Investigating the Impact of Activity Behaviour on Transport Mode Choice and Use in Cape Town

By

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DECLARATION

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ABSTRACT

The paper covers the influence of activity behaviour on the mode choice, behaviour and transport use of individuals. A trip-based model was used to forecast passenger demand for new transport projects in Cape Town. The trip-based model has proven theoretical shortcomings when used to forecast passenger demand for new projects. Previous work conducted on transport behaviour identified activity-based methodologies as a solution to the shortcomings of trip-based transport models.

The household travel survey conducted in Cape Town in 2012 included a trip diary. The data from the trip diary was used to identify activity-based variables that could improve the accuracy of the transport demand model used in Cape Town. The trip diary was analysed, and descriptive and predictive statistics were used to identify variables that could be used to help explain the relationship between activities and modal choices of individuals.

The main findings from the research are that the type of activity, distance travelled, and number of activities undertaken had an influence on modal choice. The activity-profile of low-income individuals differed from that of high-income individuals and this had an influence on the transport behaviour of individuals. High-income individuals could participate in more activities per day and lower-income individuals made more use of public transport. The research also found when comparing daily time budgets that high-income individuals were more sensitive to time and would spend more money to save time whilst low-income individuals were less sensitive to time and would prefer lower cost transport that might take a little longer to reach a destination.

The variables identified are candidates to be included in new transport models, but the research was conducted using trip diaries and the results from the diaries were sufficient for this research. If a full activity-based transport model were to be built for the City of Cape Town, the research would suggest activity diaries to be conducted as the input data for the model.

Key words:

Transport behaviour, Activity-based, Cape Town, Trip Diary, Modal choice.

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ABBREVIATIONS AND TERMINOLOGY

ACSA	Airports Company South Africa
AMU	Accelerated Modal Upgrading
BRT	Bus Rapid Transport
DoT	Department of Transport
IPTN	Integrated Public Transport Network
IRPTN	Integrated Rapid Public Transport Networks
IRTN	Integrated Rapid Public Transport Networks
MNL	Multinomial Logit Model
NDP	National Development Plan
NHTS	National Household Travel Survey
NLTA	National Land Transport Act
NMT	Non-Motorised Transport
NTP	National Transport Policy
OD	Origin-Destination
PLTF	Provincial Land Transport Framework
PTSAP	Public Transport Strategy and Action Plan
PvT	Private Transport
TCT	Transport for Cape Town
TDA	Transport and Urban Development Authority
TDM	Transport Demand Management
TOD	Transit Oriented Development

A decision is only an intention or commitment to behave. A frequently repeated behaviour is not necessarily preceded by deliberate decisions (Gärling, 1998).

1 INTRODUCTION

1.1 Statement of purpose

The way individuals make transport decisions has been researched with growing interest over the past century (Train and McFadden, 1978; Gonzales and Daganzo, 2012). This led to the realisation that decisions made by individuals regarding travel is influenced by the activities they perform. Incorporating activity-based factors when modelling the transport decision of individuals add realism and flexibility to the transport models(Algers, Eliasson and Mattsson, 2005).

Researchers have analysed the effectiveness of transport models to accurately portray transport situations (Gärling, 1998). Transport models are used to derive scenarios from the outcome of various transport policies. Most of the new transport projects implemented and policies drawn up have the purpose of alleviating city congestion and lowering pollution levels of a city, among other (Tabuchi, 1993; Yao *et al.*, 2014). The effectiveness of these policies is measured by monitoring the congestion and pollution after the implementation of the transport project or policy.

The purpose of models in transport studies has been to imitate the decision-making process of individuals regarding transport (Scheiner and Holz-Rau, 2007). The modal split of a town or city influences the congestion experienced by individuals of that town or city (Kitamura, 1988; Axhausen and Garling, 1992). Modal choice of individuals is influenced by the type and number of activities they perform.

This dissertation investigates the current planning and modelling process used in the City of Cape Town. Specific attention is given to how the planning and modelling process is used as a decision-making tool to inform and support decisions regarding transport projects and the transport policies. This is important because if an ineffective transport project or new policy is implemented, it could lead to increased levels of congestion and negative implications for the economy of Cape Town.

1.2 Background and motivation

Good transport models enable researchers and decision makers to make informed and fitting decisions regarding planning for future transport projects and the evaluation of existing transport projects (Potter and Skinner, 2000).

Inaccurate data, specification errors, calculation errors, etc. devalue the quality of a transport model's outputs. Poor quality outputs have a negative impact on the target population (Krygsman, 2004; Hensher and Rose, 2007). Poor quality transport modelling can lead to the wrong infrastructure being built, infrastructure that does not meet the transport demands of the population, underutilised transport services that lead to subsidy demands by the transport operators, and negative impacts on the affected target population (Grey and Behrens, 2013).

The current transport demand models used in Cape Town are not focussed on accurately reflecting traveller behaviour (Hitge and Vanderschuren, 2015). The main objective of these models is typically to determine the market share of each mode in the commute trip. The focus of transport planning in Cape Town is still centred on providing sufficient road capacity for the peak period and assessing the demand for public transport. The modelling framework adopted is the trip-based framework.

The travel forecasting approach used in Cape Town do not consider all the complexities and interdependencies underlying activity–travel patterns. Cape Town implemented the traditional four-step trip-based modelling approach (City of Cape Town, 2015). While this approach is suitable to determine road capacity requirements, and specifically peak period capacity demand, the trip-based approach is not really suitable to determine mode choice. The approach does not fully recognise all the forces at work in structuring activity and travel behaviour. This is because the conventional travel demand methodologies are most sensitive to public transport, NMT or softer policy and strategies, such as work from home, car pool, etc., considered by planners and transport decision makers (Chu, Cheng and Chen, 2012).

The inability of traditional trip-based modelling techniques to accurately model individuals' sensitivity for policy and network changes lies within the design of trip-based models (Jovic, 1999). Trip-based models are based on a sequential top-down process that results in assigning a modal choice and route to an individual between a given origin and destination. This process is flawed by design as transport demand is derived from the demand of individuals to perform activities (Algers, Eliasson and Mattsson, 2005). The decision-making process of individuals making transport decisions is complex and is influenced by more factors that could be incorporated in trip-based models and this has led to the adoption of activity-based models to address these shortcomings (Scheiner and Holz-Rau, 2007).

1.3 Aims and objectives

The research aims to highlight factors to improve the accuracy of transport demand modelling to support transport planning as well as the drafting of policy in Cape Town.

The specific research objectives of this research are:

- To investigate the influence of the number of activities, income group and distance travelled on the modal choice decisions of an individual.
    - Research Hypothesis 1: Number of activities has an impact on mode choice with more activities leading to fewer trips with public transport.

- To compare the range of activities in the daily schedule of low-income, lower-middle, upper-middle- and high-income individuals.
    - Research Hypothesis 2: Complex transport chains involving many transfers and stages such as public transport leads to fewer activities per day.

- Investigate the value of time by comparing the total time spent travelling per mode, activity and income group.
    - Research Hypothesis 3: The income of an individual and travel time has an inverse relationship with an increase in income resulting in a decrease in travel time.

The study therefore aimed to provide insight into how the addition of activity-based variables could deepen the understanding of how individuals make decisions regarding modal choice. The new insights could provide transport planners and local government with the information needed to implement and construct more effective infrastructure plans, projects and policies.

1.4 Structure of this dissertation

In Chapter 2 of this dissertation, a literature review that investigates the concept of transport planning is provided. To gain an understanding of how transport planning is understood and implemented, the development of transport planning and key definitions of critical parts of the transport planning process are investigated. The literature review continues with an investigation into the relationship between modal split and congestion and why congestion has a negative impact on a city. The latter part of the literature review compares trip-based and activity-based approaches to compare the advantages and disadvantages of both. The literature review concludes with a summary of transport planning in Cape Town. The

government plans and policies are investigated, and the current model used to forecast passenger demand is investigated.

Chapter 3 of this dissertation explains the data used to address the research objectives and answer the research question. The data description chapter starts with a thorough description of the trip-diary data used in the research. Next, a general descriptive analysis visualises the trip-diary data used in the research and lastly it is explained how each of the variables are calculated to help address the research objectives.

Chapters 4,5 and 6 are the main body of the research with each chapter addressing one of the research objectives. Each chapter starts with an introduction and the methodology used to address the research objective is described. This is followed by the results obtained from implanting the aforementioned methodology and the results are then discussed in accordance to how the results address the research objective and overall aim of the research

Chapter 7 concludes the dissertation by addressing the research objectives and answering the research question posed at the start of the research. The chapter discusses the potential contribution to the body of knowledge on activity-based research in the City of Cape Town and the potential for future research projects to continue broadening the understanding and implementation of activity-based research techniques.

2 LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter is twofold. First the literature review will aim to develop a clear understanding of transport planning. This will entail definitions of keywords and an explanation of the development of travel demand and the factors that influence the behaviour of individuals. Second, the review will describe the transport-planning environment in Cape Town. The governmental and municipal plans and papers will be investigated, and the transport planning policies and techniques will be evaluated.

In the process of evaluating the plans, papers and techniques of the local government in Cape Town, it will become evident that an improvement can be made in the way demand for new transport projects is calculated for the City of Cape Town.

This chapter starts by explaining the process followed to complete the literature review. The explanation is followed by an overview of transport planning. The overview includes definitions, a short history on the development of transport planning and information on how decisions regarding transport are made. Next, the issue of congestion is investigated along with the concept of modal split. The relationship between the level of congestion and the modal split of a city is investigated with the aim of creating an understanding of the causes of congestion. This leads to the investigation into trip and activity-based research approaches. Both approaches are investigated to understand the criticism against, and the advantages of, both approaches for a city like Cape Town. Lastly, this review takes an in-depth look at transport planning in the City of Cape Town. The policy and legislation surrounding transport and new transport projects are investigated and a recent transport project like the Bus Rapid Transit (BRT) system is examined to understand the planning and effectiveness of the process used to forecast passenger demand for the implemented system.

2.2 Literature review

Literature was collected by identifying keywords and searching for peer-reviewed academic articles online on depositories like Elsevier and Science Direct. Handbooks and books written by specialists in the field of transport planning were read and investigated to create a deeper understanding of the field and history of transport planning.

To better understand the climate surrounding South African and local transport planning, government reports and papers were collected and studied. The reports and papers were collected from government websites and repositories. Published and unpublished government

reports were obtained from the research team that helped to conduct the household travel survey in 2012 in the City of Cape Town.

2.3 Transport planning overview

2.3.1 What is transport planning?

Transport planning is described by De Dios Ortúzar and Willumsen (2002) as “the application of planning techniques in the operation, provision and management of facilities and services for all modes of transport”. Transport planning can further be described as the planning techniques used to predict multiple future travel demand scenarios and ensuring adequate facilities and services are in place to meet the demand for transport (Department of Transport, 2013).

Transport planning models attempt to predict the travel demand that would be experienced from the investigated population. This is done through choice modelling. Choice modelling is the attempt to model the decision-making process of individuals by making use of revealed preference or stated preference data (Donald, Cooper and Conchie, 2014). Revealed preference data is observations on actual choices made by individuals whilst stated preference data is gathered by asking individuals to make choices over hypothetical scenarios. Choice modelling attempts to use discrete choices (A over B; B over A; C over A&B) in order to infer the preference of individuals on a relevant latent scale (Arentze and Molin, 2013).

The reason why transport can be modelled and transport planning can take place lies within the repetitive patterns of traffic flows in a city (Jovic, 1999). The stable variation in traffic flows observed over set time periods make it possible to predict and model what future traffic conditions might be. Traffic displays repetitive pattern variations that can be observed every day, called hourly variation; over a week, which is daily variation; over a month, which is weekly variation; and annually, which is monthly variation in traffic flows (Jongh and Bruwer, 2017). The aim of transport models is to predict these variations, and specifically the peaks in these variations. An understanding of the peaks will provide insight in the capacity required and the need for transport infrastructure investment. This process is an essential input in transport planning

It is important to understand that public transport services have spill-over effects (Mendiola, González and Cebollada, 2014). The spill-over effects are effects that occur indirectly as a result of the public transport. An example of a spill-over effect is increased economic activity in the surroundings of a transport station because of people using the public transport and

moving through the area. These spill-over effects have to be taken into account when making transport planning decisions.

2.3.2 What is transport planning used for?

Transport planning is used to evaluate existing and future infrastructure projects and gauge whether the demand for transport is being met by the current infrastructure and what the most economically feasible projects will be to meet future transport demands. For future transport projects, multiple infrastructure solutions are considered and the solution with the lowest opportunity cost to the stakeholders is chosen to meet the demand for transport (Tabuchi, 1993).

The aim of transport planning can be further described as the optimal satisfaction of transport demand (Algers, Eliasson and Mattsson, 2005). Individuals making use of the transport infrastructure create transport demand. The satisfaction of individuals making use of transport infrastructure is a key variable to gauge the success of the transport infrastructure.

