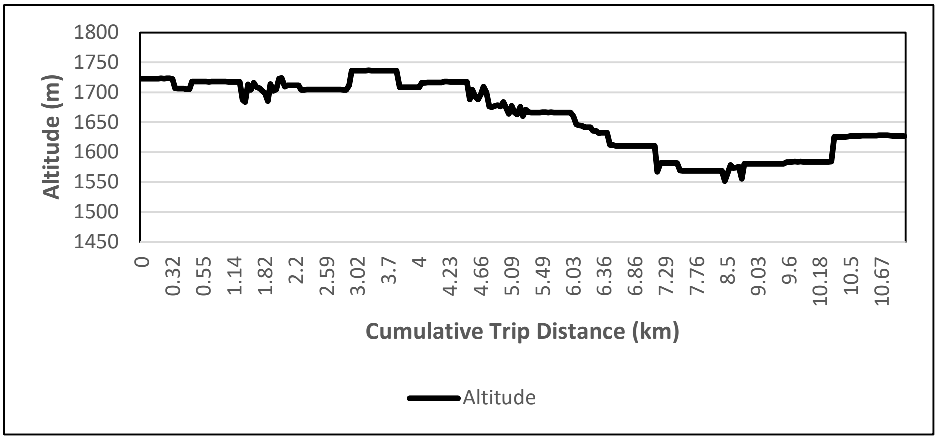


Figure 29: Altitude Variation on Killarney to Randburg Tracked Route August 2021 (m)

The conclusion drawn from the tracking of routes and collection of trip related co-ordinates and time, distance and speed data are sufficiently accurate and reliable for the execution of the route choice experiment.

5.7 RAPP-UP Route Generation Process

The route generation process is a core component of RAPP-UP and requires a detailed explanation. The route generation processes developed by TomTom® has been used without significant modification. Software platforms such as Google Maps® and TomTom® generate routes for users as route guidance driving aids. Given specified origin and destination locations (as well as any required waypoints), the platforms generate at least two alternative routes between the origin and destination with current driving times. The generation of these routes is a complex process, especially when real-time traffic data is used in the generation process and alternative routes are required. The route generation processes are patented, for example by Google in United States patents (Abraham, et al., 2010; Gesiberger, 2014).

Platforms such as TomTom® provide traffic condition data to researchers and application developers. International naming and data standards are used to define the various road, traffic operations, traffic events, lane closures or other driving hazards and other driver information. The most commonly used is the International Standards Organisation (ISO) for Intelligent Transport Systems (International Organization for Standardization (ISO), 2020). These standards were used in the development of RAPP-UP, particularly to quantify the route utility attribute levels.

While the algorithms used for route planning by Google Maps® and TomTom® are patented, they nevertheless use route building methodologies that are well established and widely used for various applications. For example, they make use of Dijkstra's tree building algorithm (Dijkstra, 1959) that is used extensively in transportation planning software to build minimum cost, distance or time trees for complex road and public transport networks. The process is known as network skimming, and the outputs are matrices of zone-to-zone times, costs, etc. Use is also made of the A* algorithm to speed up the route generation process. This algorithm uses a pre-defined set of optimal routes (for example based on historical data) to speed up the route generation process.

The following terminology and concepts are discussed in the context of route planning: trip origin and destination; traffic data; real-time traffic data; near real-time traffic data; historical traffic data; the road network database; optimal routes; alternative routes; and trip durations. Each of these is discussed in the following sections. Note that the terms *route* and *path* are interchangeable, and both are widely used in the literature. This thesis uses the term route.

5.8 Trip Origin, Destination and Waypoints

A route is defined as the patch between an origin and destination location. Each location is identified with a set of co-ordinates, i.e., latitude (*lat*) and longitude (*lon*). The location can be relatively coarse, e.g., a location that represents the centre of a suburb, or more accurately by using, for example, a street within a suburb, or even a dwelling on a street. For the RAPP-UP application, the origin and destination locations are accurate to the location of a specific dwelling or building.

In some instances, it may be necessary to define a waypoint on a journey. A waypoint is a location (also defined with coordinates) that must be passed between the trip origin and destination. For RAPP-UP the location is also accurate to a specific dwelling, school or intersection. For example, a motorist may need to drop their children at school when making their trip from home to work. The school location would define the waypoint. More than one waypoint may be specified, but this must be done in consecutive order. When waypoints are specified the route building process is broken up into determining optimal and alternative routes between waypoints.

5.9 Digitised Road Network Definition

The road network database of a suburb, city, province or country represents the supply side of the transport system, i.e., the supply of roadway capacity. Digitized road networks are provided by platforms such as OpenStreetMap® and Google Maps®, who have digitized the road networks of most countries and cities in the world to a fine level of detail. The digitized road network is made up of individual straight-line road segments (also known as legs or arcs) between sets of coordinates. Each segment is defined by an A-node, B-node and an interpolated straight-line length between the two nodes in metres as shown in **Figure 10**. The segments can represent the section of roadway between intersections or at points where the road conditions change, e.g., road narrowing or roadworks. Horizontal road curvature is defined with shorter segments to minimise the curve length error.

A route is therefore defined as the ordered sequence of segments, legs or arcs, and the total route length is the sum of the individual segment lengths. Road networks are also usually digitized in layers, with each layer representing a different road class, for example freeways, arterials and minor roads. This allows for refinement in the route generation process, for example a user may not want to use freeways on their trip.

Each segment in the road network is defined by its length, speed limit and number of traffic lanes. Additional segment parameters can also be defined such as its gradient and curvature (if this is available) as well as roadway features such as toll plaza locations and the toll tariffs for different vehicle classes.

The digitized road networks are provided to users in geodatabase map "tiles". The tiles are layered to define different road types as indicated earlier. Tile scales vary to accommodate different geographic areas. For example, a tile for the network of a whole country has a larger scale than a tile that only covers a metropolitan area. Geodata tiles have been created for a wide variety of GIS data mapping applications, for example for layered mapping of data onto land use, geology and environmental maps.

5.10 Traffic Data

A definition of "traffic data" was required as this term is widely used in route-guidance literature without defining exactly what the traffic data consists of. For route determination, traffic data means the observed vehicular speeds and travel times on the segments making up a road network. If the speed on a road segment is at or close to the speed limit, then the travel time is at or close to a minimum on that segment.

Real-time traffic data is a somewhat misleading term when applied to route determination. A more accurate term is near real-time data. It is not possible to generate accurate real-time route data as there is a time lag between the actual measurement (or observation) of the traffic data on the road segments; its transmission to a central data centre; its compilation and processing for the estimation of alternative routes; and the transmission and display of the route and traffic data to motorist. Near real-time data is derived from observed traffic data that is not more than 5 minutes old and is calculated and updated on a five-minute rolling average basis. The assumption is made that the traffic data for the last five minutes is still representative of current conditions and is sufficiently accurate to provide route guidance and other traffic information to users. In normal circumstances this is a fairly safe assumption.

Historical traffic data is the typical traffic data for a road segment based on the average for the previous month for the day and time period under consideration. For example, historical traffic data at 16:30 on a Monday would be estimated from the average previous month's Monday values for the segment between 16:25 and 16:30.

An important factor that must be taken into consideration when generating routes is whether a route is representative after it has been generated. For example, the near real-time speeds and travel times at 8:00 am when a route was generated for a 45-minute trip may no longer be accurate at any time after the generation of the route, but especially toward the latter stages of the trip. This can be addressed by using more advanced dynamic route guidance systems that update the route travel times and provide re-routing options when the trip is being made.

The near real-time data is provided from a passive feed of trip co-ordinates from cell phones and smartphones of motorists either obtained from cellular service providers or driving aid service providers such as TomTom®, as well as from crowd-sourced applications like Waze®. TomTom® use a variety of traffic data sources including from GPS devices, mobile phone signals, and embedded roadway sensors. The data is anonymous, allaying any privacy concerns. Smartphone ownership in South Africa is relatively high, with approximately 26 m people owning these devices (O'Dea, 2022). This is about one third of the country's population. 95% of South Africans have either a basic cell phone or a smartphone, indicating that some owners have more than one phone. This penetration of mobile phone users provides a significant database from which the traffic data is drawn. This is not to say that data is always available for all the roads making up a network, and when not available use is made of historical traffic data to generate routes.

Platforms such as Google Maps® and TomTom® also provide an indication of the level of congestion on route segments using a congestion level coding system. The traffic flow description is the Traffic Effect Code 001. The ISO intelligent transport systems standard for traffic congestion coding (International Organization for Standardization (ISO), 2020) enumerates the possible values for type tec001:EffectCode that is shown in **Table 2**. The route travel time classifications used for this research are free-flow time (*fft)*, slowed-down time (*sdt*) and stop-start time (*sst*). The classification of these three categories for the ISO TEC001 descriptions of traffic flows are also shown in **Table 2**. The traffic effects codes TEC 001 are used to colour code route maps according to delay severity.

Table 2: Traffic Effects Code (TEC001) for Traffic Flow Descriptions

TEC Code	TISA English "Word"	Comment	Travel Time Classification
1	Traffic flow unknown	Shall be used if traffic flow is unknown. Note: This is often the case for local hazard warnings.	Slowed-down time (sdt)
2	Free flow traffic	Traffic flow is not restricted	Free-flow time (fft)
3	Heavy traffic	Traffic flow is restricted due to a large number of vehicles	Stop-start time (sst)
4	Slow traffic	Traffic is slower than normal	Slowed-down time (sdt)
5	Queueing traffic	Traffic is in queues, but is still moving slowly	Slowed-down time (sdt)
6	Stationary traffic	Traffic is stationary or barely moving	Stop-start time (sst)
7	No flow	Traffic is completely stopped or there is no flow due to the road being closed /blocked; the cause-component may give more information about the reason for "no traffic flow". For roads with at-grade junctions, how the closure/blockage affects cross-road traffic maybe further specified with the attribute *atGradeJunctionClosure.*	Stop-start time (sst)

The traffic delay colour coding is provided on platforms such as Google Maps® and TomTom®. Typically, when a segment has blue shading, the segment speeds and travel times are close to free flow conditions and delay is low. For blue routes the near real-time speed is within 90% of the segment speed limit. This would correspond to levels of service A and B. When shaded in orange, the travel times reflect slowed-down times, i.e., the effect of increasing congestion and associated delays. Slowed-down time occurs when the near real-time speed is between 60% and 90% of the speed limit and would correspond to levels of service C and D. When the speed on the segment is less than 60% of the speed limit, it is classified as stop-start conditions and shaded in red and reflects levels of service E and F. The darker the shade of red, the slower the speed on the link.

Historical speed and travel time data is also used in the route generation process. When near real-time data is not available for all routes in a network, use is made of historical data to fill the gaps. The historical data is derived from the traffic data of the previous month. It is refined by the day of the week and the time-of-day and is generated in five-minute increments that are based on averages for the previous month. For example, if historical traffic data is required on a Monday at 16:30, then the previous month's average data for Monday between 16:25 and 16:30 is provided. There may be drawbacks to using this data, chief amongst them is the inability to identify current roadway bottlenecks (for example caused by an accident or by road works). Also, in the time of COVID, a previous month's data may represent a locked-down period with reduced demand that will hence have higher average speeds and lower travel times than for a "normal" month.

5.11 Generating Optimal and Alternative Routes between Origins & Destinations

Two steps are required in the route generation process. The first is to generate the optimal route followed by the generation of alternative routes. For RAPP-UP only one alternative route has been generated. The routes generated by TomTom use the A* algorithm. As described earlier, this algorithm is a modification to Dijkstra's algorithm that builds the trees from the origin and destination simultaneously, i.e., toward one another. To accelerate the tree building process it also uses a pre-defined set of optimal routes (for example based on historical data) to speed up the route generation process. If the pre-estimated optimal path is known, then the determination of the optimal route at the time of travel using near real-time traffic data can be accelerated.

These routes are defined by the TomTom® route generation algorithm based on the route characteristics as follows. An optimal route is defined as the route that provides the minimum trip time, trip distance or trip cost between a specified trip origin and destination and any associated waypoints. For RAPP-UP the minimum time criteria has been used. Hayes and Venter (2017) determined that trip time was the most important trip attribute for car commuters in Johannesburg and Pretoria in mode choice experiments where the alternative mode was bus rapid transit (BRT). Platforms such as TomTom® can generate optimal routes based on trip cost which is defined as the fuel consumption for the trip. This can be useful for truck fleet owners who wish to minimise the cost of their transport operations. The estimation of fuel consumption requires the user to input details about their vehicle so that a typical fuel consumption estimate can be made. Together with trip distance and the current cost of fuel, the segment-based trip fuel cost can be calculated.

Alternative routes generated by TomTom® are realistic alternatives to the optimal route, also estimated using the A* algorithm which is based on Dijkstra's algorithm. Alternative routes are generated by considering three key criteria: firstly, the extent of *overlap* of the alternative and optimal route (which is minimised); secondly *local optimality* that considers the number of unnecessary detours on the alternative route; and thirdly the *stretch,* being defined as the ratio between the length of an alternative route and the length of the optimal route. The number of alternative routes between an origin and destination in a dense road network can be substantial. The A* algorithm sorts the routes according to an objective function to reduce the number of routes and speed up the processing time. For example, alternative routes with overlaps of more than 80%, stretches of more than 1.2 and two unnecessary detours will eliminate most alternatives.

The purpose of the research was not to investigate alternative route generation methodologies, rather to use well tried and tested methods that could be relied upon to produce consistently relevant routes. The implications of using the TomTom® route generation methodology in RAPP-UP raises several important issues.

a) It ensured experimental consistency and replicability both between survey participants and for each participant in the context of repeated observations (i.e., for several trips)
b) The approach ensured portability - RAPP-UP can be used in most city across the world providing that TomTom® offers route guidance services based on historical and/or real time traffic data in those cities. In the pilot testing stage of the development process RAPP-UP was tested in Cape Town as well as in the Johannesburg / Pretoria area
c) It enabled the use of real-time traffic data to generate the choice sets attribute levels. This approach ensures that day-to-day variations in traffic conditions (including traffic incidents and accidents) are accounted for in the route generation process
d) It introduced the opportunity for further research to be done for consideration of alternatives to minimum time based optimal and alternative routes, for example, minimum distance or cost routes.

5.12 The Effect of Route Generation on Experimental Design

Stated preference experimental design requires three steps. Firstly, the form of the utility expression and the definition of the utility attributes is required for the identified alternatives; secondly the attribute levels must be specified to define the attribute level range; and thirdly the associated experimental design, e.g., orthogonal fractional factorial or an efficient design is generated from which the choice sets are defined. (For an efficient design there are additional inputs required, specifically the prior attribute coefficient values and the specification of the type of discrete choice model to be estimated). The orthogonal and efficient designs can ensure that attribute level balance can be achieved in the choice sets, i.e., each attribute level appears an equal number of times for each attribute. Attribute level balance ensures that the attribute coefficients can be estimated on the whole range of levels, instead of just a few levels.

For the RAPP-UP application the first step is also required, i.e., the form of the utility definition and the attributes to be included, but in the second step the attribute levels were defined in two ways, viz.:

a) Some attribute levels were determined by the use of the real-time time and cost levels derived from the route generation process. It was thus not possible to determine a priori what the number of attribute levels would be nor the attribute level range as these would be determined from real-time traffic conditions at the time of the trip and experienced by the survey participant.

b) Some real-time attribute levels were factored before inclusion into the choice sets. Hence the attribute levels, even though factored, still incorporated the randomness of day-to-day traffic conditions at the time of the trip. The factored attribute levels did however ensure variation in day-to-day levels and hence extended the range of the levels. Orthogonal fractional factorial designs were used to determine the number of choice sets required based on the number of attributes that were factored, the number of route alternatives and the number of factor levels. The factoring of the attribute levels provides more analyst control by widening the attribute level range but does not remove the underlying randomness in the real-time attribute level.

The experimental design process for RAPP-UP highlights two weaknesses of using the minimum time (or the trip distance or cost) criteria in the route generation process:

a) Even within the context of the day-to-day variations in traffic conditions, the same (or similar) routes in the choice sets could be generated on several occasions. This is a fundamental feature of route determination in a dense urban road network using minimum time or cost criteria to generate optimal and alternative routes. While there are a large number of possible alternative routes, there are few routes that would be considered suitable by motorists. The routes generated by route guidance platforms such as TomTom® use proven criteria (e.g., travel time minimization) to generate routes using practical criteria to generate independent routes (i.e., extent of route overlap, stretch (i.e., route length) and local optimality (i.e., avoidance of unnecessary detours on the alternative route).
b) Thus, the analyst has no control over the attribute levels derived from real-time traffic data. Potentially the attribute level range could be narrow, and while realistic for the survey participants, this may limit the range of attribute levels that can be tested in the SP setting and subsequently used to estimate the discrete choice models. In SP experiments it is preferable to use a wider range of attribute levels than a narrow range while ensuring that the levels are still within realistic limits (Bliemer & Rose, 2009; Choicemetrics, 2018). So, while the attribute levels range may be narrow, they compensate for this by displaying a high level of external validity.
c) The variation in the real-time trip attribute levels (especially the trip times) on a day-to-day have is somewhat random depending on factors such as traffic demand, time of travel, traffic incidents or accidents, road conditions (e.g., road works), and even the weather. This variation in attribute levels results in the inability to achieve attribute level balance in the choice sets. However, this was not considered a drawback of the approach. It was considered appropriate to more accurately represent typical and more realistic day to day travel conditions experienced by motorists on urban road networks than to artificially ensure attribute level balance.

5.13 Trip Duration Effect on Route Generation

For route guidance driving aids, the estimated duration of the trip between origin and destination is an important consideration when generating optimal and alternative routes. The accuracy of the real-time traffic data generated at the start of the trip for the duration of the whole trip must be considered. For example, for a 60-minute trip, the real time data may only be appropriate for the initial part of the trip as the downstream traffic data will be constantly changing. Strictly speaking real-time traffic data should be updated every five minutes to define the remaining trip time more accurately and possibly to adjust the route, i.e., dynamic routing. However, changes to the optimum route for the user while driving can cause confusion and frustration to the driver, so most guidance systems use a static optimal route approach.

To take the time delay effect into account as well as to speed up the route generation process real-time traffic data is used for the initial part of the trip, and historical data for the balance of the trip. The cut-off point between the two data sources is set by the provider and is typically about 30 minutes. Trips with a travel time of less than 30 minutes thus use near real-time data for the whole trip (if it is available for all segments), and those longer than 30 minutes only have the first 30 minutes determined from near real-time data and the balance with historical data.

For RAPP-UP, it was necessary to use static routes when generating the routes and offering route guidance to survey participants. For trips longer than 30 minutes it is likely that a portion of the routes are generated from historical traffic data.

5.14 Dijkstra's Path Building Algorithm and the A* Enhancement

In the context of the route generation process it was appropriate to provide insight into Dijkstra's tree building algorithm (Dijkstra, 1959) that is widely used for generating minimum time, distance or cost paths between a defined origin and destination in a network. Originally developed for determining minimum time distance paths between telecommunication exchanges, it was published in 1959. The original algorithm and modifications to it are extensively applied in the context of road networks and is used in most transportation demand models to 'skim' minimum time, distance, or cost matrices for application in the trip distribution, mode choice and trip assignment stages. The benefit of Dijkstra's algorithm is that it is computationally very efficient and optimal route determination on complex road networks can be done very quickly. The application of Dijkstra's algorithm for route generation requires the origin and destination locations to be identified by the user. Then the road segment real-time and/or historical traffic data, i.e., speeds and times, are used to build the optimal paths and alternative paths with the A* algorithm modifications to accelerate the path building process. The A* search algorithm uses a pre-defined set of optimal routes (for example based on historical data) to speed up the route generation process. If the pre-estimated optimal path is known, then the optimal path using near real-time traffic data can be speeded-up. This algorithm can speed up route determination between origins and destinations located far from each other on dense road networks where the number of possible paths can be substantial. The A* search algorithm is also applied when travel times are longer than 30 minutes. Tree building can be done from the origin to the near real-time cut of point and also backwards from the destination to the cut-off point using pre-determined paths based on historical data.

The Google Maps® and TomTom® route guidance systems have adopted the use of the A* algorithm. The bespoke modifications to the algorithm made by each company are confidential.

5.15 Examples of Optimal and Alternative Route Generation

Optimal and alternative routes were generated for a trip using Google Maps® between the location Home (in Dunkeld West, Johannesburg) and the Jabulani Theatre in Soweto on Monday 23rd August 2021 at 4:50 pm, i.e., in the afternoon peak hour. The optimal route has been generated on a minimum journey time basis, and two alternative routes options have been provided. In 2021 the traffic demand in South African urban areas had reduced significantly due to the COVID pandemic.

The (optimal) shortest travel time route is shown in **Figure 30**. The alternative routes are shaded in grey. The minimum travel time is 46 minutes, and the route length is 35.9 km. This implies an overall average speed of 51 kilometers per hour. There is very little slowed-down and stop-start time on the route (i.e., no orange or red shaded segments) reflecting the reduced demand caused by the COVID pandemic. Because this route has a travel time in excess of 30 minutes, the latter part of the route would have been defined using historical traffic data.

This route appears to travel north and west before turning southwards on the N1 freeway. There are tolls on the N1 freeway, but these are not shown on the route as Google Maps® did not yet have a toll calculator facility.

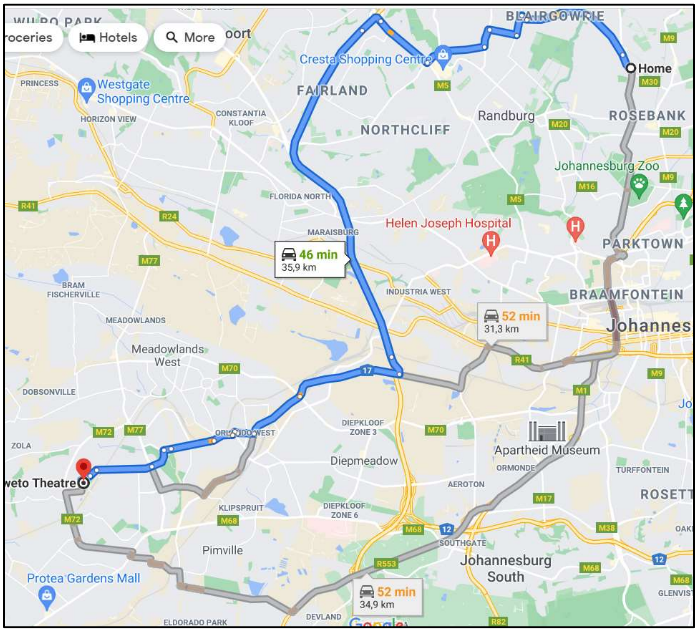


Figure 30: Optimal and Alternative Routes based on Minimum Travel Time.

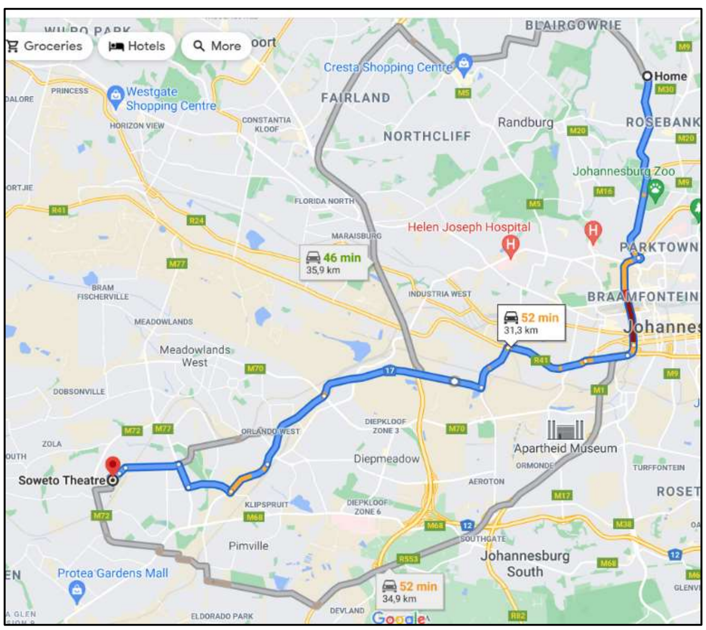
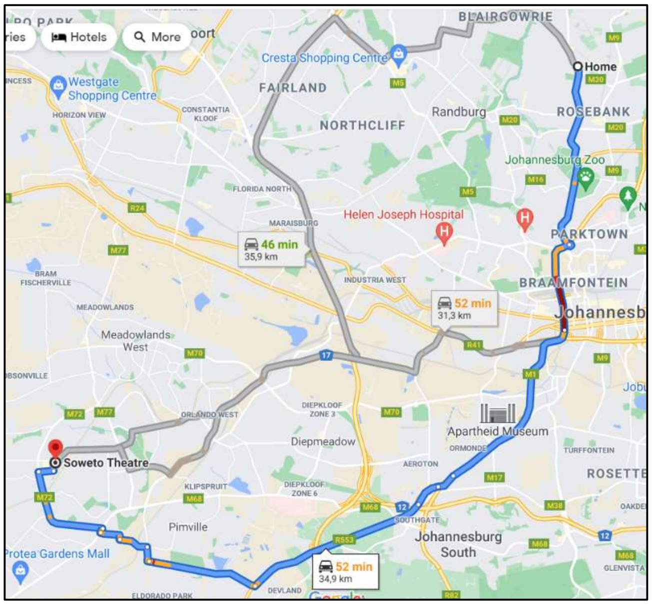


Figure 31: First Alternative Route

The first alternative route is shown in **Figure 31**. It has a travel time of 52 minutes, i.e., 6 minutes longer than the optimal route. It has a route length of 31.3 km, so is 4.6 km shorter than the optimal route. The average speed is 36 kilometers per hour, considerably lower than the optimal route. There is an overlap with the optimal route on the latter part of the route in Soweto. Red and orange segments also occur through the Johannesburg CBD area on the M1 motorway indicating slowed-down and stop-start traffic conditions on these segments. There are no freeway tolls on this route.



The second alternative route is shown in **Figure 32**. It has a travel time of 52 minutes, i.e., the same time as the first alternative and its length is 34.9 km, 3.6 km longer than the first alternative but only 1 km longer than the optimal route. The overall average speed is 40 kph. It shares part of its length with the first alternative, and so also has orange and red segments through the Johannesburg CBD indicating slowed-down and stop-start time. There are no freeway tolls on this route.

Figure 32: Second Alternative Route

These routes illustrate the following features of the optimal and second quickest route:

- Relatively narrow differences in attribute levels between the alternative routes (6 minutes in travel time or 13%, and 15% in route length).
- A wide geographic spread of routes.
- Varying levels of congestion on the routes reflecting different proportions of free-flow, slowed down and stop-start travel time.

6. SPECIFICATION OF THE ROUTE CHOICE APPLICATION: RAPP-UP

6.1 Definition of Route Utility

The development of the RAPP-UP application initially required the definition of the route utility for a road-based trip. The attributes included in the utility must be defined or derived from the traffic data that defines the routes such as travel time and route length at a particular time *t*. Trip cost and the reliability of on time arrival are calculated separately based on the trip times and lengths. The form of utility expression that was adopted was a linear-in-parameters form as follows for individual *i* using route alternative *j* out of J routes with attributes *k* and at time *t*:

$$U_{ijt} = V_{ijkt} + \varepsilon_{ijt} = \sum_{k=1}^{K} \beta_k X_{jkt} + \varepsilon_{ijt}$$

Equation 1: Linear in Parameters form of Trip Utility

Where:

- U_{ijt} is the utility of individual *i* using route *j* at time *t.*
- V_{ijkt} is the representative component of utility.
- β_k are the attribute coefficients to be estimated.
- X_{ijkt} are the utility attributes for route *j* and attribute *k* at time *t.*
- ε_{ijt} is the utility error term for individual *i* using route *j* at time *t*. The observed utility V_{ijkt} is also known as the deterministic or representative component of utility.

The number of attributes *k* to be included in the utility expression for RAPP-UP was determined practically and theoretically. Practically, the number was determined by what attributes could be fitted into the smartphone screen in the form of a choice set and still be legible. Based on several trial screen layouts, it was determined to be not more than eight. The route alignment on a MapBox® map background was also to be shown together with the choice set for each route.

From a theoretical viewpoint, the arguments for and against simple time-money trade-offs versus more complex utility expressions are described by Abrantes and Wardman (2011) and Hess et. al (2020). Simple time-money trade-offs are more commonly used in European countries for large national studies to determine national values of travel time for use in economic appraisals. The European view is held that SP exercises in these contexts should be kept simple. A meta-analysis of the values of time by Abrantes and Wardman (2011) revealed that 80% of European SP studies had 4 or less attributes. Hensher (2006) argues that it is the attribute relevance and not complexity that is important, and the focus in Australia and Latin America has been on more complex utility expressions typically developed for more localized studies where the application is in transportation demand models as well as estimating VTT for economic appraisals. Since 2010 South Africa has tended to follow the Australian approach with more complex time-money trade-offs, but for application in localised mode choice studies. In the limited number of urban route choice studies in South Africa the approach has been on more simple utility definitions, for example, there has been no investigation of travel time reliability or the effect on route choice and VTT of different proportions of travel time in congested and uncongested conditions.

For this research a more complex form of the utility expression was adopted for several reasons. Firstly, there was an objective to test more complex forms of utility expressions to ascertain whether the attribute coefficients were significant in the South African context. The second objective was to apply various forms of route choice models based on more complex forms of the utility expression. Thirdly the determination of the VTT was to be made for different amounts of travel time at different levels of service in a localised geographical area, namely the Johannesburg – Pretoria region of the Gauteng Province. Lastly, the inclusion of motorway tolls in the study area was necessary as a way of determining the motorist's willingness-to-pay for time and cost savings of the motorways in the light of the failure of the SANRAL GFIP e-toll scheme. The other important consideration, as highlighted by Wardman and Ibanez (2012) was to overcome the potential drawback of SP methods by realistically quantifying (in minutes) the actual categories of travel time using real-time traffic data for each route. This would also partially address the issue of how these travel times should be presented to participants in SP exercises.

Based on the forms of utility used by Wardman (1986), Wardman and Ibanez (2012), Hensher (2001), Hensher and Rose (2004), Vrtic et al., (2009) and Prato et al., (2014), the attributes included in the utility expression included three categories of travel time related to the levels of service, viz. free-flow time (fft), slowed-down time (sdt) and stop-start time (sst); two trip costs, viz. tolls (if applicable) and petrol cost; and the route travel time reliability. Tolls were only included for routes that included currently tolled freeways in Gauteng.

Wardman and Ibanez (2012) attribute the initial investigation into the value of congested and uncongested time using revealed preference methods to Train (1976). The first evidence of this disaggregated travel time approach using stated preference methods in the literature was Wardman (1986) followed by Hensher (2001). In 1986 Wardman confirmed statistically significant differences in the values of time for delayed and free flow time. In 2001 Hensher determined that, from a study in New Zealand, motorists valued travel time in congested conditions significantly higher than in free-flow conditions. The same study determined that trip time reliability was a significant attribute in overall trip utility.

For this experiment the utility expression was defined as the linear-in-parameters sum of six trip time, cost and reliability attributes between origin *i* and destination *j* on route *k* at time *t* as follows:

$$U_{ijkt} = b_1*fftime_{ijkt} + b_2*sdtime_{ijkt} + b_3*sstime_{ijkt} + b_4*petcost_{ijkt} + b_5*tollcost_{ijkt} + b_6*pota_{ijkt} + \varepsilon_{ijkt}$$

Equation 2: Form of Trip Utility Expression in RAPP-UP

Where:

- U_{ijkt} is trip utility between origin *i* and destination *j* on route *k* at time *t*.
- $b_1, b_2 \ldots b_6$ are coefficients to be determined.
- $fftime_{ijkt}$ is the free flow time on route *k* in minutes at time *t*.
- $sdtime_{ijkt}$ is the slowed-down time on route *k* in minutes at time *t*.
- $sstime_{ijkt}$ is the stop-start time on route *k* in minutes at time *t*.
- $petcost_{ijkt}$ is the petrol cost for route *k* in Rands at time *t*.
- $tollcost_{ijkt}$ is the toll cost of route *k* in Rands at time *t*.
- $pota_{ijkt}$ is the probability of on-time arrival using route *k* in percent at time *t*.
- ε_{ijk} is the error term for route *k*.

Note that as the experiment is unlabelled, there is no alternative specific constant (ASC). However, Hensher et al., (2015), indicate the inclusion of an ASC in an unlabelled route choice experiment can have behavioural meaning, such as the left to right (or first then second alternative) choice set response bias. This inclusion of an ASC is investigated when estimating the discrete choice models.

This form of utility expression enabled the confirmation of whether there were different values of travel time for stop-start, slowed-down and free-flow conditions in Gauteng Province. International evidence (Hensher & Rose, 2005; Wardman & Ibanez, 2012) has shown that stop-start VTT's are higher than slowed-down and free-flow values. Wardman and Ibanez (2012) refer to the ratios of attribute coefficients for free-flow, slowed-down and stop-start-time as congestion multipliers. This form of the utility expression filled in several gaps in the understanding of motorists' route choice behaviour in Gauteng Province. Firstly, the congestion multiplier ratios have never been evaluated in South African urban conditions. Secondly the VTT's derived from the ratios of the travel time and petrol and toll cost attribute coefficients fill a gap in the knowledge of motorists' willingness-to-pay for travel time savings in urban areas. The VTT was not quantified for the GFIP e-toll scheme and was identified as a shortcoming in the GFIP planning and traffic modelling process by the Gauteng Provincial E-Toll Advisory Panel (2014). Thirdly, the importance of trip time reliability has been highlighted as an important motorist trip attribute in route choice contexts (Asensio & Matas, 2007; Fayyaz et al., 2021; Brownstone & Small, 2005). This was included as an attribute in the utility expression using the probability of on-time arrival (pota) in percentage terms for each route. A percentage quantification was used instead of the more common measure of travel time standard deviation, as no measure of standard deviation was available. Further, it was intended that the unreliability should be measured as a function of all three travel time categories, i.e., the free-flow, slowed down and stop-start time. The disadvantage of this approach is the inability to quantify the value of trip time unreliability.

6.2 RAPP-UP Specification and Use

The detailed specification of RAPP-UP and its outputs are described in Annexure A. The Annexure contains the specification of the various RAPP-UP database outputs as well as the method for extracting the data for conversion to CSV, GPX, and KML format for analysis and plotting the route data.

RAPP-UP was developed to carry out unlabelled route choice experiments on congested urban road networks. While the application can be executed in any urban environment globally, the experiment was conducted on a sample of motorists in the Gauteng Province of South Africa. This includes the metropolitan areas of Johannesburg and Pretoria. This region is the economic heart of South Africa, making up 34% of the South African gross domestic product (GDP) (Department of Statistics South Africa (Stats SA), 2021).

RAPP-UP was developed for use on smartphones using the Android operating system and was downloadable from the Google Play Store®. Survey participants required a Google email account that was used as a password to enable them to download the application and install it on their smartphone.

RAPP-UP consists of two components. Firstly, it has a route tracking component that uses the GPS device in the smartphone to identify the users trip origin and destination and track the route of the smartphone and provide route guidance. The route tracking app provides detailed and accurate routes using five second pulses, i.e., a set of location co-ordinates is estimated, recorded and time stamped every five seconds during the trip. The route tracking facility provides the calculated distance and actual travel time between sets of co-ordinates, as well as the elevation of the coordinates. The space mean speed between sets of co-ordinates is calculated from the segment length and travel time. The output from the route tracking component of the App is stored on a remote database from which the data can be downloaded in JSON format for plotting and analysing.

The second component of RAPP-UP is the stated choice experiment. When RAPP-UP is activated by a user before the start of their trip the GPS device in the smartphone triangulates the users' position. The accuracy of the trip origin can be improved, if necessary, by moving the screen roadmap background with two fingers. Alternatively, users can type their positions into the app using the drop-down keyboard. When satisfied that their location was accurate, the trip origin was fixed, and a green pin was inserted into the roadmap background. This progression of steps is shown in the following sequence of screen grabs from RAPP-UP. **Figure 33** shows the welcome RAPP-UP screen and the search for a GPX location fix. The location search takes between 5 and 10 seconds. The next screen requests that the participants enter an origin suburb against a blank blue screen with the red flag locator shown in the middle of the screen. When the suburb is entered, the next screen is shown. This screen has a road background with road names and main landmarks. The participant can use their fingers on the screen to accurately locate their position on a specific street and dwelling. It is possible to zoom in and out of the map for better location accuracy.