There are internal and external factors influencing trip satisfaction of transport users. Internal factors are unique to every individual and an amount of behavioural control can be executed on the internal factors. External factors are exogenous to the individual and outside of the behavioural control of the individual. Internal factors include personal characteristics, travel preferences and mode preferences. External factors include trip characteristics and time (St-Louis *et al.*, 2014). Modes that are more affected by external factors generally display lower levels of satisfaction. This lower level of satisfaction occurs when the external factor influences the individual in a negative manner. The negative influences include prolonged travel time that result in individuals being late. Perceptions that commute has value other than arriving at a destination significantly increases satisfaction for all modes (St-Louis *et al*., 2014).

Time is important in transport as all individuals have daily time budgets (Moschandreas, 1981). The daily time budget is the time that can be afforded to be spent on certain activities per day (Andorka, 1987). The more time that is lost to individuals in transport, the less time will be available for the individuals to be economically productive. This leads to individuals having to make a decision on what transport will be chosen according to how sensitive the individual is to time (Joly, 2004). The consensus is that high-income individuals are more sensitive to time and will spend more money to spend less time travelling. Low-income individuals will rather spend more time travelling than to spend more money on transport. This means that low-income individuals are less time sensitive

2.3.3 Development of transport modelling

The first travel-demand models were simple mathematical models, such as the gravity or entropy models that quantified travel as a function of the size of the zone (Curry, 1972; Sayer, 1977). These were essentially aggregate trip-based models. The number of trips generated from a zone was considered proportional to the population in the zone. The number of trips attracted to a zone was considered proportional to the number of attractions within the zone. The travel between the zones was considered inversely proportional to the distance between the zones (Sivakumar, 2007).

Advances in modelling techniques resulted in a shift away from the aggregate models and led to the development of disaggregate trip-based models (Train and McFadden, 1978; Koppelman and Wilmot, 1982). The models use disaggregate level data on trips made by individuals between the zones of the study area and apply modelling techniques such as constrained optimisation[1] and random utility maximisation.[2] The difference between aggregate and disaggregate models is the fact that disaggregate models view the individual as the decision-making unit, whilst aggregate models do not. Disaggregate models take into account the effects of individual social-demographics on travel-related choices (Krygsman, 2004; Krygsman, Arentze and Timmermans, 2004; Sivakumar, 2007).

The limitation of trip-based modelling is the fact that the approach does not consider linkages between trips or the requirement imposed by activities on trips and transport modes (Hensher and Rose, 2007). In trip-based models all trips are treated independently. This means that a single person can be assigned two different modes of transport for their home to work and work to home trips. Tour-based models were developed to address this problem (Algers, Eliasson and Mattsson, 2005).

Tour-based models divide all individual travel into tours based at home and trips not based at home (Marlin, 1981; Antonisse, Daly and Gun, 1986). A home-based work tour involves travel from home to work and back to home. Tour-based models consider the following home-based tour purposes: work, education, shopping, personal business, employers' business and other.

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[1] Constrained optimisation is the process of optimising an objective function with respect to some of the variables in the presence of constraints to those variables. For a deeper discussion of constrained optimisation read *Constrained Optimization of Experimental Design* (Cook & Fedorov, 1995).

[2] Random utility maximisation is the theory that assigns probabilities to outcomes as if the individuals randomly chose a utility function and the picks from each option set the utility maximising element (Arentze, Kowald & Axhauzen, 2013).

The remaining non-home-based trips are classified under two purposes – non-home-based employer's business and non-home-based other (Sivakumar, 2007).

In a four-step modelling framework, the frequency of the trips and tours is first predicted. This is followed by attraction models that indicate where trips are attracted to. This is followed by mode-destination choice models or mode destination time-period-choice models in more advanced modelling systems. Lastly, the network assignment procedure allocates the tours and trips to the transport network (de Dios Ortuzar and Willumsen, 2002).

Tour-based models are limited by the fact that they suffer from a lack of behavioural realism.[3] This limitation is shared between trip and tour-based approaches (Algers, Eliasson and Mattsson, 2005).

The solution to the shortcomings of the trip and tour-based approaches is the activity-based approach (Kitamura, 1988; Axhausen and Garling, 1992). Activity-based models acknowledges that the travel needs of the population are determined by their need to participate in activities spread out over time and space. Thus, a person's activity patterns, both in-home and out-of-home, influence his or her travel patterns. To quantify the travel needs of the population, it is important to model its activity-travel patterns. The activity-travel pattern of an individual is defined as a complete string of activities undertaken by the person over the course of a day, characterised by location, time of day and mode of travel between locations (Sivakumar, 2007).

For the purposes of this research, a definition was formulated for a trip, tour and activity. There is no consensus on the definitions, so the most widely accepted definitions were used.

A trip can be defined in transport modelling as a single journey made by an individual between an origin and a destination with a specified mode for a defined purpose (Florian and Nguyen, 1978; Litman, 2003). A trip diary is the survey instrument used to extract the transport behaviour of an individual. A trip diary is typically focussed on a specific day and contains information regarding all the trips undertaken on that day (Axhausen, 1995). A tour is the total travel between two anchor destinations, such as home and work, including both direct trips and chained trips with intervening stops (Marlin, 1981).

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[3] Behavioural realism refers to the ability of transport models to accurately predict how individuals will make transport-related decisions. For a good discussion of the evolution of behavioural realism read *Behavioural Realism in Urban Transportation Planning Models* (Ben-Akiva *et al*., 1993).

An activity is a continuous interaction with the physical environment, a service or individual, within the same socio-spatial environment, which is relevant to the observation unit. It includes any waiting times before or during the activity (Kitamura, 1988). To be able to make use of activity-based modelling methods, an activity profile needs to be created for every individual in the target population. An activity profile is a journal of the activities undertaken by an individual through a day. This includes location, time and travel data (Beckx *et al.*, 2009).

It is important to acknowledge that human beings are not islands and that people interact with each other extensively. Therefore an individual's activity-travel patterns are influenced by other individuals and particularly by the activity-travel patterns of other household members (Algers, Eliasson and Mattsson, 2005).

2.3.4 Decision making process

The modelling of transport focuses on the decision-making process of individuals. If transport models can accurately forecast the decisions individuals are going to make regarding modal and route choice, it will become easier to provide and regulate sufficient transport in cities (Behrens, 2002). Modal choice is the decision-making process that happens when people choose between transport alternatives, which is determined by a combination of individual socio-demographic factors and spatial characteristics, and influenced by socio-psychological factors (De Witte *et al.*, 2013). Socio-demographic factors can be described as the characteristics of a population. This includes age, gender, ethnicity and income of the individual. Spatial characteristics refer to the physical environment describing an individual, which includes distance to work and population density. Socio-psychological factors are the feelings, thoughts and beliefs that influence the behaviour of individuals.

It is important to acknowledge that the decision-making process happens both consciously and unconsciously, as well as objectively and subjectively (De Witte *et al.*, 2013). This means that individuals make decisions whilst actively thinking about deciding and in the subconscious whilst performing other tasks. The decision-making process can be influenced by objective factors like cost and travel time, but also by subjective factors including beliefs, norms and values of the individual. A simple example can be how vehicle ownership is often regarded as a status symbol (Dissanayake and Morikawa, 2010). This means that individuals do not always act in a rational manner when making decisions on buying and driving a vehicle.

In developing countries, the travel decisions of household members are known to be interrelated (Dissanayake and Morikawa, 2010). This is supported by Gärling (1998), who found when making choices people might consider individual consequences, the collective consequences or the individual outcomes of the collective consequences. This is important,

as the behaviour of the individuals inside a household will have an impact on one another and will have to be considered if an accurate model of the transport behaviour of the individuals needs to be built.

The interrelatedness and subjective nature of decision-making can also be viewed in other fields of study outside of transport planning. In the field of recycling, attitude, subjective norm, moral norm and perceived behavioural control influence recycling intention and that influences behaviour (Chan and Bishop, 2013). Recycling can be viewed as an action that is good for the environment but not necessary for day-to-day survival. This allows for a comparison to be drawn to research done by Batty, Palacin & González-Gil (2015) that found considering the convenience, flexibility and personal space afforded by private cars to be of significant importance, a symbol of status in society. Sixty-five per cent (65%) of interviewees claimed they were willing to change their behaviour to help address environmental issues, but only 42 per cent claimed they were willing to do this by engaging in modal shift to public transport (Batty, Palacin and González-Gil, 2015). This supports the notion that individuals do not always make rational decisions when making transport decisions.

It is important to understand a decision is only an intention or commitment to behave in a particular manner. A frequently repeated behaviour is not necessarily preceded by deliberate decisions. Breaking off a habit which is not preferred presupposes that there are alternatives that people become aware of that look better. The alternatives are not forgotten and the alternatives are eventually experienced as better (Gärling, 1998).

The complexity of human behaviour allows for the criticism of the theoretical basis of travel choice modelling as an inaccurate description of how people make choices (Gärling, 1998). The criticism has led researchers to develop another way in which decisions are modelled.

2.3.1.1 Nested logit model

The nested logit model is an improvement on the way models predict the decision making process by acknowledging that not all transport options are available to all transport users within a city (Hensher and Rose, 2007). Certain individuals are captive to certain modes and the nested logit model makes provision for this fact by applying a hierarchical structure to decision making. Captive transport users are users that do not have modal choice options and must make use of a certain mode of transport. A simplified example of this would be an individual who does not have access to a vehicle. This individual can thus not make use of a vehicle as a mode of transport and is captive to non-motorised transport (NMT) and public transport systems. The nested logit model makes provision for this whilst traditional choice models would still see private transport as an option for the individual.

The figure below is a visual representation of what the nested approach might look like. If all journeys of an individual are considered, the first choice faced by the individual might be whether he or she has money to pay for transport. If the answer is no, then the individual will be forced to make use of Mode 1, which will be NMT. If the answer is yes, then the next choice the individual will have to make is between public transport and private transport.

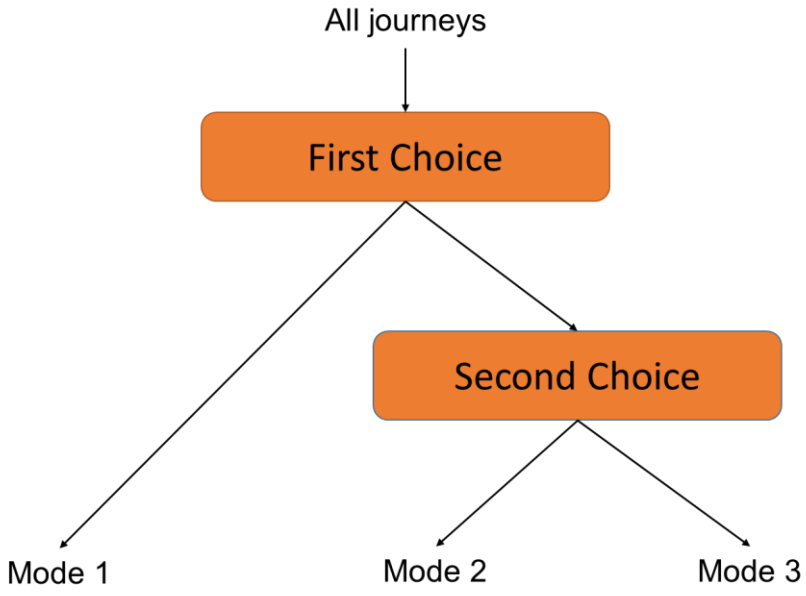

Figure 1: Nested choice model

Source: Adapted from (Birr, 2018)

The nested logit model improves on the traditional sequential choice model as certain modes are excluded from the options of the individual and a more accurate prediction can be made about the modal choice of the individual (Dissanayake and Morikawa, 2010).

2.3.1.2 Theory of planned behaviour

To develop the right policy measures and transport infrastructure for a city, a deeper and more thorough understanding of actual travel behaviour of the people and their modal choices is necessary (De Witte *et al*., 2013).

The theory of planned behaviour was designed to explain the determinants of an individual's conscious decision to perform a behaviour that is beyond reactionary behaviour or causation. According to the theory of planned behaviour, the execution of an action can be predicted by an individual's intention to perform a behaviour and the perceived control over the behaviour (Roos and Hahn, 2017).

The theory of planned behaviour also has limitations as car use is determined by intention and habit but not perceived as behavioural control, whilst public transport use is influenced solely by intention. Research clearly shows that psychological factors are better predictors of travel mode choice than socio-demographic and infrastructure differences (Donald, Cooper and Conchie, 2014).

2.4 Modal split and congestion

2.4.1 Definition of modal split and congestion

Modal split can be defined as the ratio of different transport modes in the total journey from origin to destination, modal split can also refer to the determination of the modes individuals will use for a specific trip (Matulin, Bošnjak & Šimunovič, 2009; Batty *et al*., 2015; Florian & Nguyen, 1978; Mendiola *et al*., 2014). Researchers agree on the broad definition and analysis methods of modal split, but small variances are present. Lack of harmonisation in the definition and analysis of modal split makes it hard or even impossible to compare modal choice data both longitudinal over time and cross-sectional between cities or countries (De Witte *et al*., 2013). An easier way to compare the effectiveness of the modal split present between cities and countries is to measure the mobility of individuals in the transport system. Mobility is "the capacity of entities to be mobile in social and geographic space, or … the way in which entities access and appropriate capacity for socio-spatial mobility according to their circumstances" (De Witte *et al*., 2013). If low mobility figures are present, it might indicate that the transport infrastructure is insufficient or there is congestion present (Ye and Titheridge, 2017).

A practical definition of congestion for use in transport studies would be "the condition that prevails when the entry of an additional vehicle onto the road would increase the journey time for other vehicles" (Gonzales and Daganzo, 2012). The problem of congestion can by likened to the single bottleneck. The idea introduced by Vickery (1969 cited in Gonzales & Daganzo) is that congestion is caused by a bottleneck somewhere in the transport system that is not allowing traffic to flow freely as there is not enough space or capacity. The most common bottleneck experienced in cities is the capacity of roads (Tabuchi, 1993), whilst in most developing countries the public transport is not used efficiently to maximise the number of passengers carried (Dissanayake and Morikawa, 2010). A possible solution would be to find a more optimal modal split formulation to maximise the number of passengers carried by making more use of public transport and minimising congestion on the roads. To influence the modal split of a city, the factors affecting the modal choice decision of transport users must be identified. This will enable local government and municipalities to implement policies and infrastructure that would lead to a more improved modal split in the city (Matulin, Bošnjak and Šimunovič, 2009).

Modal choice is influenced by infrastructure limitations and geographical constraints in the area in which the decision is being made. A greater understanding of what influences modal choice in every region will allow informed decisions to be made by policy makers on how to more efficiently utilise the available modes of transport (Bury *et al.*, 2017).

Mode choice and satisfaction are determined by both objective and subjective factors (St-Louis *et al.*, 2014). Subjective factors refer to personal perspectives, feelings or opinions whilst objective factors refer to the elimination of subjective factors and focus on measurable indicators that are based on facts (De Witte *et al.*, 2013).

There is a whole range of factors determining modal choice and they are interrelated, to a smaller or larger extent (Buehler, 2011; De Witte *et al.*, 2013; Donald, Cooper and Conchie, 2014; Bury *et al.*, 2017). Figure 2 illustrates the findings of a review of the factors that have an influence on modal choice. This study had access to and used car access and household income as socio demographic factors. The study did not have access to and did not use any spatial indicators and the study made use of all the listed journey characteristics apart from weather conditions.

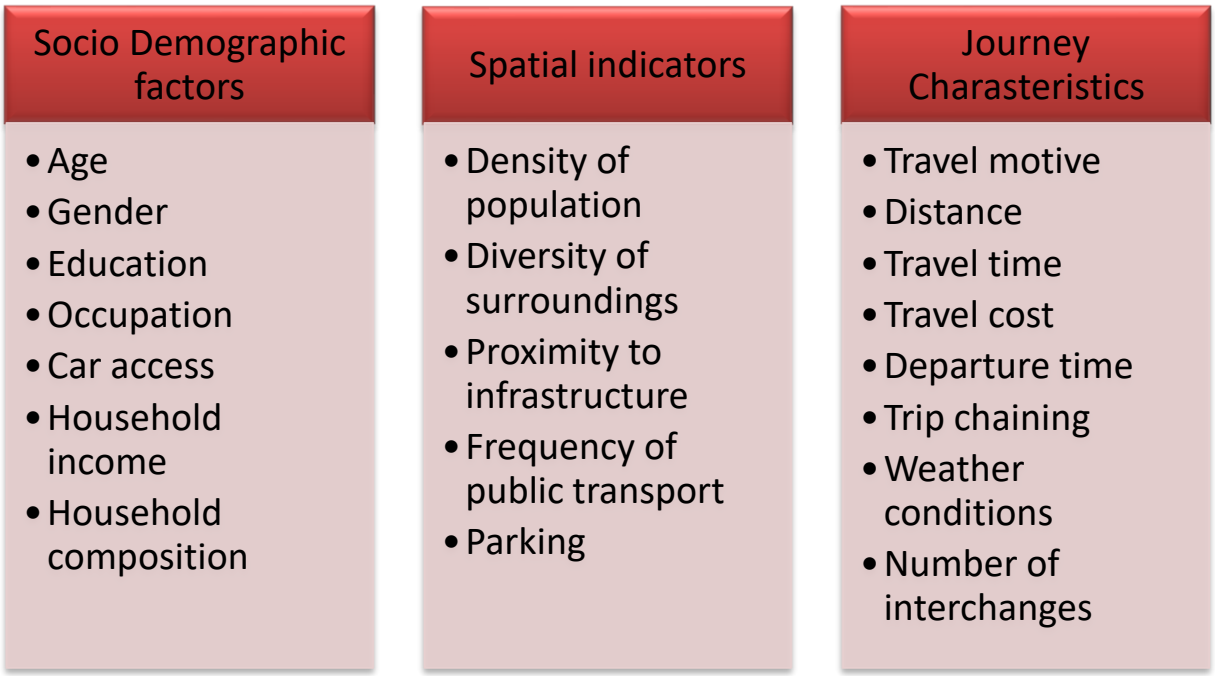

Figure 2: Factors affecting modal choice

Source: Adapted from (Buehler, 2011; De Witte *et al.*, 2013; Donald, Cooper and Conchie, 2014; Bury *et al.*, 2017)

An important consideration that allows for more validity to be granted to modal split forecasting is the fact that reasons for modal choices are stable over time (Pooley and Turnbull, 2000).

Short-term indicators like weather might have some influence but, unless an individual wins a large sum of money and moves into a new income category or relocates, the modal choice of individuals are stable over the medium to long term (Thomas, La Paix Puello & Geurs, 2019).

Rises in the income of individuals do not mean that congestion will dissipate. The transport paradox states transport is unique as the only development sector that worsens as income rises, if the rise in income is not accompanied by infrastructure and policy development to reduce the use of private transport (Potter and Skinner, 2000).

2.4.2 The relationship between modal split and congestion

A modal split dominated by private vehicles leads to high levels of congestion experienced in a city (Gonzales and Daganzo, 2012). This relationship between modal split and congestion is hard to combat as the number of individuals who own vehicles keeps increasing whilst road infrastructure can only be upgraded and expanded until physical barriers will prohibit further expansion (Matulin, Bošnjak and Šimunovič, 2009).

Public transport has the potential to carry a large number of passengers whilst using fewer resources and taking up less physical space than private vehicles. Public transport provides high-density transport in cities (Paulssen *et al*., 2014). The more access there is to public transport, the higher the percentage of journeys using it, and therefore the lower the share of modal split accounted for by private vehicles (Mendiola, González and Cebollada, 2014). A modal split with fewer private vehicles could result in a less congested city but societal, political and economic barriers have prevented the shift from occurring. These barriers to modal shift can be overcome by facing the following challenges when encouraging modal shift: internalising externalities, societal backing and cooperation, political commitment, investment, modal shift research and programs. There are two kinds of measures to encourage modal shift: pull factors that improve the quality and attractiveness of public transport and push factors discouraging and preventing car use (Batty, Palacin and González-Gil, 2015). Pull factors would include the punctuality and low cost of a transport mode, while push factors include congestion charges and high cost of parking in city centres.

2.4.3 What is modal split used for

The development of new services such as park-and-ride systems, individualised public transport services and the creation of public transport plans can significantly reduce the number of individual vehicles entering the urban area. Reducing the congestion levels and improved traffic flow performances are the most relevant uses of the modal split indicator (Matulin, Bošnjak and Šimunovič, 2009).

Modal split analysis is used as an indicator by researchers and local governments to identify and measure the effectiveness of new transport projects and regulation in the alleviation of congestion and infrastructure development (Ryu, Chen and Choi, 2017). The effectiveness is measured in the number of transport users that migrate away from less desirable modes like private transport to more desirable modes for the city like public rail or bus services.

2.4.4 Why is congestion bad for a city?

Congestion increases the time spent on the roads for all users. This has serious negative effects for the economy as the time lost to congestion is lost time that individuals are not economically active (Havenga, Simpson and Goedhals-Gerber, 2016). The impact of congestion is worsened in a city like Cape Town where most low-income individuals reside far from job opportunities. This is a remnant of the apartheid spatial planning regime that purposefully removed non-white individuals from the economic centres of towns (Schalekamp and Klopp, 2018; van der Merwe and Krygsman, 2020). This means that low-income individuals lose vital time that could have been spent earning an income.

A widely used solution to ease congestion is to implement a congestion charge (Gonzales and Daganzo, 2012). A congestion charge is shown to be effective in the short term to help curb congestion, but the long-term effects of a congestion charge are not always positive.

The impact of congestion charging is not spread evenly among the different income groups. A fixed amount is charged for entering a certain area or for the use of a specific road that would attempt to lessen the congestion experienced on a road. Tolling the use of the more desirable road worsens social inequality by tolling the rich and poor (Liu and Nie, 2011). The high-income individuals can absorb the impact of a toll and still function normally. The low-income individuals cannot afford to pay the toll but need to use the road to get to economic activities to earn an income. A toll or congestion charge would have a worsening effect on the income equality in a city like Cape Town.

2.4.5 The relationship between congestion, population growth and development

A relationship can be observed between the congestion experienced, the population growth and the development level of the transport infrastructure in a city. Congestion increases as the population of a city expands. Congestion decreases as the development of the transport infrastructure of a city increases (Matulin, Bošnjak and Šimunovič, 2009). This relationship can be seen in Cape Town, with congestion increasing along with the population of Cape Town. The infrastructure development has been a mixed bag of results, with large sums of money being invested in the BRT system with little effect on congestion whilst other forms of

public transport such as train and bus have seen low levels of development (Grey and Behrens, 2013).

2.5 Trip-based and activity-based research approaches

2.5.1 Trip-based modelling approach

The traditional four-step model has been widely used in travel demand forecasting. It considers trip generation, trip distribution, modal split and traffic assignment sequentially in a top-down process (Zhou, Chen and Wong, 2009). This means the output of the first step is the input of the second step, and so forth.

The classic four-stage transport model will be discussed in brief detail to give a better understanding of how the model works (Florian and Nguyen, 1978; Train and McFadden, 1978; Lam and Huang, 1992; Sivakumar, 2007). A visual representation of the model is illustrated in figure 3.

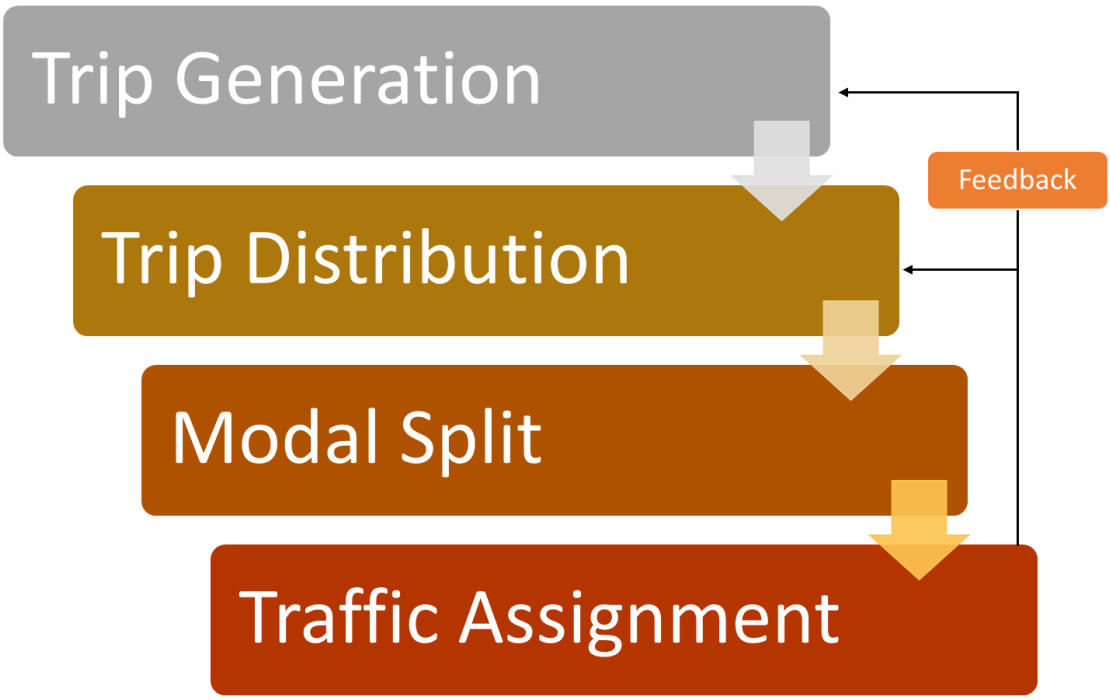

Figure 3: Trip-based modelling approach

Source: Author: Adapted from (Zhou, Chen and Wong, 2009)

1. Trip generation

Trip generation gives the transport modeller the number of trips generated in each zone, usually done with population matrixes and the number of trips attracted in each zone, which

is usually done using population statistics. This is done by using a multiple regression equation per trip purpose and income group. This step is completed using home interview survey data.