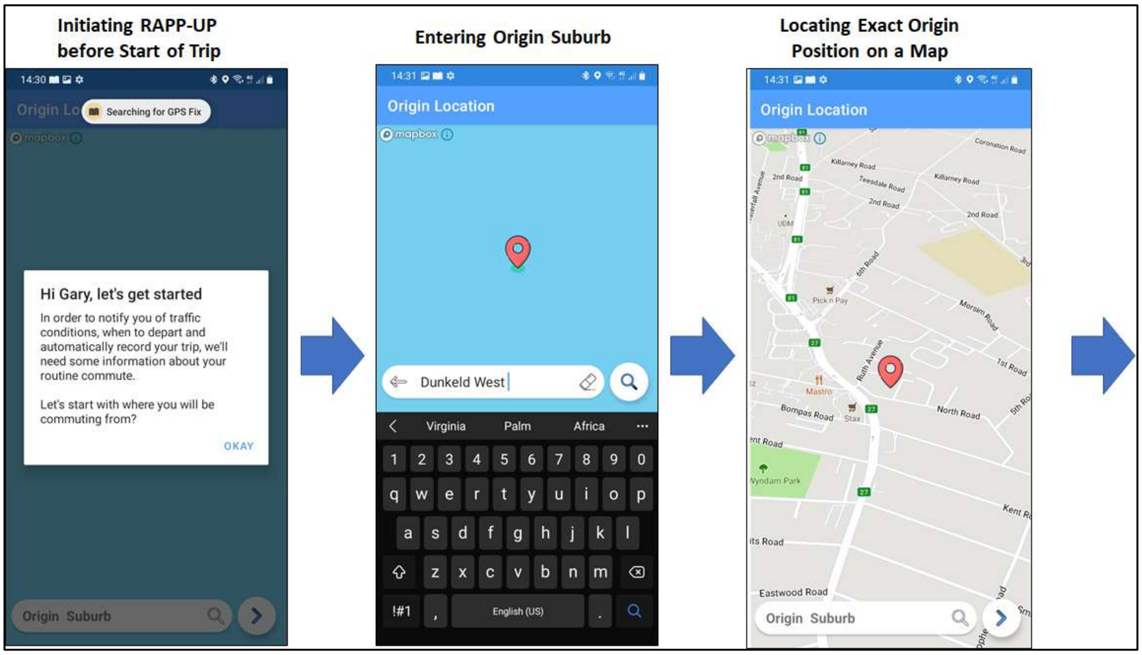


Figure 33: Initiating RAPP-UP and Setting Origin Location

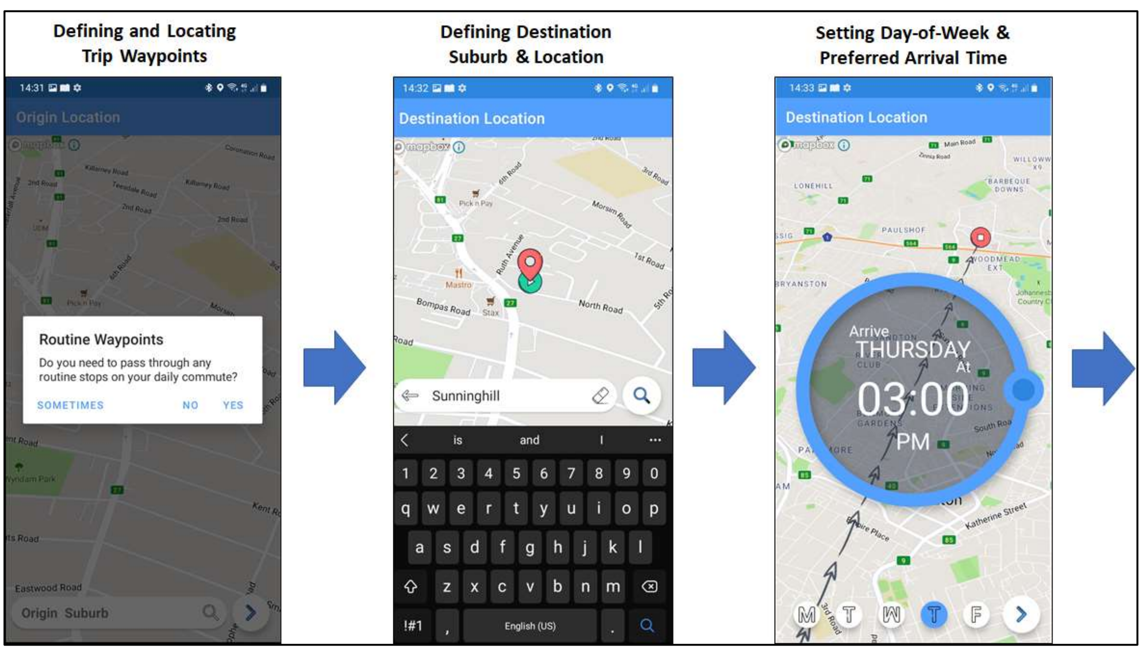


Figure 34: Waypoints, Destination Suburb and Day-of-Week Specification

Figure 34 shows the specification of waypoints on the trip. These are defined as locations that the participant must pass through on their trip between origin and destination. The waypoints are located in the same way as the origin suburb, i.e., with a suburb description and use of the map to make a more accurate location. Up to three waypoints can be defined. The destination suburb is then defined by the participant. This is done in the same way as the definition of the origin suburb and waypoints. The destination suburb is typed into the destination field and then searched for and accurately located on the screen map. Once the destination suburb has been defined a red pin is inserted into the roadmap background. RAPP-UP then asks for the day of the week that the trip is being made on, and the preferred time of arrival. This information is used to estimate the required departure time and to send a reminder to the participant to leave on time. **Figure 35** presents the screen showing the confirmation of the origin and destination, connected by sequence of arrows. Thereafter the two alternative routes are generated between origin and destination (via waypoints if there are any) and are displayed on the smartphone screen.

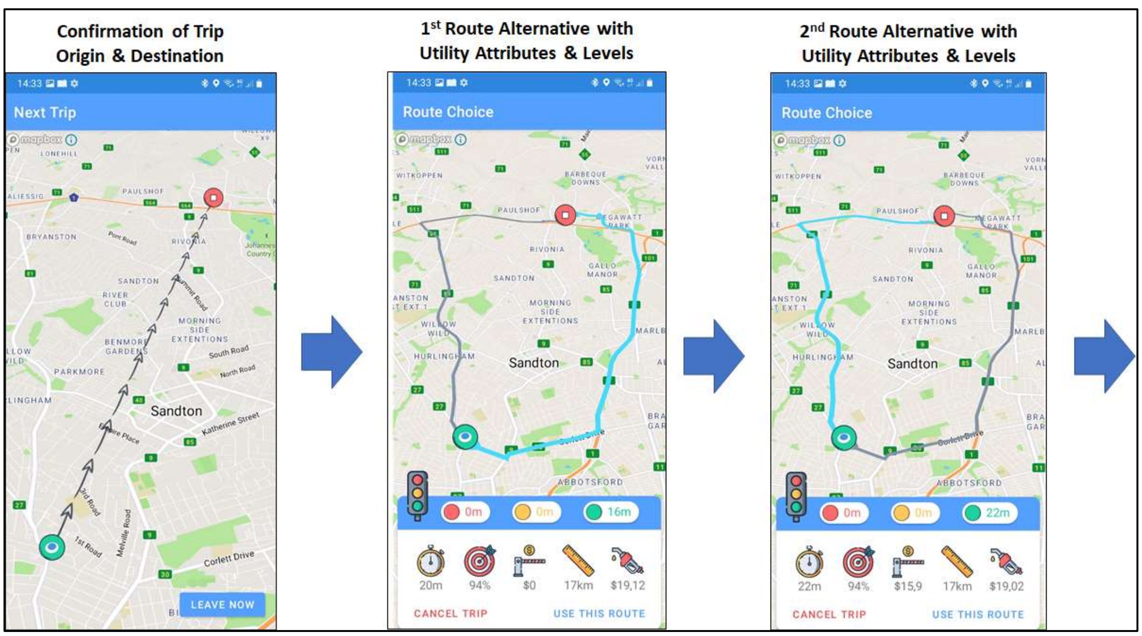


Figure 35: Confirmation of O-D and Display of Alternative Routes

The trip attributes and levels are shown for each route at the bottom of the screen. The participant can move between the routes by tapping on the route outline on the screen map. When a route is tapped, it is highlighted in a bright blue colour and the trip attributes and levels are shown in the choice table, while the other route is shaded in grey.

The route attributes shown are the total trip time in minutes (stopwatch icon); probability of on-time arrival in percent (pota) (target icon); toll fee for the route in Rands if a tolled freeway is included in (the toll barrier icon); the total trip distance (in km); and the estimated fuel consumption in Rands (fuel dispenser nozzle icon). Also shown adjacent to the traffic signal icon are the red (stop-start travel time), orange (slowed-down trave time) and green (free-flow travel time) traffic signal icons. In the examples shown, there is no stop-start or slowed-down time, so the free-flow time is the same as the total travel time, i.e., 20 minutes for the eastern route and 22 minutes for the western route. The calculation of the toll fee, the probability of on-time arrival and fuel consumption are discussed in the next section.

The western route was chosen as the preferred route and is selected by tapping on the USE THIS ROUTE script at the bottom of the screen. When the route choice is made, the attribute levels for each route and an indication of the chosen route are sent to the remote database. As well as this data, the proportion of route overlap is also calculated and stored in the database (this is not displayed to the participant).

Figure 36 shows the driver guidance provided for the chosen route (i.e., the western route). Driver guidance is provided on the smartphone screen once the route has been selected. During the trip the path is tracked, and the co-ordinate and trip time data transmitted to the remote database. When the trip is completed, the driver participant taps on the *Finish Commute* text shaded in red at the bottom of the screen and RAPP-UP is terminated and closed. When the app is used again, the process is repeated.

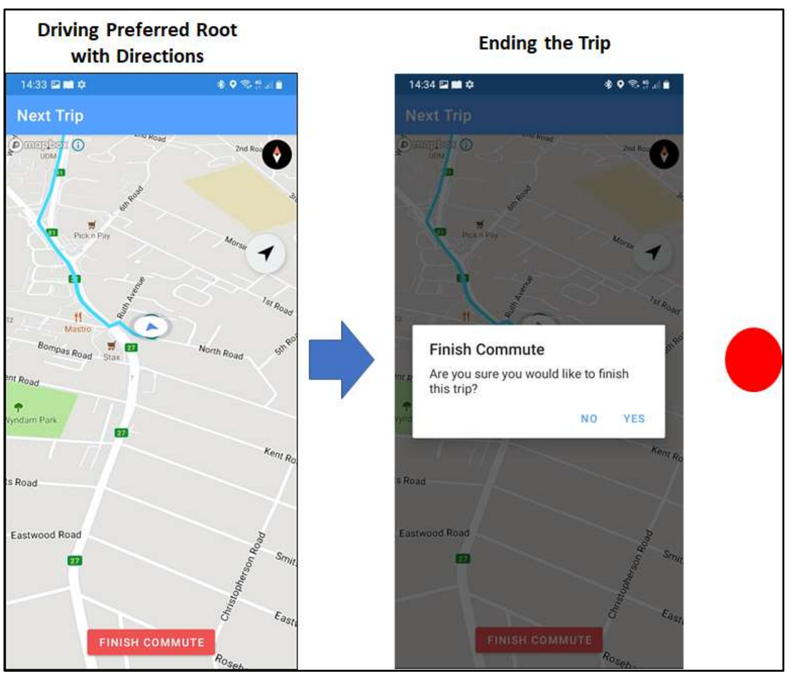


Figure 36: Driving the Preferred Route and Closing RAPP-UP

RAPP-UP route data is transmitted via the GSM network to the remote database. If the smartphone does not have 4G data available, then the route data is stored on the smartphone until internet connectivity is restored either by 4G or 5G GSM, or when a wi-fi or wireless connection becomes available. This feature enables users to download their trip data after their trip when they have an internet connection, so avoiding the cost of GSM 4G or 5G transmission.

6.3 RAPP-UP Data Structure and Definitions

The data output by RAPP-UP is structured around trips, routes, and routines. The structure is shown in **Figure 37**. The figure shows that a trip between an origin and destination (O-D) consists of two routes, each with its own attribute levels. A routine is defined as a set of trips for a particular day. Each route has its own shape files (containing the segments with co-ordinates and segment data such as lengths, speeds, travel times, etc.). The routes are presented to the user on a smartphone screen in the form of a choice set. The selected route is the preferred route chosen by the user, which they must drive between O-D. The driven route data is generated by tracking the smartphone and its shape and segment data is also stored in the remote database.

Identifiers (id's) are allocated to each trip, route, selected route, routine, and choice set. These id's are presented in the various output tables shown in Annexure C.

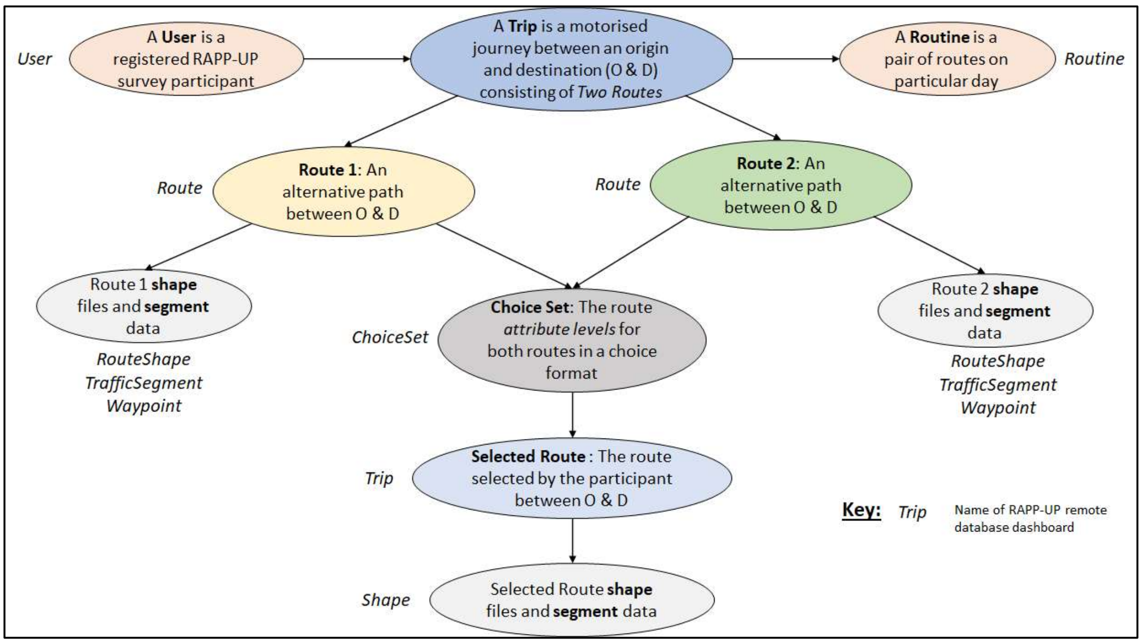


Figure 37: Structure of RAPP-UP Trips, Routes, Routines and Choice Sets

The detailed contents and definitions of the RAPP-UP database are shown figuratively in **Figure 38**. The figure is a pictorial representation showing the full data sets for two routes, viz, two alternative routes and the preferred route driven (or chosen) by the user. The highlights of the figure are:

a) The trip is for user G Hayes, with an email address (u16401868@tuks.co.za) and user id *ANRRVmCk46*. This user id is used throughout the survey, i.e., for all trips made by G Hayes

b) There are two alternative routes with route identifiers, i.e., route SCzVhhKrAF (shown in black) and route L1wd3YxS4X (shown in red). These two routes make up a routine (i.e., the set of route alternatives) with the identifier BZO6ecyZGa.

c) For each route (with identifier) there is a sequence of route segments that contains the segment latitude and longitude co-ordinates (for the a-node); the segment sequence number (the sequence is ascending from 0); the date; and the time stamp.

d) For each route there is an attribute data set that includes the total trip time; total distance; probability of on-time arrival (pota); fuel cost, toll cost, free-flow time (fft); slowed-down time (sdt) and stop-start-time (sst). These data constitute the choice set attributes and levels for each route.

e) The preferred route chosen by the user is also shown as given by the route identifier (in this case route L1wd3YxS4X shown in red)

f) The driven route is shown with a shapefile that contains the user identifier; the route identifier (L5E1HnBezP); segment identifiers (e.g., YApvq3A6Le); the shape sequence number (ascending in order); the a-node of the segment (lat and lon); segment altitude; segment bearing; and average speed on the segment.

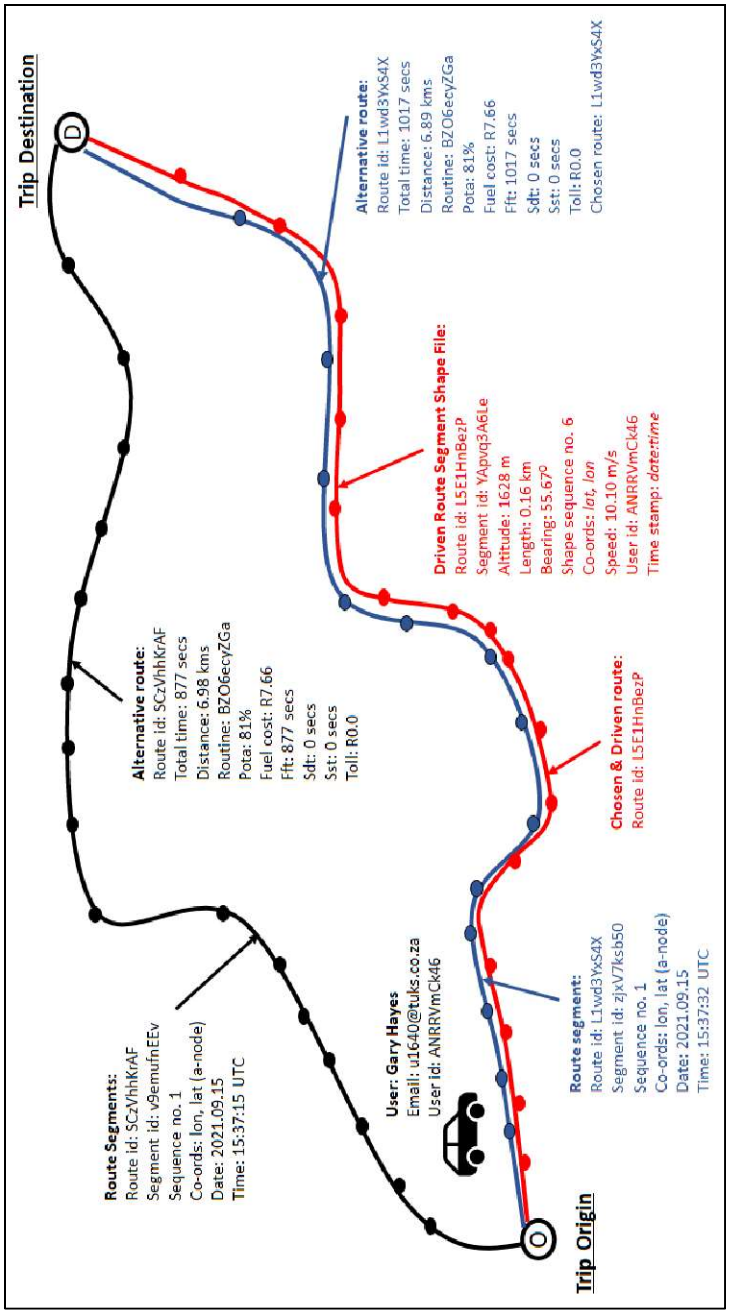


Figure 38: RAPP-UP Route Data Coding Definitions

6.4 RAPP-UP Export Scripts and Outputs

Export scripts were written to transfer data from the remote database onto a computer for processing and analysis. The detailed format of the data sets produced by RAPP-UP from the remote database are in Annexure A. Command script files executed from the Windows Command prompt were written to download the data onto a computer or laptop. There were twelve sets of outputs generated by each of the 12 command files. The following table summarises each of the data sets produced by the command script files. The output files are in JavaScript Object Notation (JSON) format. These are text files that can be imported into Excel and saved as both Excel and comma separated variable (CSV) files. The CSV file format is required for conversion of files to GPX and KML format.

Table 3: RAPP-UP Database Export Script & Output Filenames and Contents

Contents of Data Files	Name of Command Script File	Output File Name
1. User dashboard containing user ID code and name & date & time of creation	Export_user_collection_json.sh	User_collection.json
2. Trip dashboard containing the trip code; trip start time; user id code; trip duration & distance	Export_trip_collection_json.sh	Trip_collection.json
3. Shape dashboard containing the shape id; shape sequence no.; altitude; speed; user id; creation ate & time stamp; etc.	Export_shape_collection_json.sh	Shape_collection.json
4. Choice set dashboard containing choice set id; date & time stamp; route no.; toll cost factor; pota factor; etc.	Export_choiceset_collection_json.sh	Choiceset_collection.json
5. Route collection dashboard containing the route id; fuel cost; routine id; travel time; toll cost; pota; date and time stamp; distance, choice set applied, etc.	Export_route_collection_json.sh	Route_collection.json
6. Route segment shape collection dashboard containing the segment id; length; date & time stamp;	Export_routeshape_collection_json.sh	Routeshape_collection.json

sequence no.; location (lat and lon)		
7. Routine collection dashboard containing routine id; date & time stamp; user id	Export_routine_collection_json.sh	Routine_collection.json
8. Shape collection dashboard containing the segment id; shape sequence no.; altitude; trip id; speed; user id; date & time stamp; bearing; location (long & lat)	Export_shape_collection_json.sh	Shape_collection.json
9. Traffic segment dashboard containing the segment id; date & time stamp; TEC object code; shape segment start sequence no.; shape end sequence no. ; route id	Export_trafficsegment_collection_json.sh	Trafficsegment_collection.json
10. Trip collection dashboard containing trip data for the trip driven including trip id; departure time; arrival time; date & time stamp; user id; selected route id; duration; distance	Export_trip_collection_json.sh	Trip_collection.json
11. Waypoint collection dashboard containing the waypoint id; date & time stamp; waypoint name; location (lat & lon)	Export_waypoint_collection_json.sh	Waypoint_collection.sh

7. GENERATION OF CHOICE SET ATTRIBUTE LEVELS FOR ALTERNATIVES

7.1 Introduction

The route attributes and value derivation are summarised in **Table 4**. These were the total trip time; the free-flow time (*fftime*); slowed-down time (*sdtime*); stop-start time (*sstime*); route length; route petrol cost; probability of on-time arrival (*pota*) and the toll cost (if any). The travel time attributes were based on real-time values as previously described. For a given route, the segments with the same travel time category (e.g., free-flow time) are summed to give a total route free-flow time in minutes. The probability of on-time arrival (*pota)* is calculated from the *fftime, sdtime* and *sstime* travel time categories, and is expressed as a percentage, i.e., the probability of arriving at the destination on time. The petrol cost was calculated from the route length using an average vehicle fuel consumption rate and the current pump price of fuel per litre, and the toll cost was the actual toll cost for the use of Gauteng freeways that are included in the GFIP e-toll system. For reasons previously described the toll cost and *pota* levels were also factored by a factor in accordance with an orthogonal fractional factorial design. The derivation of the fuel consumption, toll values and *pota* are now discussed.

Table 4: RAPP-UP Attributes and Source of Attribute Values for each Route

Utility Attribute	**Source of Attribute Value for Route i**
Free flow time (*fftime*) (minutes)	Real-time value
Slowed down time (*sdtime*) (minutes)	Real-time value
Stop Start time (*sstime*) (minutes)	Real-time value
Trip petrol cost[1] (*petcost*) (Rand)	Calculated value based on route length
Probability of on-time arrival (*pota*) %	Calculated value * look-up factor
Toll cost (*tollcost*)[2] (Rand)	Actual value * look-up factor

Notes

1. Petrol cost calculated using route length and assuming current price of unleaded 95 petrol and average vehicle fuel consumption of 8 liters per 100 km
2. Tolls only applied to routes that utilise the Gauteng freeway sections of GFIP

7.2 Trip Petrol Cost (Rands)

The trip petrol cost for each alternative route was calculated from the route length (in km) multiplied by the current inland cost of 95 octane unleaded fuel which was approximately R11/km at the time of the survey. An average vehicle fuel consumption rate for peak period driving of 10 litres per 100 km was assumed. Thus, for example, the petrol cost for a 20 km trip was R22.00.

7.3 Probability of On Time Arrival (*pota*) (%)

Trip time reliability is often expressed as the time that the respondent will arrive early or late at the destination. A different approach was adopted in RAPP-UP as the real-time travel times were known at the time of the generation of the attribute levels in the choice sets. Using this trip time data allowed the probability of on-time arrival to be estimated and expressed as a percentage in the choice sets.

The trip total trip time, based on real-time traffic data, was determined for each route alternative as part of the route generation process. The total trip time is the quickest possible travel time on the route and hence provides the most optimistic arrival time at the destination. For the purposes of the experiment, it was assumed that there is a randomness associated with the optimistic arrival time that can be expressed as a probability of on-time arrival which will be less than 1.0. It was further assumed that this probability will decrease as the proportion of slowed-down and stop-start travel time increase on the route, as these travel times reflect increasing travel times.

An equation for calculating the probability of on-time arrival using the free-flow, slowed-down and stop-start times for a route was developed. The relationship was not calibrated as it was only used to give an *indication* of the probability of on-time arrival and hence does not require accurate estimation. The relationship indicates lower levels of on-time arrival probability with increasing proportions of slowed-down and stop-start time. The expression that has been adopted is linear in form as follows:

Probability of On Time Arrival (%) $Pota = factor * [1- \frac{(0.8*sstime+0.6*sdtime+0.1*fftime)}{Total\ travel\ time}]\ \%$

Equation 3: Probability of On Time Arrival

Where:

- *factor* = a two-level factor to widen the range of the attribute levels. Values of 0.9 and 1.1 were applied using an orthogonal fractional factorial design (note these levels can be altered by the analyst to widen or narrow the range).
- *sstime* = real-time total stop-start travel time on the route in minutes.
- *sdtime* = real-time total slowed-down travel time on the route in minutes.
- *fftime* = real-time free-flow travel time on the route in minutes.
- *Total travel time* is the total route travel time in minutes (=*sstime* + *sdtime* + *fftime*).

The definition of pota introduced possible correlation between the values of trip time and the *pota* value. Because the uncertainty in trip time is caused by variations in the categories of trip time (and especially by *sdtime* and *sstime*), it was thought worthwhile to test this approach and verify whether this correlation actually occurs. The pota level is calculated for each route when the alternative routes have been identified and the various travel time proportions have been determined. The *pota* value is reduced by higher levels of stop-start and slowed-down time (weights of 0.8 and 0.6 respectively were applied) and much less by free-flow time (weight of 0.1). Thus, if a route had no stop-start of slowed-down time the *pota* value would only be determined by free-flow time with a weighting of 0.1. The factor applied to the *pota* value was either 0.9 or 1.1 depending on the sequence of choice sets for each observation.

Figure 39 shows the effect on increasing stop-start time as a proportion of total travel time on the pota value. The total travel time has been set at 100 minutes, the slowed-down time has been fixed at 20 minutes and the free-flow time adjusted to balance with the total travel time. The pota value decreases from 73% for a *sstime* value of 10 minutes, to 10% for a *sstime* value of 100 minutes. **Figure 40** shows the effect of increasing proportions of slowed down time on the pota value. The total travel time has been set at 100 minutes, the stop-start time has been fixed at 10 minutes and the free-flow time adjusted to balance with the total travel time. The *pota* value decreases from 80% for an *sdtime* value of 10 minutes, to 30% for a *sdtime* value of 100 minutes.

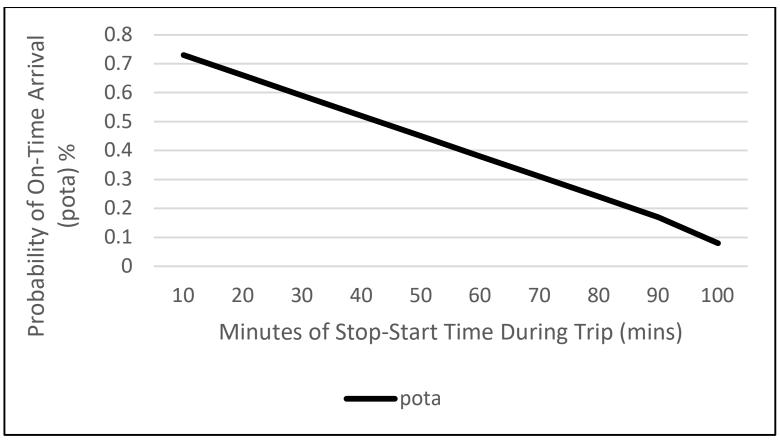


Figure 39: Effect of Increasing Stop-Start Time on the Probability of Arriving On-Time (pota) %

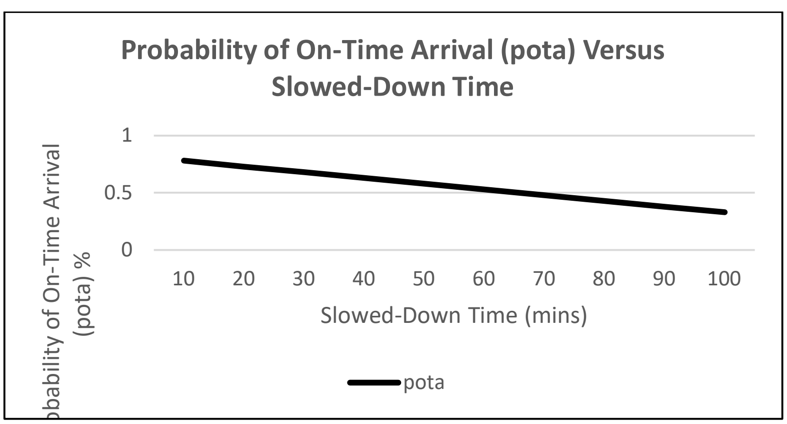


Figure 40: Effect of Increasing Slowed-Down Time on the Probability of Arriving On-Time (pota) %

7.4 Route Toll Cost (Rands)

The toll cost was only applied if a freeway that is currently tolled as part of the GFIP e-toll system was included as part of the overall route. Whether the survey participant actually paid e-tolls is not relevant in this experiment, and this was highlighted to survey participants. The issue of e-tolls in the Gauteng Province is very sensitive, and no reference to the actual payment of tolls by participants was deliberately made to avoid any bias that this may introduce to the experiment. (As an aside, the current level of toll payment non-compliance is more than 80%, so it is unlikely that survey participants actually paid tolls).

The 2021 discounted toll tariff for Class 2 vehicles (i.e., private motor vehicles) was R0.40/km. This rate was applied to the length of freeway for which tolls are levied to obtain a trip total trip toll charge. A factor was applied to the calculated toll level as shown in the utility expression. A two-level factor regime was also applied to the toll cost viz. 0.8, and 1.2. This range was considered practical as it provided a realistic range of toll cost attribute levels that was confirmed in the pilot survey stage of testing RAPP-UP.

7.5 Experimental Designs for Toll Cost and Probability of On Time Arrival Attributes

Given that the trip time categories (i.e., *sstime, sdtime and fftime*), petrol cost and trip distance are fixed for each route alternative based on real-time data, the experimental design for factors applied to the *pota* and toll charges was estimated using an unlabeled orthogonal fractional factorial design with two alternative routes, two attributes, each with two levels. A total of eight choice sets were required. The NGENE® experimental design software was used to generate the design. The choice set designs are shown in **Table 5**. The attribute level factors applied were 0.9 and 1.1 for pota the toll cost. These factors were considered adequate to provide a sufficiently wide range of levels for model estimation. The pota factors defined a narrower level range due to the experimental nature of using this attribute in this form the utility expression. The factors can be easily changed in the RAPP-UP lookup tables. However, if the number of levels is changed, the RAPP-UP lookup tables require modification.

The factors were applied to pota and toll costs in the choice sets on each survey day, i.e., choice set 1 is applied on survey day 1, choice set 2 on survey day 2 etc. to all 8 days. The factors were placed into a look-up table in RAPP-UP. Note that it was not necessary for survey participants to make trips on successive weekdays, but it was required that they completed all eight trips over a period of three weeks, i.e., 15 working days.

Table 5: Experimental Design for POTA and Toll Cost (TC) (2 Attributes with 2 Levels)

Choice Set No.	route_1.pota	route_1.tc	route_2.pota	route_2.tc
1	0.9	0.8	0.9	0.8
2	1.1	0.8	0.9	1.2
3	1.1	0.8	1.1	0.8
4	0.9	1.2	0.9	0.8
5	0.9	0.8	1.1	1.2
6	1.1	1.2	0.9	1.2
7	1.1	1.2	1.1	0.8
8	0.9	1.2	1.1	1.2

7.6 The Quantification of Route Overlap

A consideration for the estimation of discrete choice models for route choice was the extent of the route overlap. The overlap of alternative routes in dense urban road networks is a possibility given that routes are likely to use common roads, especially higher order roads that offer reduced travel times (i.e., with higher capacity and higher speeds). However, as described earlier, the TomTom® route generation process deliberately limits the extent of route overlap. The importance of this parameter would only be assessed after the completion of the main survey.

The measurement of the route overlap by distance was calculated post-survey from the data presented in the database from the alternative route segments. The proportion of route overlap was determined by identifying the common route segments in the routes. For example, if two routes have a common section (or sections) totaling 2 km, and Route A has a total length of 10 km and Route B has a total length of 12 km, then the overlaps for each route are Route A = 2/10 = 20% and Route B = 2/12= 16.6%.

The route segment data contained in the *RouteShape* database can be used to identify and quantify the route overlap. In this database the route segments for each alternative are listed. These were exported to an Excel spreadsheet and a LOOKUP command used to identify common segments. The lengths of the overlapping segments were provided, that together with the total route lengths enable the computation of the common length proportions for each route.

Figure 41 shows an example of two routes with a short overlap for a trip from Rosebank in Johannesburg to Hatfield in Pretoria on a Monday afternoon during the afternoon peak period at 15:53 pm. The choice sets for each alternative route are shown in the following figures. Route A is the western route and Route B the eastern route. The *RouteShape* database segment numbers and sequences in an overlap analysis showed that there was a total of 74 route segments that overlapped totalling 1.74 km. Route A (58 km) has a total of 844 segments and Route B (51 km) a total of 703.

The proportion of overlap for Route A (total length 58 km) was 1.74/58 = 2.94% and for Route B (total length 51 km) was 1.74/51 = 3.37%.

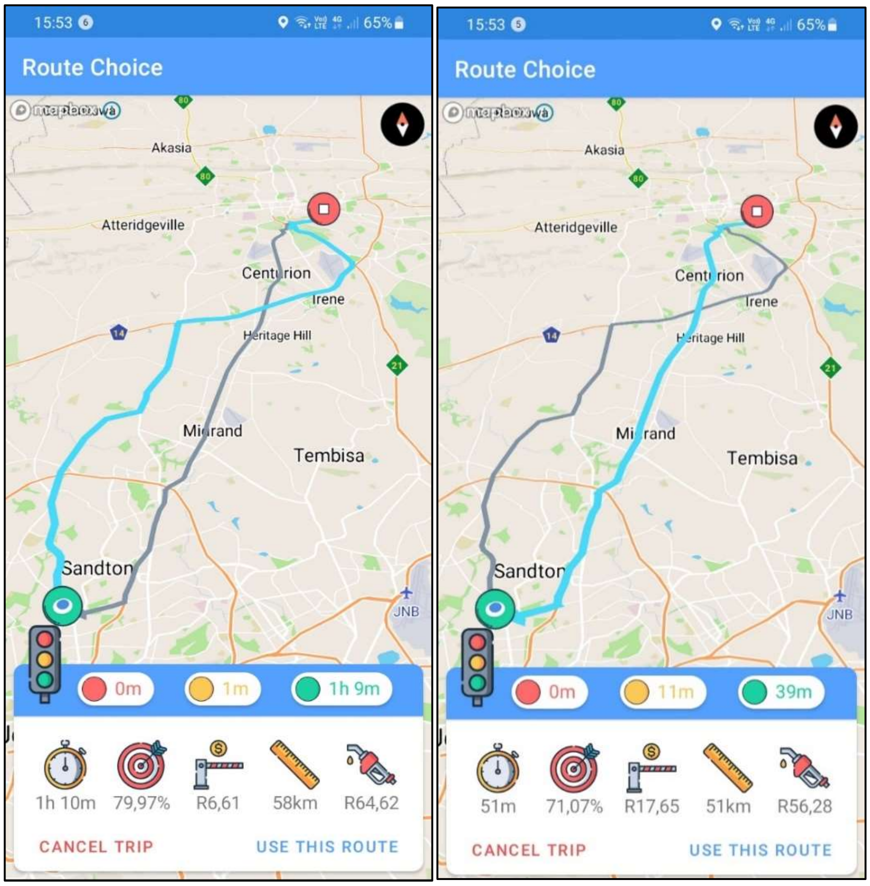


Figure 41: An Example of Route Overlap

7.7 An Example of RAPP-UP Use for a Route Choice Survey

The data sets generated by RAPP-UP are shown in **Table 6**. The details of the user, alternative routes, choice set, and actual route driven are shown. The trip took place on 17 November 2021 at 04:50:08 UTC (i.e., at 6:50 AM South African time). **Table 6** summarises the key data sets and the tables from which it was extracted in the remote database. The data was extracted from the database using the command files and downloaded into Excel files.

Table 6: Example of Data Sets Provided by RAPP-UP Remote Database

Data Item	**Code**	**Table Data Source (Excel)**
Trip and Route Data		
User id	SUqlnwt7FA	Trip_collection.xls
Trip id	VCOIYJ92XZ	Trip_collection.xls
Route 1 id	4JbeHmflgn	Trip_collection.xls
Route 2 id *(* selected route)*	Sm704dUW9s	Trip_collection.xls
Alternative Route Details		
Routine id	9msWz1DP9s	Route_collection.xls
Route 1	4JbeHmflgn	Route_collection.xls
Route 2	Sm704dUW9s	Route_collection.xls
For each route:		
Route length	Length in metres	Route_collection.xls
Route total travel time	Total travel time in minutes	Route_collection.xls
Choice set applied	No. of choice set	Route_collection.xls
Pota factor	Pota factor from look-up table	Route_collection.xls
Toll cost factor	Toll factor from look-up table	Route_collection.xls
Pota value	Pota value in %	Route_collection.xls
Toll cost (if any)	Toll value in Rand	Route_collection.xls
Fuel cost	Fuel cost in Rand	Route_collection.xls
Slowed down time	sdtime in minutes	Route_collection.xls
Stop-start time	sstime in minutes	Route_collection.xls
Free-flow time	fftime in minutes	Route_collection.xls
Route segment shape data for alternative routes		
Route id	The unique route id code	Routeshape_collection.xls
Segment id	The unique segment id code	Routeshape_collection.xls
Segment sequence	The segment sequence number (ascending order)	Routeshape_collection.xls
Segment length	Segment length in metres	Routeshape_collection.xls
Segment a-node	Segment a-node latitude and longitude (lat & lon)	Routeshape_collection.xls
Date & time stamp	Date and time of segment creation	Routeshape_collection.xls
Shape Data for Actual Route Driven		Shape_collection.xls
User id	SUqlnwt7FA	Shape_collection.xls

Trip id	VCOIYJ92XZ	Shape_collection.xls
Segment id	The unique segment code	Shape_collection.xls
Segment sequence id	The sequence of the segment (ascending order)	Shape_collection.xls
Segment a-node	Segment a-node latitude and longitude (lat & lon)	Shape_collection.xls
Segment length	Segment length in metres	Shape_collection.xls
Segment time stamp	Date and time of segment creation	Shape_collection.xls

Figure 42 shows two alternative routes derived from RAPP-UP. The routes have been plotted by converting the segment co-ordinate files in CSV format to KMZ format. The figure shows the two alternative routes plotted in Google Earth®. The selected route is the northern route, i.e., route 2. The routes were generated at 06:50 am on 17th November 2021. Note that this was during the COVID pandemic when traffic demand was reduced. The choice sets for these trip alternatives is shown in **Table 7**.