Trip generation is an important step as this defines the overall level of transport in the system.

The final formulas used to calculate the trip production and trip attraction for the trip generation process is as follows:

Trip Production= a0 + (a1 ×Forecasted Population) + (a2 ×Forecasted Income)

Trip Attraction= b0 + (b1 ×Forecasted Employment) + (b2 ×Forecasted Land Price)

2. Trip distribution

This step is used to produce a trip distribution pattern, which can be referred to as an origin–destination (OD) pattern and can be presented in an OD matrix. This is done by forming gravity distribution of modes per trip purpose and income group. This step is completed using home interview survey data where the respondent provides the address of where they live and where they travel to (such as their work or educational institution facility).

The following formula is used to calculate the trips from 1 zone to any other zone in the model:

Trip of any zone = Total Trip /Total Impedance Factor * Impedance factor for this particular zone

3. Mode choice

The role of mode choice models is to determine the split between transport modes. This is done using a multinomial logit model per trip purpose and income group that assigns a probability of every mode that can be used. This is done using home interview survey data along with revealed preference and stated preference data.

The calculation starts by calculating the probability of using each mode. This calculation is done by dividing the probability of using a car with the total utility of the transport system. The equation is as follows:

$$\text{Probability}_{\text{Car}} = \frac{e^{U_{Car}}}{e^{U_{Car}} + e^{U_{Bus}} + e^{U_{Rickshaw}}}$$

The following variables are usually included in the equation to determine the modal share of each transport mode: travel cost, in-vehicle travel time, transfers, walking time and waiting

time. The modal share is calculated by the trip making (generating) from one zone to another multiplied by the probability of using that mode. The equation is as follows:

Modal Share for any Mode = Trip (i− j) × Probability (i− j)

One weak point of the multinomial logit model, used to determine the modal share figures, is the functional form of the model. The model accepts that all users have access to all the modes available in the system whilst this is not true in real life. Certain users are captive to certain modes of transport. To help address the problem it might be fruitful to look at the nested model approach. The nested approach creates a hierarchy in which there are more levels in the decision-making process. This might help to improve the accuracy of transport demand models by removing options not available to certain transport users.

4. Trip assignment

Trip assignment assigns transport to the network. The assignment is based on the OD-matrices, which have been split by mode and a corresponding network, for each of the modes to be assigned.

The outcome of the assignment is a network flow, which enables us to identify transport demand at separate road stretches and links in the network.

The generalized travel cost factor is calculated for each mode using the equation below:

GTC = TC + (a1/a2) * TT

Where, TC=Travel Cost TT=Travel time, a1 =Co-efficient of the Travel Time factor, a2 = Co-efficient of the Travel Cost factor. The values a1 & a2 come from the utility functions mentioned earlier in the Modal Choice step.

The shortest distance in terms of the GTC from one node to another is calculated and the trip assignment is completed.

2.5.1.1 Advantages of the trip-based technique

The four-step trip-based model produces clear and statistically robust results that are easy to convey to decision and policy makers to help support the implementation of new transport projects and policy regarding transport (Lam and Huang, 1992). The four-step model is tried and tested and has been the central part of most transport planning activities over the past 40 years (Zhou, Chen and Wong, 2009).

2.5.1.2 Criticism of trip-based techniques

The traditional four-step trip-based model is an integral part of transport planning but has shortcomings when the effects of transport demand management (TDM) are modelled (Shiftan, 2000). The traditional four-step trip-based model struggles to model TDM as the model can only model changes that can be expressed in time and cost and these are not the only factors influencing individuals when making transport decisions (Algers, Eliasson and Mattsson, 2005).

This apparent weakness can be described as the lack of a single unifying rationale that would explain or legitimise all aspects of the model. Jointly, it also suffers from inconsistent consideration of travel times and congestion effects in various steps of the procedure (Zhou, Chen and Wong, 2009).

The trip-based approach has a further disadvantage of modelling trips as independent and isolated, with no connection between the different trips acknowledged in the model (Gärling, 1998). This would realise in individuals being assigned different transport modes between legs as recognition of previously used modes is not present in the model. This leads to trip-based models only being able to model one-way single trips for a set period like the peak morning or afternoon period (Shiftan, 2000). The trip-based approach also lacks a time component. The model does not recognise the time of day or any time related variables. The model also does not include any direction or sequential information. This results in transport users being assigned different modes on return journeys if an AM and PM peak is modelled for a specific day. This restricts the model in not allowing for full day models of a city to be built, but only single direction-specific situations (Chu, Cheng and Chen, 2012).

The trip-based modelling approach uses objective determinants to model the transport behaviour of individuals. Objective determinants can be identified quantitively whilst subjective determinants are qualitative. More attention is paid to objective factors as they can be measured easily (De Witte *et al.*, 2013). Subjective factors refer to personal feelings and perspectives and opinions in the decision-making process. Objective factors refer to a process that is based on observable facts that cannot be called into question (Scheiner and Holz-Rau, 2007). Trip-based modelling does not include subjective factors. The activity-based modelling approach uses both objective and subjective determinants to model transport behaviour.

Activity-based modelling approach

Activity-based approaches aim at predicting activities that will be undertaken by individuals and model the transport requirements to meet the demand created by the undertaking of an activity (Algers, Eliasson and Mattsson, 2005).

Activity-based models are based on the principle that travel demand is derived from individuals' daily activity patterns. Activity-based models predict which activities are conducted when, where, for how long, for and with whom and the travel choices individuals will make to complete the activities. Having this type of detailed model at the disposal of researchers, practitioners, and policy makers allows for the evaluation of the effect of alternative policies on individuals' travel behaviour at a high level of time-based and spatial richness and the selection the best policy alternative considering a potential range of performance indicators (Axhausen and Garling, 1992; Chu, Cheng and Chen, 2012). Figure 4 is and visual representation of the information flow in an activity-based modelling system.

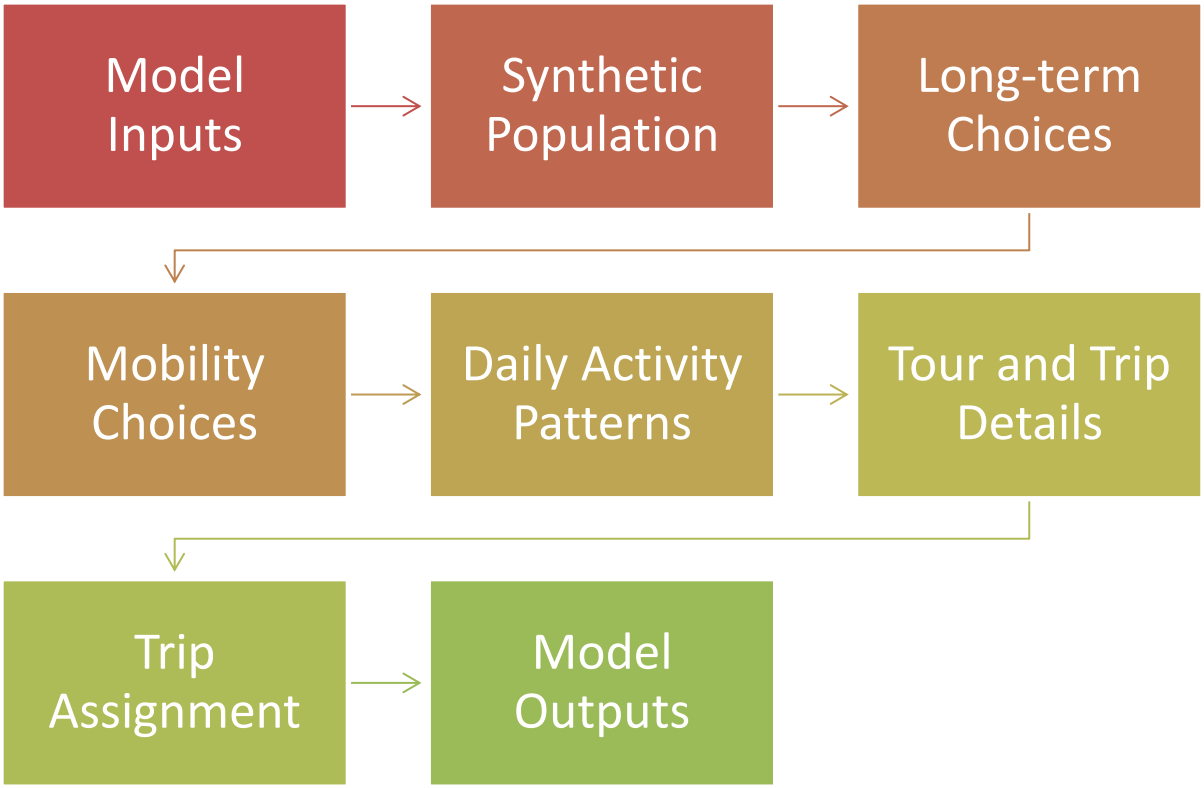

Figure 4: Major steps in an Activity-based modelling system

Source: Author, adapted from (Beckx *et al.*, 2009)

The development of activity-based models can be identified by three distinct theoretical approaches that have built on the shortcomings of the previous model.

The first generation of activity-based models was constraint-based models. The main objective of constraint-based models was to predict whether a transport user's activity agenda was feasible within the space-time constraints of the individual. Examples include PESASP (Lenntorp, 1978), CARLA (Jones *et al.,* 1983), BSP (Huigen, 1986), MAGIC (Dijst, 1995; Dijst & Vidakovic, 1997), and GISICAS (Kwan, 1997). This constraints-based approach had some limitations as individual accessibility was considered but not household accessibility. This is a limitation, as research has found that the household composition and accessibility has an effect on the modal choice of individuals (Dellaert, Ettema and Lindh, 1998). The constraints-based approach also falls into the trap of assuming individuals can travel in all directions equally easily.

The shortcomings of the constraints-based approach led to the development of utility-maximising models. Utility-maximising models are an improvement on constraint-based models as individuals are modelled with the household constraints included in the model. Utility-maximising models are built on the premise that individuals maximise utility when planning and organising daily activity schedules. Examples of utility-maximising models are the daily activity schedule model (Ben-Akiva *et al.,* 1996), and PCATS (Kitamura & Fujii, 1998).

Some researchers have found the notion unrealistic that individuals wanted to or could even maximise the utility of the individual's daily schedule. This notion was supported by research that found individuals do not always act or make decisions in a utility maximising manner and that decisions are based on a whole range of factors. Such factors include the past experiences of the individual, cognitive biases, age and individual differences (Dietrich, 2010). This has led to the development of computational process models, which aim to mimic the decision-making behaviour of transport users to develop an activity schedule and transport demand. Examples of computational process models are ALBATROSS (Arentze & Timmermans, 2000) and TASHA (Roorda & Miller, 2005).

2.5.1.3 Criticisms of the activity based technique

The activity-based transport models require rich and information dense input data to be able to accurately model the decision-making process of individuals. This data is hard and expensive to obtain and is not readily available in most countries and specifically developing countries (Chu, Cheng and Chen, 2012). Activity and travel diaries are often used to collect data of daily household activity behaviour. More recently, cell phones and GPS has been used to extract individual activity data (Krygsman and Schmitz, 2005; Krygsman, Nel and De Jong, 2008). The process, however, is technology intensive and require extensive data manipulation expertise.

The outputs of activity-based models are not as easy to understand and implement as the four-step trip-based model. This results in policy and decision makers requiring the assistance of transport and statistical specialist to help understand and implement the outputs of the activity-based transport model.

2.5.1.4 Advantages of activity-based techniques

Activity-based approaches have several advantages over traditional trip-based approaches (Shiftan, 2000; Krygsman, 2004; Algers, Eliasson and Mattsson, 2005; Beckx *et al.*, 2009; Behrens and Masaoe, 2009; Chu, Cheng and Chen, 2012). The first advantage lies in the fact that the demand for transport is derived from the demand for participation in activities. If models can accurately model the demand for activities, then the model would be able to model the demand for transport. The next advantage is the fact that sequences and patterns of behaviour are the unit of analysis, not individual trips. This allows for the building of much more robust and accurate models of daily travel demand. Households and other social structures have an influence on activities and the travel behaviour of transport users. Activity-based models account for this by incorporating the effect of activity schedules on each other. Another advantage of activity-based models over trip-based models is the inclusion of constraints on activity and travel behaviour. These constraints include spatial, transportation and interpersonal interdependencies. The final advantage of activity-based models is the reflection of scheduling and activities in time and space that cannot be done with trip-based models.