Table 7: Choice Set for Alternative Routes

Route Attribute	Route 1 Attribute Levels	Route 2 Attribute Levels
Toll Cost (Rands)	R0.00	R0.00
Fuel Cost (Rands)	R12.98	R13.37
Length of Route (km)	11.80	12.15
Total Travel Time (mins)	25.5	22.9
Stop-Start Time (mins)	2.3	0.0
Slowed-Down Time (mins)	0.0	0.0
Free-Flow Time (mins)	23.1	22.9
Probability of On-Time Arrival (pota) %	75%	81%

When the selected route was driven it had a total driving time of 28.0 minutes and the route adherence compliance was 100%.

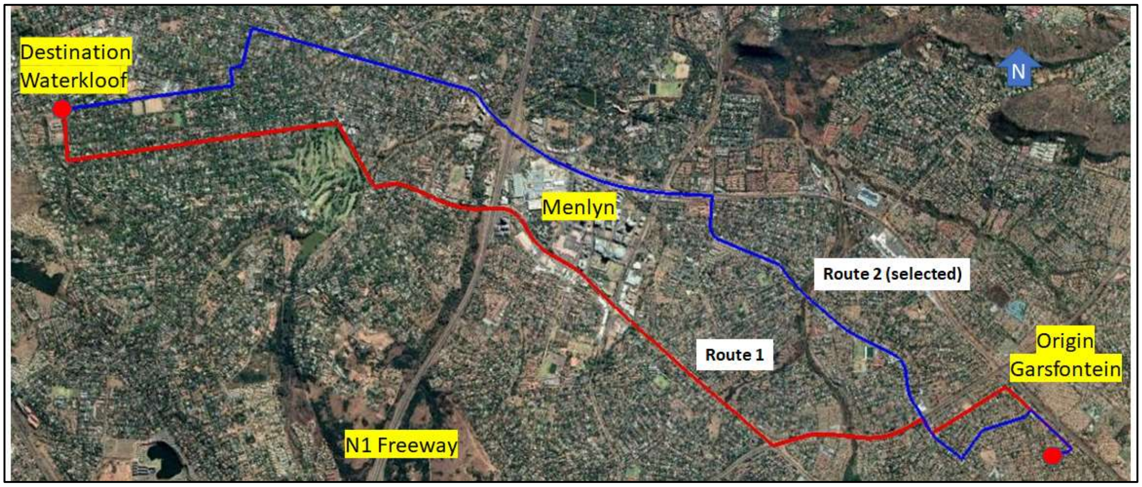


Figure 42: Alternative Routes for Trip from Garsfontein to Waterkloof in Pretoria East

Several important issues are highlighted from this example. Firstly, even though the routes are distinctly different and are geographically separated, the route lengths are very similar, and this gives rise to the similar levels of fuel consumption and cost. Secondly, the travel times are also similar and had a difference of only 2.5 minutes. Route 1 had a stop-start time component of 2.3 minutes and route 2 had none. Thirdly, the probability of on-time arrival was 75% for route 1 and 81% for route 2. Fourthly, as neither of the routes use the N1 Freeway shown in **Figure 42** they do not have a toll charge. As neither route had a toll charge there would be no deduction of a toll charge from the participants survey account as part of the economic experiment. The toll fee loss aversion would therefore not constitute part of the behavioural factors influencing the choice of route in this choice set.

Finally, there is a very small section of route overlap at the origin of the trip. This example demonstrates an important characteristic of route alternative options on a dense urban road network, i.e., that even though the routes may be spatially separated, they may have similar route lengths and total travel times.

8. FORMS OF DISCRETE CHOICE MODELS FOR ROUTE CHOICE SIMULATION

8.1 Introduction

This section describes the various forms of discrete choice modelling appropriate for route choice simulation using random utility theory. The models are described in the context of the route utility defined used in RAPP-UP, i.e., the total utility is the linear-in-coefficients form as follows for user *i* using route *j* at time *t*:

$$U_{ijt} = b_1*fftime_{ijt} + b_2*sdtime_{itj} + b_3*sstime_{ijt} + b_4*petcost_{itj} + b_5*tollcosti_{ijt} + b_6*pota_{ijt} + \varepsilon_{ijt}$$

Where:

- U_{ijt} is the total utility for user *i* using route *j* at time *t*.
- $b_1, b_2 \ldots b_6$ are coefficients to be determined.
- $fftime_{ij}$ is the free flow time on route *j* in minutes at time *t*.
- $sdtime_{ij}$ is the slowed-down time on route *j* in minutes at time *t*.
- $sstime_{ij}$ is the stop-start time on route *j* in minutes at time *t*.
- $petcost_{ij}$ is the petrol cost for route *j* in Rands at time *t*.
- $tollcost_{ij}$ is the toll cost of route *j* in Rands at time *t*.
- $pota_{ij}$ is the probability of on-time arrival using route *j* in percentage at time *t*.
- ε_{ijt} is the stochastic (random) unobserved term for route *k* and captures the factors that affect utility but are unobserved by the analyst.

The specification of the random component term ε_{ij} is a key consideration in the application of different forms of discrete choice model.

8.2 Multinomial Logit Model (MNL)

The MNL is considered the workhorse of discrete choice models. It is a closed form model that is efficiently estimated due to simple structure and its closed form. However, it must be applied within the constraints of the independence of irrelevant alternatives (IIA) that prohibits the estimation of MNL models with correlated alternatives. If this is the case another form of discrete choice model is suitable, for example the nested logit model.

MNL models are those class of random utility models that are derived under the assumption that the unobserved effects in ε_{ij} (i.e., the residuals) are drawn from a multivariate generalized extreme value type 1 (Gumbel) distribution (also termed the EV1 distribution). This requisite that the residuals are independent and identically distributed (IID) essentially means that the alternatives should be independent and not correlated (Ortuzar & Willumsen, 2011).

In the route choice context, if the alternatives in the route choice set have overlapping or common road sections, then the IIA and IID constraints may be contravened and the use of the MNL is not appropriate. Nevertheless, Hensher et al. (2015) recommend the MNL as a good starting point in the discrete choice model estimation process.

The form of the MNL model is as follows for individual *i* using route *j* with *k* attributes.

$$P_{ij} = \frac{\exp(\beta_k V_{jk} + \varepsilon_{ij})}{\sum_{k=1}^{K} \exp(\beta_k V_{jk} + \varepsilon_{ij})}$$

Equation 4: Multinomial Logit Model (MNL)

Where:

- P_{ij} is the probability of individual i choosing route j from a total of J routes.
- V_{jk} is a vector of utility attributes for route j for attribute *k* also known as the representative (observed) utility.
- β_k is a vector of attribute coefficients to be estimated.
- ε_{ij} is the stochastic (i.e., random) term associated with individual *i* using route *j* and captures the factors that affect utility but are not measured within V_{jk} or observed by the analyst.

8.3 Random Parameters Logit (RPL) Model (also known as Mixed Logit Model)

The RPL model was considered to be the "model for the new millennium" by Ortuzar and Willumsen (2011). This is because the RPL is a highly flexible model that can approximate *any* random utility model (McFadden & Train, 2000). It overcomes the three limitations of the closed form of MNL's by firstly allowing for random taste variation thereby relaxing the IID constraint; secondly it allows unrestricted substitution patterns and relaxes the IIA constraint; and thirdly it considers the correlation of unobserved factors over time, i.e., panel effects that take into account the variation in choice by individual decision makers making repeated choices. The MNL model constraints are overcome by means of the simulation of the choice probabilities. The simulation of the choice probabilities requires use of the user defined distribution functions (i.e., mixing distributions) for each of the non-random attribute coefficients in the utility expression. RPL models yield estimates of the first and second moments (e.g., mean and standard deviation) of the distribution of tastes across the population of interest. The coefficient mean and standard deviations are reported in the RPL outputs.

However, caution should be exercised when using RPL models and several authors have warned about the potential pitfalls of the models (Hensher & Greene, 2002), and the UK Department for Transport warn that *"issues of model identification are highly complex and it should not be presumed* *that a convergent MXL (mixed logit) is necessarily a valid MXL (mixed logit)".* (UK Department for Transport, 2014).

The issues with model identification relate to:

a) The definitions of the mixing functions for the attribute coefficients. A wide variety can be specified, but often these are convenient statistical constructs that may not bear resemblance to actual behaviour heterogeneity, for example specification of distributions to ensure that willingness-to-pay measures are positive. Train (2009) warns that each behavioural specification provides a particular interpretation of the model
b) Which attribute coefficients to randomise and which to fix. This decision has an important effect on the estimation of willingness-to-pay based on the ratio of the time and cost attribute coefficients. The ratio of two distributions can lead to counterintuitive estimates of values of travel time, including negative VTT's. To overcome the estimation of an average value from the ratio of two distributions, Train (2009) recommends fixing the price coefficient (denominator) so that the willingness-to-pay measures are estimated from a single (time) distribution in the numerator.

RPL probabilities are the integrals of the standard MNL probability over the specified density function of the coefficients. An RPL model is any model whose choice probability for individual i using route *j* with *k* attributes can be specified in the form:

$$P_{ij} = \int L_{ij}(\beta k) f(\beta k) d\beta$$

Equation 5: Form of RPL Model

Where:

- P_{ij} is the probability of individual *i* using route *j*.
- $L_{ij}(\beta_k)$ is the logit probability at coefficient β_k and $f(\beta_k)$ is a density function specified by the user and the logit probability at coefficient β_k is as follows:

$$L_{ij}(\beta) = \frac{e^{Vijk(\beta k)}}{\sum_{j=1}^{j} e^{\beta x_{ijk}}}$$

Equation 6: Logit Probability Function

Where:

- $V_{ijk}(\beta_k)$ is the representative portion of the utility for attribute *k* which is depends on the coefficient β_k.
- X_{ijk} are the observed attributes *k* for individual *i* using route *j*.

The solution to the RPL model can only be estimated using simulation where random draws of the coefficients β are made from the defined distribution. Various methods have been estimated for ensuring random and quasi-random draws of β, with a widely used method being Halton Draws that generates quasi-random draws. Hensher et al., (2015) recommend a minimum of 500 Halton Draws in a simulation.

The RPL model is thus a mixture of the logit function evaluated at different values of the coefficient β with f(β) as the mixing distribution. In most applications f(β) is a continuous distribution of the normal, uniform, log-normal or triangular distribution. The log-normal and (one-sided) triangular distributions will ensure only positive willingness-to-pay measures but should be used with caution. The log-normal distribution has a "thick" tail and can itself lead to distorted values of willingness-to-pay (Hensher, et al., 2015). Ortuzar and Willumsen (2011) recommend estimation of RPL models with different mixing functions to determine whether there is actually heterogeneity in tastes.

8.4 Commonality Logit Model (C-LOGIT)

Recognising the IIA constraint of MNL models in a route choice context and the unrealistic choice probabilities for routes with common sections, Cascetta et al. (1996) suggested the Commonality-Logit model normally termed the C-Logit model. This model is a modified form of the MNL that draws on the benefits of efficient estimation from the closed logit form and the relatively simple mathematical structure. The behavioural basis of the C-Logit model is the adjustment of the observed or representative part of utility for routes between and origin and destination that overlap, i.e., have common roadway sections that introduces route correlation.

C-Logit models introduce a commonality factor for route j, i.e., CF_j that is estimated for each route in the choice set based on the extent of overlap of the routes in the choice set. Route overlap can be defined as a common distance, time or cost for the routes in the choice set. The route commonality factor CF_j is included in the utility expression as an additional attribute with its own coefficient (β_{CF}) and is used to proportionally adjust the representative utility of a route and hence account for correlation between routes.

The C-logit expression for the probability of individual i choosing route j from L routes and k attributes in choice set C, i.e., (P_{ij}) is as follows (Prato, 2009):

$$\boxed{P_{ij} = \frac{\exp(V_{kj} + \beta_{CF} CF_j)}{\sum_{l \in C} \exp(V_{kl} + \beta_{cf} CF_l)}}$$

Equation 7: C-Logit Model Expression

Where:

- V_{kj} and V_{kl} are the representative components of the utility functions for routes j and l with k attributes.
- C is the choice set of all routes.
- CF_j and CF_l are the commonality factor attributes for routes j and l respectively.
- β_{CF} is the commonality attribute coefficient to be estimated.

The sign of β_{CF} should be negative, as substantially overlapping paths will be more correlated and hence should have large commonality factors resulting in smaller representative utilities when compared to similar but independent paths. For two paths with similar V_k and a high degree of overlap i.e., if CF_k and CF_L were approaching a value of 1, then the exp(V_k) and exp(V_L) expressions would be close to exp(0) = 1, and the P_{ik} would then be 0.5, i.e., equal proportions of trips on each path. Conversely, for two paths with very little overlap, the CF_k and CF_L values will approach zero and the effect of the correction factor will be marginal. The C-Logit model then collapses back to the MNL form.

Several forms of the commonality factor C_{FK} have been proposed as follows (Prato, 2009):

$$\boxed{CF_k = \ln \sum_{l \in C} \left[\frac{L_{kl}}{\sqrt{L_k L_l}} \right]^{\gamma_{CF}}}$$

Equation 8: First Form of Commonality Factor CF_k

$$\boxed{CF_k = \ln \sum_{a \in \tau_k} \left(\frac{L_a}{L_k} \sum_{l \in C} \delta_{al} \right)}$$

Equation 9: Second Form of Commonality Factor CFk

$$\boxed{CF_k = \sum_{a \in \tau_k} \left[\frac{L_a}{L_k} \ln \sum_{l \in C} \delta_{al} \right]}$$

Equation 10: Third Form of Commonality Factor CFk

$$\boxed{CF_k = \ln \left[1 + \sum_{\substack{l \in C \\ k \neq l}} \left[\frac{L_{kl}}{\sqrt{L_k L_l}} \right] \left[\frac{L_k - L_{kl}}{L_l - L_{kl}} \right] \right]}$$

Equation 11: Fourth Form of Commonality Factor CFk

Where L_k and L_l are the total lengths of routes k and l respectively; C is the choice set of all routes; L_a is the length of link a with a being the total length of overlapping links in k; Γ_k is the set of links in route k; L_{kl} is the common length between routes k and l; δ_{al} is a link-path incidence dummy, equal to one if route l uses links a, and zero otherwise; and γ_{CF} is a parameter to be estimated.

Each equation provides an estimation of CF_k based on a degree of route similarity between routes k and l. Equation 8 describes the commonality only in terms of route length overlap i.e., L_{kl}; Equation 9 and Equation 10 consider each link in paths k and l, and weigh the common links in proportion to the ratio between the link and route lengths i.e., L_a / L_k. Equation 11 introduces the lengths of the non-shared links (i.e., through the $(L_k - L_{kl})$ and $(L_l - L_{kl})$ terms) and implies that ratio of the commonality factor between two routes should increase when the when the overlapping of the two routes increases. The estimation of the factor δ_{al} in equations 9 and 10 is complex and requires an iterative approach for solution. For this reason, equations 7 and 8 have not been used to estimate the commonality factor and equations 6 and 9 have been used.

The advantage of the C-Logit model is the consistency of the estimation of the utility value. The disadvantage of the C-Logit model is that the commonality factor only captures part of the similarity of the routes based only on overlapping lengths. Other trip attributes are excluded, e.g., travel cost and time. Also, no guidance is given as to which equation for CF_k is most suitable.

It was anticipated that the route generation process employed in RAPP-UP, i.e., to minimise route overlaps may limit the successful estimation of C-Logit models.

8.5 Path Size Logit Model (PS-LOGIT)

The Path-sized Logit (PS-Logit) model was suggested by Ben-Akiva and Ramming (1998). The C-Logit and PS-Logit models are structurally similar, but with C-Logit considering the length of path overlap, and PSL considering the proportion of path overlap. The PS-Logit proposes an adjustment to the representative utility through the introduction of a utility attribute called the path size factor (PS) with its own attribute coefficient β_{PS}. The form of PSL model is as follows for individual i and routes j and l, with attributes k.

$$P_{ij} = \frac{\exp(V_{jk} + \beta_{PSC} PSC_j)}{\sum_{l \in C}^{L} \exp(V_{lk} + \beta_{PSC} PSC_l)}$$

Equation 12: Path-Size Logit (PSL) Model Expression

Where:

- P_{ij} is the probability of individual i choosing route j.

- C is the choice set of alternative routes.
- V_{jk} is the representative utility of route j with attributes k.
- β_{Psc} is the path size attribute coefficient.
- PS_j is the path size attribute for route j.
- PS_l is the path size attribute for route l.

The path size is defined as the proportion of a route that constitutes a "full" alternative. A fully unique route has a path size equal to one and less than one if it has common segments with another path. If there are N duplicate (common) paths, then the path size is $1/N$. Two other forms for the estimation of the path size overlap for route k and route l have been proposed as shown in the following equations.

$$PS_k = \sum_{a\in\Gamma_k} \frac{L_a}{L_k} \frac{1}{\sum_{l\in C} \delta_{al}}$$

$$PS_k = \sum_{a\in\Gamma_k} \frac{L_a}{L_k} \frac{1}{\sum_{l\in C} \left(\frac{L_k}{L_l}\right)^{\gamma_{PS}} \delta_{al}}$$

Equation 13: Expressions for Calculation of Path Size Parameters

Where:

- The L_k, L_a, and L_l are the route length definitions as for the commonality factor
- δ_{al} is a link-path incidence dummy, equal to one if route L uses link a, and zero otherwise
- γ_{PS} is a parameter to be estimated.

The first path size formulation estimates the weighting based on the proportion of the path coming from a specific link as the ratio between the link length and route length, i.e., L_a/L_k. The δ_{al} term is based on the number of paths using a specific link and is therefore equal to one for links used by only one path. Note that the impedance of paths using a specific link is not affected by δ_{al} term, and hence the formulation can account for different size contributions due to routes with different lengths.

The intention of the second formulation for PS_K is to reduce the influence of long paths on the utility of short paths in the choice set. High values of γ_{PS} tend to improve the goodness of fit of the PS-L model in several case studies. The estimation of the γ_{PS} is computationally demanding, and it is mostly estimated its value by iterating the PS-L model to obtain the best goodness-of-fit.

The weakness of the PS-Logit, (and the C-Logit model) is that the correlation of alternatives is only captured by the path size proportions in the representative component of utility, and not in the random error (stochastic) component of utility.

The nature of the route generation process employed in RAPP-UP, i.e., to minimise route overlaps may limit the successful estimation of PS-Logit models.

9. RAPP-UP SURVEY PARTICIPANT AND CHOICE SET DESCRIPTIONS

This chapter describes the implementation of a car commuter route choice survey using RAPP-UP. The survey was implemented after the completion of a pilot survey amongst a small group of car commuters in the Pretoria and Johannesburg area of Gauteng Province in South Africa.

9.1 Recruitment of Survey Participant Sample

To demonstrate proof-of-concept for RAPP-UP a small sample of 51 participants were recruited for the survey. A market research company provided a sample of participants from their Gauteng panel of consumers who were required to meet four criteria, viz:

i. Ownership of a recent model Android smartphone
ii. Ownership of their own vehicle
iii. Make regular commute trips to work using their vehicle in the weekday morning peak period
iv. Commute to work in the Johannesburg / Pretoria and Ekurhuleni urban regions of the Gauteng Province.

Three participants withdrew early from the survey citing their unsuitability (too few trips and irregular O-D patterns); a lack of financial motivation (i.e., the R300.00 survey inducement was inadequate); and hence their unwillingness to participate. The RAPP-UP data sets for 48 participants were used for the estimation of the route choice models. Participants were required to complete eight trips, and while most completed this number, five participants completed only four trips. Thus, a total of 364 observations (choice sets) were used to estimate the various discrete route choice models. For the panel based RPL models 344 observations were used i.e., the participants who completed all eight trips.

9.2 Survey Context

It is important to highlight the issue of the timing of the surveys. All the trips were completed between April and July 2022. This period corresponded to the recovery of private vehicle and public transport commuting patterns and traffic demand in Gauteng after the COVID-19 pandemic. Vehicle traffic and public transport demand at this time had not yet fully recovered to pre-COVID levels, resulting in lower than pre-COVID congestion levels. In addition, COVID-19 legacy issues such as working from home (WFH) have suppressed travel demand and hence congestion levels. Anecdotal evidence from a South African insurance company suggest that car commuters have adopted a hybrid work regime and are working from home for two days per week and at the office for three days per week (Business

Insider, 2022). Unpublished passenger demand data provided by the Gautrain Management Agency for the Gauteng Rapid Rail system serving commuters in Pretoria, Johannesburg and Ekurhuleni showed that in August 2022 the weekday passenger demand was at 60% of pre-COVID levels. The lower levels of traffic were reflected by lower than anticipated proportions of slowed-down and stop-start travel times on the routes generated by RAPP-UP.

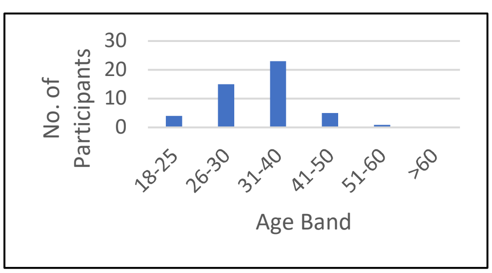
The non-compliance levels of toll payment of the GFIP e-toll system at the time of the survey was approximately 80%. The survey participants were not asked if they paid e-tolls but were instructed to not take this into consideration when choosing their preferred routes from RAPP-UP and when driving their chosen route. The proportion of the 728 routes generated by RAPP-UP that were tolled was 56%, i.e., just over half. The minimum toll fee applied for a route in the choice sets was R0.83 and the maximum value was R26.20.

9.3 Socio-Demographic Characteristics of Participants

Before starting the survey, each participant completed a socio-demographic survey where the following information was solicited. The questionnaire is in Annexure A.

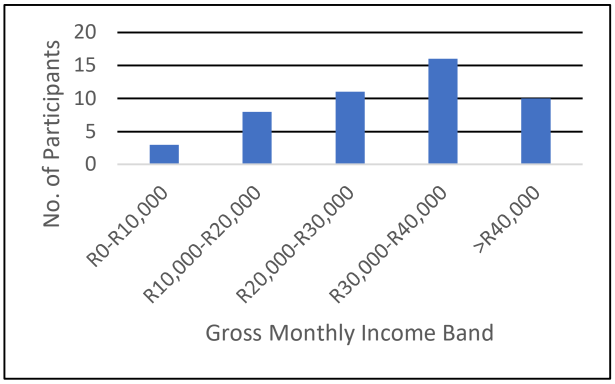
a) Communication details (email and smartphone number).
b) Age bracket.
c) Gender.
d) Personal income bracket.
e) Home and work suburbs.
f) Typical commute trip start and end times.
g) Whether they used a route guidance service for their trip to work.
h) Trip times and costs for typical route for commute to work.
i) Employment status.

Of the 48 participants, 60% were female and 40% were male. All the participants were employed on a full-time basis, and RAPP-UP was deployed for their morning commute to work. Only 10% of the participants indicated that they used a route guidance system for their trip to work, with 90% indicating they used the same route every day. The following series of figures describe the characteristics of the sample as determined from the socio-demographic questionnaire.



The majority of participants (80%) were between 26 and 40 years age. 48% of participants were in the 31 to 40 year age band. There was only one participant who was over 50 years of age and four in the 18 to 25 band.

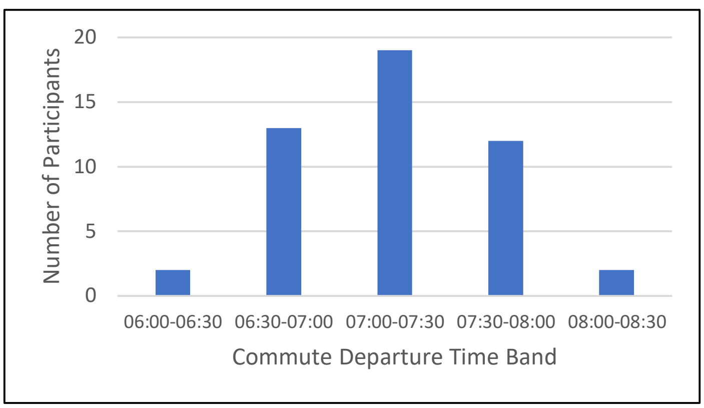
Figure 43: Survey Participant Age Distribution



The majority of participants (56%) had a personal gross monthly income of between R20,000 and R40,000. 23% earned less than R20,000 per month and 21% earned more than R40,000 per month. Most participants fell into the high-income level as defined by Statistics South Africa *(Stastitics South Africa, 2015)*.

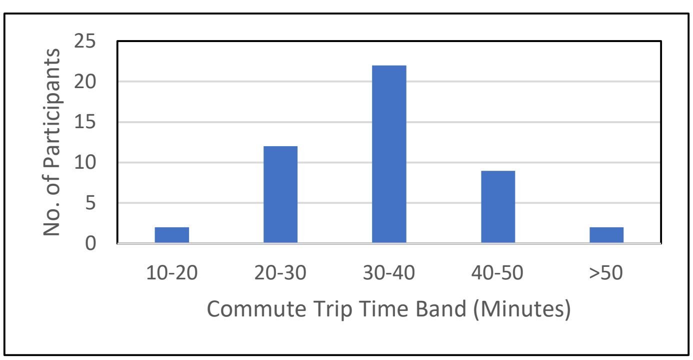
Figure 44: Participant Gross Monthly Income Distribution

The survey participants can be categorised as belonging to high income households. These households are defined as those earning more than R307k per annum (2011 values). The 2011 national census determined that only 7.3% of South Africa households fall into the high-income category. The high personal income levels of the survey participants are largely reflective of the recruitment requirements for the survey, i.e., ownership of their own car for commuting to work and ownership of a recent model smartphone.



Most of the participants indicated that they start their commute trip between 06:30 and 08:00, with the majority starting their commute between 07:00 and 07:30. Only 2 participants normally start their commute before 06:30 and after 08:00.

Figure 45: Distribution of Typical Commute Trip Start Times



The participant perceived commute travel time is shown in the following figure. The majority of participants perceive their commute time is between 20 and 50 minutes (90%), with most perceiving a travel time of between 30 and 40 minutes (46%).

Figure 46: Participant Perceived Commute Trip Cost (Rand)

The participant perception of their commute trip petrol cost is shown in Figure 47. Most participants perceived their trip cost to be between R20 and R30 (44%). Only 7 of the participants (14%) indicated they incurred a trip toll cost. It is uncertain whether other participants used the GFIP e-toll system but did not pay the toll.

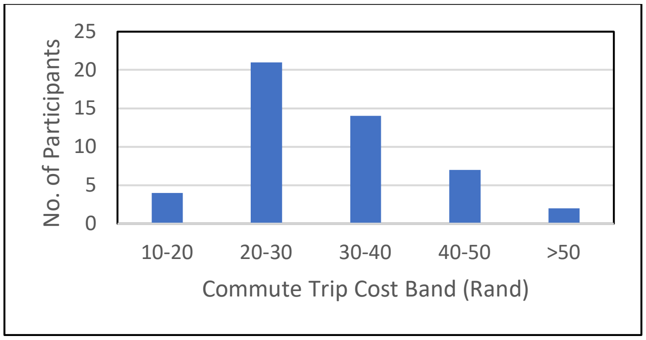


Figure 47: Participant Perceived Commute Trip Cost (Rand)

In summary, the sample of survey participants are not representative of the wider car commuting public in Gauteng. While they may have similar commuting patterns, e.g., times of departure, trip costs and commuting times, they are high income individuals within a relatively narrow income range. The route choice behaviour of this sample of car commuters cannot therefore be assumed to be representative of the wider car commuting population in Gauteng province. The purpose of the RAPP-UP route choice survey was to illustrate proof-of-concept. A significantly larger and representative sample of car commuters is required to fully explore and explain route choice behaviour.

The characteristics of the routes generated by RAPP-UP are discussed in the following sections.

9.4 RAPP-UP Route Trip Time and Cost Data

This section provides an insight into the nature of the route alternatives generated by RAPP-UP. The intention is to describe the characteristics of the routes. A series of distributions is shown for the various trip travel times and costs. The distributions were generated using all 738 observations.

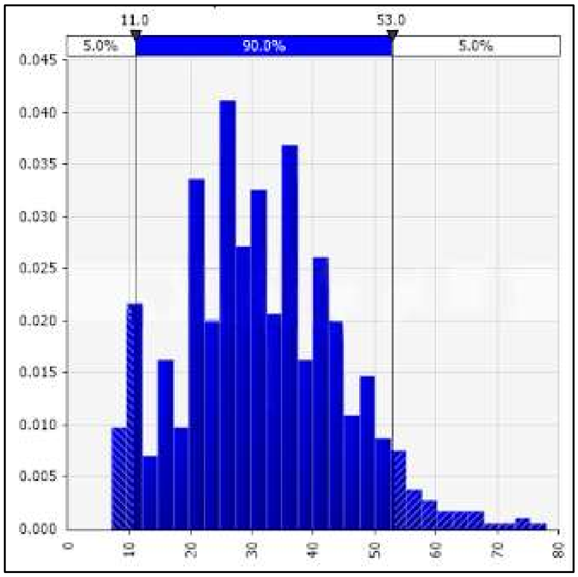


Figure 48: Distribution of Total Travel Time (Minutes)

The total travel time distribution shows that 90% of the generated routes fell between 11 minutes and 53 minutes. The average trip time was 31.5 minutes, with a minimum time of 7 minutes and a maximum of 78 minutes.

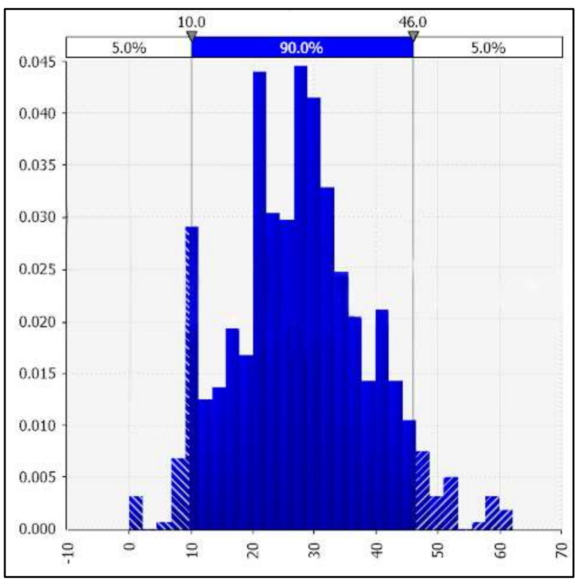
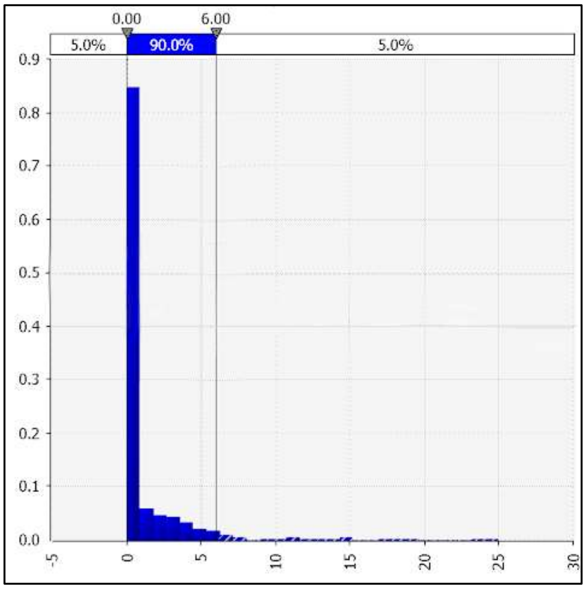


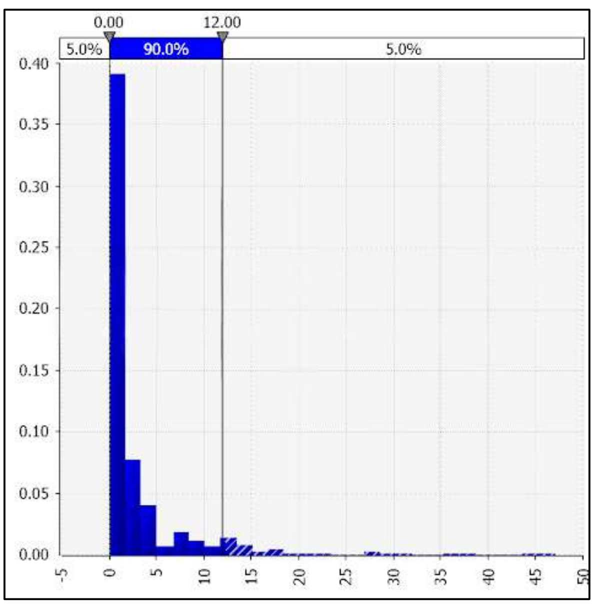
Figure 49: Distribution of Free Flow Travel Time (Minutes)

The free flow travel time distribution shows that 90% of the generated routes fell between 0 minutes and 46 minutes. The average free flow trip time was 27.6 minutes, with a minimum time of 0 minutes and a maximum of 62 minutes. Free-flow time made up 88% of the total travel time for all observations.



The slowed-down travel time distribution is exponential in shape and shows that 90% of the generated routes fell between 0 minutes and 12 minutes. The average slowed-down trip time was 2.6 minutes, with a minimum time of 0 minutes and a maximum of 46 minutes. The slowed-down travel time as a proportion of total travel time is considerably lower than for the free flow time, i.e., 8% compared to 88%.

Figure 50: Distribution of Slowed-Down Travel Time (Minutes)



The stop-start travel time distribution is exponential in shape and shows that 90% of the generated routes fell between 0 minutes and 25 minutes. The average stop-start trip time was 1.1 minutes, with a minimum time of 0 minutes and a maximum of 25 minutes. Stop-start time made up only 4% of the total travel time. The low proportions of slowed-down and stop-start time were also caused by travel in off-peak directions for all or part of the trips.

Figure 51: Distribution of Stop-Start Travel Time (Minutes

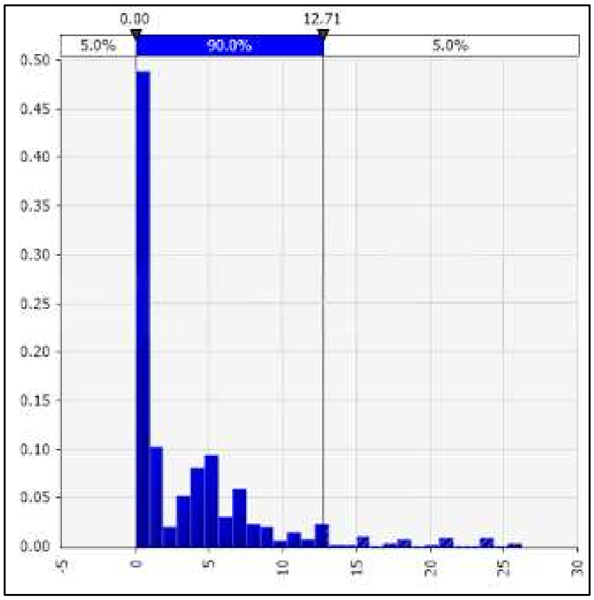


Figure 52: Distribution of Route Toll Costs (Rand)

The route toll cost distribution is exponential in shape and shows that 90% of the generated routes had toll costs between R0.0 and R12.71. The average toll cost was R3.43 with a minimum value of R0.0 and a maximum value of R26.20. Approximately 56% of all the routes generated by RAPP-UP were tolled.

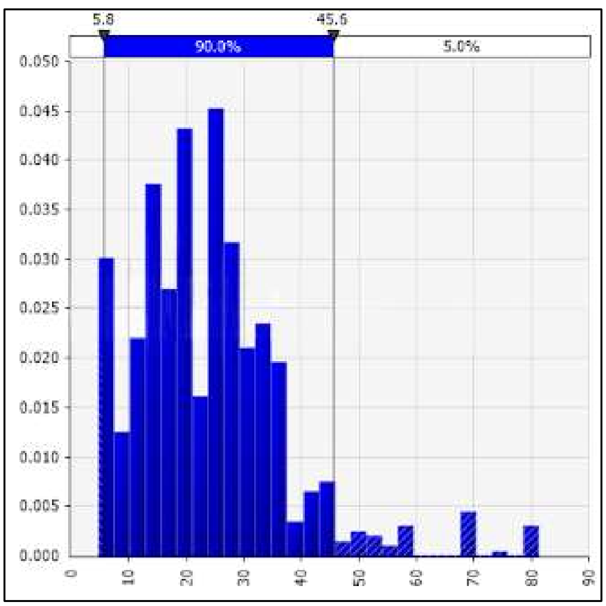
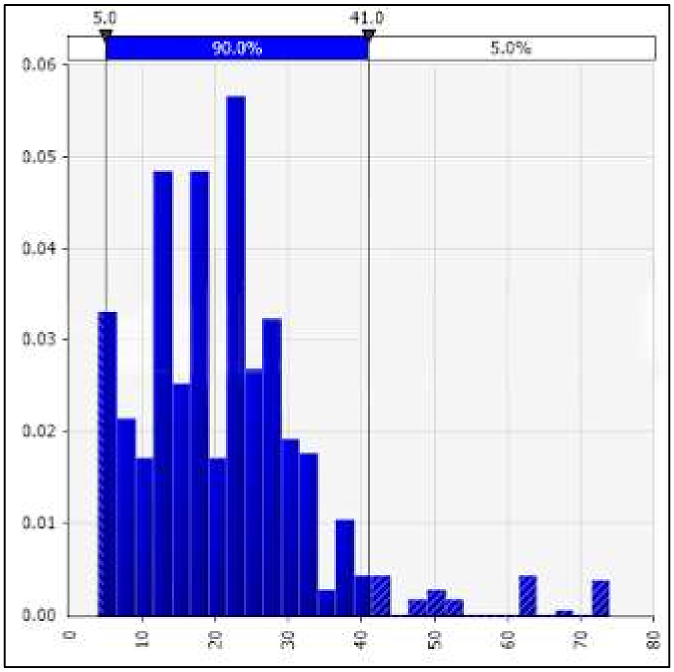


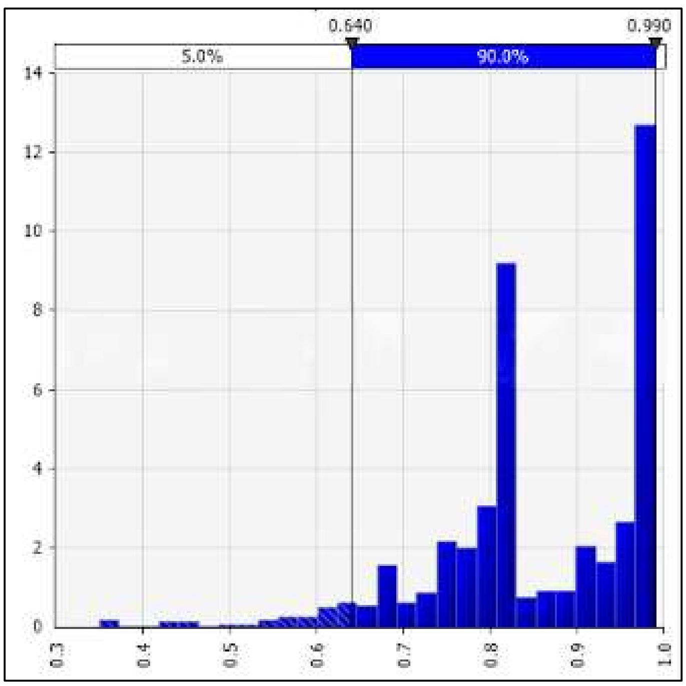
Figure 53: Distribution of Route Petrol Costs (Rand)

The route petrol cost distribution shows that 90% of the generated routes had petrol costs between R5.8 and R45.6. The average petrol cost was R24.03 with a minimum value of R4.74 and a maximum value of R81.32. It is important to note that the average route petrol cost: toll cost ratio is 7.0, i.e., on average petrol costs make up 85% of the trip cost and the toll cost 15%.



The route length distribution shows that 90% of the generated routes had a length between 5 and 41 kilometers. 95% of the trips were shorter than 41 km. The average route length was 21.4 km's, with a minimum length of 4.0 km and maximum length of 74 km. Based on the average trip length of 21.4 km and the average total trip time of 31.5 minutes, the average trip speed was 42 kph.

Figure 54: Distribution of Route Lengths (Km)



The probability of on time arrival (*pota*) distribution shows that 90% of the generated routes had a value between 0.64 and 0.99. The average value was 0.86 and the minimum and maximum values were 0.35 and 0.99 respectively. The spikes in the distribution are due to the high proportion of *pota* values of 0.81. This was caused by a high number of pre-factored *pota* values of 0.9 determined from trips with no observed values of slowed-down and stop-start trip time.

Figure 55: Distribution of Probability of on Time Arrival (pota)

When these values are multiplied by the *pota* factor of 0.9, produce the result of 0.81. The high proportion of values of 1.0 has also occurred for this reason, viz., pre-factored values of 0.81 multiplied by the *pota* factor of 1.2.

The following table summarises the total travel times and petrol and toll costs in the choice sets on the tolled routes only, the un-tolled routes, all the routes, the chosen routes and the unchosen routes. The table highlights that the tolled routes in the choice sets reflected higher petrol costs (and were hence longer routes); had higher average total travel times; and higher toll values. The chosen routes had lower toll costs, lower petrol costs, and lower total travel times. The high ratios of petrol to toll costs is an important consideration when interpreting the willingness-to-pay for travel time savings as petrol trip costs dominate the total trip cost.

Table 8: Route Choice Set Average Travel Time, Petrol Costs and Toll Costs

Average Attribute Values	**Routes with a Tolled Section**	**Routes without a Tolled Section**	**All Routes**	**Chosen Routes**	**Unchosen Routes**
Toll cost (Rands)	R6.05	-	R3.41	R2.71	R4.10
Petrol cost (Rands)	R30.13	R16.17	R24.03	R22.06	R26.00
Total travel time (minutes)	35	27	32	30	34
Petrol: toll cost ratio	6.3	-	7.1	8.1	6.3

The results in **Table 8** demonstrate rational choice behaviour amongst the individual participants as follows:

a) Longer trips (in kilometers and in minutes) are being made using freeways to benefit from the higher speeds and increased travel time savings even though there is a toll payment requirement, demonstrating a willingness-to-pay tolls for time savings.
b) This observation is reinforced by the petrol cost on routes without a tolled section being substantially lower than on routes with tolled sections.
c) The toll costs on the routes that were chosen were lower than on the routes that were not chosen indicating that, when possible, routes without a tolled section were chosen before those with tolled sections.

9.5 Route Choice Set Examples and Overlap Characteristics

The extent of the route overlaps is an important consideration when estimating route choice discrete models, as increasing degrees of overlap is likely to increase the correlation between routes. The route generation process employed by RAPP-UP is the algorithm used by TomTom® and as described, the algorithm generates alternative routes by considering three key criteria: the extent of *overlap* of the alternative and optimal route; the *local optimality* that considers the number of unnecessary detours on the alternative route; and the *stretch,* being defined as the ratio between the length of an alternative route and the length of the optimal route. It could thus be anticipated that the overlap criteria that seek to minimise the overlap would result in few generated routes that overlap, and for those that do overlap, a relatively short section of the optimal and alternative routes would overlap. For the 364 choice sets generated by RAPP-UP, only 10% had routes that overlapped. The maximum extent of overlap was 15% of the optimal and alternative route. It could thus be anticipated that the discrete choice models that specifically account for route correlation would not produce significantly improved models over those models that did not specifically account for route overlap.

The following figures and choice set tables show examples of routes generated by RAPP-UP and used in the C-Logit and PS-Logit models. **Figure 56** shows two routes generated between Roodepoort in the West Rand to the Randburg CBD. The trip was started at 06:50 on Wednesday 13th July 2022. The figure shows the two routes in the choice set generated by RAPP-UP, with the blue route being chosen by the survey participant. The two routes are unique with no overlap. The blue route uses the N1 freeway (and hence incurs a toll) while the red route runs through several suburbs between origin and destination. The blue route was 21.03 km and the red route 17.73 km long.

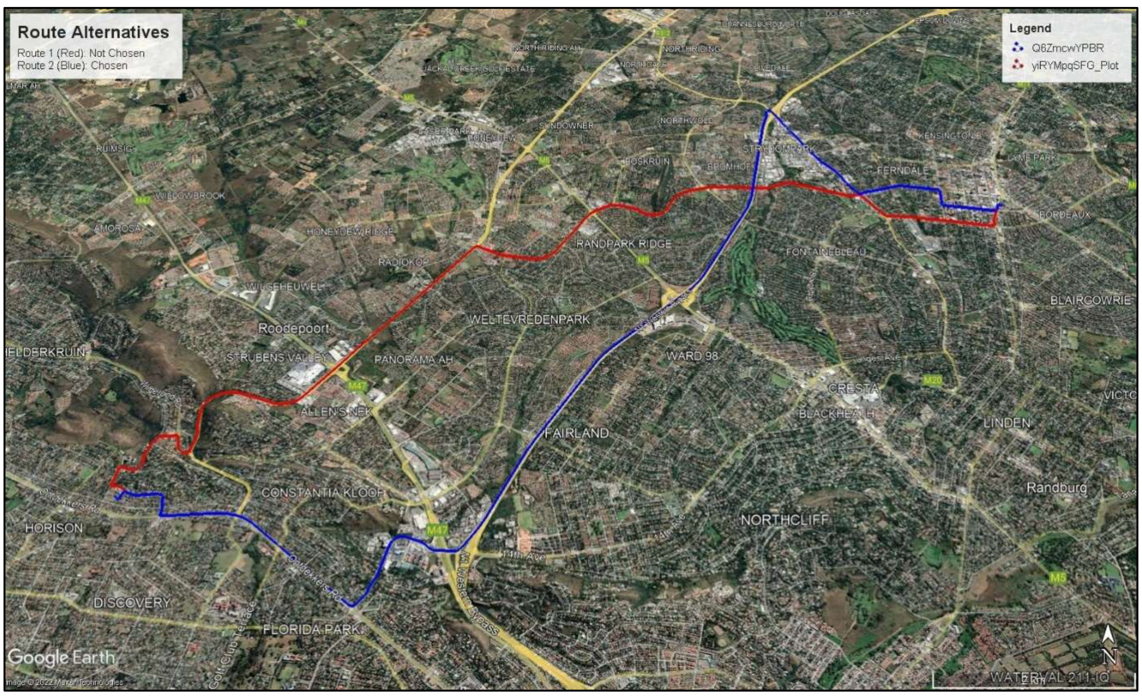


Figure 56: Route Example Roodepoort to Randburg

The choice set associated with these routes is shown in **Table 9**. The routes have similar travel times and no slowed-down or stop-start trip time. The petrol cost of the blue route is R3.63 more expensive than the red route and has a toll fee of R3.23. The total cost of the blue route is R6.86 higher than the red route. The blue route offers higher probability of arriving at the destination on time.

Table 9: Choice Set for Trip Between Roodepoort and Randburg

Route	Free-Flow Time (mins)	Slowed-Down Time (mins)	Stop-Start Time (mins)	Petrol Cost (Rand)	Toll Cost (Rand)	Pota %
Route 1 (Red)	29	0	0	19.50	0	81
Route 2 (Blue)	27	0	0	23.10	3.23	99

The next example in **Figure 57** shows two routes generated by RAPP-UP between a trip origin in Soweto and the destination in the Sandton CBD. The blue route was chosen by the survey participant. It can be that the red route uses the N1 (tolled) freeway for part of the trip and the blue route the M1 (un-tolled) motorway through the centre of Johannesburg. The red route length was 33.7 km and the blue route 29.6 km. The route overlap at the start of the route was 3.2 km.

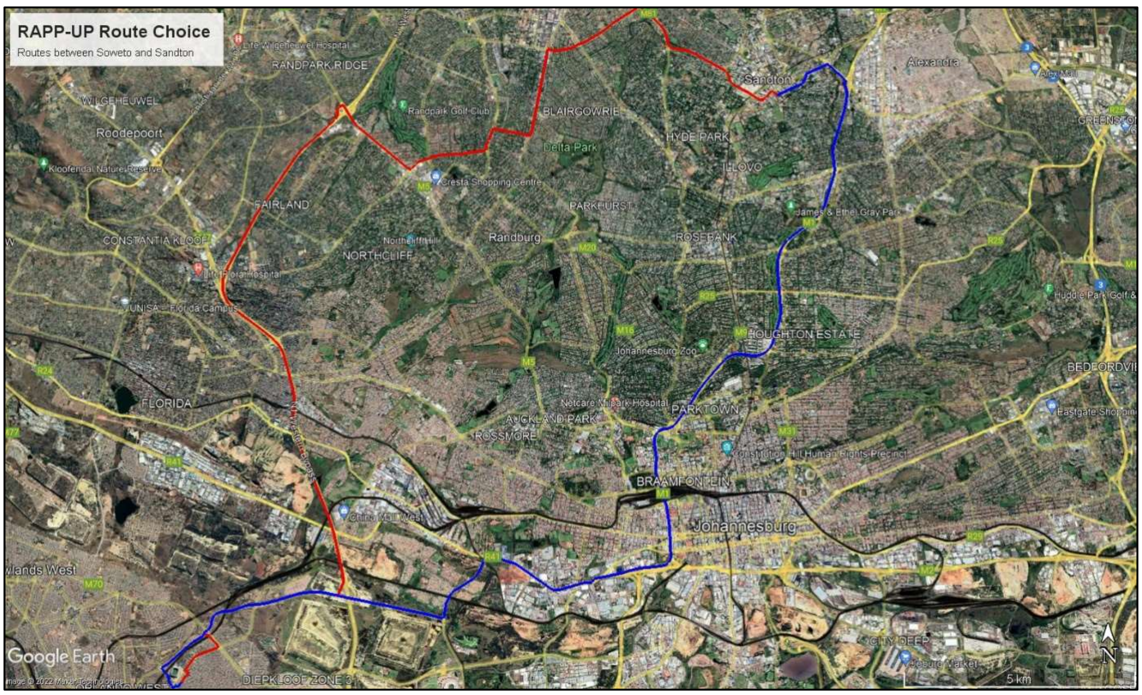


Figure 57: Route Example Soweto to Sandton

The choice set for this trip is shown in **Table 10**. While the blue route has slightly lower travel time, it has a lower petrol cost and no toll. It has a lower probability of on-time arrival.

Table 10: Choice Set for Trip Between Soweto and Sandton

Route	Free-Flow Time (mins)	Slowed-Down Time (mins)	Stop-Start Time (mins)	Petrol Cost (Rand)	Toll Cost (Rand)	Pota %
Route 1 (Red)	27	0	0	37.10	5.33	99
Route 2 (Blue)	25	0	0	32.60	0	82

Figure 58 shows a choice set of routes between Bedfordview to the east of Johannesburg and Sandton. The red route uses the N3 (tolled) freeway while the blue route runs through suburbs to Sandton. The blue route was chosen by the respondent. The blue route is 14 km long and the red route 19 km. There is no overlap between routes. The choice set for this set of routes is shown in **Table 10**.

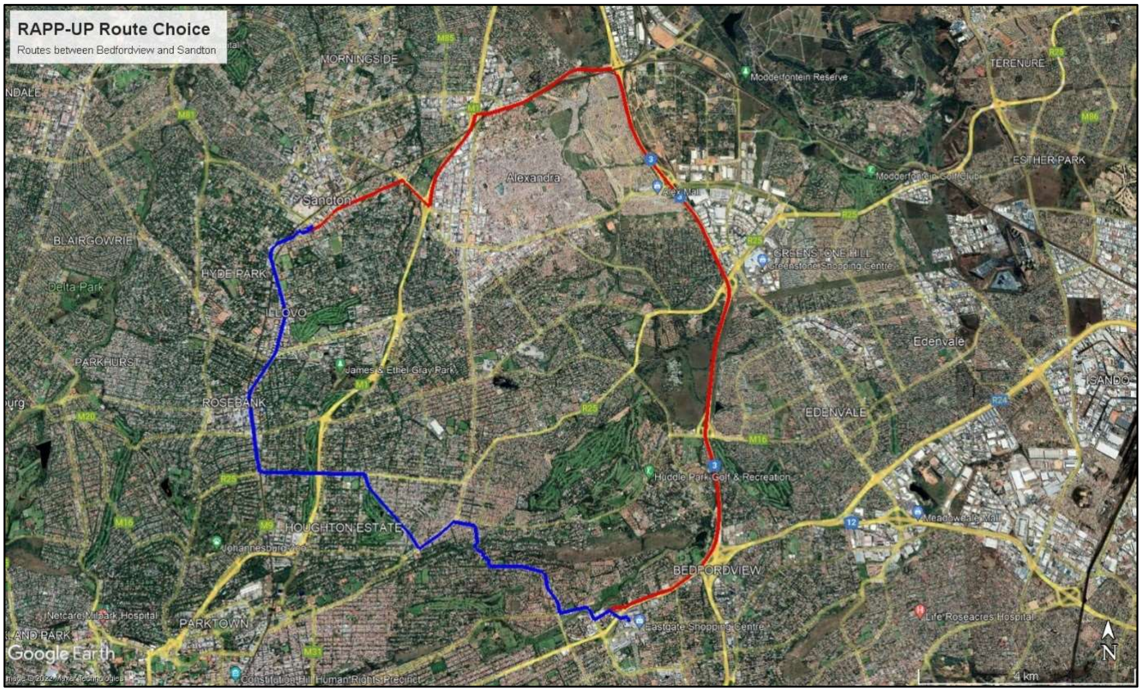


Figure 58: Route Example Bedfordview to Sandton

In **Table 11** the chosen blue route has significantly longer travel time (10 minutes) but has no slowed-down time. It also has a lower petrol cost and no toll. It's *pota* value is also significantly higher than the alternative red route.

Table 11: Choice Set for Trip Between Bedfordview and Sandton

Route	Free-Flow Time (mins)	Slowed-Down Time (mins)	Stop-Start Time (mins)	Petrol Cost (Rand)	Toll Cost (Rand)	Pota %
Route 1 (Red)	23	7	0	20.90	3.09	70
Route 2 (Blue)	33	0	0	15.40	0	90

Figure 59 shows a route pair generated by RAPP-UP between Rosebank in Johannesburg and Midrand. The blue route runs along the M1 and N1 (tolled) freeway while the red route runs on roads alongside the freeways and through suburbs. The choice set for these routes is shown in **Table 12**. The survey participant chose the blue route for which a toll was payable but offered a significantly lower travel time (by 11 minutes) and higher *pota* value. The blue and red routes were of similar length, i.e., about 22 km long and hence have similar petrol costs. There is a very short route overlap of 0.9 km in Midrand.

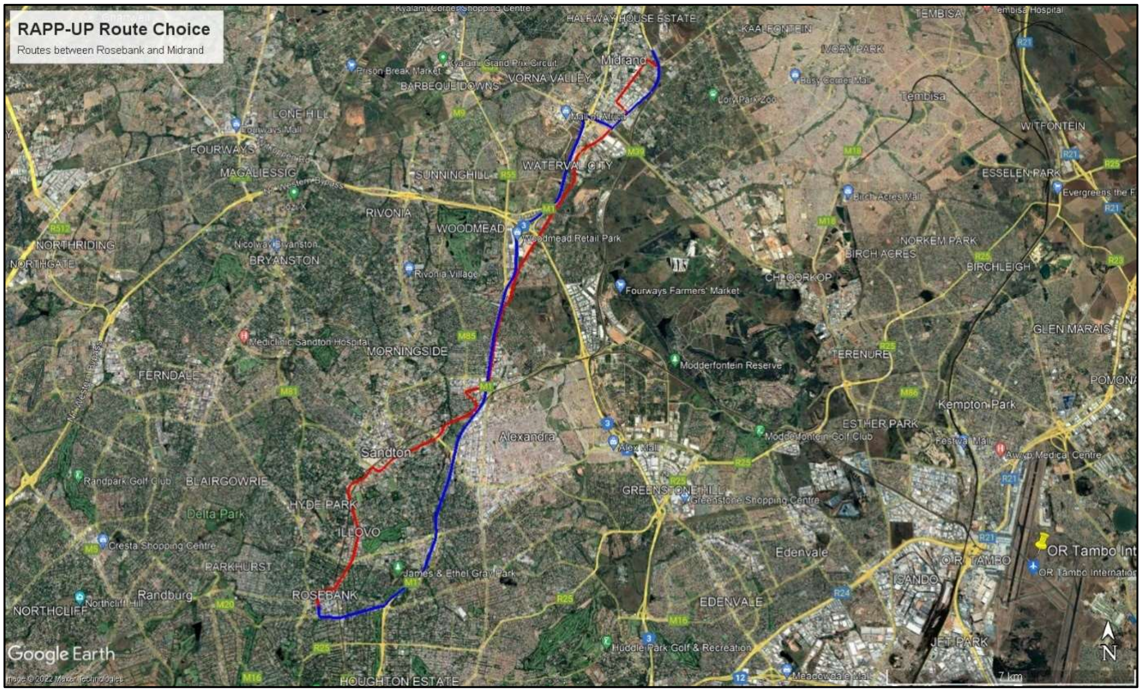


Figure 59: Route Example Rosebank and Midrand

Table 12: Choice Set for Trip Between Rosebank and Midrand

Route	Free-Flow Time (mins)	Slowed-Down Time (mins)	Stop-Start Time (mins)	Petrol Cost (Rand)	Toll Cost (Rand)	Pota %
Route 1 (Red)	34	2	0	24.89	0	81
Route 2 (Blue)	23	0	0	24.28	5.39	96

Figure 60 illustrates a set of long routes between the origin in Florida on the West Rand and Menlyn in eastern Pretoria. The blue route runs along the N1 freeway for which a toll is payable. The red route runs along the N14 and N1 freeways and overlaps with the blue route for its length along the northern part of the N1 freeway for a distance of 15.95 km. A toll is also payable for the red route. The survey participant chose to use the blue route. The red route is 74 km in length and the red route is 63 km long, so the length difference is significant at 11 km, the difference in petrol cost is significant as is the trip duration of 13 minutes. The blue route has 5 minutes of slowed down time and a lower *pota* value. The choice set for these routes is shown in **Table 13**.

Table 13: Choice Set for Trip Between Florida and Menlyn

Route	Free-Flow Time (mins)	Slowed-Down Time (mins)	Stop-Start Time (mins)	Petrol Cost (Rand)	Toll Cost (Rand)	Pota %
Route 1 (Red)	58	0	0	81.40	24.18	99
Route 2 (Blue)	45	5	0	69.30	21.44	76

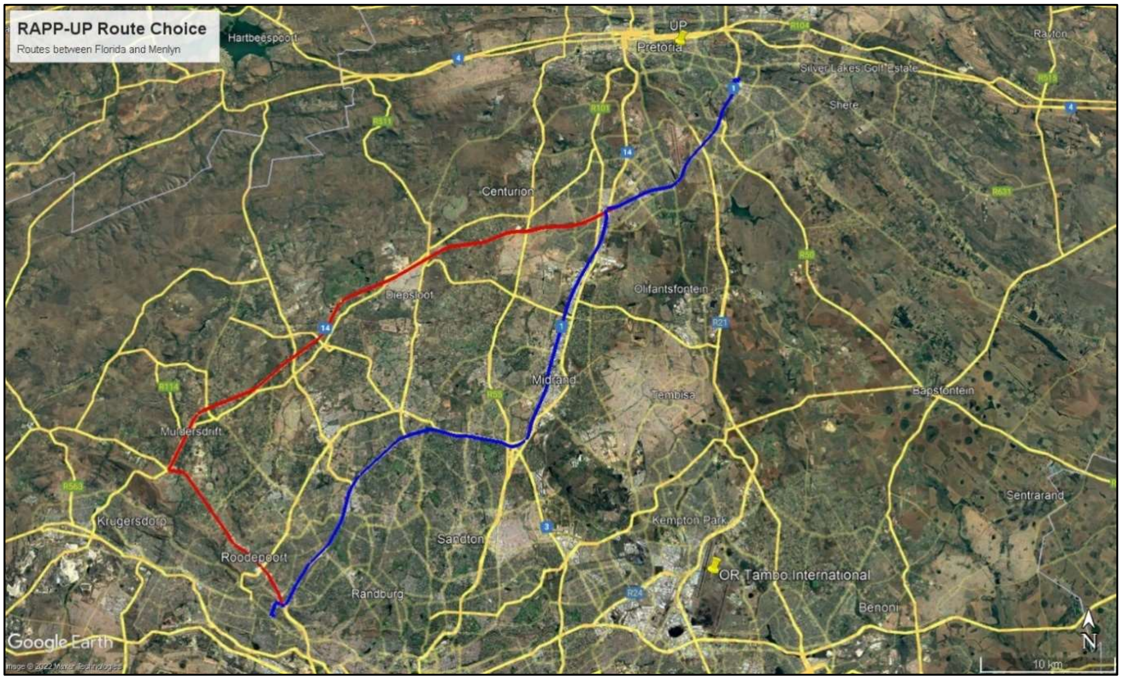


Figure 60: Route Example Florida and Menlyn

The final example of route choice set is for a trip between Midrand the Pretoria CBD. The route alternatives are shown in **Figure 61**. The blue route (30 km) runs along the N1 freeway for which a toll is payable. The red route is considerably longer and more circuitous (41 km) and hence has a higher petrol cost and because it also user the N1 freeway a toll is payable. The blue route has a higher pota value. The participant chose to use the blue route. The choice set is shown in **Table 14**.

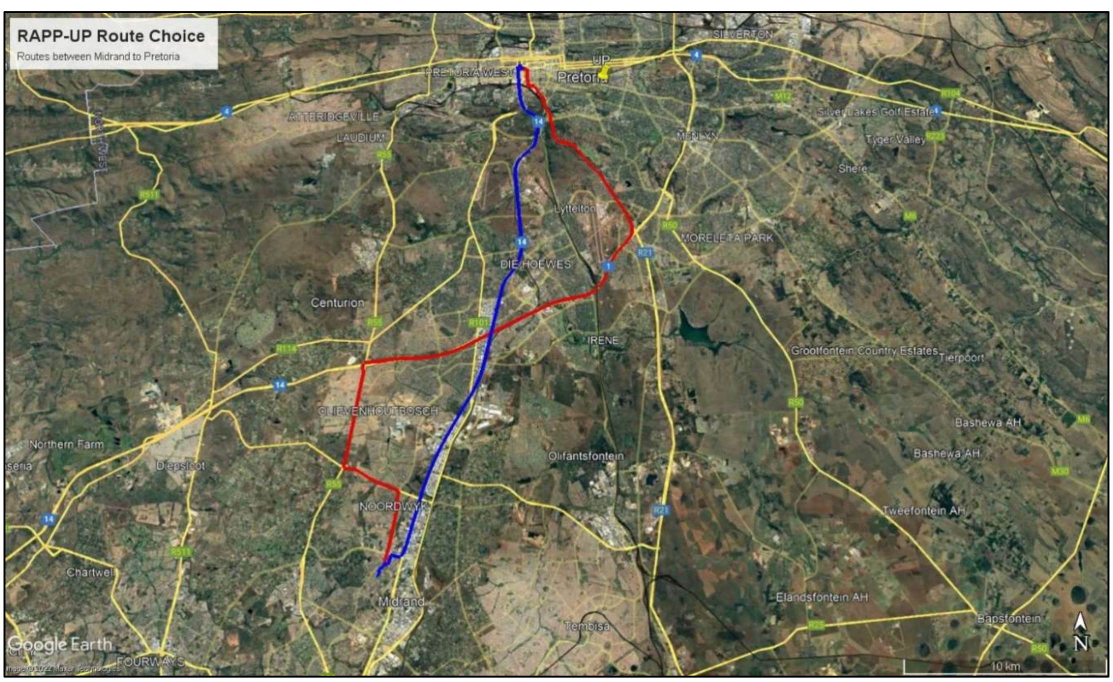


Figure 61: Route Example Midrand to Pretoria CBD

Table 14: Choice Set for Trip Between Midrand and Pretoria CBD

Route	Free-Flow Time (mins)	Slowed-Down Time (mins)	Stop-Start Time (mins)	Petrol Cost (Rand)	Toll Cost (Rand)	Pota %
Route 1 (Red)	42	1	0	45.27	8.08	80
Route 2 (Blue)	30	0	0	33.56	9.11	97

The choice set examples illustrated several points:

a) There can be significant differences in the attribute levels between alternatives ensuring that the attribute level ranges are adequate.
b) The attribute levels presented in the choice set require the respondent to trade-off the various time, cost and pota attributes before a route choice is made.
c) The toll costs can be significant for longer trips, ensuring that the participant carefully considers the impact of the toll cost deduction from their survey account.

Lastly, the variation in the attribute levels for a sample of long and short route O-D's is shown in **Table 15**. The table shows that, as expected, there is more variation in the attribute level ranges of the longer routes than shorter routes. The range of total travel time levels when measured as the percentage difference between maximum and minimum values for this sample is between 30% and 110%, and for the petrol costs is between 17% and 66%. This level range is considered adequate for modelling purposes. The shorter routes do not incur toll costs.

Table 15: Comparison of Maximum, Minimum and Mean Values of Total Travel Time (ttt), Toll Cost (tc), Petrol Cost (pc) for a Sample of O-D's

Origin & Destination Suburb	ttt (max)	ttt (min)	ttt mean	tc max	tc min	tc mean	pc max	pc min	pc mean
Florida - Menlyn:	66	49	57	26	19	23	81	70	74
Roodepoort - Randburg	41	27	32	4	0	1	23	19	20
Midrand-Pretoria	46	22	35	11	0	8	54	33	40
Lombardy East - Wynberg	13	10	11	0	0	0	8	5	6
Northcliff - Linden	10	7	9	0	0	0	6	5	6
Note: Total travel time (ttt) measured in minutes; toll cost (tc) measured in Rands; petrol cost (pc) measured in Rands									

To further illustrate the range of attribute levels generated by RAPP-UP, the choice set variation of three survey participants is shown in the following sequence of figures. The figures illustrate the attribute levels differences for all eight choice sets for participants who undertook short (participant number 41), medium (participant number 2) and long (participant number 1) total trip durations.

Figure 62 shows the free-flow time and petrol cost variation for a short duration trip (on average, the mean total trip duration was less than 10 minutes). There was no toll payment for this trip and there was little variation on in the slowed-down, stop-start and pota attribute levels and these are not shown. The variation in free-flow trip time was a maximum of 2 minutes (or 20% variation), and zero for choice set number 1. On average, the difference in choice set attribute levels was 17%. While there was some petrol cost variation between choice sets, within the choice sets there was little variation. This is to be expected for short trips when petrol costs are low. The petrol cost mean difference in attribute levels within choice sets was 4%.

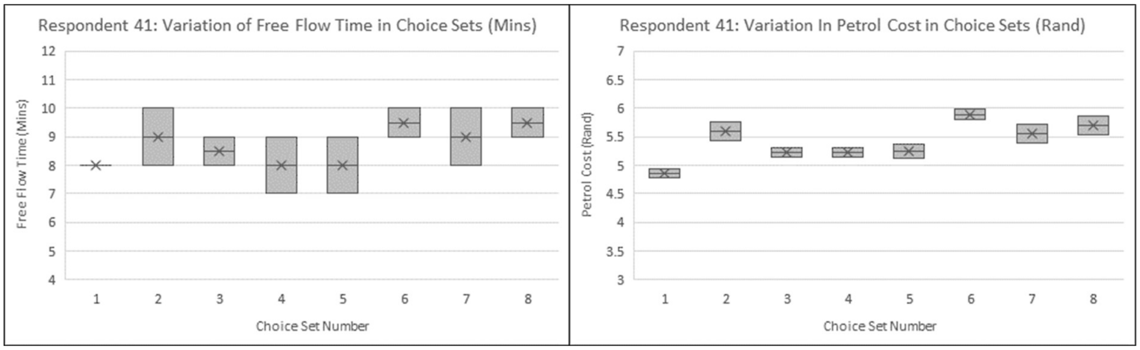


Figure 62: Choice Set Variation for Short Trip Duration (Participant No. 41)

Figure 63 shows the variation in attribute levels by choice set for a medium duration trip (the average trip duration was 25 minutes). There was a higher level of attribute level variation for more attributes, including the free-flow time, petrol cost, toll cost and pota. There was little variation in attribute level for the slowed-down and stop-start times. The free-flow times varied between and within choice sets (except for choice set no. 2 when they were the same). The mean variation in free-flow time within choice sets was 11%, with a minimum difference of zero and a maximum difference of 19%.

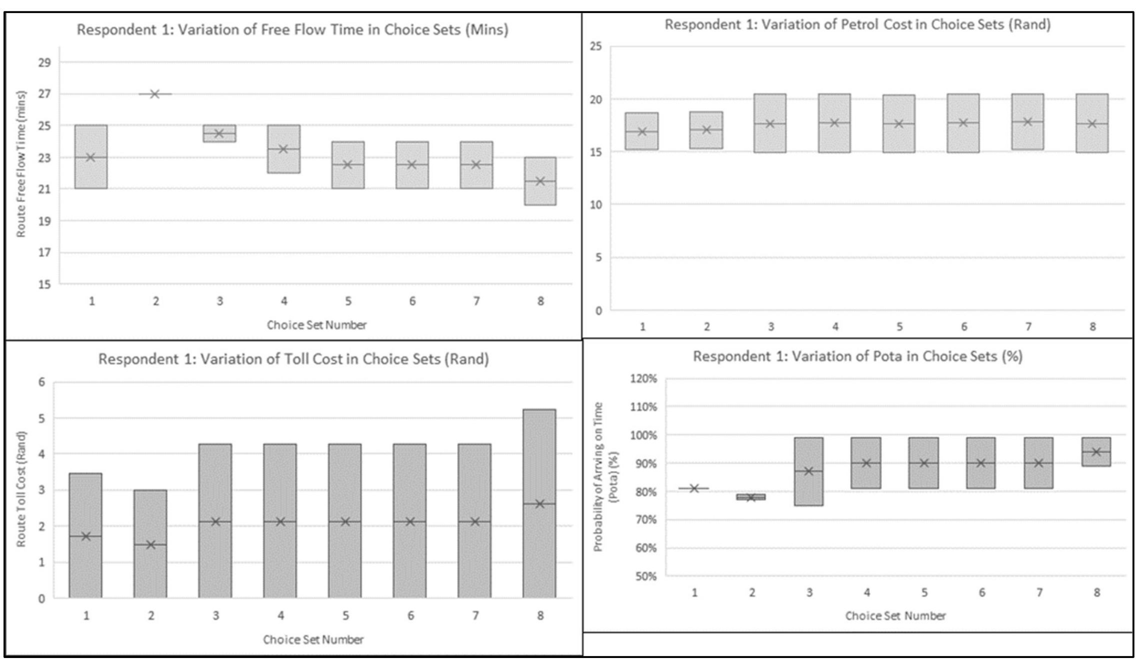


Figure 63: Choice Set Variation for Medium Trip Duration (Participant No. 1)

There was little variation in route petrol cost between choice sets, but within the choice sets the variation was on average 25%, with a maximum difference of 27%. Because one route was always tolled and the other un-tolled, the toll variation in percentage terms is significant. On the tolled route the highest toll fee was R5.10 and lowest was R3.00. There was significant variation in pota within the choice sets, with a minimum difference of zero and maximum difference of 32%.

The long duration trip (average total trip time exceeds sixty minutes) attribute level variations are shown in **Figure 64.**

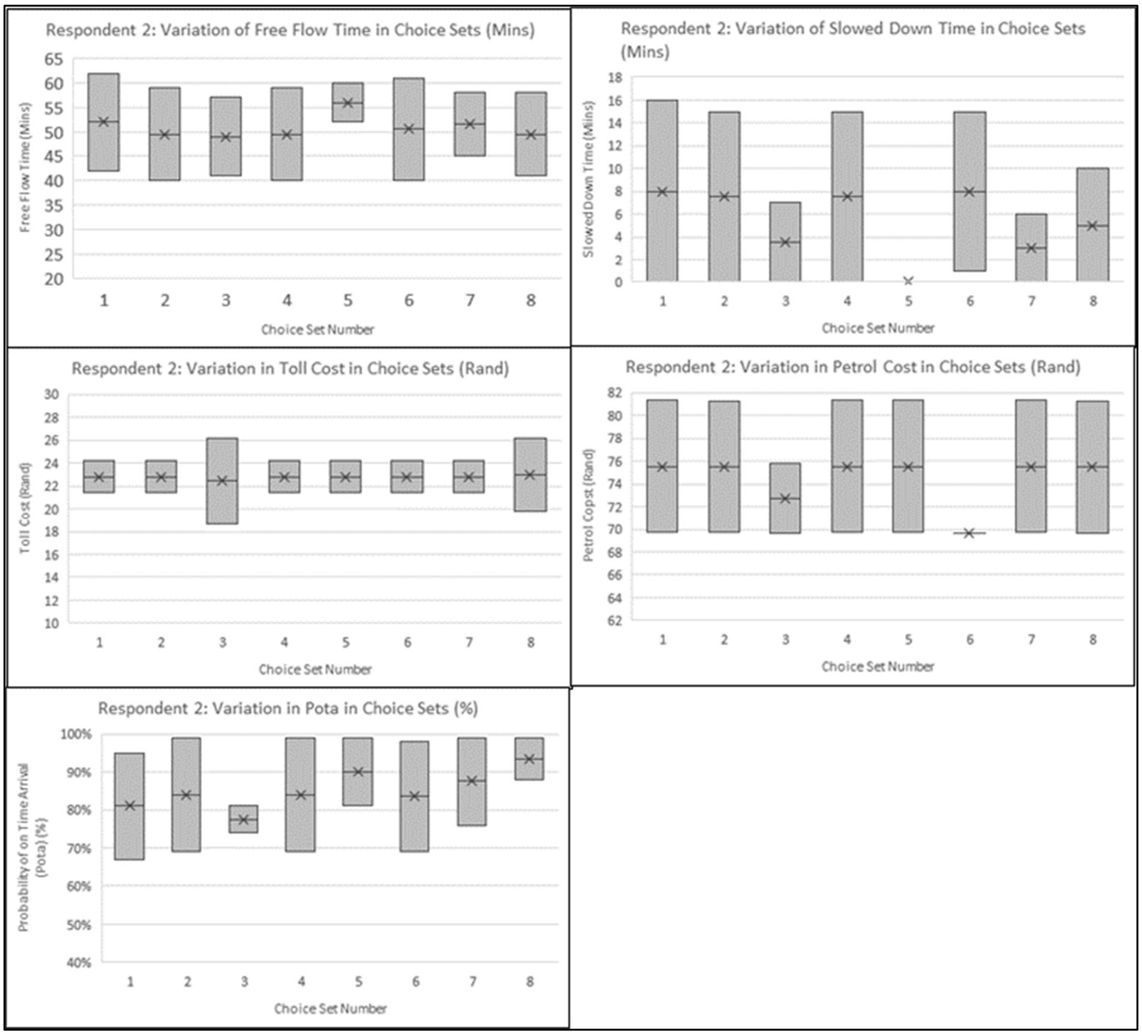


Figure 64: Choice Set Variation for Long Trip Duration (Participant No. 2)

There was attribute level variation within choice sets for more attributes for the long duration trip. The variation was noticeable for the free-flow and slowed-down trip times, as well as the petrol and toll costs and the pota values. The maximum free-flow time difference within the choice sets was 48%, the minimum difference 29%, and the average difference 40%. The slowed-down time variation within choice sets was significant as one route nearly always had zero slowed-down time. The maximum difference within choice sets was 16 minutes, a minimum of 0 minutes and an average of difference of 10 minutes. The median toll cost between choice sets was very consistent at approximately R23.00. The variation of toll cost within the choice sets was a maximum of 29%, a minimum of 13% and an average of 16%. Within choice sets the petrol cost variation was significant, with a maximum difference of R11.58 (or a 17% variation), a minimum difference of zero, and an average of 14%.