2.6 Transport planning in Cape Town

2.6.1 Overview of development in Cape Town

The bulk of travel data collection and analysis methods applied in South Africa are drawn from methods developed in the United States in the 1950s and 1960s in the context of a ‘predict-and-provide’ transport policy environment. These methods are in the form of inter-zonal OD surveys and four-step traffic forecasting models. The models have been refined and improved over time, procedurally and substantively, but the analysis and methods used are the same as those first developed in the late 1950s in cities like Detroit and Chicago (Grey and Behrens, 2013). The analysis and methods remain centrally focused on the problem of traffic congestion, and the construction of highways in its alleviation. A focus on traffic congestion, together with the labour transportation requirements of the remnants of urban apartheid, has led to a focus on home-based work trips and morning peak periods in past South African travel analysis (Del Mistro, Proctor and Moyo, 2017).

The focus on building roads as a solution to relieve congestion has theoretical and physical limitations. The physical limitation is the lack of space in Cape Town required to expand the road network. The theoretical limitation is the fact that when new roads are built an economic effect known as induced demand occurs. Induced demand is demand that is generated by improvements in transport infrastructure. The improved transport infrastructure lowers the opportunity cost of using the road and thus results in higher demand for the use of the road as the high cost of using road transport has been lowered by the improved road infrastructure (De Dios Ortuzar & Willumsen, 2002).

Research done in the early 1990s found that roads can be compared to an hourglass, with roads being the bottleneck and cars being compared to this and the speed of the falling sand is much faster than that of the accumulated sand with the speed fixed and independent of the amount of sand (Tabuchi, 1993). This means that the speed of vehicles on roads will be negatively affected by the number of vehicles on the road. This has led governments and municipalities, just like the City of Cape Town, to move towards integrated transport systems that try to reduce the number of private vehicles on the roads and promote public transport (Schalekamp and Klopp, 2018).

The new approach calls for a more efficient and effective use of integrated public transport systems (Janic, 2006). Multiple transport modes are necessary to provide an integrated, accessible and inclusive public transport system, but at the core of a good system must be a high capacity, high efficiency mode. The two most common modes are bus and urban rail (Batty, Palacin and González-Gil, 2015).

The City of Cape Town decided to implement a Bus Rapid Transport (BRT) system in Cape Town to help build an integrated public transport system. The MyCiTi BRT system was implemented with various degrees of success. The capacity provided by the MyCiTi bus system may not be fully utilised over the entire lifespan of the MyCiTi infrastructure, estimated at 40 years if densification and mixed-use development objectives and modal split targets are not realised (Grey and Behrens, 2013). The suboptimal utilisation can be attributed to the isolation of the BRT system from supporting development policies, tools and mechanisms to help the modal shift from private vehicles to public transport (Schalekamp and Klopp, 2018).

The suboptimal performance might also be a result of unrealistic expectations of passenger counts for the new mode. The demand for the new transport project was modelled using the four-step trip-based modelling technique. The trip-based modelling approach is proven to be effective in modelling the ‘predict and provide’ environment of road expansions but lacks flexibility and behavioural realism in predicting transport behaviour of individuals in integrated

transport systems. The inclusion of more choice-related measures could enhance the performance of the modelling of transport networks (Thomas *et al.*, 2019).

2.6.2 Government plans and policy papers

The Constitution of the Republic of South Africa of 1996 identifies the legislative responsibilities of the different sectors of government regarding airports, roads, traffic management and public transport. Transport is a function that is legislated and executed at the national, provincial and local sectors of government (Schmidt, 2014).

The implementation of transport functions at the national level takes place through public entities that are overseen by the Department of Transport (DoT), each with a specific delivery mandate, as specified in legislation establishing these entities. Examples include the public rail entity Transnet Ltd and the Airports Company South Africa (ACSA), which owns and operates the nine provincial airports in South Africa.

The 1996 White Paper on Transport defines the infrastructure and operations of rail, pipelines, roads, airports, harbours, and the intermodal operations of public transport and freight. The DoT is responsible for the legislation and policies for all the sub-sectors. The department is therefore responsible for conducting sector research, formulating legislation and policy to set the strategic direction of sub-sectors, assigning responsibilities to public entities and other spheres of government, regulating through setting norms and standards, and monitoring implementation (Diana, 2010).

In Chapter 4 of the National Development Plan (NDP) the development of economic infrastructure as the foundation of social and economic development is described. This is given action by outcome 6 (an efficient, competitive and responsive economic infrastructure network) of government's 2014–2019 Medium Term Strategic Framework, which is directly aligned with the work of the DoT (Schalekamp and Klopp, 2018).

The national framework on National Transport Policy (NTP), and the 2007 Public Transport Strategy and Action Plan (PTSAP) support the planning and implementation of quality public transport networks. These documents highlight that quality public transport will enable South Africans to access employment, education, and other essential activities and services. The PTSAP has two key enablers of transport development, namely Accelerated Modal Upgrading (AMU) and Integrated Rapid Public Transport Networks (IRTN). The former refers to initiatives to transform and upgrade existing bus, taxi and rail services in the short to medium term while the latter seeks to implement high quality networks of rail priority corridors and BRT corridors. The plan started in the six metro cities of the country in 2010, extending to the next six large

cities by 2014. The Integrated Public Transport Network (IPTN) plan is a key mechanism towards achieving this quality public transport system and putting the PTSAP into action.

The Provincial Land Transport Framework (PLTF) states that by 2050 the transport system in the Western Cape is envisaged to be defined by the following elements:

- Fully Integrated Rapid Public Transport Networks (IRPTN) in the higher-order urban regions of the province.
- Fully Integrated Public Transport Networks (IPTN) in the rural regions of the province.
- A safe public transport system.
- A well-maintained road networks.
- A sustainable, efficient, high-speed, long-distance passenger rail and freight transport network.
- An efficient international airport that links the rest of the world to the choice gateway of the African Continent.
- International-standard ports and logistics systems.
- A transport system that is not fully dependent on fossil fuel.
- A transport system that is integrated with land use.

The City of Cape Town has established a transport authority to be the custodian of all transport matters within the City itself and to be the interface with surrounding municipalities and other transport-related stakeholders, with the sole responsibility for transportation within the Cape Town functional region. The transport authority, Transport for Cape Town (TCT), focuses on providing resources, skills, and finances for targeted and investment-oriented service delivery to the citizens and other partners of the City. TCT is constituted in terms of the National Land Transport Act (NLTA) and the TCT Constitutional Bylaw, No. 7208 of 2013, and mandated to fulfil several functions to allow it to plan and implement integrated, good quality transport in Cape Town, amongst others the IPTN.

An example of the work done and overseen by TCT is the implementation of a BRT system for the City of Cape Town. The BRT programme is the road-based component of the BRT Public Transport Strategy that was approved by Cabinet in March 2007. It was designed to move large numbers of people to all parts of a city quickly and safely.

The aim of the BRT system is to link different parts of a city into a network. Government wants to ensure that by 2020 most city residents are no more than 500 meters away from a BRT station. The system features dedicated bus-only lanes, as well as bus stations that are safe,

comfortable, protected from the weather and friendly to passengers with special needs, such as children, the elderly, and the sight and hearing impaired.

It is part of a public-private partnership in which cities build and maintain the infrastructure, stations, depots, control centres and a fare collection system. Private operators own and manage the buses, hire staff and provide services on a long-term contract.

BRT systems combine the best features of rail with the flexibility and cost advantages of road-based transport and have the added advantage of being easier and faster to build than a light rail transport system.

The bus rapid public transport networks which contribute to economic development, job creation and tourism in South Africa include:

- MyCiTi, which operates in Cape Town, Western Cape.
- Rea Vaya in Johannesburg, Gauteng.
- A Re Yeng (Let's go) in Pretoria, Gauteng.
- Go George in George, Western Cape.
- Harambee in Ekurhuleni, Gauteng.
- Yarona in Rustenburg, North West.
- GO!Durban in Durban, KwaZulu-Natal.

The BRT system implemented in Cape Town is part of Transit Oriented Development (TOD). TOD represents the intricate relationship between "Transit" (the operational/ access imperative of an urban environment) and "Development" (the spatial manifestation of those that are within the urban economy). TOD is about changing, developing and stimulating the built form of the city in such a way that the movement patterns of people and goods are optimised to create urban efficiencies and enable social equality and economic development.

2.6.3 How the demand for the transport modes were calculated in Cape Town

The transport demand model used in Cape Town applies the EMME/4 software to forecast the demand for transport according to the traditional four-step trip-based process. The modal split was modelled in step 3 of the analysis by estimating the probability of a transport user choosing a specific mode of transport. The consultant team made use of the 2013 National Household Travel Survey and the 2013 Stated Preference Survey as inputs to the modal split model. The Household Travel Survey was used to identify the transport users' current modal choice given the transport users' travel time, modal alternatives, vehicle ownership, etc. The Stated Preference Survey was used to determine the modal split of a user by asking the

transport user to make a choice between hypothetical transport modes given specific cost, waiting time, number of transfers, etc. This forces the transport user to make a trade-off between the modal alternatives and allows the research team to test which mode the transport user would have chosen if a certain mode was available, such as the MyCiTi BRT system (City of Cape Town, 2013a).

A multinomial logit model was estimated by the consultancy team using a probability function that incorporated the travel cost, in-vehicle time, number of transfers, walking time and waiting time. The transport users were divided into four income groups. This made it possible to compare the modal decisions of different individuals based on the income group they belonged to. The utility functions were included in the EMME/4 model to help make the model more dynamic and sensitive than previous models (City of Cape Town, 2013a).

Unfortunately, the demand for the MyCiTi BRT system in Cape Town was overestimated.

The overestimation of demand for a transport system has serious implications. These include financial deficits, choosing the wrong technology, and increased levels of congestion.

- Financial deficits

The MyCiTi BRT system is currently running at a yearly deficit of around R 400 000 000 (City of Cape Town, 2015). This places huge strain on the City to fund this deficit. In 2012 the system revenue received from passengers for the 2015/2016 financial year was estimated to be R 429 651 000 (City of Cape Town, 2012). In 2015, this was lowered to R 244 836 000 (City of Cape Town, 2015). This is a realisation of only 57 per cent of what was initially anticipated. This indicates that the demand for the transport system was lower than initially forecasted.

The lower system revenue is supported by lower than anticipated modal share figures. In 2010, the transport model predicted that ten per cent of all private transport users would shift to the BRT system along with all captive transport users (City of Cape Town, 2010). This was not the case, with the 2015 IPTN model indicating only two per cent of transport users were using the BRT service (Venter and Vermeulen, 2015).

The financial deficits are not entirely the fault of a lack of demand for the transport systems. The initial forecast for the operating cost and the capital cost required to build the infrastructure was substantially underestimated. After labour negotiations and the tendering process, the operating cost per year rose substantially and the capital cost required from the start of the project in 2007 until the end of the 2013/2014 financial year rose from R 3.8 billion to R 4.8

billion for phase 1A of the MyCiTi BRT system. That is a rise of more than 25 per cent from the initial estimation (City of Cape Town, 2015).

- Choice of technology (mode)

Researchers have analysed the way in which the effectiveness of potential future transport projects is measured, and the effect this has on the provision of transport and legislation (Diana, 2010; Mendiola *et al.*, 2014; Jennings, 2015; Rich, 2015; Sivakumar, 2007). If the effectiveness of future transport projects in alleviating congestion is overestimated, the wrong projects might be constructed, and congestion might not decrease as anticipated.

When choosing an appropriate mode for a new transport system there are important characteristics to consider. These include the volume of passengers, direction of demand and flexibility of demand. If the demand is continuous and not very flexible, then a fixed right-of-way system like trams or metro rail systems are appropriate. If a greater degree of flexibility is required, then a more flexible mode is required that is not bound by a single ROW like bus or taxi services. This has major cost implications because the more separated the mode is from regular traffic, the higher the capital and operating cost (De Dios Ortuzar & Willumsen, 2002).

The MyCiTi BRT system was chosen because it combines the high speed and capacity of having its own ROW but still has the potential to be flexible by being able to change routes with ease.

- Increased congestion

The impact of congestion is not spread evenly among individuals from different income categories. The impact is felt much more by individuals in lower income categories. The individuals in high-income categories are sheltered from feeling the impact (Manville and Goldman, 2018). With increasing congestion levels in Cape Town and the ever-increasing divide between the rich and the poor, something needs to be done to stop and address the issue (Meiring, Kannemeyer and Potgieter, 2018).

The investment in infrastructure development in the City of Cape Town did not lead to the desired reduction in congestion levels experienced within the city (Transport and Urban Development Authority [TDA], 2017). The MyCiTi BRT system has not done much to ease the levels of congestion in Cape Town. According to the TOMTOM Traffic Index, the congestion levels in Cape Town have been slowly rising since the implementation of the MyCiTi BRT system in 2010. The figure below is a representation of the congestion level history (extra travel time), from 2009 to 2016.

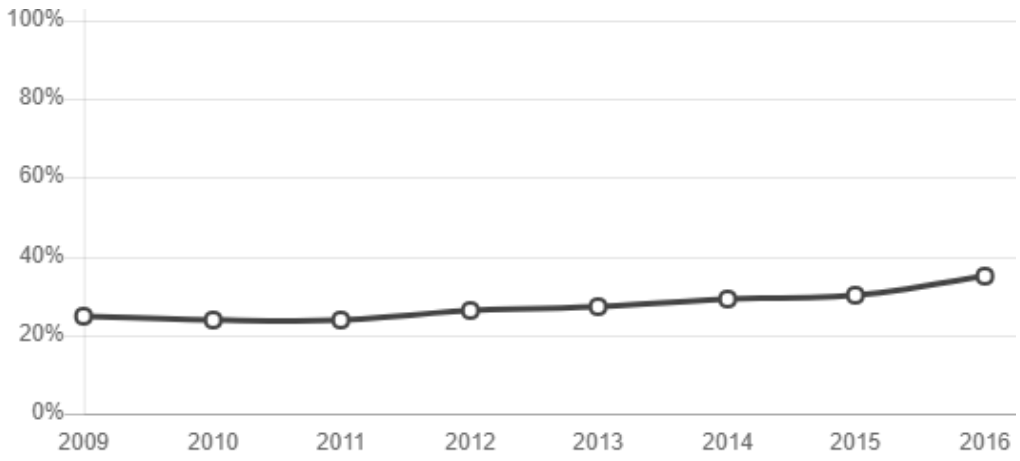

Figure 5: Cape Town congestion

Source: TomTom International (2016)

It is important to note that the rise in congestion is not solely the result of the underperforming MyCiTi BRT system. The City has seen a constant rise in population over the past ten years as a result of urbanisation and general population growth. Figure 6 is a visual representation of the population of Cape Town from 2011 to 2021. The figures were calculated by using the average growth rate from 2001 up to 2011 and extrapolating the data from 2011 until 2021 when the next population census will be held.

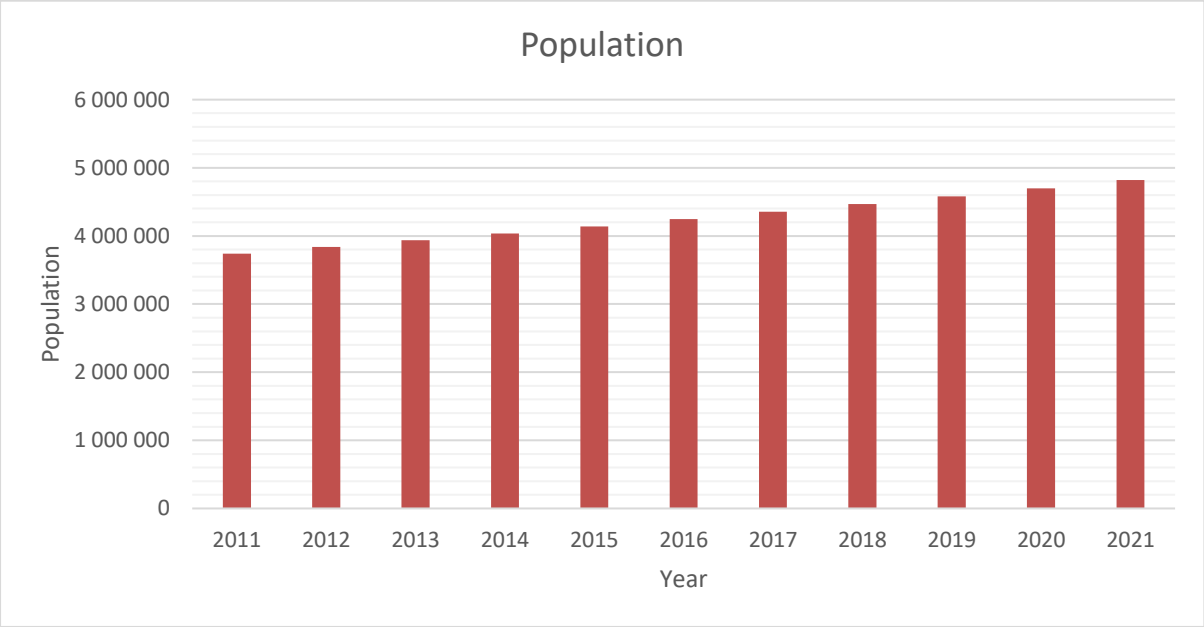

Figure 6: Population growth of Cape Town

Source: Adapted from StatsSA (2012)

Troubles in other parts of the city's transport system have not helped the situation. Passenger rail has seen a drop from 620 000-passenger journeys per day in 2014 to less than 300 000 in 2019 (Petersen, 2019).

The rise in congestion experienced in Cape Town could indicate that an improved modelling approach may be helpful in forecasting future travel demand conditions in Cape Town (Grey and Behrens, 2013). This is hard, as there is an unavoidable trade-off between simplicity and elegance on the one hand and accuracy on the other in travel behaviour research (Gärling, 1998). This means that the researchers will have to decide whether to attempt to make the modal demand predictions more accurate, and also make them more complicated and "ugly" or to keep using the simple and elegant four-step model in its current form and sacrifice accuracy for usability and simplicity.

2.7 Concluding remarks

The literature review finds that transport planning can be described as the planning techniques used to predict multiple future travel demand scenarios and ensuring adequate facilities and services are in place to meet the demand for transport. Activity-based transport modelling techniques are represented as a solution to the limitations of trip and tour-based modelling techniques. Transport planning is used to evaluate existing and future infrastructure projects and gauge whether the demand for transport is being met by the current infrastructure and what the most economically feasible projects will be to meet future transport demands. The decision-making process was found to be important because, when transport models can accurately forecast the decisions individuals are going to make regarding modal choice, it will become easy to provide and regulate sufficient transport in the City of Cape Town. The nested logit model is an improvement on the way models predict the decision-making process by acknowledging that not all transport options are available to all transport users within a city. According to the theory of planned behaviour, the execution of an action can be predicted by an individual's intention to perform a behaviour and the perceived control over the behaviour.

Modal split was defined as the ratio of different transport modes in the total journey from origin to destination. Congestion was defined as the condition that prevails when the entry of an additional vehicle onto the road would increase the journey time for other vehicles. The different factors influencing modal choice were collected from various sources and grouped in three categories: socio-demographic factors, spatial indicators, and journey characteristics. The relationship between modal split and congestion was investigated and a relationship between the number of private vehicles on the road and congestion was found. It was found that the higher the percentage of modal split that is made up by private transport, the higher

the level of congestion. A relationship could also be observed between the congestion experienced, the population and the development level of the transport infrastructure in a city. Congestion increases as the population of a city expands. Congestion decreases as the development of the transport infrastructure of a city increases.

Both the trip-based and activity-based research approaches were investigated to find the best approach for Cape Town. The trip-based modelling approach was easy to implement and find statistically significant results but lacked behavioural realism that could only be provided when adopting an activity-based modelling approach. The incorporation of activity-based indicators into the modelling of transport behaviour would improve the accuracy of modal split predictions.

The development of transport planning methods used in Cape Town illustrates that a shift away from trip-based methods developed in the United States in the 1950s and 1960s in the context of a 'predict-and-provide' transport policy environment is needed. The methods remain centrally focused on the problem of traffic congestion, and the construction of highways in its alleviation. This has physical and theoretical limitations. Physical limitation is the lack of space in Cape Town and the theoretical limitation is the presence of induced demand that leads to more private vehicles on roads in Cape Town. A solution to the congestion was the MyCiTi BRT system. The Government plans and policy papers revealed an incentive to implement an integrated transport network in Cape Town and the BRT system was identified to be the first step to an integrated transport network. The estimated passenger demand for the MyCiTi BRT system was overestimated and led to an underutilised new mode and prevailing levels of congestion. The method by which the demand for the new BRT system was calculated was investigated and it was found that the consultants made use of the traditional four-step trip-based transport modelling technique. There might be room to improve the accuracy of the model by proposing activity-based variables to improve the accuracy of the modal split calculation and in turn the demand for new transport projects.

3 DATA DESCRIPTION

3.1 Introduction

The literature review helped to identify that there is room to improve the transport models used by transport planners in Cape Town. The data description chapter will describe the data that was used to address the three research objectives in chapter 4, 5 and 6.

This research made use of secondary data. The travel diary data used in the research is part of a larger set of data collected as part of the 2012 Household Travel Survey for Cape Town. The travel diary data was not used previously due to the complexity of analysing activity diary data and incorporating activity data in transport models (City of Cape Town, 2013c).

A household travel survey[4] was commissioned by the City of Cape Town to support the Integrated Public Transport Network plan. The household travel survey was accompanied by a (recall) travel diary, which asked participants to recall the details about all the trips undertaken in the last 24 hours. All persons in the household five years and older were asked to complete the travel diary (City of Cape Town, 2013c).

An internationally renowned transport consultant proposed that a 20 per cent sample of the 25 000 administered household surveys should include a trip dairy, resulting in a sample of 5 000 households (City of Cape Town, 2013a).

The population (N) for the household travel survey was 22 332 households who managed to complete the household travel survey and were eligible to complete the trip diary. This excludes Paarl and Malmesbury, as the regions were added to the survey population at a later stage when the sample limit for the travel diaries had already been reached. Of the 22 332 households, a sample (n) of 5 063 individuals successfully completed the trip diary.

The trip dairy used by the City of Cape Town appears in Figure 5. Data collected includes all the trips undertaken in the day, the start and end time of each trip, trip purpose, from – to (origin and destination), mode used, payment method, fare/parking cost, and the number of persons inside the vehicle.

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[4] The data is not open to the public domain, but access can be requested from the City of Cape Town. Data request url: http://www.capetown.gov.za/City-Connect/Access-information/Request-access-to-information

3.2 Data description

The data was collected to help the City of Cape Town review the current transport and land use model and develop future transport and land use scenarios. Three types of surveys were conducted during the survey process: household travel surveys, trip diaries and stated preference surveys.

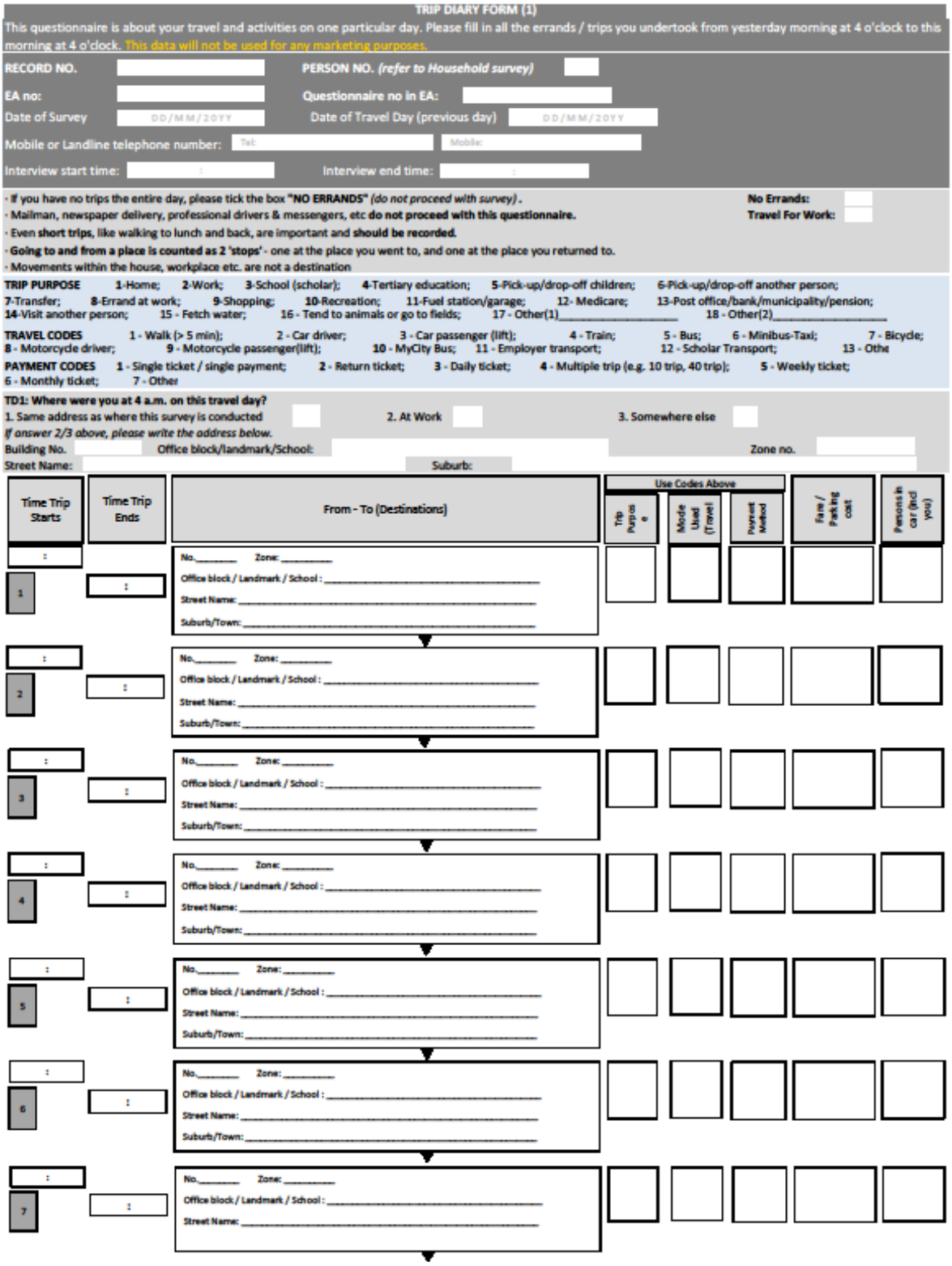
Table 1 shows 7 577 individuals from the 22 332 initial households started the trip-diary and 1 672 individuals completed the stated preference survey. Not all the individuals who started to complete the trip diary met the qualification criteria and could complete the trip diary. This resulted in only 5063 individuals qualifying to complete the trip-diary. As a result of time constraints and to prevent participant fatigue, an individual was not allowed to complete both the trip diary and stated preference surveys along with the household travel survey.