In conclusion, the attribute level differences between and within choice sets were dependent on the nature of the alternative routes generated by RAPP-UP. Shorter duration route alternatives tended to display less variation in attribute levels within the choice sets. This is to be expected, as the route alternatives are similar in length and duration, and experience similar levels of traffic congestion. However, as the route durations increase, more attributes are subject to level differences and the variation in attribute levels within the choice sets also increases.

Overall, the magnitude of attribute level differences within the choice sets are adequate for the estimation of robust route choice models.

10. ESTIMATION OF DISCRETE ROUTE CHOICE MODELS

10.1 Introduction

Several types of discrete route choice models with different utility specifications were estimated. These were the multinomial logit model (MNL); the more sophisticated random parameters logit (RPL) (also known as the mixed logit model); the latent class multinomial logit model (LCMNL); and forms of the MNL model that specifically take route overlap (i.e., correlation) into consideration as follows:

a) Multinomial logit (MNL) models. It is always recommended as good practice to first estimate an MNL no matter what the ultimate (preferred) model is (Hensher, et al., 2015), as the MNL is likely to highlight any model or data insufficiencies. The assumption of the independent and identical distribution (IID) of Type II Gumbel extreme value distribution of the error component is an important constraint on the use of the MNL. In addition, the Independence of Irrelevant Alternatives (IIA) constraint is equally important, i.e., the possibility of correlated alternatives. These constraints are relaxed using the Random Parameters Logit (RPL) models (also known as Mixed Logit models) that have become more commonly used.
b) Random parameters model (RPL) (also known as the mixed logit model). The RPL is a highly flexible model that can approximate any random utility model (McFadden & Train, 2000). The open-ended form of the RPL requires that it is solved by simulation which in turn requires the specification of continuous mixing distributions for the attribute coefficients. A powerful characteristic of the RPL model is the ability to address respondent response correlations, i.e., panel effects.
c) Latent Class Models (LCM) were developed to address the IIA constraint of the MNL. They assume there is latent heterogeneity in the sample of observations that varies with factors that are unobserved by the analyst. It resembles the RPL model but uses non-continuous distributions to identify latent classes of respondents within the sample of survey participants. LCM models provide an alternative approach to accommodating heterogeneity in models such as the MNL and RPL. LCMs assume that a population consists of a finite number of groups (or classes) of individuals that are heterogenous, but the groups are different from each other. The classes are distinguished by the different attribute coefficients. The analyst is required to specify the number of classes when setting up the model and iteratively determine the number of classes that estimate the most statistically significant coefficients.
d) C-Logit: The C-Logit model is the most commonly used model based on the MNL that specifically takes consideration of the route overlap by introducing a commonality factor into the utility expression as previously described.

e) PS-Logit: The path-sized logit model is also based on the MNL form and takes the route overlap into consideration with the introduction of a path size factor (of a different form to C-Logit) in the utility expression as previously described.

The models were used to evaluate the systemic variation in behaviour by including socio-economic attributes using covariable approaches, specifically dummy attributes. Income, trip length and gender covariables were tested.

10.2 MNL Base Model

Several MNL models were estimated, each with a different form of utility expression. The MNL Base Model was estimated with the utility expression shown in **Equation *2***. This form of expression has a richer disaggregation of travel time into free-flow, slowed-down time and stop-start time measured in minutes. The trip petrol and toll cost are individually specified in the utility expression and are measured in Rands. The probability of on-time arrival (*pota*) is also specified in the expression and is measured as a decimal value between zero and one. Note that the route choice experiment was unlabelled, so there was initially no allowance for an Alternative Specific Constant (ASC) in the expression. Hensher (2015) argues that the inclusion of an ASC in a model based on data collected from an unlabelled experiment has behavioural meaning, including survey response bias). If WTP measures are required from the model, then the ASC is irrelevant as it is ignored in these calculations. However, if the model is to be used for forecasting purposes, the inclusion of an ASC may be problematic. Several MNL models were estimated starting with the Base Model that does not include an ASC. The MNL Base Model output is shown in **Table 16**.

Table 16: MNL Base Model Output

Variable	Coefficient	Std. Error	t-ratio	P-value	Lower CIL	Upper CIL
Free-flow time	-0.177***	0.036	-4.90	0.000	-0.247	-0.106
Slow-down time	-0.218***	0.055	-3.94	0.000	-0.326	-0.109
Stop-start time	-0.397***	0.090	-4.42	0.000	-0.574	-0.221
Petrol cost	-0.394***	0.068	-5.79	0.000	-0.527	-0.260
Toll cost	-0.288***	0.079	-3.66	0.000	-0.443	-0.134
Pota	2.779***	1.072	2.59	0.010	0.678	4.880
Log-Likelihood	-122.07					
Sample size	364					
McFadden R^2	0.51					
***, **, * ==> Significance at 1%, 5%, 10% level.						

The base MNL results show that:

a) The coefficient signs are all correct, i.e., negative for the free-flow, slowed-down and stop-start times (as these times increase disutility); negative for the petrol and toll costs (as these costs increase disutility); and positive for the *pota* value (as *pota* increases the trip disutility decreases).

b) All the attribute coefficients are significant at the 99% confidence level, with the absolute values of the t-ratios greater than the $t_{critical}$ value of 1.97. This means that the null hypothesis can be rejected, i.e., the coefficient values are all significantly different from zero. The high t-ratios indicate that the standard errors are small, and the ranges of the 95% lower and upper confidence interval limits are narrow.

c) The coefficient P-values are all significant at the 95% confidence interval (i.e., the values are all less than 0.05).

d) The McFadden R^2 value (analogous to the goodness-of-fit coefficient of determination (R^2) for linear regression models) is 0.51. This is a high value for a non-linear model in which values are typically between 0.2 and 0.4 (Hensher, et al., 2015). The empirical relationship between pseudo-R^2 and R^2 was estimated by Domencich and McFadden (1975). A McFadden Pseudo-R^2 value of 0.5 is the equivalence of a linear regression R^2 value in excess of 0.85.

e) The free-flow coefficient is lower in magnitude than the slowed-down and stop-start time values. This means that the survey participants associate less disutility with free-flow time. The petrol (operating) cost coefficient is larger in magnitude than the toll cost value (ratio of 1.37), indicating that, for every R1.00 spent on either of these out-of-pocket costs, the survey participants perceive that the petrol cost contributes more to trip disutility than a toll fee. It also implies that the participants are more willing-to-pay a toll to save travel time. However, it must also be kept in mind that there is a scale effect of trip petrol cost to toll cost, i.e., in the survey the ratio of trip petrol and toll costs for the chosen routes was 8.1, indicating that, on average, trip petrol costs were eight times higher than trip toll costs. Therefore, on average, the toll cost of a route will contribute substantially less to total trip disutility than the cost of petrol.

f) The absolute value of the probability of on-time arrival (*pota*) coefficient is substantially larger than the time and cost coefficients. However, the scale of the attribute levels for *pota* is significantly lower and measured in decimal values less than one. This dilutes the impact of the contribution of *pota* to the overall trip utility.

g) The base MNL can correctly replicate the route choices made by the participants 89% of the time and can hence be considered to be a reliable predictor of route choice for the sample of survey participants.

A comparison of the free-flow, slowed-down and stop-start travel time coefficient ratios with those determined by Hensher (Hensher & Rose, 2005; Parsons Brinkerhoff, 2002; Hensher, 2001) is shown in the following table. These ratios have been termed congestion multipliers by Wardman and Ibanez (2012). The table illustrates that the RAPP-UP survey participants associate a high disutility for slowed-down and stop-start travel times with similar patterns shown in the other studies. While there is a wide range of ratios between studies, there is behavioural conformity between the RAPP-UP survey participants and international findings. The ratios determined by Hensher (2001) are noticeably higher and are for longer-distance inter-city trips in New Zealand whereas the other studies are urban-based. The study by Hensher and Rose in 2005 was based in Brisbane and Parsons Brinkerhoff in 2001 in Sydney. These disaggregated time findings have important implications for their application in road economic appraisals and transport demand models.

Table 17: Comparison of Free-Flow, Slowed-Down and Stop-Start Congestion Multipliers

Study/ Source	Ratio of Slowed-Down to Free-Flow Coefficients	Ratio of Stop-Start to Free-Flow Coefficients	Ratio to Stop-Start to Slowed-Down Coefficients
RAPP-UP (2022) *	1.23	2.24	1.82
Hensher & Rose (2005)**	1.43	1.86	1.30
Parsons Brinkerhoff (2002)**	1.40	-	-
Hensher (2001)**	3.60	7.45	2.16
*Derived from MNL model; **Derived from RPL models			

A comprehensive meta-analysis of congestion multipliers was undertaken by Wardman and Ibanez (2012). The meta-analysis assessed the congestion multipliers based on the ratios of congested, slowed-down, and stop-start coefficients ratioed with the free-flow coefficient. The strict definition of congestion is not clear from the studies, but it is assumed to be a blend of slowed-down and stop-start time and is hence not directly comparable with the RAPP-UP congestion multipliers. These congestion multipliers for *commuting* trips are summarised in the following table. The cities or country in which the studies were undertaken, and the year of the study are also shown.

Table 18: Summary of Congestion Multipliers for Commuting Trips (Ratio of Congested and Free-flow Coefficients)

City / Country	Year	Travel Time Type	Congestion Multiplier
UK	1986 - 2008	Congested	1.59
Canada	1993	Congested	1.37
New Zealand	2001	Slowed down	1.33
Copenhagen	2002	Congested	1.31
Brisbane	2005	Stop-start	1.34
Copenhagen	2007	Congested	1.15
Sydney	2008	Slowed down	1.35
Montreal	2005	Stop-start	1.65
Riga	2005	Stop-start	1.00
Serbia	2007	Stop-start	1.73
Brisbane	2007	Stop-start	1.19
Sydney	2010	Slowed down	1.68
Singapore	2009	Light & heavy congestion	1.16

The RAPP-UP congestion multiplier of 1.23 for slowed-down time is lower than the values for this category shown in **Table 18**, i.e., values of 1.33, 1.35 and 1.68. There is a wide range of multipliers for stop-start travel time in the table. The RAPP-UP value of 2.24 is higher than all of the values in the table. Furthermore, if it is assumed that the RAPP-UP congested time can be defined by a weighted combination of slowed-down and stop-start time based on the proportions of observed times for each of these categories (i.e., 8% for slowed-down time and 4% for stop-start time), the estimated RAPP-UP congested time multiplier is 1.55. This is within the range of congested time multipliers shown in the table. It can be concluded that the behavioural tendencies of the sample of Gauteng commuters in regard to the relative disutility of the travel time categories as defined by the congestion multipliers is within the range defined by international studies. However, it appears that the sample of Gauteng commuters in the survey perceive a high disutility for stop-start time.

Table 19 shows the MNL Base Model coefficient correlation matrix. The correlations are relatively low, and the signs are correct. The higher value of 0.622 for the free-flow and slowed-down time implies that the participants perceived a positive association between a route's free-flow time and the slowed-down time, i.e., as the free-flow time on a route increased, so did the slowed-down time. The negative correlation of -0.142 between a route's free-flow time and petrol cost indicates that participants perceived petrol cost decreasing with increasing free-flow time which is intuitively correct. A route toll cost has a high positive correlation with free-flow time indicating that the participants associated higher proportions of free-flow travel on the freeways when a toll was paid. The toll coefficient correlation with slowed-down and free-flow time are significantly lower with there being little correlation between paying a toll and stop-start time. The probability of on time arrival (*pota*) has low correlations with the other coefficients indicating that the participants did not perceive a correlation between the various trip categories from which it was defined.

Table 19: Base MNL Coefficient Correlation Matrix

Correlation Matrix	Free-flow time	Slow-down time	Stop-start time	Petrol cost	Toll cost	Pota
Free-flow time	1.000					
Slow-down time	0.622	1.000				
Stop-start time	0.234	0.233	1.000			
Petrol cost	-0.142	0.031	0.294	1.000		
Toll cost	0.771	0.407	0.258	-0.217	1.000	
Pota	0.125	-0.226	-0.178	-0.013	0.020	1.000

The willingness-to-pay for travel time savings as measured by the value of travel time (VTT) are shown in **Table 20**. The values are determined on the basis of the cost of marginal changes in time spent travelling and are estimated from the ratio of the time and cost coefficients. Values were determined for each of the travel time categories for the petrol and toll costs.

Table 20: Commuting Values of Travel Time from Base MNL Model (Rands/Hour)

VTT (Rands/Hour)	VTT Free-Flow Time (Rand/hour)	VTT Slowed Down Time (Rand/Hour)	VTT Stop-Start time (Rand/hour)
VTT (Petrol)	R26.93	R33.17	R60.53
VTT (Toll)	R36.78	R45.30	R82.67

Table 20 shows that when operating (i.e., petrol) cost is used to derive the VTT, the value is relatively low, i.e., R26.93 per hour. This value is relatively low in the context of the high participant income levels, but is intuitively correct, i.e., commuters are not willing-to-pay much for travel time savings when the trip is made in free-flow conditions. However, the VTT for the slowed-down and stop-start portions of a trip increase to R33.17 and R60.53/hour respectively which is also intuitively correct, i.e., if a trip was made in stop-start conditions commuters would be willing-to-pay more to save travel time.

The willingness-to-pay a toll for travel time savings is higher than that for operating costs, but still relatively low for the high-income survey participants. This result is somewhat unexpected, as there has been a high resistance by motorists using the Gauteng GFIP freeways to pay e-tolls. However, the context of the experiment is likely to have resulted in participant disassociation from the negative sentiment attached to the GFIP e-toll system. This result should be viewed in the context of the relative magnitude of average toll costs compared to petrol costs for a trip using a tolled section. The average petrol: toll cost ratio was eight, meaning that toll fees make up a significantly lower proportion of total trip disutility than petrol costs.

Benchmarking this finding produced mixed results. The result is contrary to findings by Hensher and Rose (2005) and Parsons Brinkerhoff (2002) who determined that the toll cost coefficient was lower in magnitude than the operating (petrol) cost coefficient resulting in lower VTT's produced by using the toll cost as the numeraire (i.e., the monetary units in which the VTT is expressed). In a comprehensive meta-analysis of the values of travel time, Wardman et al. (2016), also found that when the toll cost was used as the numeraire to estimate the VTT the value was 25% less than when the numeraire was the petrol cost. However, the finding is supported by Hensher (2001) who also determined that the toll coefficient is larger in magnitude than the operating cost coefficient. The relative magnitudes of these coefficients are clearly context specific and dependent on the petrol and toll costs of routes used in the choice experiment; the income and trip characteristics of the survey participants; and the in the case of Gauteng e-tolls, the historical context and unpopularity of the e-toll scheme.

The following MNL models were also investigated:

i. A Fundamental MNL model that only considered the total travel time of a route, not the disaggregated times in free-flow, slowed-down and stop-start conditions.
ii. An MNL with the inclusion of a toll road quality bonus (TRQB) as a dummy attribute (resembling an ASC) that was intended to determine whether there were any unobserved factors of utility influencing the utility of toll roads.
iii. An MNL with the inclusion of a dummy attribute (BIAS) to determine whether the order of the presentation of the routes in the choice sets influenced the respondent's choice of route.
iv. An MNL to determine whether the adjustment of the scale of the travel time coefficients is required. This was achieved by introducing a route length adjustment factor. The factor essentially normalizes the various trip times in order to ensure that the same route time differences between short and long trips is accounted for.
v. Several MNL's that investigated whether any observed participant socio-demographic covariates (e.g., age, gender, and income) influenced the choice of route and identified any observed heterogeneity. These covariates were included as interaction effects (as is required with unlabelled choice models) with the various observed time and cost attributes in the utility expression.

10.3 Fundamental MNL Model

A Fundamental MNL was estimated by aggregating the three travel time attributes into a single travel time attribute, and the petrol and toll costs into a single trip cost attribute. This is a highly simplified model that diminishes the richness of the disaggregated trip time and cost attributes but provides a useful insight into the willingness-to-pay for a weighted trip time and cost route and enables more appropriate comparisons with VTT estimates from earlier studies in Pretoria and Johannesburg. The utility expression is as follows for user *i* using route *j* at time *t*:

$U_{ijt} = b_1 * tttime_{jt} + b_2 * ttcost_{jt} + b_6 * pota_{jt} + \varepsilon_{ij}$

Where:

- b_1, b_2 and b_3 are coefficients to be estimated.
- $tttime_{jt}$ is the total travel time of route *j* (i.e., the sum of free-flow, slowed-down and stop-start time) at time *t*.
- $ttcost_{jj}$ is the total trip cost for route *j* (i.e., the sum of petrol and toll cost) at time *t*.
- $pota_{ij}$ is the probability of on-time arrival for route *j* at time *t*.
- ε_{ij} is the random term representing unobserved factors.

The Fundamental MNL Model results are shown in **Table 21**. The model log-likelihood is -117.1 which is a slight improvement over the Base MNL Model (-122.07). The coefficient signs are correct, and all are significant with their absolute t-ratios higher than t_{crit} of 1.97. The weighted VTT based on the sum of the operating and toll costs is R39.45 per hour. This value is higher than the consolidated Tshwane and Ekurhuleni Metropolitan area value of R25.18 determined in 2013 (Hayes & Venter, 2017). This comparison is not fully valid as the value of R25.18/hour was determined in a mode choice context between car use and bus rapid transit (BRT). There are additional factors to keep in mind when making this comparison. Most importantly are the average sample income levels which were higher for the RAPP-UP sample; the years in which the surveys were undertaken (the car: BRT mode choice model was estimated in 2013, meaning current values would be approximately R31/hour in 2022 Rands assuming an average of 5% increase in wages and a 0.50 income: VTT elasticity); and lastly the survey methodology which adopted conjoint methods for Pretoria and Ekurhuleni.

Table 21: Fundamental MNL Model Output

Variable	Coefficient	Std. Error	t-ratio	P-value	Lower CIL	Upper CIL
Total travel time	-0.240***	0.031	-7.65	0.000	-0.301	-0.178
Total travel cost	-0.365***	0.047	-7.73	0.000	-0.457	-0.272
Pota	4.08***	0.988	4.17	0.000	2.164	5.994
Log-Likelihood	-117.1					
Sample size	364					
McFadden R^2	0.52					
***, **, * ==> Significance at 1%, 5%, 10% level.						

10.4 Base MNL Model with Toll Road Quality Bonus (TRQB) Attribute

Hensher & Rose (2004) estimated route choice models for the proposed Brisbane River Crossing in 2004. In this study the introduction of a toll road quality bonus (TRQB) was investigated and found to be significant with a negative coefficient sign, i.e., it reflected a user perceived disutility of toll roads. The TQRB is a factor of utility that accounts for those attributes of a tolled route that have not been included in the various trip time, trip cost and on-time arrival attributes.

The TRQB was introduced as a dummy attribute, with a value of 0 for non-tolled roads and a value of one for tolled roads. The form of the utility expression including the TRQB is thus as follows for individual *i* using route *j* at time *t* where the attribute coefficients and names are described before in **Equation *2***:

$$U_{ijt} = b_1{*}fftime_{jt} + b_2{*}sdtime_{jt} + b_3{*}fftime_{jt} + b_4{*}petcost_{jt} + b_5{*}tollcost_{jt} + b_6{*}pota_{jt} + b_7{*}TRQB_{jt} + \varepsilon_{ij}$$

The results of the Base MNL Model estimated with the TRQB included in the utility expression is shown in **Table 22**. The log-likelihood is -119.5 which is a slight improvement over the Base MNL Model. As with the Base MNL Model the coefficient signs are all correct, and the travel time and petrol cost coefficients are significant at the 99% confidence limit, and the toll cost, and the pota and TRQB at the 95% confidence limit. The McFadden R^2 value is 0.52 which is a very good result indicating a good fit between modelled and observed choices. The TRQB coefficient has a negative sign that indicates the tolled routes have a disutility when the factors other than trip time, cost and on-time arrival are considered. As highlighted by Hensher and Rose (2005), not all commuters may perceive the TRQB as having a net utility and found in Brisbane that the TRQB had a negative sign. For the RAPP-UP survey participants it cannot be excluded that they had a negative perception of the GFIP toll system consistent with wider public negative sentiment toward the system.

Table 22: Base MNL Model with Toll Road Quality Bonus Attribute (TQRB)

Variable	Coefficient	Std. Error	t-ratio	P-value	Lower CIL	Upper CIL
Free-flow time	-0.193***	0.037	-5.19	0.000	-0.265	-0.120
Slow-down time	-0.226***	0.055	-4.12	0.000	-0.334	-0.119
Stop-start time	-0.374***	0.090	-4.16	0.000	-0.551	-0.198
Petrol cost	-0.360***	0.068	-5.30	0.000	-0.493	-0.227
Toll cost	-0.196**	0.084	-2.32	0.020	-0.361	-0.030
Pota	+2.800**	1.091	2.57	0.010	0.661	4.939
TRQB	-0.786**	0.351	-2.24	0.025	-1.474	-0.098
Log-Likelihood	-119.5					
Sample size	364					
McFadden R^2	0.52					
***, **, * ==> Significance at 1%, 5%, 10% level.						

The MNL model with the TQRB attribute has lower free-flow and slowed-down time coefficient values than the Base MNL Model (the coefficients have reduced by 8.3% and 3.6% respectively over the Base MNL Model values) but has a higher stop-start time coefficient value (an increase of 5.8%). The petrol and toll cost coefficients are also smaller, but the *pota* value is unchanged. It is important to note that the toll cost coefficient has decreased more than the petrol cost coefficient i.e., an 8.6% decrease for petrol cost coefficient versus a 31.9% decrease for the toll cost coefficient. The effect of this disproportionate large decrease in the toll cost coefficient has a significant impact on the willingness-to-pay a toll for travel time savings as shown in **Table 23**, i.e., it increases the willingness-to-pay a toll for travel time savings in free-flow, slowed-down and stop-start conditions. The large reduction in the magnitude of the toll cost coefficient is explained by the introduction of the TRQB attribute that has disaggregated the utility associated with using a tolled freeway. However, an analysis of an average freeway trip with and without the TQRB shows no net gain in disutility due to the introduction of the TQRB, i.e., the proportion of disutility of the toll and TQRB attributes (11% of total disutility) remains similar when compared to the Base MNL Model with toll only (10% of total disutility) when all other attribute levels are held constant. This result is insightful and implies that when predicting the demand for a toll road, the first cent of the toll tariff should be valued higher than any subsequent cents.

The reduction in coefficient values between the Base MNL Model and Base MNL Model with TQRB can be explained by the increased explanatory power of the MNL utility specification and the reduction of the error component in the utility expression as reflected by the reduction of the log-likelihood value. The coefficient values are proportional to the magnitude of the error term and reducing the error term through the introduction of the TRQB attribute will reduce the coefficient values.

The values of travel time derived from the operating and toll costs are shown in **Table 23**. The willingness-to-pay for travel time savings derived from operating costs and toll costs have increased over those estimated from the Base MNL Model.

Table 23: Values of Travel Time from Base MNL Model with TRQB (Rands/Hour)

VTT (Rands/Hour)	VTT Free-Flow Time (Rand/hour)	VTT Slowed Down Time (Rand/Hour)	VTT Stop-Start time (Rand/hour)
VTT (Petrol)	R32.17	R37.67	R62.33
VTT (Toll)	R59.08	R69.18	R114.49

10.5 MNL with RAPP-UP Route Order Presentation Bias Correction

A dummy attribute (BIAS) was included in the utility expression to account for the order of the route presentation in RAPP-UP. The routes that were presented first on the smartphone screen were given a value of 1 and the second route a value of zero. For this model the TRQB was excluded. The result is shown in **Table 24**. The BIAS coefficient is not significant. The result illustrates that survey participants were not biased in their choice of route by the order in which the routes were presented in RAPP-UP and that they considered both route options before choosing their preferred route. The remaining attribute coefficients are similar in magnitude and significance to the Base MNL Model and MNL model with the TRQB.

Table 24: MNL Model with Inclusion of Route Order Dummy Attribute (BIAS)

Variable	Coefficient	Std. Error	t-ratio	P-value
Free-flow time	-0.193***	0.043	-4.45	0.000
Slow-down time	-0.229***	0.058	-3.95	0.000
Stop-start time	-0.401***	0.091	-4.42	0.000
Petrol cost	-0.397***	0.068	-5.79	0.000
Toll cost	-0.287***	0.079	-3.62	0.000
Pota	+2.671**	1.079	2.47	0.013
Bias	-0.172	0.244	-0.70	0.481
Log-Likelihood	-121.82			
Sample size	364			
McFadden R^2	0.52			
***, **, * ==> Significance at 1%, 5%, 10% level.				

10.6 MNL with Route Length Correction for Travel Times

The route length correction model adjusted the utility travel times to adjust the scale of the travel time coefficients. This was done to ensure that a difference in travel time for two short route alternatives (e.g., 10 minutes versus 11 minutes) is perceived differently to the same difference between two longer duration route alternatives (e.g., 50 versus 51 minutes). The need for this correction is dependent on the proportion of short and longer trips in the data set and the travel time attribute level variation in the choice sets. The normalising of the route trip times (i.e., free-flow, slowed-down and stop-start times) was done using the route average speed. The average speed (total route length divided by total route time) was calculated. The average speed was then used to normalize the individual trip time components by multiplying the observed trip times on a route by the average speed. This adjustment had the effect of increasing the attribute level gap for longer trips and reducing them for shorter trips.

The MNL model estimated on this basis did not produce statistically significant coefficients for any of the attributes. This result is most likely due to:

- The low number of total observations in the experiment.
- A low number of observed trip times between routes in the slowed-down and stop-start categories.
- Few route observations with low travel times (17 choice sets out of 364 (5%) had travel times less than 10 minutes); 100 choice sets had travel times between 10 and 20 minutes (27%) and most choice sets had travel times of over 20 minutes (68%).

10.7 MNL Models with Socio-Demographic Covariates

Socio-demographic covariates were introduced into the utility expression as interaction effects. In particular, participant income was introduced by calculating the relative income for each participant (based on the middle of the income band) divided by the weighted average income of the sample (also calculated from the middle of the income bands) and interacting these values with the petrol and toll cost attribute values in each choice set for the respondent. The MNL model estimated on this basis did not produce statistically significant coefficients for the petrol and toll attributes.

The socio-demographic attributes of gender (male/female) and income (less than R30k and more than R30k per month income) were also added as main effect dummy attributes added individually and collectively to the utility expression. These models also did not produce statistically significant coefficients.

Overall, the inclusion of socio-demographic covariates into the MNL models did not produce statistically significant coefficients. The reason for this result should be explored further when a larger sample of participants is used to estimate models.

10.8 Base Random Parameters Model (RPL)

The Base RPL Model was estimated using the same utility expression as for the Base MNL Model (i.e., as shown in **Equation *2***). The TQRB was included in the RPL models, having shown to be significant in the MNL models. The decision as to what attribute coefficients to randomise and what form of mixing distribution to apply required several models to be estimated and evaluated. The first model estimated allowed all the travel time, pota and TRQB coefficients to be randomised (normal) and the cost coefficients (i.e., petrol and toll) were fixed. This was termed the Base RPL Model. The Base RPL Model was estimated in an unconditional and conditional manner. The unconditional approach uses the full sample population without consideration of the correlation of responses from individuals, i.e., the coefficients are not conditioned on a particular individual's choice patterns but rather on the sample population as a whole. The process of estimating unconditional random parameters is similar to the estimating process of non-random parameters in the MNL and RPL models, i.e., maximisation of the log-likelihood function over the data for the sample population. All the survey participant responses can be used when estimating the unconditional RPL, i.e., a total of 364 responses from all 48 participants.

Conditional RPL models consider individual-specific choice patterns, specifically the correlation between successive choices by individuals, i.e., the panel effect. For conditional RPL models the number of choice sets answered by each individual must be specified when estimating the model, and importantly, the number of choice sets must be the same for each respondent. Because a total of 43 participants completed all eight choice sets and four participants completed less than this, the responses from the 43 participants were when estimating the conditional RPL model, i.e., a total of 344 observations with a panel value of eight. All the RPL models were run with 700 Halton draws.

The RPL model log-likelihoods can be directly compared with that of the Base MNL Model (that has a log-likelihood value of -122.1 with TRQB attribute included in the utility expression). The log-likelihood from the equivalent MNL model with 43 participants and 344 observation is -119.5 with the TRQB attribute included in the utility expression. Both of the RPL models thus show significantly improved goodness-of-fit compared to their equivalent MNL models. The RPL model outputs are shown in **Table 25**.

Table 25: Base RPL Model Outputs (All Coefficients Randomised Normal)

Attribute	Unconditional RPL Model			Conditional RPL Model		
	Coefficient	Std Error	t-Ratio	Coefficient	Std Error	t-Ratio
Free-flow time	-0.312***	0.095	-3.28	-0.249***	0.054	-4.62
Slowed-down time	-0.453**	0.179	-2.52	-0.361***	0.115	-3.13
Stop-start time	-0.746***	0.246	-3.03	-0.633***	0.162	-3.91
Petrol cost	-0.799***	0.197	-4.05	-0.481***	0.144	-3.33
Toll cost	-0.367*	0.191	-1.92	-0.224*	0.129	-1.74
Pota	2.826	1.905	1.48	2.463	1.571	1.57
TRQB	-0.969*	0.587	-1.65	-1.153**	0.505	-2.28
Standard Deviations						
Free-flow time	0.099	0.111	0.89	0.009	0.061	0.14
Slowed-down time	0.279	0.197	1.42	0.294**	0.105	2.80
Stop-start time	0.011	9.796	0.00	0.007	0.195	0.04
Petrol cost	0.438**	0.184	2.37	0.148	0.144	1.03
Toll cost	0.141	0.309	0.46	0.019	0.225	0.09
Pota	0.002	134.07	0.00	4.502*	2.496	1.80
TRQB	0.049	17.17	0.00	0.014	0.512	0.03
Log-Likelihood	-106.9			-101.6		
McFadden Pseudo R^2	0.56			0.56		
***, **, * ==> Significance at 1%, 5%, 10% level.						

The following findings were drawn from the Base RPL Models:

a) For both models the coefficients all have the right signs.
b) The three travel time and petrol cost coefficients are significant at the 99% confidence limit, the toll coefficient at the 95% limit, the TRQB coefficient at the 90% levels and the *pota* is not significant in both models.
c) For the conditional RPL model, all the standard deviation values (except for slowed-down time and pota attributes) are not significant. This means that that the dispersion of values around the mean for these attribute coefficients are not statistically different to zero suggesting that all the information in the distribution is captured within the mean value. This

means that it is appropriate to use the average coefficient values for forecasting and for estimating the value of travel time.

d) The significant standard deviation of the slowed-down time attribute raises the possibility of estimating negative VTT's for this attribute.

e) The statistical insignificance of the pota coefficient in the RPL models is unexpected, as trip time reliability has been found to be significant in international studies. The value of trip reliability was found to be similar to that of the value of travel time savings (Bliemer, 2020). This finding requires further investigation of the pota attribute, either in its form in RAPP-UP, i.e., as a probability of on-time arrival that may be misinterpreted by survey participants, or in the units measured, i.e., its specification as a percentage in RAPP-UP. Its specification as early or late arrival in minutes may be more suitable and requires investigation. That the Base MNL model determined little correlation between pota and the various categories of trip time also emphasises the need for this investigation into the calculation and presentation of the value in the choice sets.

f) While there is some variation around the mean for the petrol coefficient in the conditional model (standard deviation is 0.148), it is not significant (t-ratio is 1.03). There is no variation in the toll coefficient (standard deviation is 0.019) but it is also not significant (t-ratio is 0.09). These low and insignificant variations around the mean coefficient values for these attributes suggest that the VTT values do not differ significantly between participants.

g) In the conditional model the pota coefficient has a significant standard deviation and hence there is heterogeneity associated with this coefficient. However, the mean pota coefficient value itself is not significant in the conditional model.

h) The low coefficient standard deviations indicate that it is not necessary to use mixing distributions to ensure positive willingness-to-pay measures such as log-normal and one-sided triangular distributions.

The values of travel time savings derived from the petrol and toll cost numeraires are summarised in **Table 26** for both models. It is noticeable that the VTT's derived from the conditional RPL model are significantly higher than those derived from the unconditional model. The conditional RPL model VTT's estimated far higher than those of the Base MNL Model (see **Table 23**). Amador et al., (2005) indicate that it is common for RPL models to estimate higher VTT's than the more restrictive MNL models, although there is no general rule that this will occur. Amador et al. (2005) also suggest that the estimated values of travel time are dependent on the variables included in the model, the functional form chosen for the indirect utility function and the nature of the data.

Table 26: Values of Travel Time (VTT) from Unconditional and Conditional Base RPL Models with TRQB (Rands/Hour)

VTT (Rands/Hour)	Free-Flow VTT (Rand/hour)	Slowed Down VTT (Rand/Hour)	Stop-Start VTT (Rand/hour)
Unconditional RPL			
VTT (Petrol)	R23.43	R33.98	R55.95
VTT (Toll)	R51.01	R73.90	R121.96
Conditional RPL			
VTT (Petrol)	R31.06	R45.03	R78.96
VTT (Toll)	R66.70	R96.70	R169.55

The distribution of individual willingness-to-pay for travel time savings can be obtained from the conditional RPL model. The distribution of VTT's is shown in the following figures. **Figure 65** shows that there is one participant that has a negative value of slowed-down value of travel time. The possibility of this occurrence was highlighted by the significant standard deviation of the slowed-down time coefficient. There is more variation in the slowed-down and stop-start VTT's and noticeably less variation in the free-flow VTT.

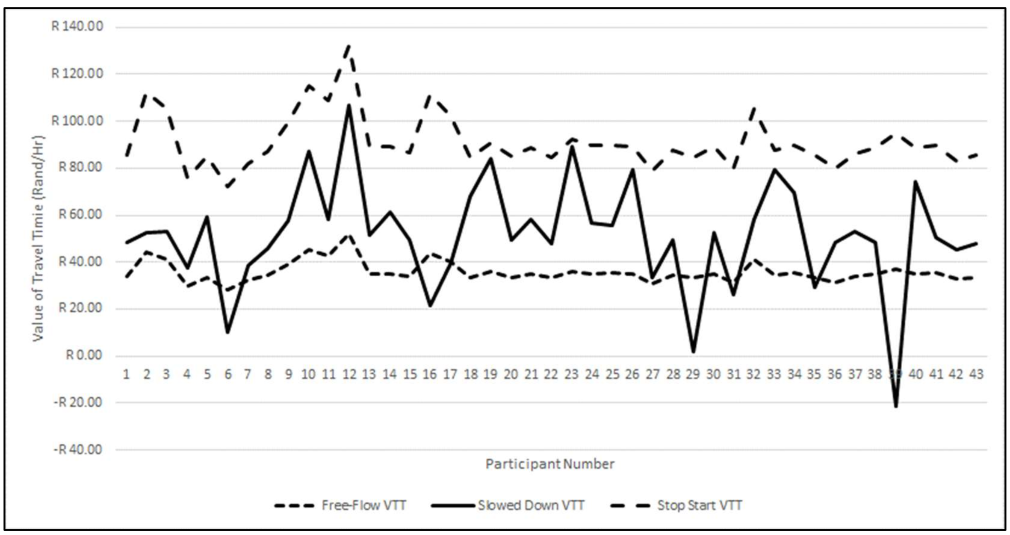


Figure 65: Distribution of Value of Travel Time Derived from Petrol Cost Coefficient (Rand/Hour)

The VTT's derived from the toll fee in **Figure 66** show dissimilar patterns to those from the petrol cost. There is little variation in the free-flow and stop-start VTT's, but significant variation in the slowed-down VTT. The negative VTT is repeated for one participant. The smooth curves for the free-flow and stop-start VTT's reflect the low standard deviations for these coefficients and that the standard deviations are not significantly different from zero. For the slowed-down time the standard deviation is significantly different to zero.

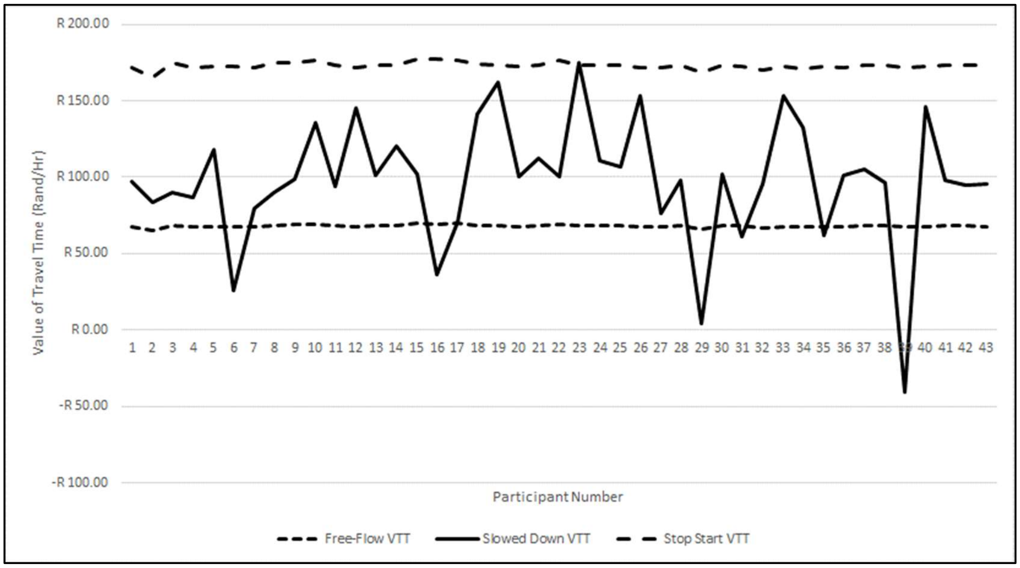


Figure 66: Distribution of Values of Travel Time Derived from Toll Cost Coefficient (Rand/Hour)

10.9 RPL Model with Fixed Coefficients

When estimating RPL models it is possible to either fix the cost coefficients to avoid the consequences of estimating willingness-to-pay measures from the ratio of two distributions (Train, 2009), or to use mixing distributions that ensure only positive willingness to pay measures (Hensher, et al., 2015). An RPL model was estimated with non-random petrol and toll cost coefficients and the random coefficients for the other coefficients (normally distributed). A conditional (i.e., panel) RPL was estimated for this case, and the model output is shown in **Table 27**. It is noticeable that the log-likelihood of -101.80 is very similar to the RPL with randomised cost coefficients (-101.6) and has the same McFadden Pseudo R^2 value.

Table 27: RPL Model Output with Non-Random Cost Coefficients

Attribute	Conditional RPL Model with Non-Random Cost Coefficients & Normal Distribution for Randomised Coefficients		
	Coefficient	**Std Error**	**t-Ratio**
Free-flow time	-0.251***	0.052	-4.85
Slowed-down time	-0.363***	0.112	-3.25
Stop-start time	-0.590***	0.137	-4.30
Petrol cost	-0.420***	0.091	-4.60
Toll cost	-0.219*	0.1213	-1.77
Pota	2.355	1.511	1.56
TRQB	-1.189**	0.492	-2.42
Standard Deviations			
Free-flow time	0.003	0.066	0.04
Slowed-down time	0.290***	0.105	2.75
Stop-start time	0.012	0.267	0.05
Petrol cost	-	-	-
Toll cost	-	-	-
Pota	4.213	2.513	1.68
TRQB	0.003	0.516	0.01
Log-Likelihood	-101.8		
McFadden Pseudo R^2	0.56		

From **Table 27** it is evident that for this model:

a) The coefficients have the correct signs, and the various travel time and petrol coefficients are significant at the 99% confidence level. The TRQB coefficient is significant at the 95% confidence level and the toll cost coefficient at the 90% confidence interval. The pota coefficient is not significantly different to zero.

b) As with the RPL model with all coefficients randomised, the standard deviations are not significantly different to zero except for the slowed-down time that is significant. Although the pota standard deviation is high, the coefficient itself is not significant. Hence it can be anticipated that the slowed-down time VTT will vary significantly between survey participants and as before give rise to negative VTT estimates.

The VTT's are shown in **Table 28** for the various travel times based on the operating (petrol) cost and the toll cost. The VTT's are higher than for the Base MNL Model and vary when compared to the conditional RPL with randomised petrol and toll cost coefficients. The distribution of VTT can be expected to show little variation for the free-flow and stop-start values and some variation for the slowed-down VTT.

Table 28: Values of Travel Time from Conditional Base RPL Model with TRQB (Rands/Hour)

VTT (Rands/Hour)	Free-Flow VTT (Rand/hour)	Slowed Down VTT (Rand/Hour)	Stop-Start VTT (Rand/hour)
VTT (Petrol)	R35.86	R51.86	R84.29
VTT (Toll)	R68.76	R99.45	R161.64

10.10 RPL Model with Uniform and Triangular Distributions

Conditional RPL models with several types of mixing distributions were also tested. The distributions that produced sensible outcomes were the uniform and triangular distributions. The triangular distribution was the one-sided type that ensures positive willingness-to-pay values (even though only one of the participants displayed negative value of travel times in the Base RPL model). For these RPL models the petrol and toll costs were non-randomised. The model outputs are shown in **Table 29**. Constrained (i.e., panel) models were estimated for both with 700 Halton draws.

Table 29 shows that both models have the correct signs. The magnitude of the coefficients is similar except for the toll cost coefficient for the triangular model which is significantly larger than for the uniform model. This will result in lower values of travel time based on the toll cost numeraire. The standard deviation coefficients of the model with triangular distributions are the same value as the attribute coefficient values which is to be expected. The standard deviations are all significant. The RPL model with uniform mixing distributions has a lower log-likelihood than the model with triangular distributions. The model log-likelihood is also lower than that for the RPL estimated with normal mixing distributions (see **Table 27**). The magnitude of the coefficients is similar for both models in **Table 29** except for the pota value which is an important distinction. The pota coefficient is significant at the 95% confidence interval for the model with the triangular mixing distributions but is not significant for the model with uniform mixing distributions. It must be emphasized that the one-sided triangular distribution is a mathematical convenience to ensure positive willingness-to-pay measures and does not imply a behavioural phenomenon.

Table 29: RPL Models with Uniform and Triangular Mixing Distributions

Attribute	Conditional RPL Model with Triangular Mixing Distributions			Conditional RPL Model with Uniform Mixing Distributions		
	Coefficient	**Std Error**	**t-Ratio**	**Coefficient**	**Std Error**	**t-Ratio**
Free-flow time	-0.239***	0.057	-4.16	-0.249***	0.051	-4.88
Slowed-down time	-0.331***	0.095	-3.47	-0.334***	0.105	-3.19
Stop-start time	-0.492***	0.133	-3.68	-0.590***	0.140	-4.21
Petrol cost	-0.398***	0.081	-4.91	-0.419***	0.092	-4.55
Toll cost	-0.265**	0.128	-2.08	-0.214*	0.125	-1.72
Pota	2.642**	1.260	2.10	2.186	1.604	1.36
TRQB	-0.881**	0.443	-1.99	-1.196**	0.495	-2.41
Standard Deviations						
Free-flow time	0.239***	0.057	4.16	0.001	0.113	0.01
Slowed-down time	0.331***	0.095	3.47	0.498***	0.145	3.42
Stop-start time	0.492***	0.133	3.68	0.003	0.475	0.01
Pota	2.642**	1.260	2.10	6.976	4.573	1.53
TRQB	0.881*	0.443	1.99	0.006	0.880	0.01
Log-Likelihood	-109.8			-101.7		
McFadden Pseudo R^2	0.54			0.57		
***, **, * ==> *Significance at 1%, 5%, 10% level.*						

The values of travel time derived from the operating (petrol) cost and the toll cost are shown in **Table 30**. The VTT's estimated using the petrol cost numeraire are similar between models, but values derived from the toll cost numeraire are significantly higher.

Table 30: Values of Travel Time Savings for RPL Models

VTT (Rands/Hour)	Free-Flow VTT (Rand/hour)	Slowed Down VTT (Rand/Hour)	Stop-Start VTT (Rand/hour)
RPL Triangular			
VTT (Petrol)	R36.03	R49.90	R74.94
VTT (Toll)	R54.11	R74.94	R111.39
RPL Uniform			
VTT (Petrol)	R35.64	R47.86	R84.60
VTT (Toll)	R69.81	R93.54	R165.34

10.11 Latent Class Models (LCM)

An LCM model with two classes was found to produce the more statistically significant estimates of the attribute coefficients. Two models were estimated, both with two classes. Firstly, a model with randomised normal time coefficients and fixed cost, pota and TQRB coefficients was estimated. Secondly, a fully randomised (normal) coefficient (RPL) form of LCM was estimated. When more than two classes were specified, the models estimated non-significant coefficients. The model log-likelihood values were significant improvements over the MNL models, and similar to the RPL models. The probability of both classes was statistically significant. However, both the models produced counter-intuitive results for Class 2 with the slowed-down time coefficient for this class having a positive sign, even though the coefficient is not significant. The results of the fixed cost coefficient LCM model are shown in **Table 31**. The reason for the incorrect sign for slowed-down time may be due to the small sample size and the model's inability to define two distinct classes.

Table 31: Latent Class Model (LCM) with Fixed Cost Coefficients and Randomised Normal Time Coefficients.

Attribute	Coefficient	Standard Error	t-Value
Class 1			
Free-flow time	-0.638**	0.270	-2.34
Slowed-down time	-1.110**	0.502	-2.21
Stop-start time	-0.746***	0.263	-2.83
Petrol cost	-0.577**	0.276	-2.09
Toll cost	-0.912**	0.389	-2.34
Pota	2.810	4.576	0.61
TRQB	-0.959	0.983	-0.98
Class 2			
Free-flow time	-0.103*	0.057	-1.78
Slowed-down time	*0.162*	0.114	1.42
Stop-start time	-0.622**	0.244	-2.54
Petrol cost	-0.837***	0.315	-2.65
Toll cost	0.016	0.239	0.07
Pota	2.770	4.716	0.59
TRQB	-0.778	0.989	-0.79
Estimated Latent Class Probabilities			
Probability Class 1	0.57***	0.155	3.64
Probability Class 2	0.43***	0.155	2.79
Log-Likelihood	-99.40		
McFadden Pseudo R^2	0.61		
***, **, * ==> Significance at 1%, 5%, 10% level.			

10.12 MNL Models with Route Choice Correlation: C-Logit and PS-Logit

The C-Logit and PSL-Logit models were tested to determine whether route correlation resulted in any significant difference to the Base MNL Model. There are various formulations for the determination of the commonality factor (CF) for the C-Logit Model and the path size (PS) factor for the PSL model, but in general they are estimated as the ratio of the common length of routes *i* and *j* and the total lengths of routes *i* and *j*. For the estimation of C-Logit and PSL-Logit models, the formulations for the commonality factor were based on **Equation 8** and **Equation 9** for C-Logit and **Equation 12** for PS-Logit.

As highlighted previously the route generation algorithm used in RAPP-UP three criteria when generating route alternatives, one being the minimization of route overlap of the alternative and optimal route. Only 10.3% (i.e., 75 of 728 individual observations) of the routes generated by RAPP-UP had route overlaps. The following route overlap characteristics in the choice set database were noteworthy:

- The maximum extent of route overlap for a single observation: 44%
- The average proportion of route overlap for those routes with overlaps: 16%
- The average proportion of route overlap for all routes: 1.7%

The low proportion of the number of routes with overlaps and the low proportion of total length of these overlaps was expected to influence the significance of the commonality and path size attributes in the C-Logit and PSL Logit models.

10.13 C-LOGIT Models

The C-Logit model was estimated with two forms of the commonality factor (CF), i.e., that shown in **Equation 8** and **Equation 9**. The form of the utility function used to estimate the C-Logit models was as follows for individual *i* using route *j* at time *t*:

$$U_{ijt} = b_1{*}fftime_{jt} + b_2{*}sdtime_{tj} + b_3{*}fftime_{jt} + b_4{*}petcost_{jt} + b_5{*}tollcost_{jt} + b_6{*}pota_{jt} + b_7{*}TRQB_{tj} + b_8{*}CF_{tj} + \varepsilon_{ij}$$

Where (the *ij* notation has been excluded):

- b_1, b_2,..b_8 are the coefficients to be estimated.
- *fftime*, *sdtime* and *sstime* are the free-flow, slowed-down and stop-start time attributes respectively.
- *petcost* is the petrol cost and *tollcost* is the toll cost.
- *Pota* is the probability of on-time arrival.

- *TRQB* is the toll road quality bonus.
- CF is the commonality factor.
- ε_{ij} is the random (error) term.

The C-Logit model outputs are shown in **Table 32**. For both models the coefficient signs are correct, and all the coefficients are significant at either the 99% of 95% confidence interval except for the commonality coefficient which is not significantly different to zero for both models. As highlighted earlier, this result is not surprising given the limited number of route overlaps in the choice data set and the low degree of overlap.

It is useful to compare these models with the result from the Base MNL Model with the toll road quality bonus (TRQB) shown in **Table 22** that has a log-likelihood value of -119.5. The C-Logit models do not add any further information or insights into the choice of route indicating that route correlation did not play a role in the model estimation. The coefficient magnitudes and degrees of significance between the Base MNL Model and the C-Logit models are similar.

Table 32: C-Logit Model Outputs

Utility Attribute	C-Logit Model with CF1 Formulation			C-Logit Model with CF2 Formulation		
	Coefficient	**Std Error**	**t-Ratio**	**Coefficient**	**Std Error**	**t-Ratio**
Free-flow time	-0.188***	0.037	-5.08	-0.192***	0.0371	-5.18
Slowed-down time	-0.223***	0.055	-4.06	-0.227***	0.055	-4.12
Stop-start time	-0.372***	0.090	-4.13	-0.374***	0.090	-4.16
Petrol cost	-0.348***	0.068	-5.10	-0.357***	0.069	-5.21
Toll cost	-0.188**	0.085	-2.22	-0.195**	0.085	-2.30
Pota	2.800**	1.096	2.55	2.760**	1.100	2.51
TRQB	-0.779**	0.351	-2.22	-0.791**	0.351	-2.25
Commonality CF Factor	-3.240	3.152	-0.92	-1.247	4.697	-0.27
Log-Likelihood = -118.9				-119.5		
McFadden $R^2 = 0.50$				0.49		
****, **, * ==> Significance at 1%, 5%, 10% level.*						

10.14 Path Size (PS) Logit Model

The path size logit model was also estimated with the same utility function as for the C-Logit models, but with the path size (PS) factor in place of the commonality factor (CF). Both a conventional PSL was estimated (i.e., an MNL model with PS utility correction) as well as an RPL model with PS utility correction. The PS-Logit model outputs are shown in **Table 33**. It is important to note that the MNL version was estimated with the full data set (364 observations) while the RPL model (with panel effects) was estimated with 344 observations. The log-likelihoods therefore cannot be compared. All the coefficients in the RPL model were assumed distributed normal and the cost coefficients were fixed. 700 Halton draws were for the RPL.

Table 33: Path-Size Logit (PS-L) MNL and RPL Model Outputs

Attribute	PS-Logit Model (MNL)			PS-Logit Model (RPL)		
	Coefficient	Std Error	t-Ratio	Coefficient	Std Error	t-Ratio
Free-flow time	-0.193***	0.037	-5.19	-0.247***	0.051	-4.81
Slowed-down time	-0.226***	0.055	-4.11	-0.357***	0.111	-3.21
Stop-start time	-0.374***	0.090	-4.15	-0.586***	0.136	-4.30
Petrol cost	-0.361***	0.068	-5.28	-0.406***	0.091	-4.56
Toll cost	-0.196**	0.084	-2.33	-0.213*	0.123	1.73
Pota	2.817**	1.100	2.56	2.397	1.510	1.59
TRQB	-0.784**	0.351	-2.23	-1.175**	0.490	-2.40
Path Size (PS) Factor	0.089	0.751	0.12	3.566	4.014	0.89
Standard Deviations						
Free-flow time	-	-	-	0.003	0.064	0.04
Slowed-down time	-	-	-	0.290**	0.104	2.17
Stop-start time	-	-	-	0.009	0.239	0.04
Pota	-	-	-	4.160*	2.514	1.64
TRQB	-	-	-	.0.003	0.502	0.01
Path Size (PS) Factor	-	-	-	0.011	4.504	0.00
Log-Likelihood = -119.5				Log-Likelihood = -101.3		
McFadden Pseudo R^2 = 0.49				McFadden Pseudo R^2 = 0.58		
****, **, * ==> Significance at 1%, 5%, 10% level.*						

Table 33 shows that the PS factor is not significantly different to zero in both models, although there is an improvement in the RPL model. This finding confirms the insignificance of the CF factor estimated for the C-Logit models. The PS-L RPL model log-likelihood can be compared to the Base RPL model results shown in **Table 27** that has a log-likelihood value of 101.8 and McFadden Pseudo R^2 value of 0.56. Therefore, while the PS-Logit (RPL) model has a better outcome than the Base RPL model, the PS factor itself is not significant. Furthermore, the PS-L RPL model coefficient values are similar to the RPL without the path size correction shown in **Table 27**. The values of travel times from the Base RPL model and PS-L RPL model are in **Table 34**. There are small differences in VTT values between the models.

Table 34: Values of Travel Time Savings for Standard and PS RPL Models

VTT (Rands/Hour)	Free-Flow VTT (Rand/hour)	Slowed Down VTT (Rand/Hour)	Stop-Start VTT (Rand/hour)
Standard RPL (Table 27)			
VTT (Petrol)	R35.86	R51.86	R84.29
VTT (Toll)	R68.76	R99.45	R161.64
PS-L RPL			
VTT (Petrol)	R36.50	R52.76	R86.10
VTT (Toll)	R69.58	R100.56	R165.07

11. CONCLUSIONS AND RECOMMENDATIONS

11.1 Achievement of Research Objectives

The objectives of this research were four-fold:

i. To undertake a review of transport choice modelling in South Africa for both mode and route choice contexts and appraise historical values of travel time that have been derived. The review of mode choice studies revealed that very few have been conducted. Those that have been conducted have suffered from poor experimental design and survey execution. The review highlighted large gaps in our understanding of route choice behaviour in South Africa, especially in the urban context. No urban route choice surveys of any type have been carried out in South Africa over the last 20 years nor has any route choice modelling research or studies been undertaken in this period despite the introduction of a large urban tolling scheme in Gauteng Province in 2011. This scheme subsequently failed, in no small part due to the lack of insight into motorists' willingness to pay tolls for travel time savings in urban areas. Reliable values of travel time for commuting motorists do not exist in South Africa drawing question marks under the economic appraisals that have been undertaken for transport schemes in this period. The review emphasised the need for research into motorists' route choice behaviour in urban settings in South Africa

ii. To develop a smartphone application for the collection of route choice data based on real-time traffic information. The definition of the route trip utility was the starting point for the app development. It was especially important to include the route travel time attribute in three different categories, i.e., free-flow, slowed-down and stop-start conditions. Other route attribute data to be included in the route choice sets and presented to the survey participant on their smartphone are the petrol cost (in Rands and derived from average retail petrol price and vehicle fuel consumption); and the route toll cost (if any) in Rands; and the probability of on-time arrival. The Route Choice Application - University of Pretoria (RAPP-UP) was developed for this purpose. RAPP-UP was successfully developed and implemented, so this objective has been achieved

iii. To undertake a small sample survey using RAPP-UP to collect route choice preference data for car commuters during the morning peak period in Gauteng Province. A sample of 48 commuters was recruited, providing a total of 364 choice sets. The sample was characterised by high incomes, their own car to commute to work, and having permanent employment. The participants also had to own a smartphone to be able to download the RAPP-UP application and take part in the survey. The survey was successfully implemented and so this objective has been achieved

iv. To estimate a range of route choice models based on discrete choice methods using on random-utility maximisation. Three model forms were used, i.e., multinomial logit (MNL) models; random parameters logit (RPL) (i.e., mixed logit) models; and C-Logit and path size (PS) logit models that specifically account for route overlap (i.e., route correlation). The models were estimated so this objective has been achieved. Where possible the results of the models were benchmarked against international experience.

Thus, all of research objectives have been achieved. The findings highlighted areas of further research required for the enhancement of the RAPP-UP application and the need for evaluation of the survey method and route choice models with a larger sample of participants. The model results and findings confirmed those found in international studies and have provided a good foundation on which further insights into commuter route choice behaviour in South African urban areas can be achieved.

11.2 The RAPP-UP Application

The RAPP-UP application was successfully developed and is now a stable platform for the execution of large-scale route choice surveys. The application was designed to be flexible and can hence be easily modified to accommodate:

a) Fewer or more utility attributes.
b) Attribute level data that can either be derived from platforms such as TomTom® in real time or can be externally determined and input into the application by means of look-up tables.
c) Manipulation (e.g., factoring) of the attribute levels to put more experimental control in the hands of the analyst.

The nature of smartphone survey applications is that their upfront design and coding cost may be large, but their application after that initial cost is low. Even modifications to the application can be done at low cost. It should be kept in mind that for largescale use of TomTom data downloads there is a fee that should be included in the survey cost.

From a user's perspective the application was considered by survey participants to be user friendly and easy to understand and use. Suggested enhancements from users were:

a) An improved alarm notification system to remind users to use the application at the start of their trip.
b) An automated method for displaying the users' survey account balances and cumulative trip data in real time.

c) Improved methods for regularly communicating general survey information to participants during the course of survey.
d) The development of a survey website to more efficiently communicate with participants and provide timeous feedback.

Three of the original participants considered the survey too onerous, i.e., after using the application once or twice they felt that further participation would be inconvenient. The inconveniences raised included not travelling to work from home every day, i.e., their destinations changed regularly, their trip to work was too infrequent to be completed in the three-week timeframe requirement, and the financial inducement to participate in the survey was insufficient. These issues highlighted that participant recruitment should be more selective, potential recruits should be better informed of the survey requirements, and perhaps the financial inducement to participate could be increased.

11.3 The Survey Execution

The practicalities of the survey execution involved:

a) Obtaining ethics approval from the University Ethics Committee
b) Preparation of the survey material for the participants. This included the preparation and distribution of the informed consent form; the socio-demographic questionnaire; the survey briefing and information note. Summarising the survey methodology and participant information in a short note of not more than two pages was challenging, as this included describing the downloading and use of RAPP-UP
c) Recruitment and briefing of the survey participants
d) Monitoring of the remote database to ensure the data sets that are downloaded on a daily basis are not corrupted. If users' data was found to be corrupted in transmission, they were contacted directly to identify the cause of the corruption.

The main obstacle found in this process was the recruitment of the survey participants. Difficulty was found recruiting participants from the university students and staff and using social media. It was found to be more practical to recruit participants from a market research company.

11.4 Remote Database

The transmission and storage of the route data in the remote cloud-based database was found to be efficient and effective. The transmission of route data from smartphone to database was fast and efficient and was usually completed within a few minutes of trip completion. The remote database was available at all times and there was never any data loss.

The downloading of the datasets from the database using Windows command files in JSON format was efficient and rapid. The conversion of JSON files into CSV format was straightforward and the conversion of CSV files to GIS formats using an online converter for plotting is also straightforward.

11.5 Route Choice Model Outcomes

Several model types were estimated, i.e., MNL, RPL, LCM, C-Logit and PS-Logit models. The models were all statistically significant to varying degrees. However, the small sample size meant that the model outputs were only applicable to a small sample of Gauteng motorists that was biased toward high income motorists. The main findings from the estimated models were as follows:

a) Multinomial logit models can successfully be estimated from the RAPP-UP preference data due to the small proportion of overlapped routes in the sample (i.e., 10%) as well as the low proportions of overlap for those routes with overlapped sections (average percentage overlap for overlapped routes was 16%). If there were higher proportions of overlapped routes, the statistical significance of these models may deteriorate.
b) It is noticeable that the pota coefficient is significant in the MNL models at the 99% confidence interval, but not significant in the RPL models. The statistical significance of the toll cost coefficient also deteriorates in the RPL models.
c) For the same reasons, the application of C-Logit and PS-Logit revealed that the commonality factor (for C-Logit) and path size factor (for PS-Logit) coefficients were not statistically significant. The application of an RPL model with the PS factor improved the significance of the factor, but it was still not statistically significant different to zero.
d) The LCM models produced counter-intuitive positive coefficient values for slowed-down time, even though the coefficient was not statistically significant.
e) Random Parameter Logit (RPL) models with different mixing distributions useful insights into the route choice behaviour of the survey sample. The low coefficient standard deviations reflected little choice heterogeneity in the sample of participants. The only attribute coefficient that had a significant standard deviation was the slowed-down time. The coefficients of these models were more statistically significant than their equivalent MNL models, with normal mixing distributions providing the most robust solutions. A larger sample size is likely to reveal heterogeneity in route choice behaviour requiring different forms of RPL models to be estimated and evaluated.
f) The low variance in the RPL model attribute coefficients meant that there was little heterogeneity in the free-flow, slowed-down and stop-start values of travel time. However, the RPL models provided higher estimates of VTT than the MNL models.

g) All the MNL and RPL models showed high statistical significance (at the 99% confidence limit) for the free-flow, slowed-down and stop-start time attribute coefficients. Therefore, the survey participants perceived differences between these three levels of congestion. The magnitudes of the coefficients for these attributes increased with increasing congestion and these results confirm the findings from international studies. The congestion multiplier analysis revealed conformity with internally estimated values.

h) The MNL and RPL model petrol cost coefficients were consistently significant at the 99% confidence interval. The petrol cost constituted the largest proportion of total trip cost when a participant used a tolled section in their route and incurred a toll cost.

i) The toll cost attribute coefficients were significant at the 99% confidence interval for the MNL models but reduced to 90% in the RPL models. In all the models the petrol cost coefficient was larger in magnitude than the toll cost coefficient. This result reflected a scale effect – the average trip petrol cost on tolled routes is several magnitudes higher than the average toll (on tolled routes). This effect of this difference in coefficient magnitudes resulted in significantly higher levels of willingness-to-pay a toll for travel time savings.

j) The probability of on-time-arrival (pota) coefficient was significant in all of the MNL models, but not significant in any of the RPL models. This result in the RPL models was surprising given that international studies have shown that on-time arrival is a significant utility attribute, and motorists are willing-to-pay for on-time arrival at similar to levels to that for travel time savings (Bliemer, 2020). The reason why the attribute was not significant in the RPL models requires investigation. Possible reasons are the measurement of the attribute i.e., a probability of on time arrival in percent may not be fully understood by participants, and it may be better understood if the number of minutes early or late is specified. Specifying the measure in minutes will also make it easier to quantify the value of on-time arrival.

k) The toll road quality bonus (TRQB) (a dummy attribute in the utility expression) that quantified the benefits (or disbenefits) of using tolled freeways (other than the observed trip times and costs in the utility expression) in Gauteng was found to be significant. Importantly the coefficient had a negative sign which means that survey participants had a negative perception of using the tolled freeways. This is an interesting result that may confirm the negative perception of the GFIP e-toll system held by the Gauteng public and perhaps a broader negative perception toward the payment of urban tolls.

11.6 Values of Travel Time (VTT)

The RAPP-UP surveys were done during a time of traffic demand recovery from the COVID pandemic between April and July 2022. Traffic volumes were ramping up to pre-COVID levels at that time, but the demand legacies of COVID were still present. The most important of these was working from home (WFH), that has had a material (but as yet formally unquantified) impact on traffic demand. The net result of the demand suppression has been an observed higher proportion of free-flow time on routes than slowed down and stop-start time. This may have impacted on the values of travel time associated with the three components of trip time.

The values of travel time between the various models show consistency in several ways:

a) The VTT's derived from operating and toll costs all increase with increasing levels of congestion. The VTT for start-start driving conditions is approximately double that of the free-flow time across all the models. This finding is in line with international experience.
b) The willingness to pay a toll for travel time savings is consistently higher than the values derived from operating costs. On average, for the MNL models the VTT derived from toll costs are 36% higher than those derived from operating costs across all model types. For the RPL models this ratio increases to 100%. However, there is a scale effect is in play with this result as the average petrol cost (on tolled routes) is a factor of five times higher than the average toll charge (on tolled routes).
c) The following chart shows the range of VTT's estimated from the MNL and RPL models for derived from operating (petrol) and toll costs. The TRQB is included in both models. These models are described in **Table 22** and **Table 27**. The table illustrates the consistently higher values derived from the route toll charge, as well as the higher values obtained from the RPL model. The highest VTT of R160/hour is derived from the RPL and derived from the willingness-to-pay a toll for time savings in stop-start conditions. The lowest value of R32/hour is derived from the operating cost in free-flow time using the MNL model.

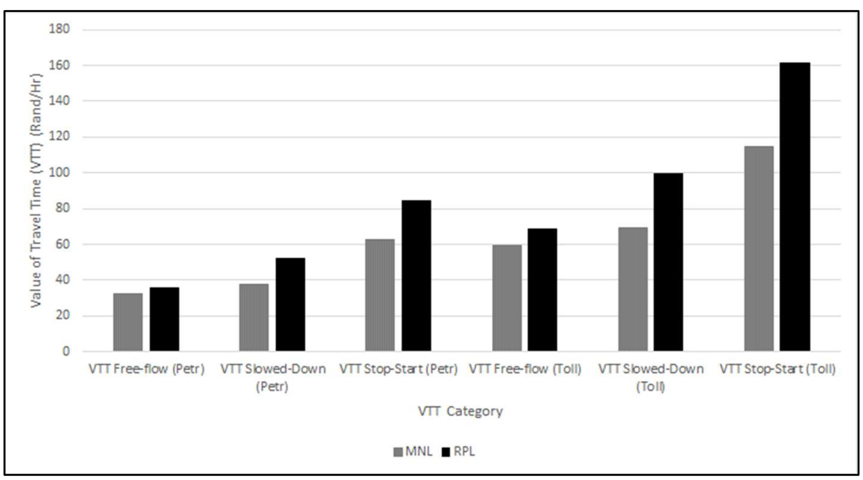


Figure 67: Comparison of Values of Travel Time (VTT by Category) from MNL and RPL Models (Rand/Hour)

The analysis highlights that using a single VTT for all users in a transport demand model or economic appraisal is not appropriate and will lead to potentially significant errors in mode and route choice modelling, as well as under or overestimating the economic feasibility of a road-based transport initiative.

11.7 Further Research

Each stage of the research gave rise to important issues that requires further investigation and research. These were:

- The utility attribute that was introduced to indicate the route travel time reliability, i.e., the probability of on-time arrival (p*ota*) was found to be significant in the MNL models, but not in the RPL models. International experience has shown that the trip time reliability is an important component of trip utility and commuters are willing-to-pay for this reliability. The specification of *Pota* as a probability (percentage) needs to be investigated and possibly changed to an actual time (measured in minutes) of arriving early or late at the destination. This would make route trip time reliability clearer to the survey participants and would also enable the quantification of the willingness-to-pay for trip time reliability.
- Due to the nature of the route generation algorithm used in RAPP-UP, there was seldom any route overlap between the optimal route and the alternative route. If there was an overlap it was short. This impacted on the statistical significance of the commonality factor and path-size factors included in the utility expression of the C-Logit and PS-Logit models. There are two possible schools of thought on this matter. The first (Prato, 2009) is that in dense urban road networks, it is very likely that there will common sections on two alternative routes and hence the adoption of MNL models will not be appropriate and utility adjustment as per the C-Logit and PS-Logit models is necessary. On the other hand, the route generation algorithms of route guidance platforms such as TomTom®, Waze® and Google Maps® generate realistic optimal and alternative routes and apply these algorithms across the world for millions of travellers every day. If users did not place reliance on these routes, the platforms would not be popular, seldom used and either changed or be taken off the market. It is also evident that research and project studies (Hensher, 2001; Bierlaire, et al., 2010; Hensher, 2001; Hensher & Rose, 2004) have not considered the implications of route overlap on route choice, and have applied RPL models, a discrete choice model that can approximate *any* random utility model (McFadden & Train, 2000).
- The small sample that was recruited for the proof-of-concept investigation was biased toward high-come car commuters. The model results thus reflect the route preferences of this limited, focused market segment and should be interpreted with this kept in mind. A significantly larger sample of car commuters should be recruited across a wider socio-economic and demographic population in order to draw firmer conclusions about route choice preference from the broader motoring public. This larger sample size would require consideration of the

very large remote preference database that would result and how to automate the processing of the data, plotting of routes and formatting the data for input into NLOGIT.

- The impact of traffic demand suppression should also be kept in mind, as this may have affected the estimated values of travel time. Any new surveys using RAPP-UP should ideally be done when traffic demand has stabilised.

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APPENDIX A: RAPP-UP SURVEY PARTICIPANT SOCIO-DEMOGRAPHIC QUESTIONNAIRE

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA
Faculty of Engineering, Built Environment and Information Technology
Centre for Transport Development

SOCIO-DEMOGRAPHIC QUESTIONNAIRE FOR PARTICIPANTS IN THE ROUTE CHOICE TRAVEL SURVEY

SEPTEMBER 2021

Thanks you for participating in the survey. Please note that the information provided in this questionnaire will be kept in the strictest confidence and will not be shared with any third party. The information will be retained at the Centre for Transport Development and destroyed when the research is complete.

Question 1: Please provide you Gmail email and cell phone number. These will be used for communications between the survey manager Mr Gary Hayes. Your final Takealot voucher will be emailed to you at this email address.

Email address: ________________@gmail.com __

Cell phone number: ____________________________________

Question 2: Your Gender (mark with an X): Male:_____ Female:______ Other:_______

Question 3: Your Age Bracket: Please place an X into the age bracket you fall into:

Age band 18-25 years:_____________ Age band 26 – 30 years: _______________

Age Band 31-40: years ____________ Age band 41-50 years: ________________

Age band 51-60 years: ____________ Age band > 60 years: __________________

Question 4: Income Bracket: Please place an X next to the income bracket that you fall into. This income is your gross income per month, i.e., before taxes and deductions:

Income bracket 1: R0 - R10,000 per month: __________________

Income bracket 2: R10,001 – R20,000 per month: __________________

Income bracket 3: R20,001 – R30,000 per month: __________________

Income bracket 4: R30,001 – R40,000 per month: __________________

Income bracket 5: More than R40,000 per month: __________________

I do not have salary income: __________________

__Question 5:__ Home and Work Suburbs: Please write the name of the suburb and city where you live and where you work:

Home suburb & city: ___________________________

Work suburb & city: ____________________________

__Question 6:__ Commute trip departure and arrival times. Please indicate your *typical* time of departure from home and arrival at work when you commute.

Typical departure time from home: _____________am ___

Typical arrival time at work: ______________ am ___

__Question 7:__ Typical route to driven to work: Please answer the following questions with a Yes/No answer:

Do you always use the same route to work (assuming no traffic accidents or incidents)? _________

Do you change your route based on real-time traffic information, e.g., from TomTom, Waze, radio etc? _________

Question 8: The trip times and costs for your normal commute route: Please provide your typical travel times and costs for the route you normally use to travel to work from home:

Typical total travel time (door to door): ________ minutes

Total petrol cost (per trip): __________ Rands

E-Tolls (if any per trip): ______________ Rands

Total trip distance: ________________ km.

__Question 9:__ Your employment status. Please select from the following list by marking with an X:

Full time employed: ____________

Part-time employed: _________

Unemployed: ______________

Retired: ________

Other: ______________

__Thank you for completing the survey.__

ANNEXURE B: RAPP-UP SURVEY PARTICIPANT INSTRUCTION FORM

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA
Faculty of Engineering, Built Environment and Information Technology
Centre for Transport Development

UNIVERSITY OF PRETORIA: ROUTE CHOICE TRAVEL SURVEY

GUIDELINES FOR SURVEY PARTICIPATION

Thank you for participating in the University of Pretoria Route Choice survey. The purpose of the survey to is to understand the route preferences of motorists commuting between home and work. The survey data will be used to estimate route choice models that will be used to assist with the planning of roads in Gauteng Province. The research is being undertaken by Gary Hayes, a doctoral student at the Centre for Transport Development at the University.

The survey requires you to download two smartphone applications from the Google Play Store onto your smartphone. The first is called the *Travel Diary*, and the second is called *RAPP-UP* (Route choice Application at UP). Each is used separately starting with the Travel Diary app followed by RAPP-UP. The following links can be used to download the apps from the Google Play Store onto your smartphone. Your @gmail account has been registered to allow you to download the apps.

Travel Diary: https://play.google.com/store/apps/details?id=io.flyingmongoose.traveldiary

RAPP-UP: https://play.google.com/store/apps/details?id=io.flyingmongoose.rappup

At the start of the survey each participant is allocated R250 into their survey incentive account. When they choose a route with a toll fee, it is deducted from their incentive account. At the end of the survey the balance of the incentive account will be paid into the bank account of each participant or they will be sent a Takealot voucher for the same value. Participants will be asked which they prefer.

For any questions or queries about using the apps please contact Gary Hayes either by email or WhatsApp at:

- Email: u16401868@tuks.co.za
- Cell number: 063 618 1855

A WhatsApp Group will be established for easier communication with Gary. When the Apps are installed please follow these instructions.

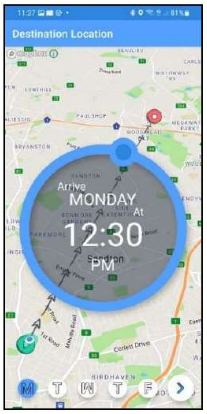
1. Travel Diary: This app simply records your route when you travel from home to work and is used to make sure your smartphone can be tracked. When you start your trip to work simply activate the app and wait for your location to be fixed. A small window will tell you when the fix has been made. Then drive to work as you normally would using your preferred route. Deactivate the app when you have finished your trip at work.

Please use the *Travel Diary App* for two (2) trips to work. The days do not have to be consecutive.

2. RAPP-UP: This app presents the route choice experiment to you on your smartphone and should also be used for the trip from home to work. When entering the app you will see a road map background. For each trip please reset your trip settings by tapping on the reset button, and the app will reset itself.

When activated the app fixes your trip origin (i.e. start) location and shows it on your smartphone screen map. Alternatively you can type your suburb into the search window and then refine your location by moving the background screen map to your exact position.

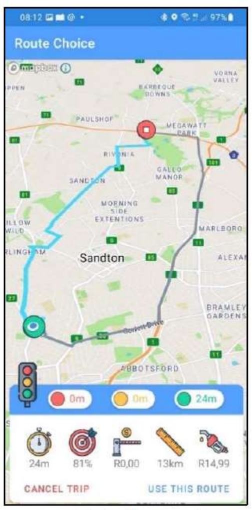
1



Then you are asked to enter your trip destination (i.e. work) location. You can type the suburb name into the search window, and then refine the location by moving the background screen map. You can also specify any waypoints between your trip origin and destination. Waypoints are places you must pass by on your trip, for example to drop children at school. Set the waypoint locations as for the origin and destination locations.