Table 1: Household travel survey household and people entries

	Household survey	Trip Diary	Stated Preference
Households	22 332	2 513	1 665
Individuals	63 571	7 577	1 672

Each household in the household travel survey was assigned a unique number (identifier) to assist the researcher in cross-referencing the three surveys. The unique identifier helped to identify the 5 063 individuals who completed the travel diary.

The trip-diary that individuals had to fill in is represented in Figure 7. For this survey the respondents were asked to recall the trips made in the previous 24 hours. This is the day on which the individual was asked to recall all the travel activities undertaken (a recall survey). The travel survey covered the days Monday to Thursday. The primary goal of the household travel survey research was to plan for peak period home–work trips and Sunday and Saturday are not representative of a typical workday.



TRIP DIARY FORM (1)

This questionnaire is about your travel and activities on one particular day. Please fill in all the errands / trips you undertook from yesterday morning at 4 o'clock to this morning at 4 o'clock. This data will not be used for any marketing purposes.

RECORD NO. PERSON NO. *(refer to Household survey)*

EA no: Questionnaire no in EA:

Date of Survey DD/MM/20YY Date of Travel Day (previous day) DD/MM/20YY

Mobile or Landline telephone number: Tel: Mobile:

Interview start time: : Interview end time: :

- If you have no trips the entire day, please tick the box **"NO ERRANDS"** *(do not proceed with survey)*. **No Errands:**
- Mailman, newspaper delivery, professional drivers & messengers, etc **do not proceed with this questionnaire.** **Travel For Work:**
- Even **short trips**, like walking to lunch and back, are important and **should be recorded**.
- **Going to and from a place is counted as 2 'stops'** - one at the place you went to, and one at the place you returned to.
- Movements within the house, workplace etc. are not a destination

TRIP PURPOSE 1-Home; 2-Work; 3-School (scholar); 4-Tertiary education; 5-Pick-up/drop-off children; 6-Pick-up/drop-off another person; 7-Transfer; 8-Errand at work; 9-Shopping; 10-Recreation; 11-Fuel station/garage; 12- Medicare; 13-Post office/bank/municipality/pension; 14-Visit another person; 15 - Fetch water; 16 - Tend to animals or go to fields; 17 - Other(1)_____ 18 - Other(2)_____

TRAVEL CODES 1 - Walk (> 5 min); 2 - Car driver; 3 - Car passenger (lift); 4 - Train; 5 - Bus; 6 - Minibus-Taxi; 7 - Bicycle; 8 - Motorcycle driver; 9 - Motorcycle passenger(lift); 10 - MyCity Bus; 11 - Employer transport; 12 - Scholar Transport; 13 - Othe

PAYMENT CODES 1 - Single ticket / single payment; 2 - Return ticket; 3 - Daily ticket; 4 - Multiple trip (e.g. 10 trip, 40 trip); 5 - Weekly ticket; 6 - Monthly ticket; 7 - Other

TD1: Where were you at 4 a.m. on this travel day?

1. Same address as where this survey is conducted 2. At Work 3. Somewhere else

If answer 2/3 above, please write the address below.

Building No. Office block/landmark/School: Zone no.

Street Name: Suburb:

	Time Trip Starts	Time Trip Ends	From - To (Destinations)	Use Codes Above: Trip Purpose	Mode Used (Travel)	Payment Method	Fare / Parking cost	Persons in car (incl you)
1	:	:	No._____ Zone: _____ Office block / Landmark / School: _____ Street Name: _____ Suburb/Town: _____					
2	:	:	No._____ Zone: _____ Office block / Landmark / School: _____ Street Name: _____ Suburb/Town: _____					
3	:	:	No._____ Zone: _____ Office block / Landmark / School: _____ Street Name: _____ Suburb/Town: _____					
4	:	:	No._____ Zone: _____ Office block / Landmark / School: _____ Street Name: _____ Suburb/Town: _____					
5	:	:	No._____ Zone: _____ Office block / Landmark / School: _____ Street Name: _____ Suburb/Town: _____					
6	:	:	No._____ Zone: _____ Office block / Landmark / School: _____ Street Name: _____ Suburb/Town: _____					
7	:	:	No._____ Zone: _____ Office block / Landmark / School: _____ Street Name: _____					

Figure 7: Trip Diary questionnaire

The transport zone number (Figure 6) was noted and can be used as the location information where the person travel from in the morning and return to in the evening, i.e. the origins and destinations. The Cape Town metropolitan area is divided into more than 1 500 transport zones.

The trip diary data excluded the Paarl and Malmesbury districts along with Stellenbosch and Somerset-West. After the exclusions, 822 transport zones were left. Of these transport zones, 97 did not meet the minimum sampling standard of at least 50 households per transport zone and could not be considered for the survey. This left 725 transport zones from which the household travel survey could draw responses. The responses from the trip diary survey are from 394 unique transport zones. Figure 8 is a visual representation of the transport zones, road network and centroids[5] of the transport zones.

A person number was included in the travel diary. The person includes everyone who usually lives at the specific address, even if they are not currently present on the day of the survey. Persons were only included if they stayed in the household for at least four nights per week during a four-week period. Domestic workers living at the residence were included. Children under the age of 5 years were excluded.

[5] When distance is calculated, the distance is measured from centroid to centroid between the transport zones. This is the straight line distance.

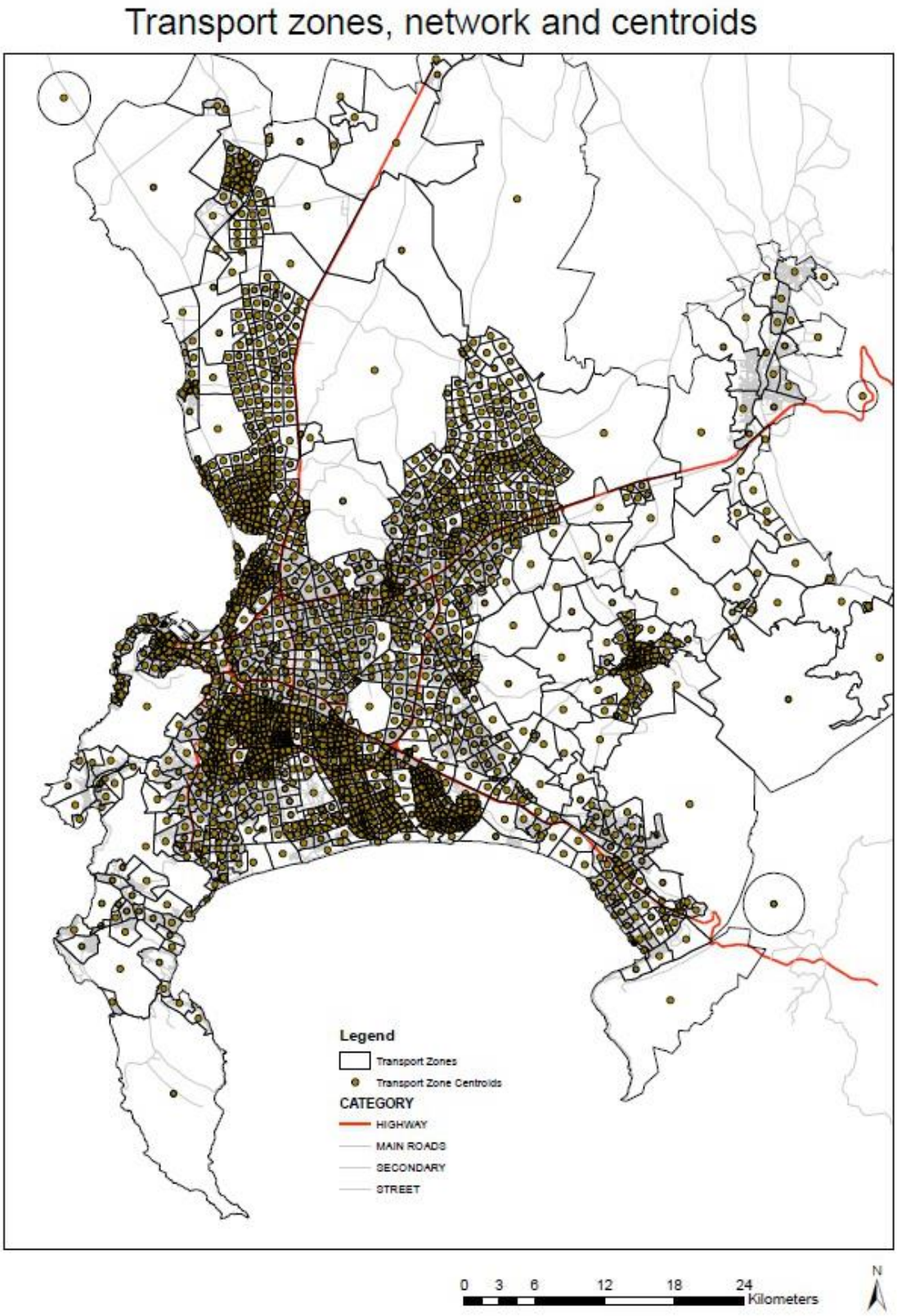
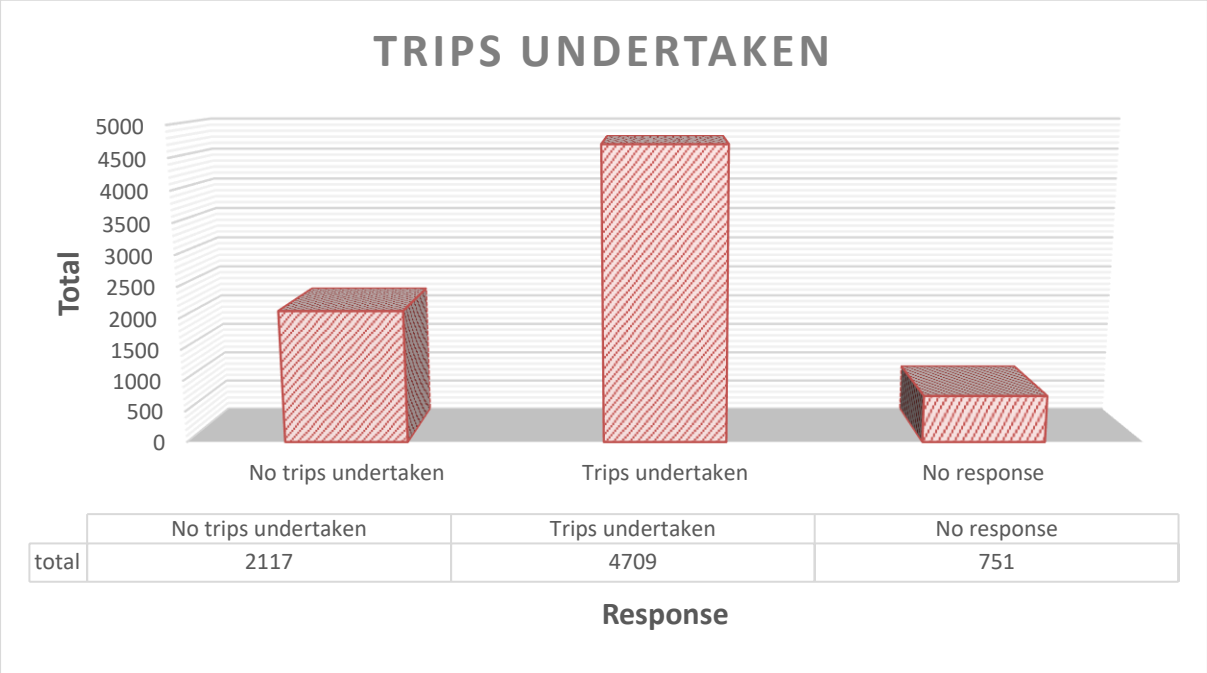


Figure 8: Transport zones of the Cape Town Metropolitan (Author: Data from City of Cape Town)

3.3 General descriptive analysis

The trip-diary included two qualifier questions that was asked to the individuals identified to complete the trip-diary. If an individual did not undertake any trip or had to travel for work related activities then the interview would be stopped. 7 577 individuals started the trip-diary and 5 063 qualified to complete the trip-diary.