When you have completed this, the app then asks you to confirm the day you are travelling on, and your preferred time of arrival using the circular clock as shown in the figure on the left. Adjust the clock by moving the button on the outer edge of the clock.

When you have done this, the app will present you with two alternative routes on the background map between your current location (green pin) and your destination (red pin). The routes are shaded in either blue or grey as shown in the next figure. For the route in blue, the trip times and costs are shown at the bottom of the screen. To swop between routes simply tap on the grey route. The objective is for you to carefully trade-off the route time and cost characteristics and then choose your preferred route. You then need to actually drive your preferred route.



The route times and costs have the following meanings:

- The total travel time in minutes is  shown by the stopwatch icon. This is the real trip time for the route taken from TomTom for current traffic conditions
- The green, orange & red traffic lights  show the proportions of trip time in minutes for the route stop-start time (red) for high congestion; the slowed-down time (orange) for less congestion; and the free-flow time in green for low congestion levels
- The target  icon shows the route trip time reliability measured in percent and shows the likelihood of reaching your destination on time using that route. If the target value is 85%, then there is an 85% chance of getting to your destination on time
- The toll barrier icon  shows the cost of the toll fee for the route in Rands. The tolls are only applicable to the current Gauteng e-toll freeways
- The ruler icon is the total length of the route in  kilometres. This distance is very accurate
- The petrol nozzle icon  is the cost of petrol in Rands when using this route. The petrol cost is based on the current price of petrol in Gauteng

After you have chosen your preferred route, please drive to work using that route. To assist you the application shows you the route on your screen and your location on the route in real time. If for any reason you are unable to use your preferred route do not abandon the survey but complete your trip.

Please use the *RAPP-UP App* for eight (8) trips to work. They do not have to be consecutive days.

Thank you once again for participating in this survey.

ANNEXURE C: RAPP-UP APPLICATION TECHNICAL SPECIFICATION

TECHNICAL SPECIFICATION OF RAPP-UP REMOTE PARSE DATABASE

1. The Transmission of Data from Satellite to Remote Database

The transmission of signals between satellites and smartphone GPS devices and then onto remote databases via cell phone towers is shown in the following figure. Satellites in earth's orbit continually send signals to earth at specific frequencies that are received by GPS devices. Longitude and latitude coordinates are generated for each pulse received by the GPS device. This enables the straight-line distance between the successive two points on the surface of the earth to be accurately measured. The shorter the pulse frequency, the shorter the straight-line distance between successive pulses, and the more accurate the distance between them. The time difference between signal transmission from the satellite and receipt by the GPS receiver is also accurately measured. This time together with the straight-line difference allows an average speed between the two points to be calculated. Three satellite signals are required for location triangulation, and a fourth is required for altitude estimation. The location data is calculated by the GPS device, and then transmitted terrestrially via GSM using cell towers to the remote database that has been established for this research. There is a time lag between calculation of the location data by the cell phone GPS and receipt by the remote database and this difference is shown in the time stamps received by the database. MongoDB has been used as the cloud-based software platform for the remote database. This database is accessed using the internet, and the security restriction requires a username and password for access.

shows the communication links between the satellite, smartphone, cell tower and remote database.

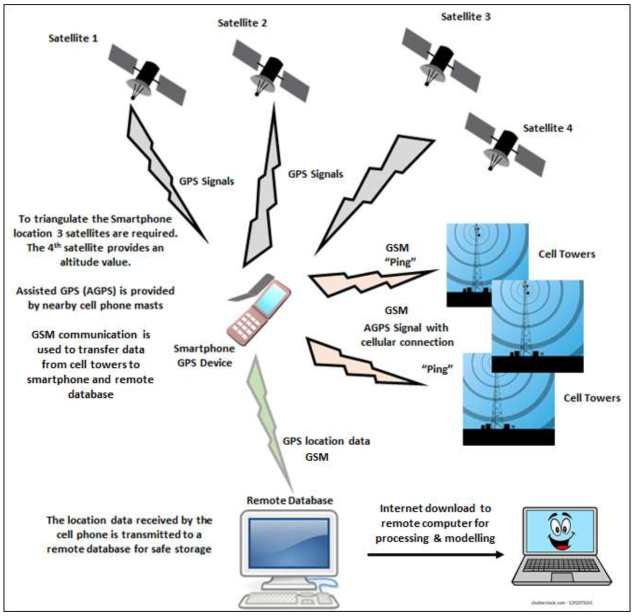


Figure 1: Illustration of the Transmission of Location Data between Satellite (GPS) and Remote Database (GSM).

2. Route Choice Survey Applications

There are separate two separate smartphone applications (apps) that have been developed and used for obtaining travel data from the route choice survey participants. The apps only operate on Android smartphones, and are as follows:

i. **Travel Diary App**: This app simply records the routes that participants have used. It has been used in the context of observing the typical routes used by participants, i.e., without any route preference data
ii. **RAPP-UP App**: This is the route choice experiment app that is used to generate alternative routes and their associated choice tables.

Each app has a separate MongoDB database. These are discussed in the next sections.

3. MongoDB Database Structure

MongoDB is an internet-based open-source document-oriented database. It is used to store a large amounts of data in the cloud and also allows manipulation of the data. MongoDB is not based on the table-like relational database structure but provides an altogether different mechanism for storage and retrieval of data, that's why known as NoSQL database. Here, the term 'NoSQL' means 'non-relational'. The format of storage is called BSON (similar to JSON format).

Important parts of MongoDB are as follows:

- **Drivers:** Drivers are used to communicate with MongoDB. The drivers support by the MongoDB are C, C++, C#, and .Net, Go, Java, Node.js, Perl, PHP, Python, Motor, Ruby, Scala, Swift, Mongoid.
- **MongoDB Shell:** MongoDB Shell or mongo shell is an interactive JavaScript interface for MongoDB. It is used for queries, data updates, and it also performs administrative operations. Data is exported from the MongoDB Shell in the Windows command window using export scripts that are linked to the database
- **Storage Engine:** It is an important part of MongoDB which is generally used to manage how data is stored in the memory and on the disk. MongoDB can have multiple search engines. Any search engine can be used or the default search engine, known as *WiredTiger Storage Engine*. It works efficiently for reading and writing data.

Two MongoDB databases have been used for collecting trip data from survey participants. The first collects trip data from the Travel Diary app, and the second from the RAPP-UP app.

Each MongoDB database is located on a remote server and contains several parse dashboards that have been developed to store the various Travel Diary and RAPP-UP data sets. A parse dashboard is a spreadsheet like database that allows for editing and manipulation of large datasets. Each dashboard contains specific data either related to the routes that were tracked using the Travel Diary app, or route options presented in RAPP-UP (i.e., the choice sets) or for the route actually driven after selection in RAPP-UP. Within each dashboard are several, separate databases within which the various data sets are stored. The dashboard layout is shown in Figure 2**Error! Reference source not found.**.

The Travel Diary and RAPP-UP MongoDB parse dashboards require permissions to access the database, specifically a username and password. The MongoDB Travel Diary remote dashboard is located at the following internet address:

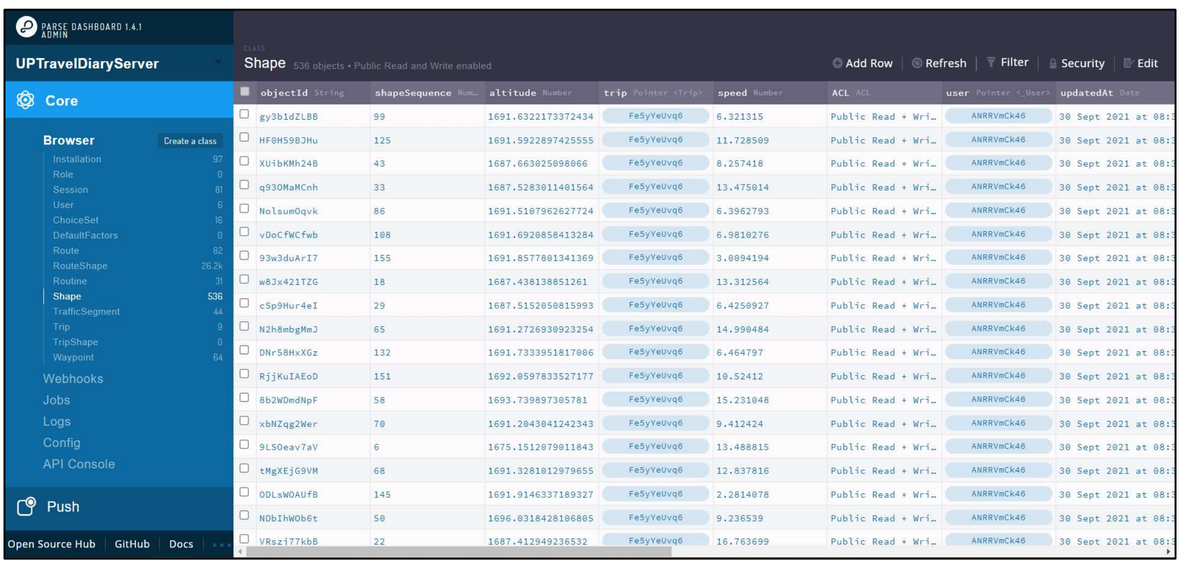
https://up-travel-diary-server.herokuapp.com/dashboard/apps/UPTravelDiaryServer/browser/_Installation

The RAPP-UP dashboard is located at:

https://up-travel-diary-server-dev.herokuapp.com/dashboard/apps/UPTravelDiaryServer/browser/_Installation

Figure 2 shows a screenshot of the RAPP-UP shapefile dataset dashboard. The other dashboards can be seen on the left hand side of the figure, i.e., User, *ChoiceSet*, *DefaultFactors* etc. The contents of each of these dashboards is described in a following sections. For the Shape dashboard shown, it can be seen that it contains data related to the *objectId*, shape sequence, altitude, trip id, speed etc. This data can be extracted from the dashboard using Windows script files. This process is described in the next section.

Figure 2: MongoDB Remote Server with Dashboards



4. Downloading Data from the Remote MongoDB Database

Downloading the various route and trip databases from the parse database requires running short command files from the Windows Command Prompt window. The user must be logged into the parse database when this is done, but not into a specific dashboard. When entering the command prompt window in Windows, the root directory is shown, e.g., c:\\Users. The path to the directory where the command files are stored must then be specified using Dos commands, e.g., *cd Routes* if Routes is the directory where the command files are stored. When the command files are run, the output files are stored in the same directory.

The command files are small script files with a *.sh* extension that execute the commands for downloading the data from the parse dashboards. The names of the command files and output file names are shown in the next sections for each database.

When running a command file, the Dos command *bash* should be used. For example, if the command files name is *route_collection_JSON.sh*, then the command file is:

bash route_collection_JSON.sh.

This command will execute the commands and create the output file in the same directory. Important points to note are:

- When the command file is run, the output file is created, and it overwrites any old output files. It is best to change the name of the output file after running the command file and putting the output file into a separate directory
- The command files can be edited in a text editor if it required to change the output file name.

The output files are in JSON format (Java Script Object Notation). The files are named *filename.json*. These files can be edited in a text editor and converted to CSV format. CSV files can be read into Excel for analysis. The CSV files containing coordinates can be converted into XML, GPX and KMZ files and then read into platforms such as Google Maps® and Google Earth®.

The following figure shows the process, from extracting the json file from the database to plotting the route in Google Maps® (GPX format), Google Earth (kml format), ArcGIS® (GPX format) or OpenStreetMap® (GPS format).

Figure 3: Data Extraction Process – from Database to Google Maps®

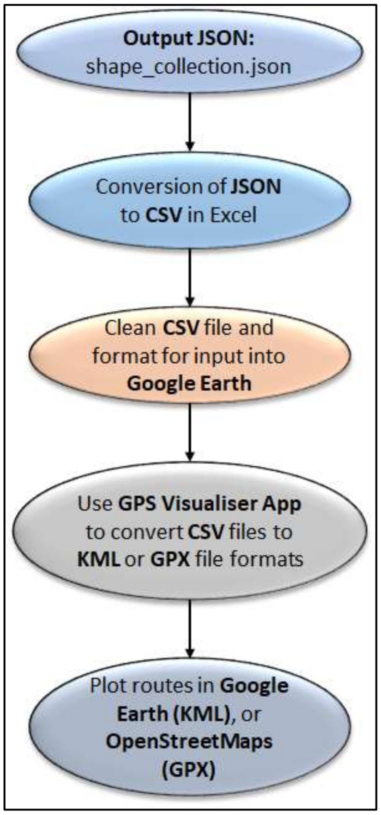


Figure 3 shows the process of downloading the various data files from the parse database, and then converting the files to CSV & Excel format for converting to the required format, i.e., KML, GPX etc. The analysis of the data is done using the Excel files, and the plotting using the KML and GPX files.

It is best to manipulate the data (e.g., splitting columns of data) in Excel as this relatively straightforward. The final data set should be saved in a CSV file format for importation into various software platforms for viewing the route such as Google Earth®, Google Maps®, OpenStreetMap® or ArcGIS®. The CSV file can be converted into the GPX format using online converter software. The recommended free platform is GPS Visualizer at the following address: https://www.gpsvisualizer.com

It is important to note that to convert the CSV files to KML or GPS format, the files must be in the correct format with the required headings. For example, to plot a route with a GPX file using Google Maps®, the CSV file must have at least three fields for the segment number and longitude and latitude coordinates for each segment.

The format of the CSV input files for conversion to GPX, KML and other formats is described at the following website:

https://www.topografix.com/gpx_manual.asp

5. MongoDB Database for Travel Diary App

The Travel Diary App is a passive route tracker. It records the route details of trips made by the survey participants. The MongoDB database records three data sets:

i. A user data table. This table contains the survey participant id's with their email addresses and a date stamp for when they were added to the user list by the administrator. The users can be added directly to the user data table in the dashboard
ii. A trip collection table: This table records the trips made by each survey participant. Each trip is allocated an id together with the date and time stamp for the trip. The user id is included in the trip data for cross referencing
iii. A shape table: This table contains the details of the routes travelled by each participant. The routes are defined by route segments and node coordinates for each segment (these are recorded every 5 seconds). A sequence of segments makes up a route. Each coordinate is allocated an id together with various date and time stamps. Pairs of coordinates define segments of the routes for which a straight-line distance is calculated and presented. Other data provided for each segment are the bearing, average speed and travel time.

It is important to note that three date and time stamps are provided in the various outputs as follows:

i. *ReceivedAt*: This is the date and time that the GPS device in the smartphone received the signal pulse from the overhead satellite/s. An example is *30 Sept 2021 at 08:25:05 UTC.* The data entry can be for any identifier e.g., a user, route or route segment
ii. *CreatedAt*: This is the date and time that the entry was created in the remote database. An example is *30 Sept 2021 at 08:30:26 UTC.* Note that this time will always be delayed from the *ReceivedAt* time. This can be for several reasons such as the smartphone GSM signal was poor and the data was transmitted when the signal improved or when the smartphone entered into a wi-fi area that enabled data transmission
iii. *UpdatedAt*: This date and time indicates when the data entry to the remote database was updated for any reason. An example is *30 Sept 2021 at 08:30:26 UTC.* If this time is the same as the *CreatedAt* timestamp, then the data has not been updated.

Note that UTC is standard universal time, which is the same as Greenwich Mean Time (GMT). South African time is UTC + 2 hours.

For trip data specifically, two additional date and time stamps are provided, i.e.,:

i. *DepartAt*: The date and time of the departure of the trip (i.e., the trip start time)

ii. *ArriveAt*: The date and time of the arrival of the trip (i.e., the trip end time).

The following tables summarises the individual data sets contained in each dashboard. Each table describes the data name as well as a description of the data. In addition, the export script file name is shown and the output file name that is generated in JSON format. The full text script of the export process is shown.

Note that:

- The user does not need to specify this full script if the Dos command scripts are run as described earlier
- There are common data names in the tables that enable users, trips and shape data to be linked.

Access Control Dashboard

This dashboard is used by the database administrator to add now survey participants to the database. The users name (forename and surname) and gmail email address must be entered. Once entered the database generates an ObjectId, i.e., a user code. The user id is a 10 digit alphanumeric code that is used to identify the user in the subsequent database dashboards. An objectd example is JLlujkY2Mx. The participants gmail address is also used to grant permission to download the Travel Diary and RAPP-UP applications from the Google Play Store®.

User Dashboard

The user dashboard stores several sets of data as per the following table.

Table 1: User Dashboard

Data Name	**Description**
ObjectID	10 digit alphanumeric User ID code, e.g., JLlujkY2Mx
Name	The users name, e.g., Gary Hayes
UpdatedAt	The date and time the user was created in the database, e.g., 15 Sept 2021 at 17:35:10 UCT
Username	This is the email address of the user, e.g., u16401868@tuks.co.za
Export script file name	Export_User_Collection_JSON.sh

Export file name:	User_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldiaryphase1.pq2x9.mongodb.net/TravelDiaryPhase1 --collection _User --type json --out ./User_Collection.json	

The next table shows the structure of the trip data file, i.e., the trip that was tracked for a specific user.

Table 2: Trip Dashboard

Data Name	**Description**
ObjectID	10 digit alphanumeric trip ID code, e.g., 07zsQsoZwk
Departuretime	The time of the start of the trip i.e., when the Travel Diary App was activated, e.g., 12 Sept 2021 at 05:15:30 UTC
Username	The user id code as per the User Table
UpdatedAt	The date and time the trip id was updated in the database, e.g., 15 Sept 2021 at 17:35:10 UCT
Duration	The duration of the trip (i.e., between app activation and deactivation) in seconds
Distance	The trip length in kilometres
CreatedAt	The date and time the trip id was created in the database, e.g., 15 Sept 2021 at 17:35:10 UCT
Export script file name	Export_Trip_Collection_JSON.sh
Export file name:	Trip_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldiaryphase1.pq2x9.mongodb.net/TravelDiaryPhase1 --collection Trip --type json --out ./Trip_Collection.json	

This last table shows the shape collection dashboard. This data contains the detailed trip information, i.e., coordinates, coordinate altitude etc.

Table 3: Shape Collection Dashboard (Shape)

Data Name	**Description**
Objectid	Alphanumeric segment ID code for the route segment e.g., YApvq3A6Le. The segment identifiers for each route are unique
Shape Sequence No	The segment sequence number (in ascending order) from 0….n for n segments.
Altitude	Segment altitude in meters, e.g., 1613.1 m
TripID	Alphanumeric trip ID code e.g., L5E1HnBezP. The trip identifier is constant for all segments in the route
Speed	The average speed on the segment in meters/second
User id	The user id for whom the routine was created, e.g., ANRRVmCk46 for Gary Hayes
CreatedAt	The date and time that the segment data was created (or first entered into) in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
UpdatedAt	The date and time that the segment data was updated in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
Bearing	The segment bearing (i.e., direction of travel) in decimal degrees
ReceivedAt	The date and time that the segment was received by the smartphone GPS device , e.g., 15 Sept 2021 at 17:39:20 UCT
Location	The segment a-node coordinates in decimal latitude and longitude. The next sequential segment a-node is effectively the b-node of the preceding segment
Distance	The length of the segment in meters. Note this is a straight line distance
Export script file name	Export_Shape_Collection_JSON.sh
Export file name:	Shape_Collection.JSON
Script: ongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldiaryphase1.pq2x9.mongodb.net/TravelDiaryPhase1 --collection Shape --type json --out ./Shape_Collection.json	

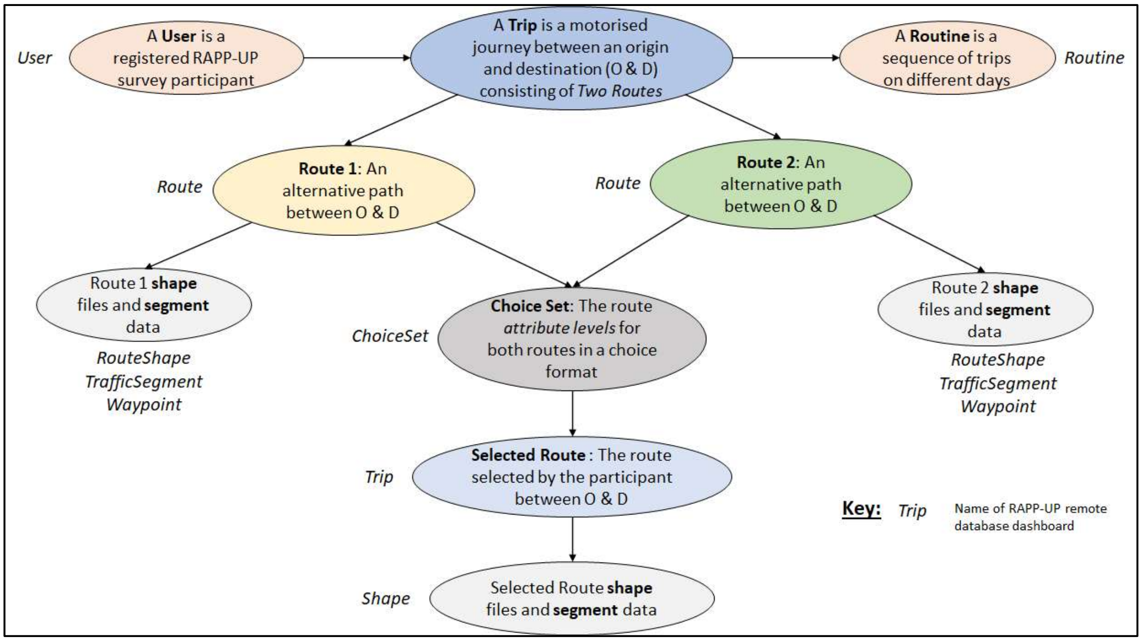
5. RAPP-UP Data Structure and Definitions

The data structure and terminology of RAPP-UP is shown in Figure 4. The figure shows the definition of a trip; the routes, a choice set; the selected route and the selected route shape and segment data. The parse database dashboard names are also shown.

Note that:

- A user is a survey participant who is registered to download RAPP-UP from the Play Store
- A trip is undertaken on a particular day and consists of two route alternatives
- A routine is a sequence of trips on consecutive (or non-consecutive) days making up the total survey for a particular user
- A route is a path between O & D, for which shape and segment data are provided for plotting and analysis
- The choice set contains both routes and their associated attribute levels, some of which are derived from near real-time data, e.g., the travel times
- The selected route is the route chosen for travel by the user
- The selected route "as driven" data is transmitted to the remote database by the GPS tracking device on the users smartphone.

Figure 4: File Structure and Terminology of RAPP-UP Application



The following table summarises the parse database dashboard names, the data in the dashboards and the export file names for extracting the data.

Table 4: Summary of Parse Database Dashboard Names, Contents and Extraction Filenames

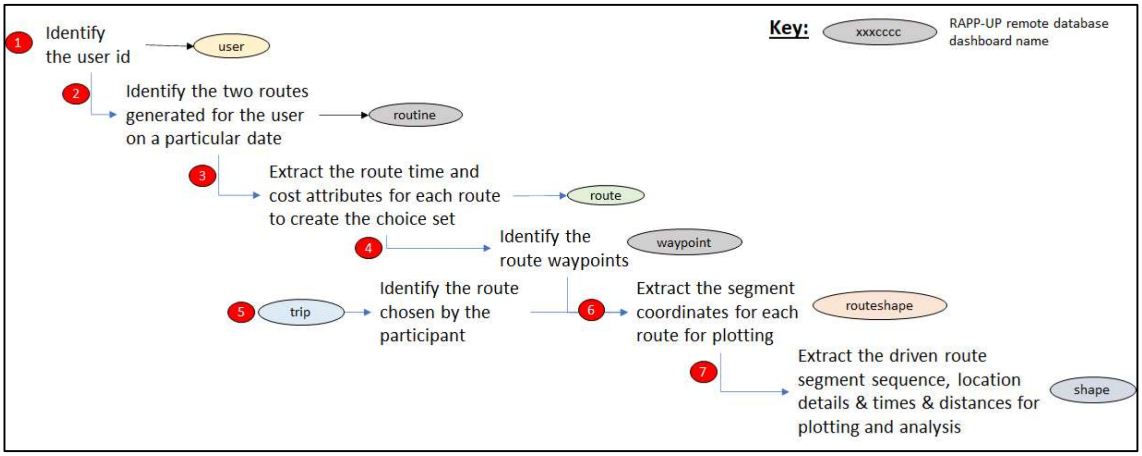
Parse Database Dashboard Names	**Description of Contents**	**Extraction Command File Name**
User	List of users participating in the survey with allocated id's	Export_user_collection_json.sh
Routine	Summary of routes generated ion subsequent days of the survey	Export_routine_collection_json.sh
ChoiceSet	Set of fixed data and factors that are used in the eight choice sets. These include the toll and pota factors for each observation; the day for which the choice set is applied; and the route number against which the factors are applied.	Eport_choicest_collection_json.sh
Routine	A set of trip id's made by the participant over the 8 surveys days	Export_routine_collection_json.sh
Route	The route id and time and cost attribute levels for the two alternative routes used in the choice set for a particular survey day. These are used in the survey choice set	Export_route_collection_json.sh
TrafficSegment	The segment data for each of two alternative routes for a particular survey data including segment no., segment length and travel time classification code	Export_trafficsegment_collection_json.sh
Routeshape	The alternative route segment data including the route id, segment sequence	Export_routeshape_collection_json.sh

	no., the location (i.e., latitude and longitude coordinates)	
Shape	For the route driven by the participant, the segment id & sequence, locations coordinates, speed, time and altitude	Export_shape_collection_json.sh
Trip	The trip information for the ***chosen route*** including route id, trip tine and duration	Export_trip_collection_json.sh
Waypoint	The waypoint coordinates for each alternative route for a specific survey	Export_waypoint_collection_json.sh

Users (i.e., survey participants) are added to the database using the *AccessControl* dashboard in the database. Only an authorized administrator is permitted to add additional or new users. The names and email addresses of each survey participant must be added to firstly allow them to download the application from the Play Store, and secondly to start recording their survey data in the database.

When extracting data from the database for plotting and analysis, the sequence of data sets from the remote database are as per the following figure. There are seven steps required to prepare the choice set data for the two alternative routes for input into NLOGIT, i.e., steps 1, 2 and 3; extracting the route segment and location data for plotting and analysis.

Figure 5: File Structure and Terminology of RAPP-UP Application

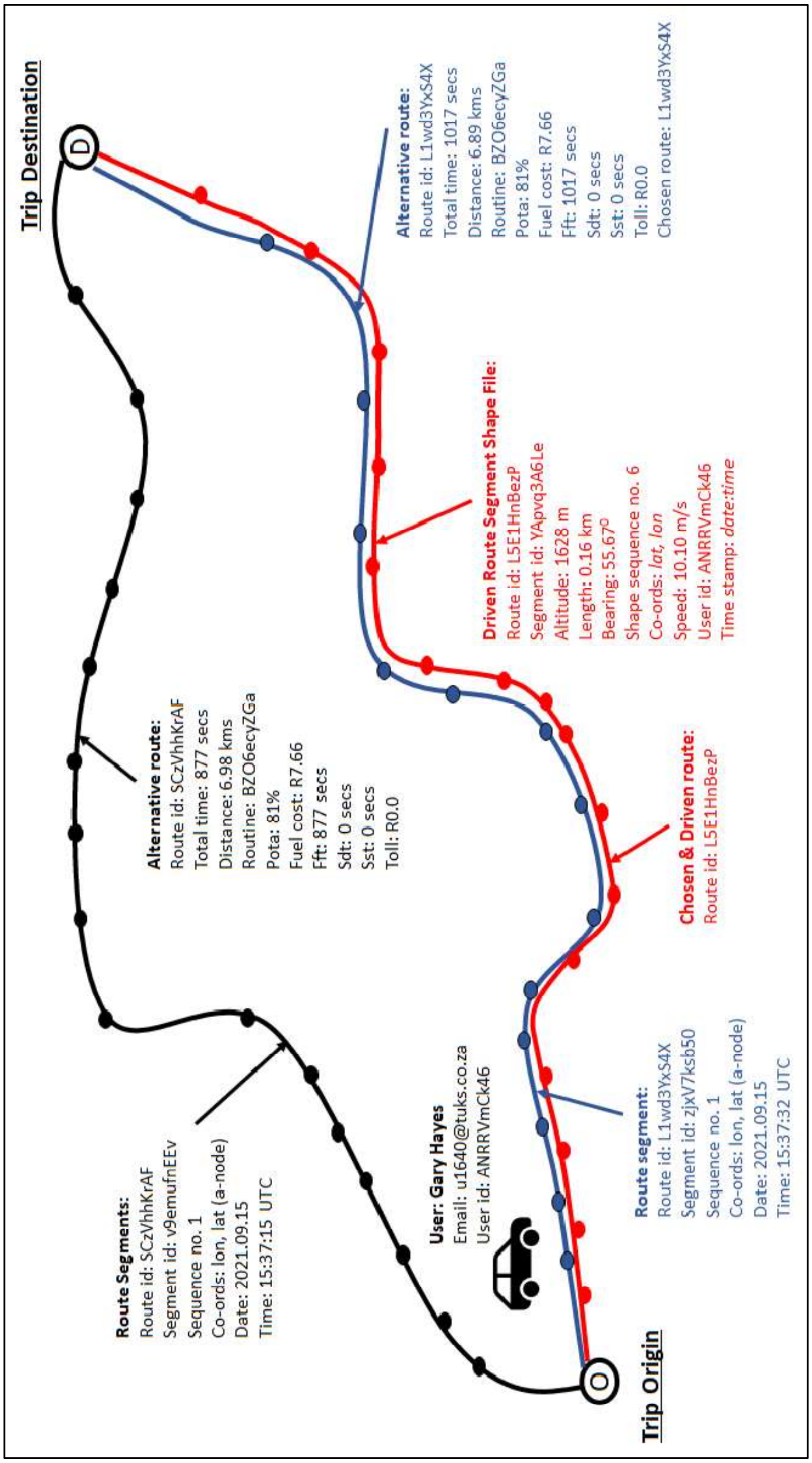


Understanding the contents and definitions of the RAPP-UP database are shown figuratively Figure 6. The figure is a pictorial representation showing the full data sets for two routes, viz, two alternative routes and the route driven (or chosen) by the survey participant.

The highlights of the figure are:

- The trip is for G Hayes, with an email address (u16401868@tuks.co.za) and user id *ANRRVmCk46*. This user id is used throughout the survey
- There are two alternative routes with route identifiers, i.e., route SCzVhhKrAF (shown in black) and route L1wd3YxS4X shown in red. These two routes make up a routine (i.e., choice set al.ternatives) with the identifier BZO6ecyZGa
- For each route (with identifier) there is a sequence of route segments that contains the segment latitude and longitude co-ordinates (for the a-node); the segment sequence number (the sequence is ascending from 0); the date; and the time stamp
- For each route there is an attribute data set that includes the total trip time; total distance; probability of on-time arrival (pota); fuel cost, toll cost, free-flow time (fft); slowed-down time (sdt) and stop-start-time (sst). These data constitute the choice set attributes and levels for each route
- The route chosen by the user is also shown as given by the route identifier (in this case route L1wd3YxS4X shown in red)
- The driven route is shown with a shapefile that contains the user identifier; the route identifier (L5E1HnBezP); segment identifiers (e.g., YApvq3A6Le); the shape sequence number (ascending in order); the a-node of the segment (lat and lon); segment altitude; segment bearing; and average speed on the segment.

Figure 6: Structure of RAPP-UP Parse database Outputs



The subsequent sections present tables that describe the RAPP-UP dashboards and the data in each. The left side margin of the parse dashboard in Figure 2**Error! Reference source not found.** shows the various dashboards in the overall database. These tables are:

i. The User data table that contains the registered survey participants with their security access emails
ii. The choice set data set that contains the attribute levels for each route in the choice set
iii. The route data set for each alternative that contains includes the route id, travel times, toll cost, length, pota and toll cost factors, fuel cost, stop-start, sowed-down and free-flow travel times, etc.
iv. The route shapefile that contains the route geometric data, i.e., route segments with a-node co-ordinates, lengths, travel times etc. These files are the largest in size
v. The routine file that contains the series of trips made by the user on different days
vi. The shape files that contain the summarised data for each trip
vii. The traffic segment data file that contains the data for all the traffic segments on each route
viii. The trip data file that contains the individual route identifications
ix. The waypoint data set that contains the details of the waypoints on each route, i.e., the waypoint co-ordinates.

Each table is now presented with the details of the contents.

6. Choice Set Dashboard (*ChoiceSet*)

The choice set dashboard contains the attributes and attribute levels included in the choice sets for each route.

Table 5: Data Sets in Choice Set Database (ChoiceSet)

Data Name	Description
Choice set id	ID code for choice sets. There are a total of 8 choice sets determined by orthogonal design for unlabeled experiment. Experimental design is with 8 choice sets and two attribute levels for probability of on time arrival (pota) (0.9 and 1.1) and toll cost attributes (0.9,1.1). The choice sets are applied on a "per day" is, i.e., choice set 1 is applied on day 1, choice set 2 on day 2, etc. Note that two alternative routes are generated, and the pota and toll cost factors are applied differently to each route on each day.
CreatedAt	The date and time the segment data was created in the database, e.g., 15 Sept 2021 at 17:35:10 UCT
UpdatedAt	The date and time on which the choice set factors were updated in the remote database, e.g., 15 Sept 2021 at 17:35:40 UCT
RouteNumber	The choice set route (i.e., either route 1 or 2) to which the pota and fuel cost factors are applied
ChoiceSetforDay	The day to which the pota and toll cost factors are applied
FactorTollCost	The toll cost factor applied to the actual toll cost (i.e., i.e., either 0.9 or 1.1)
ChoiceSetVersion	The version of choice set table (for this first set the default is 1)
FactorPota	The pota factor applied to the actual estimation of on-time arrival (i.e., either 0.9 or 1.1)
Export script file name:	Export_ChoiceSet_Collection_JSON.sh
Export file name	Choiceset_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldairy-	

```
dev.tvrdw.mongodb.net/TravelDairy-Dev --collection ChoiceSet --type json --out ./ChoiceSet_Collection.json
```

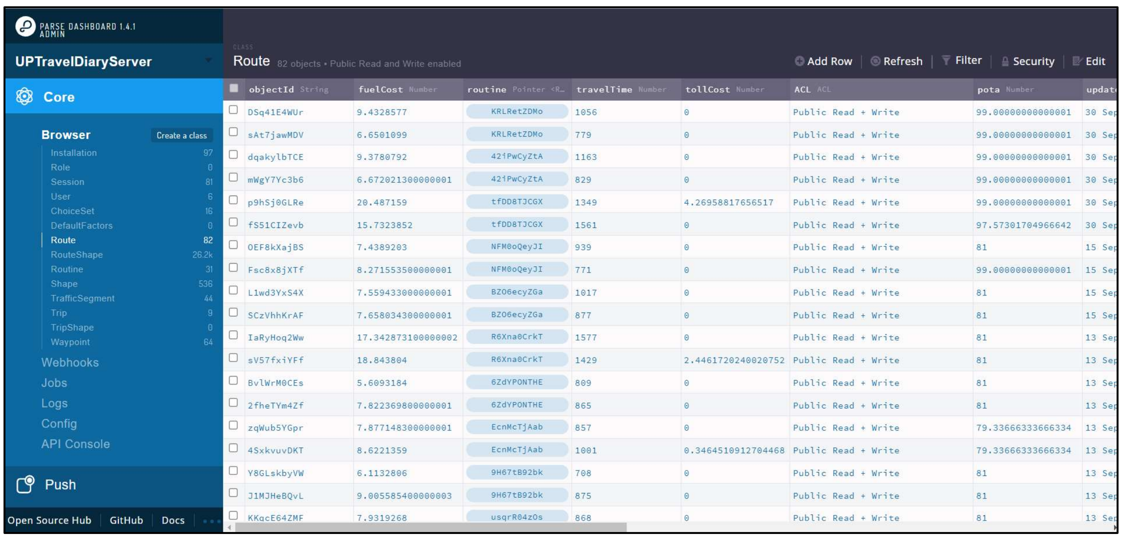
7. Route Collection Dashboard (*Route*)

This dashboard is continually updated with alternative route data as the survey progresses. It contains the alternative route data that make up the choice sets. The data items in the dashboard are as follows:

Table 6: Route Collection Data Set Definitions

Data Name	Description
Route id	Alphanumeric ID code for each route, e.g., SCzVhhKrAF. Two routes, each with different id's make a routine that also has a unique identifier, e.g., routes SCzVhhKrAF and route L1wd3YxS4X are the route pair making up routine BZO6ecyZGa
FuelCost	This is the estimated fuel cost for the route, calculated from the total route length; the current cost per litre of 95 octane unleaded petrol (R15.10/l); and an average vehicle fuel consumption of 8 litres per 100 km
Routine id	This is the common alphanumeric routine name for two alternative routes as described earlier, e.g., BZO6ecyZGa
TravelTime	This is the total travel in seconds for the route derived from real-time TomTom traffic data
TollCost	This is the toll cost in Rands for a route if it includes a Gauteng e-toll freeway. The actual toll cost has been based on the private vehicle discounted toll rate of R0.40/km and factored by the TollCostFactor
Pota	The probability of on-time arrival (in %) calculated from a weighted sum of the stop-start, slowed-down and free-flow time multiplied by the FactorPota
UpdatedAt	The date and time stamp of the generation of the route, e.g., 15 Sept 2021 at 17:35:10 UCT (Co-ordinated Universal Time). Add +2 hours for South African time.
Distance	The total length of the route in meters

ChoiceSetApplied	This data field indicates the toll cost and pota factors used from the ChoiceSet dashboard, i.e., either 0.9 or 1.1
Traffic	This data field shows the stop-start time (sst); slowed-down-time (sdt) and free-flow time (fft) in seconds used for the route in the choice set. The values displayed in the choice sets are in minutes. These proportions are derived from the TomTom TEC definitions of traffic flow per segment and are summed for the total route. The sum of sst+sdt+fft will equal the TravelTime
Export script file name:	Export_Route_Collection_JSON.sh
Export file name	Route_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldairy-dev.tvrdw.mongodb.net/TravelDairy-Dev --collection Route --type json --out ./Route_Collection.json	

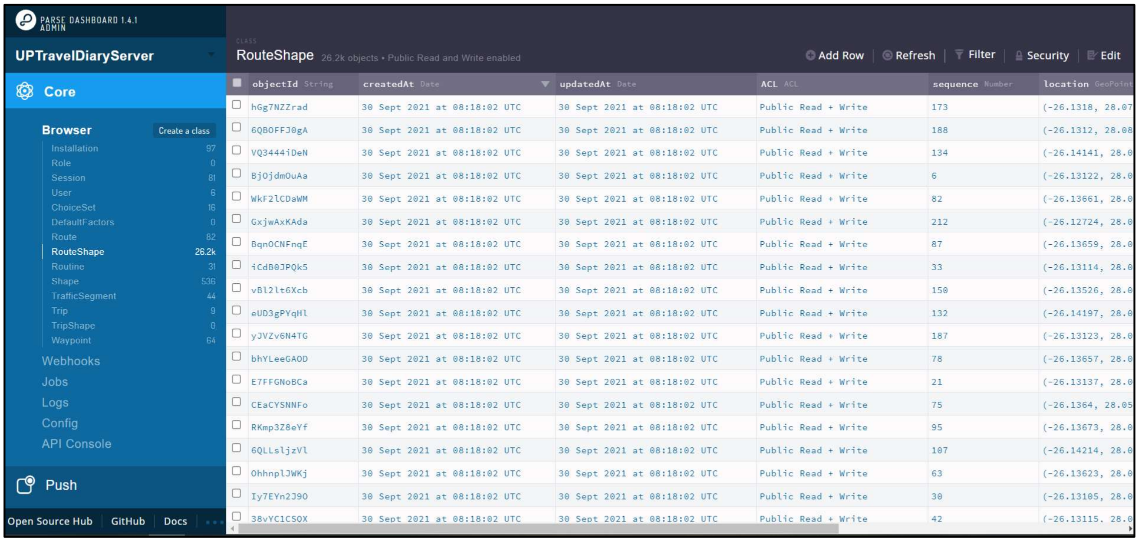


8. Route Shape Collection Dashboard (*RouteShape*)

This dashboard provides the alternative route segment data, i.e., route segment identifiers and co-ordinates. The sequence of segments in ascending order make up a route. The data for each segment includes its length and coordinate for the a-node. This data can be used to plot and analyse the routes. The segment length data is used for the computation of the route overlap.

Table 7: Route Shape Collection Dashboard (RouteShape)

Data Name	Description
Segment id	Alphanumeric segment ID code for a route, e.g., zjxV7ksb50. Each segment has a unique id
Length	The cumulative segment lengths in meters. For individual segment lengths the cumulative length must be adjusted
CreatedAt	The date and time the segment data was created in the database, e.g., 15 Sept 2021 at 17;35:10 UCT
UpdatedAt	The date and time the segment data was updated in the database, e.g., 15 Sept 2021 at 17:35:10 UCT
Sequence number	The sequence number for the segment. The ascending order of these numbers makes up a route
Location	The latitude (lat) and longitude (lon) of the a-node of the segment. The b-node of the segment will be the a-node of the sequential segment
Route id	The alphanumeric route identifier, i.e., Routine id e.g., BZO6ecyZGa (see Table 5)
Export script file name	Export_RouteShape_Collection_JSON.sh
Export file name	Routeshape_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldairy-dev.tvrdw.mongodb.net/TravelDairy-Dev --collection RouteShape --type json --out ./RouteShape_Collection.json	

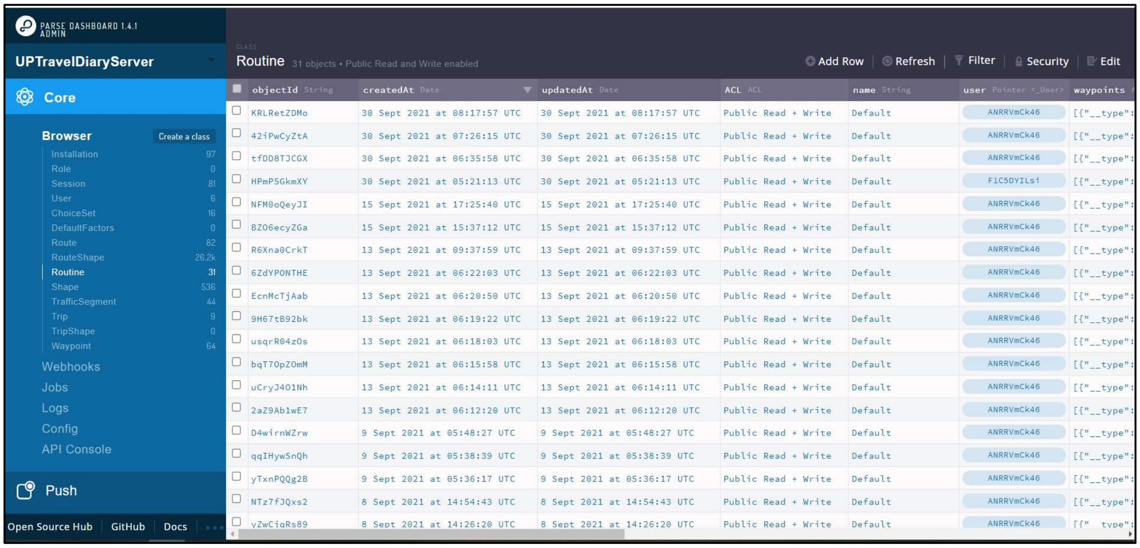

PARSE DASHBOARD 1.4.1
ADMIN
UPTravelDiaryServer
Core
Browser
Create a class
Installation 97
Role 0
Session 81
User 6
ChoiceSet 16
DefaultFactors 0
Route 82
RouteShape 26.2k
Routine 31
Shape 536
TrafficSegment 44
Trip 9
TripShape 0
Waypoint 64
Webhooks
Jobs
Logs
Config
API Console
Push
Open Source Hub
GitHub
Docs
CLASS
RouteShape
26.2k objects • Public Read and Write enabled
Add Row
Refresh
Filter
Security
Edit
objectId String
createdAt Date
updatedAt Date
ACL ACL
sequence Number
location GeoPoint
hGg7NZZrad 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 173 (-26.1318, 28.07
6QBOFFJ0gA 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 188 (-26.1312, 28.08
VQ3444iDeN 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 134 (-26.14141, 28.0
BjOjdmOuAa 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 6 (-26.13122, 28.0
WkF2lCDaWM 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 82 (-26.13661, 28.0
GxjwAxKAda 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 212 (-26.12724, 28.0
BqnOCNFnqE 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 87 (-26.13659, 28.0
iCdB0JPQk5 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 33 (-26.13114, 28.0
vBl2lt6Xcb 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 150 (-26.13526, 28.0
eUD3gPYqHl 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 132 (-26.14197, 28.0
yJVZv6N4TG 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 187 (-26.13123, 28.0
bhYLeeGAOD 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 78 (-26.13657, 28.0
E7FFGNoBCa 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 21 (-26.13137, 28.0
CEaCYSNNFo 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 75 (-26.1364, 28.05
RKmp3Z8eYf 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 95 (-26.13673, 28.0
6QLLsljzVl 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 107 (-26.14214, 28.0
OhhnplJWKj 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 63 (-26.13623, 28.0
Iy7EYn2J9O 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 30 (-26.13105, 28.0
38vYC1CSOX 30 Sept 2021 at 08:18:02 UTC 30 Sept 2021 at 08:18:02 UTC Public Read + Write 42 (-26.13115, 28.0

9. Routine Collection Dashboard (*Routine*)

This dashboard provides a summary of the routines that have been generated in the choice set on a particular day. A routine consists of the two alternative routes in a choice set.

Table 8: Routine Collection Dashboard (Routine)

Data Name	Description
Routine id	Alphanumeric segment ID code for a routine e.g., BZO6ecyZGa. Note that each routine consists of two routes
CreatedAt	The date and time the routine was created in the remote database e.g., 15 Sept 2021 at 17;35:10 UCT
UpdatedAt	The date and time the segment data was updated in the database, e.g., 15 Sept 2021 at 17:35:10 UCT
User id	The user id for whom the routine was created, e.g., ANRRVmCk46 for Gary Hayes
Waypoints	A listing of the segment names identified as waypoints for the routine
Schedule	The day of the week, date and time of the routine generation, e.g., Wednesday 15 Sept 2021 at 17:35:10 UCT
Export script File name	Export_routine_collection_JSON.sh
Export file name	Routine_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldairy-dev.tvrdw.mongodb.net/TravelDairy-Dev --collection Routine --type json --out ./Routine_Collection.json	


PARSE DASHBOARD 1.4.1
ADMIN
UPTravelDiaryServer
Core
Browser
Create a class
Installation 97
Role 0
Session 81
User 6
ChoiceSet 16
DefaultFactors 0
Route 82
RouteShape 26.2k
Routine 31
Shape 536
TrafficSegment 44
Trip 9
TripShape 0
Waypoint 64
Webhooks
Jobs
Logs
Config
API Console
Push
Open Source Hub
GitHub
Docs
CLASS
Routine 31 objects • Public Read and Write enabled
Add Row
Refresh
Filter
Security
Edit
objectId String
createdAt Date
updatedAt Date
ACL ACL
name String
user Pointer <_User>
waypoints
KRLRetZDMo 30 Sept 2021 at 08:17:57 UTC 30 Sept 2021 at 08:17:57 UTC Public Read + Write Default ANRRVmCk46
42iPwCyZtA 30 Sept 2021 at 07:26:15 UTC 30 Sept 2021 at 07:26:15 UTC Public Read + Write Default ANRRVmCk46
tfDD8TJCGX 30 Sept 2021 at 06:35:58 UTC 30 Sept 2021 at 06:35:58 UTC Public Read + Write Default ANRRVmCk46
HPmP5GkmXY 30 Sept 2021 at 05:21:13 UTC 30 Sept 2021 at 05:21:13 UTC Public Read + Write Default F1C5DYILs1
NFM0oQeyJI 15 Sept 2021 at 17:25:40 UTC 15 Sept 2021 at 17:25:40 UTC Public Read + Write Default ANRRVmCk46
BZO6ecyZGa 15 Sept 2021 at 15:37:12 UTC 15 Sept 2021 at 15:37:12 UTC Public Read + Write Default ANRRVmCk46
R6Xna0CrkT 13 Sept 2021 at 09:37:59 UTC 13 Sept 2021 at 09:37:59 UTC Public Read + Write Default ANRRVmCk46
6ZdYPONTHE 13 Sept 2021 at 06:22:03 UTC 13 Sept 2021 at 06:22:03 UTC Public Read + Write Default ANRRVmCk46
EcnMcTjAab 13 Sept 2021 at 06:20:50 UTC 13 Sept 2021 at 06:20:50 UTC Public Read + Write Default ANRRVmCk46
9H67tB92bk 13 Sept 2021 at 06:19:22 UTC 13 Sept 2021 at 06:19:22 UTC Public Read + Write Default ANRRVmCk46
usqrR04zOs 13 Sept 2021 at 06:18:03 UTC 13 Sept 2021 at 06:18:03 UTC Public Read + Write Default ANRRVmCk46
bqT7OpZOmM 13 Sept 2021 at 06:15:58 UTC 13 Sept 2021 at 06:15:58 UTC Public Read + Write Default ANRRVmCk46
uCryJ4O1Nh 13 Sept 2021 at 06:14:11 UTC 13 Sept 2021 at 06:14:11 UTC Public Read + Write Default ANRRVmCk46
2aZ9Ab1wE7 13 Sept 2021 at 06:12:20 UTC 13 Sept 2021 at 06:12:20 UTC Public Read + Write Default ANRRVmCk46
D4wirnWZrw 9 Sept 2021 at 05:48:27 UTC 9 Sept 2021 at 05:48:27 UTC Public Read + Write Default ANRRVmCk46
qqIHywSnQh 9 Sept 2021 at 05:38:39 UTC 9 Sept 2021 at 05:38:39 UTC Public Read + Write Default ANRRVmCk46
yTxnPQQg2B 9 Sept 2021 at 05:36:17 UTC 9 Sept 2021 at 05:36:17 UTC Public Read + Write Default ANRRVmCk46
NTz7fJQxs2 8 Sept 2021 at 14:54:43 UTC 8 Sept 2021 at 14:54:43 UTC Public Read + Write Default ANRRVmCk46
vZwCjqRs89 8 Sept 2021 at 14:26:20 UTC 8 Sept 2021 at 14:26:20 UTC Public Read + Write Default ANRRVmCk46

10. Shape Collection Dashboard (*Shape*)

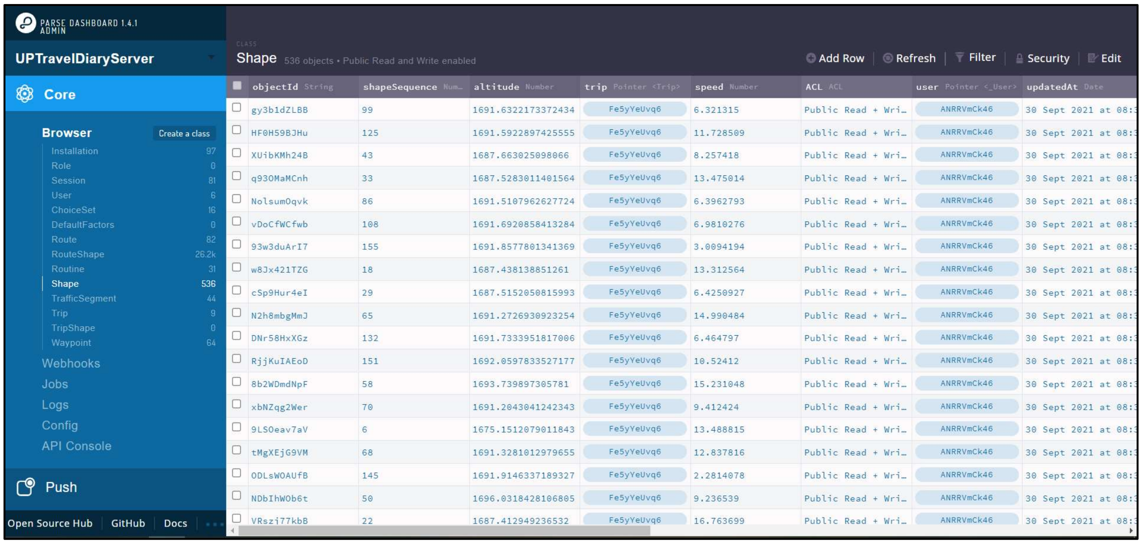
This dashboard contains the details of the route driven by the participant, i.e., the actual route used. It is defined by a route id; segment numbers; co-ordinates, segment speeds, lengths etc.

Table 9: Shape Collection Dashboard (Shape)

Data Name	Description
Segment id	Alphanumeric segment ID code for the route segment e.g., YApvq3A6Le. The segment identifiers for each route are unique
Shape Sequence No	The segment sequence numbers (in ascending order from 0….n for n segments.
Altitude	Segment altitude in meters, e.g., 1613.1 m
Trip identifier	Alphanumeric trip ID code e.g., L5E1HnBezP. The trip identifier is constant for all segments in the route
Speed	The average speed on the segment in meters/second
User id	The user id for whom the routine was created, e.g., ANRRVmCk46 for Gary Hayes
CreatedAt	The date and time that the segment data was created (or first entered into) in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
UpdatedAt	The date and time that the segment data was updated in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
Bearing	The segment bearing (i.e., direction of travel) in decimal degrees
ReceivedAt	The date and time that the segment was received by the smartphone GPS device , e.g., 15 Sept 2021 at 17:39:20 UCT
Location	The segment a-node coordinates in decimal latitude and longitude. The next sequential segment a-node is effectively the b-node of the preceding segment
Distance	The length of the segment in meters. Note this is a straight line distance

Export script file name	Export_Shape_Collection_JSON.sh
Export file name:	Shape_Collection.JSON

Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldairy-dev.tvrdw.mongodb.net/TravelDairy-Dev --collection Shape --type json --out ./Shape_Collection.json



objectId String	shapeSequence Num…	altitude Number	trip Pointer <Trip>	speed Number	ACL ACL	user Pointer <_User>	updatedAt Date
gy3b1dZLBB	99	1691.6322173372434	Fe5yYeUvq6	6.321315	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
HF0H59BJHu	125	1691.5922897425555	Fe5yYeUvq6	11.728509	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
XUibKMh24B	43	1687.663025098066	Fe5yYeUvq6	8.257418	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
q93OMaMCnh	33	1687.5283011401564	Fe5yYeUvq6	13.475014	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
NolsumOqvk	86	1691.5107962627724	Fe5yYeUvq6	6.3962793	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
vDoCfWCfwb	108	1691.6920858413284	Fe5yYeUvq6	6.9810276	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
93w3duArI7	155	1691.8577801341369	Fe5yYeUvq6	3.0094194	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
w8Jx421TZG	18	1687.438138851261	Fe5yYeUvq6	13.312564	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
cSp9Hur4eI	29	1687.5152050815993	Fe5yYeUvq6	6.4250927	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
N2h8mbgMmJ	65	1691.2726930923254	Fe5yYeUvq6	14.990484	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
DNr58HxXGz	132	1691.7333951817006	Fe5yYeUvq6	6.464797	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
RjjKuIAEoD	151	1692.0597833527177	Fe5yYeUvq6	10.52412	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
8b2WDmdNpF	58	1693.739897305781	Fe5yYeUvq6	15.231048	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
xbNZqg2Wer	70	1691.2043041242343	Fe5yYeUvq6	9.412424	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
9LSOeav7aV	6	1675.1512079011843	Fe5yYeUvq6	13.488815	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
tMgXEjG9VM	68	1691.3281012979655	Fe5yYeUvq6	12.837816	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
ODLsWOAUfB	145	1691.9146337189327	Fe5yYeUvq6	2.2814078	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
NDbIhWOb6t	50	1696.0318428106805	Fe5yYeUvq6	9.236539	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:
VRszi77kbB	22	1687.412949236532	Fe5yYeUvq6	16.763699	Public Read + Wri…	ANRRVmCk46	30 Sept 2021 at 08:

11. Traffic Segment Collection Dashboard (*TrafficSegment*)

The traffic segment collection contains the list of segments for each route for specific traffic conditions. The TEC codes define the traffic effect conditions and are found in ISO 21219-15. The TEC codes are described for the sequence of segments for which the traffic conditions apply. The segment sequence is defined by the starting sequence number and ending sequence number.

Table 10: Traffic Segment Collection Dashboard (TrafficSegment)

Data Name	Description
Object id	
CreatedAt	The date and time that the segment data was created (or first entered into) in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
UpdatedAt	The date and time that the segment data was updated in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
TEC object	The TEC standard traffic code for traffic conditions, i.e., code from 1 to 7 (see table 16 page 20 of ISO 21219-15) for definition of values from 1 – 7. Also provide are main cause code for the traffic conditions – see table 20 page 17 of ISO 21219-15
ShapeStart	The starting segment sequence number for which the tec code applies
ShapeEnd	The ending segment sequence number for which the tec code applies
Route id	The route id code for the starting and ending segment sequence numbers, for example route VGjTABO6o6
Export script file name	Export_trafficsegment_collection_JSON.sh
Export file name	Trafficsegment_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldairy-dev.tvrdw.mongodb.net/TravelDairy-Dev --collection TrafficSegment --type json --out ./TrafficSegment_Collection.json	

12. Trip Collection Dashboard (*Trip*)

The dashboard contains the trip information for the route driven and the associated chosen route.

Table 11: Trip Collection Dashboard (Trip)

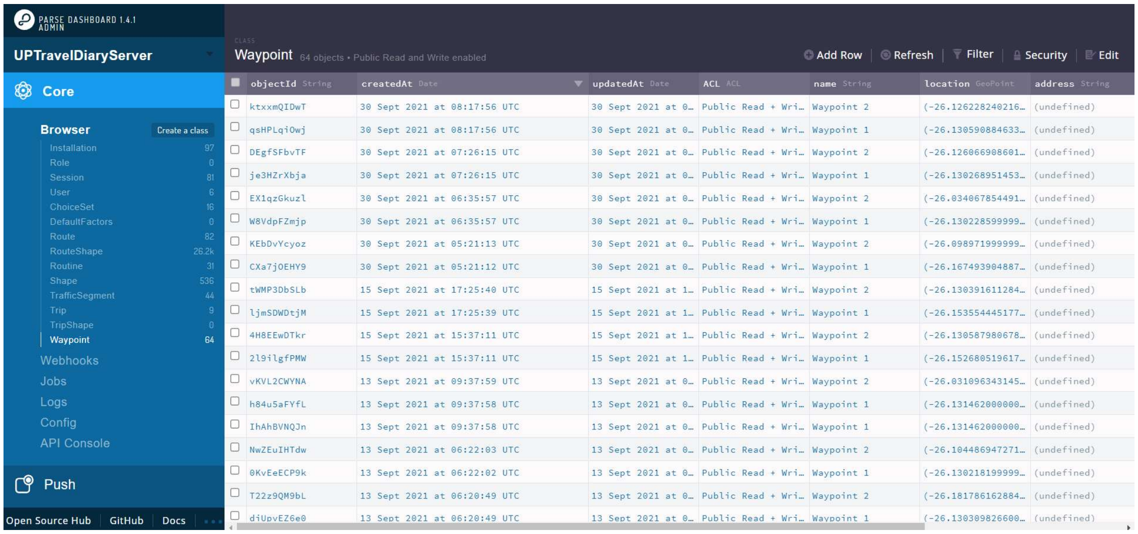
Data Name	Description
Trip id	Alphanumeric segment ID code for the route that was driven e.g., L5E1HnBezP
DepartureAt	The departure date and time of the driven route, e.g., 15 Sept 2021 at 17:35:10
ArrivalAt	The arrival date and time of the driven route, e.g., 15 Sept 2021 at 17:55:40
CreatedAt	The date and time that the segment data was created (or first entered into) in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
UpdatedAt	The date and time that the segment data was updated in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
User id	The user id for whom the routine was created, e.g., ANRRVmCk46 for Gary Hayes
Selected Route	The route was selected from the two alternatives, e.g., L1wd3YxS4X
Duration	The trip time in seconds
Distance	The length of the chosen trip in metres
Export script file name	Export_Trip_Collection_JSON.sh
Export file name	Trip_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldairy-dev.tvrdw.mongodb.net/TravelDairy-Dev --collection Trip --type json --out ./Trip_Collection.json	

13. Waypoint Collection Dashboard (*Waypoint*)

The dashboard contains the trip waypoint information for the route that was driven. Waypoints are an option and hence many trips to work will not have defined waypoints.

Table 12: Waypoint Collection Dashboard (Waypoint)

Data Name	Description
Waypoint id	Alphanumeric segment waypoint ID code for the route that was driven e.g., 0KvEeECP9k
CreatedAt	The date and time that the segment data was created (or first entered into) in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
UpdatedAt	The date and time that the segment data was updated in the database, e.g., 15 Sept 2021 at 17:39:20 UCT
Name	Waypoint name, e.g., Waypoint 1, Waypoint 2, etc. for all waypoints on the driven route
Location	The latitude and longitudinal coordinates of the waypoint/s that was defined
Export script file name	Export_Waypoint_Collection_JSON.sh
Export file name	Waypoint_Collection.JSON
Script: mongoexport --uri mongodb+srv://AndroidClient:T0lGPkcYhOWDjpUI@traveldairy-dev.tvrdw.mongodb.net/TravelDairy-Dev --collection Waypoint --type json --out ./Waypoint_Collection.json	


PARSE DASHBOARD 1.4.1
ADMIN
UPTravelDiaryServer
Core
Browser
Create a class
Installation 97
Role 0
Session 81
User 6
ChoiceSet 16
DefaultFactors 0
Route 82
RouteShape 26.2k
Routine 31
Shape 536
TrafficSegment 44
Trip 9
TripShape 0
Waypoint 64
Webhooks
Jobs
Logs
Config
API Console
Push
Open Source Hub
GitHub
Docs
CLASS
Waypoint
64 objects • Public Read and Write enabled
Add Row
Refresh
Filter
Security
Edit
objectId String | createdAt Date | updatedAt Date | ACL ACL | name String | location GeoPoint | address String
ktxxmQIDwT | 30 Sept 2021 at 08:17:56 UTC | 30 Sept 2021 at 0… | Public Read + Wri… | Waypoint 2 | (-26.126228240216… | (undefined)
qsHPLqiOwj | 30 Sept 2021 at 08:17:56 UTC | 30 Sept 2021 at 0… | Public Read + Wri… | Waypoint 1 | (-26.130590884633… | (undefined)
DEgfSFbvTF | 30 Sept 2021 at 07:26:15 UTC | 30 Sept 2021 at 0… | Public Read + Wri… | Waypoint 2 | (-26.126066908601… | (undefined)
je3HZrXbja | 30 Sept 2021 at 07:26:15 UTC | 30 Sept 2021 at 0… | Public Read + Wri… | Waypoint 1 | (-26.130268951453… | (undefined)
EX1qzGkuzl | 30 Sept 2021 at 06:35:57 UTC | 30 Sept 2021 at 0… | Public Read + Wri… | Waypoint 2 | (-26.034067854491… | (undefined)
W8VdpFZmjp | 30 Sept 2021 at 06:35:57 UTC | 30 Sept 2021 at 0… | Public Read + Wri… | Waypoint 1 | (-26.130228599999… | (undefined)
KEbDvYcyoz | 30 Sept 2021 at 05:21:13 UTC | 30 Sept 2021 at 0… | Public Read + Wri… | Waypoint 2 | (-26.098971999999… | (undefined)
CXa7jOEHY9 | 30 Sept 2021 at 05:21:12 UTC | 30 Sept 2021 at 0… | Public Read + Wri… | Waypoint 1 | (-26.167493904887… | (undefined)
tWMP3DbSLb | 15 Sept 2021 at 17:25:40 UTC | 15 Sept 2021 at 1… | Public Read + Wri… | Waypoint 2 | (-26.130391611284… | (undefined)
ljmSDWDtjM | 15 Sept 2021 at 17:25:39 UTC | 15 Sept 2021 at 1… | Public Read + Wri… | Waypoint 1 | (-26.153554445177… | (undefined)
4H8EEwDTkr | 15 Sept 2021 at 15:37:11 UTC | 15 Sept 2021 at 1… | Public Read + Wri… | Waypoint 2 | (-26.130587980678… | (undefined)
2l9ilgfPMW | 15 Sept 2021 at 15:37:11 UTC | 15 Sept 2021 at 1… | Public Read + Wri… | Waypoint 1 | (-26.152680519617… | (undefined)
vKVL2CWYNA | 13 Sept 2021 at 09:37:59 UTC | 13 Sept 2021 at 0… | Public Read + Wri… | Waypoint 2 | (-26.031096343145… | (undefined)
h84u5aFYfL | 13 Sept 2021 at 09:37:58 UTC | 13 Sept 2021 at 0… | Public Read + Wri… | Waypoint 1 | (-26.131462000000… | (undefined)
IhAhBVNQJn | 13 Sept 2021 at 09:37:58 UTC | 13 Sept 2021 at 0… | Public Read + Wri… | Waypoint 1 | (-26.131462000000… | (undefined)
NwZEuIHTdw | 13 Sept 2021 at 06:22:03 UTC | 13 Sept 2021 at 0… | Public Read + Wri… | Waypoint 2 | (-26.104486947271… | (undefined)
0KvEeECP9k | 13 Sept 2021 at 06:22:02 UTC | 13 Sept 2021 at 0… | Public Read + Wri… | Waypoint 1 | (-26.130218199999… | (undefined)
T22z9QM9bL | 13 Sept 2021 at 06:20:49 UTC | 13 Sept 2021 at 0… | Public Read + Wri… | Waypoint 2 | (-26.181786162884… | (undefined)
diUpvEZ6e0 | 13 Sept 2021 at 06:20:49 UTC | 13 Sept 2021 at 0… | Public Read + Wri… | Waypoint 1 | (-26.130309826600… | (undefined)

14. Route Overlap Calculation

Route overlap can either be by distance of the overlapped segments, or by time of the overlapped segments.

14.1 Route Distance Overlap

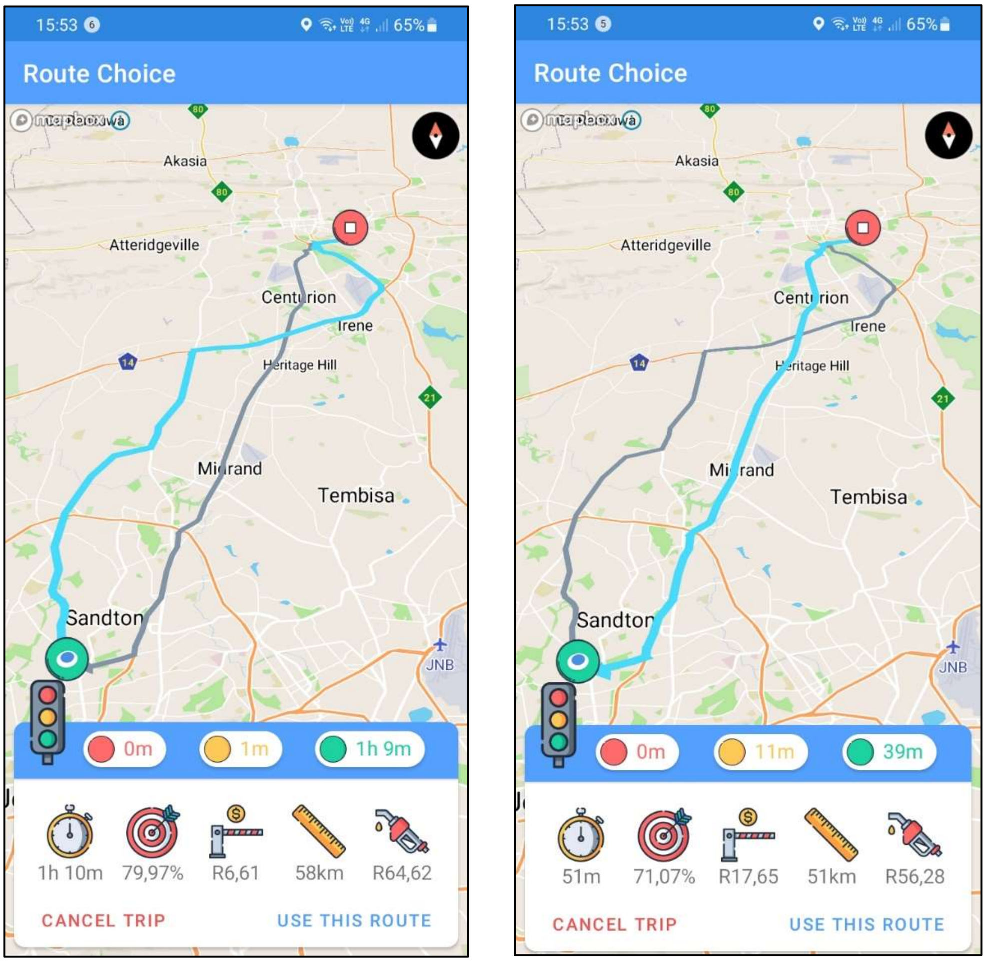
An important variable for the estimation of discrete choice models for route choice is the extent of the route overlap. The overlap of alternative routes in dense urban road networks is likely given that routes are likely to use common roads, especially higher order roads that offer reduced travel times (i.e., with higher capacity and higher speeds).

The measurement of the route overlap by distance is calculated post-survey from the data presented in the parse dashboard from the alternative route segments. The proportion of route overlap is unique to each route. For example if two routes have a common section (or sections) totaling 2 km, and Route A has a total length of 10 km and Route B has a total length of 12 km, then the overlaps for each route are Route A = 2/10 = 20% and Route B = 2/12= 16.6%.

The route segment data contained in parse dashboard RouteShape (see **Error! Reference source not found.**) can be used to quantify the route overlap. In this database the alternative route segments are listed. These can be exported to an Excel spreadsheet and a LOOKUP command used to identify common segments. The lengths of the segments are provided, and together with the total route lengths the common length proportions can be calculated.

An example of two routes with a small overlap is shown in the following example for a trip from Rosebank to Hatfield in Pretoria on a Monday afternoon during the peak period (4 pm). The choice sets for each alternative route are shown in the following figures. Route A is the western route and Route B the eastern route.

Figure 7: Route Overlap Example



The *RouteShape* database segment numbers and sequences in an overlap analysis showed that there were a total of 74 route segments that overlapped totalling 1.74 km. Route A (58 km) has a total of 844 segments and Route B (51 km) a total of 703. Therefore the proportion of overlap for Route A (total length 58 km) was 1.74/58 = 2.94% and for Route B (total length 51 km) was 1.74/51 = 3.37%.

14.2 Route Time Overlap

The route time overlap on the common route segments can also be calculated. This is done by extracting the common route segments as before, and then identifying the travel times of each of the common segments.

15. Interrogating and Formatting the RAPP-UP Output from JSON Files

The RAPP-UP survey data is downloaded in JSON (Java Script Object Notation) file format from the remote database. The JSON data is not formatted. The data sets are separated by a combination of commas, periods, semicolons and more. An example of JSON output is shown below. The JSON file can be edited using a text editor such as UltraEdit or Notepad++.

Figure 8: Example of RAPP-UP Output File in JSON Format

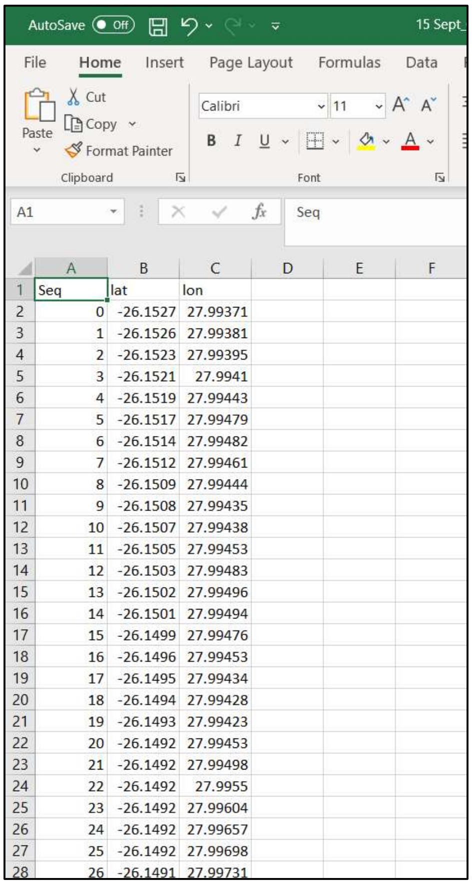
In order to format the file and covert it to CSV format, it must be imported into Excel. To do this the following steps are required:

i. Open Excel and open the JSON file. An import menu will pop up
ii. Use the *Delimited* file type option and click enter
iii. The next screen lets you ser the *delimiter*s that separate the individual sets of data
iv. Commas and colons are the most commonly used delimiters so set the comma delimiter and specify the colon delimiter in the "*other*" box
v. Then click *Finish* and the file will be imported into Excel
vi. It may require further modification to remove unwanted characters such as ", ; { and } from a specific set of data
vii. To do this use the *Data / Text to Columns* option and again set the delimiters you wish to specify. *Note that you may need to add a column to the right of the data you wish to separate otherwise data may be overwritten*
viii. *S*everal iterations of steps vi and vii may be required to fully format the data set
ix. When finished, save the file as an Excel file and then again as a CSV file. The Excel file can be used to manipulate the data further if required, and the CSV file must be used for conversion to GPX, KML and MKZ files.

Note that the preparation of the CSV file is required before conversion to GPS or KML format. For example. A file to plot a route requires a consecutive set of longitude and latitude co-ordinates. The segment coordinates must be arranged in ascending order. This can be done by creating a file that consists of three columns, i.e., the sequence no. in column 1; the latitude value in decimal degrees in columns two with the heading *lat*; and the longitude coordinate in decimal degrees in column 3 under the heading *lon.* The following figure shows the format. Note that the *lat* coordinate will be negative in the southern hemisphere.

The recommended free platform for the conversion of CSV files to GPX, kML or KMZ format is GPS Visualizer at the following address: https://www.gpsvisualizer.com

Figure 9: Format of a CSV File of Sequenced Route Coordinates for Conversion to GPS or KML Format for Plotting



	A	B	C	D	E	F
1	Seq	lat	lon			
2	0	-26.1527	27.99371			
3	1	-26.1526	27.99381			
4	2	-26.1523	27.99395			
5	3	-26.1521	27.9941			
6	4	-26.1519	27.99443			
7	5	-26.1517	27.99479			
8	6	-26.1514	27.99482			
9	7	-26.1512	27.99461			
10	8	-26.1509	27.99444			
11	9	-26.1508	27.99435			
12	10	-26.1507	27.99438			
13	11	-26.1505	27.99453			
14	12	-26.1503	27.99483			
15	13	-26.1502	27.99496			
16	14	-26.1501	27.99494			
17	15	-26.1499	27.99476			
18	16	-26.1496	27.99453			
19	17	-26.1495	27.99434			
20	18	-26.1494	27.99428			
21	19	-26.1493	27.99423			
22	20	-26.1492	27.99453			
23	21	-26.1492	27.99498			
24	22	-26.1492	27.9955			
25	23	-26.1492	27.99604			
26	24	-26.1492	27.99657			
27	25	-26.1492	27.99698			
28	26	-26.1491	27.99731			