Figure 9 indicates that 2 117 individuals did not undertake trips in the previous 24 hours and could not participate in the trip diary; 4 709 individuals indicated that trips were undertaken in the previous 24 hours and could continue with the diary; and 751 individuals did not complete the question. This adds up to 7 577 individuals in total.

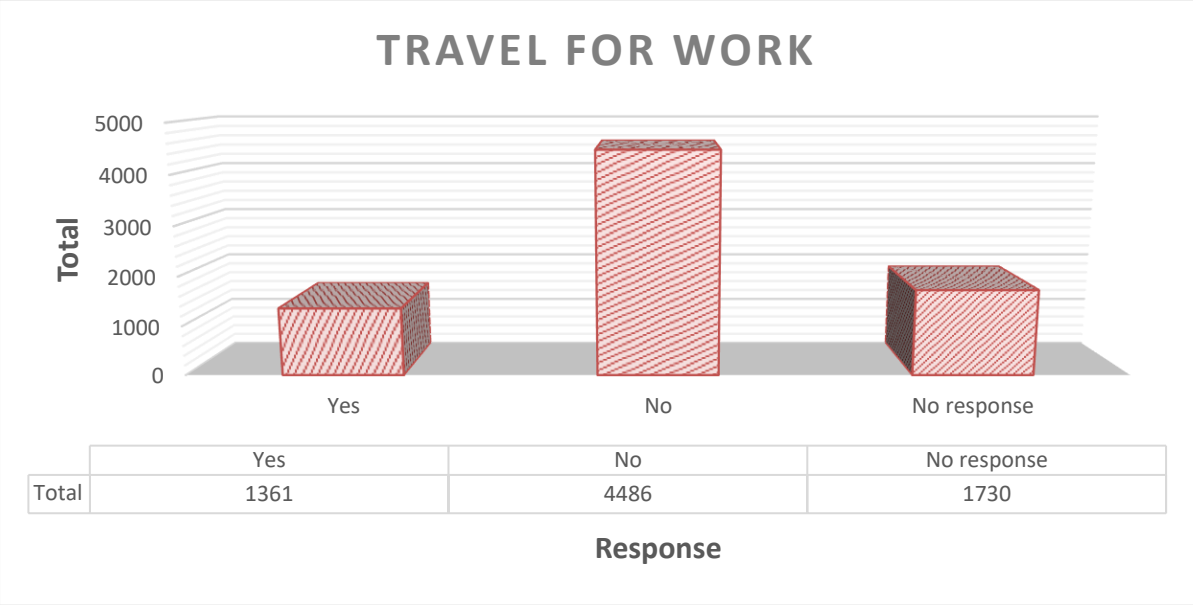


	No trips undertaken	Trips undertaken	No response
total	2117	4709	751

Figure 9: Were trips undertaken?

The respondents whom had to travel for work could not continue with the trip-diary. Examples of travelling for work include taxi drivers who work from home or sales representatives who need to drive for work. If the respondent did not travel for work, but for other reasons, then the interview would continue. If the respondents had to travel for work, then the interview would stop. Figure 10 illustrates that 1 361 individuals had to travel for work and could not continue with the trip diary. This left 4 486 individuals who continued with the survey of which 1 730 individuals did not give a response for the question. The high no response rate could partly be described by the 575 individuals who indicated that no trips were undertaken in the previous question and did not fill in the next question. Interestingly, 411 individuals indicated that they

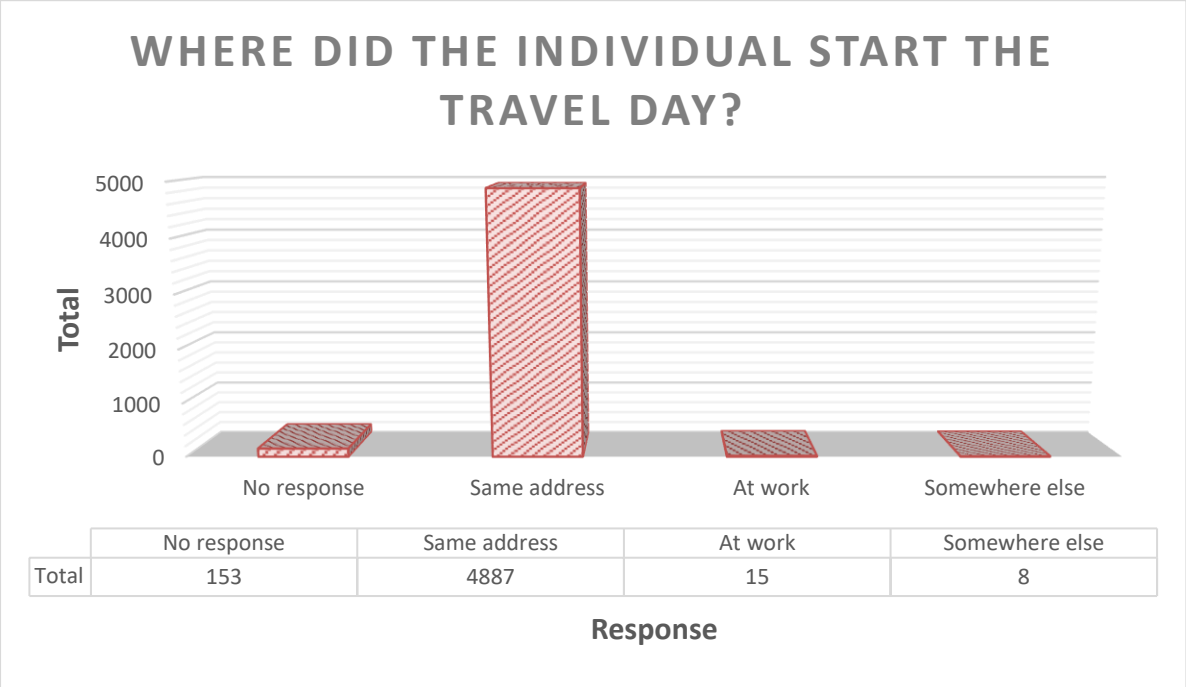
did not travel in the previous 24 hours and that they had to travel for work. Following the two qualifier questions, 5 063 individuals qualified to participate and complete the trip diary.



	Yes	No	No response
Total	1361	4486	1730

Figure 10: Did the individual travel for work?

A total of 4 887 individuals started the travel day at the same address as the address where the interview was conducted, which can be used as the home location for the respondent. A mere 153 respondents did not respond to the question, 15 individuals started the day at work and eight individuals found themselves somewhere else. The 2 514 individuals who did not meet the qualification criteria for the trip diary were excluded from the question as seen in Figure 11.



	No response	Same address	At work	Somewhere else
Total	153	4887	15	8

Figure 11: Where did the travel day start?

Figure 12 will reveal the number of trips made by all individuals in the trip diary. The figure illustrates that 5 063 individuals made at least one trip. This is done by adding all the totals and finding the number of individuals that made trips. A total of 5 036 of the 5 063 individuals made a second trip (27 individuals therefore only made one trip in the previous 24 hours). Only 1 168 individuals from the 5 036 individuals who made two trips made a third trip, which indicates that 3 868 individuals only made two trips in the previous 24 hours. The total number of trips made by all the trip diary participants was 12 960.

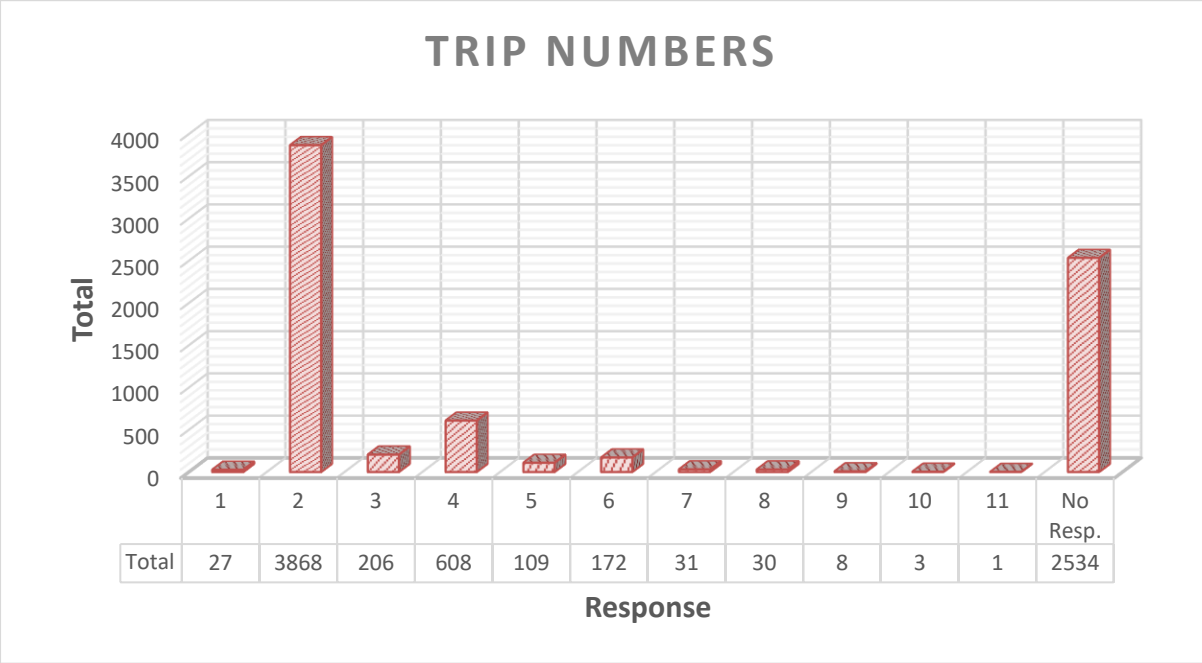


Figure 12: The number of trips undertaken

Figure 13 shows the start time of trips. The figure illustrates the two peak times experienced in Cape Town: the sharp morning peak, where the majority of trips start between 06:00 and 08:00, and the afternoon peak that is more spread out with the majority of trips starting between 14:00 and 18:00. This can be interpreted as the typical commute profile to and from work.

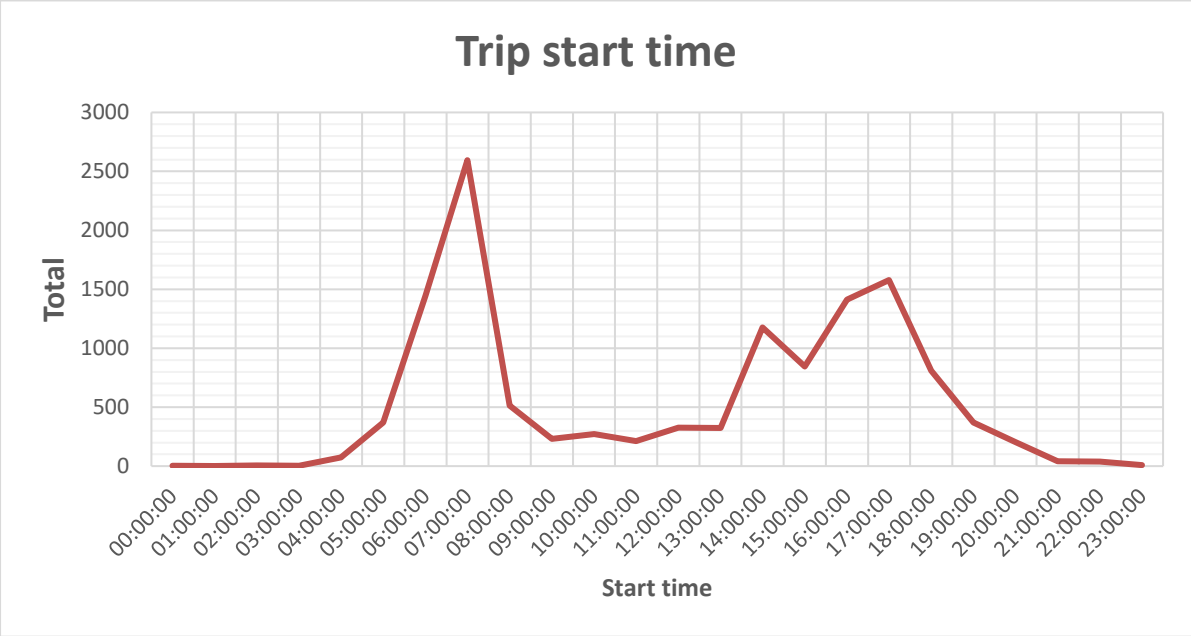


Figure 13: Trip start time

The respondents were asked to provide the destination address, and this was used to identify the destination zone of each trip that was undertaken. Every trip is therefore associated with an origin (O) and a destination (D) transport zone. These zones allowed a distance table to be created between the O-D pairs. The distance tables reflect the road trip distance between each activity location for all trips. ArcMap together with Flowmap[6], a software package used to visualise and analyse geographical- and flow data, was used to develop a distance and travel time matrix between main places within South Africa.

Figure 14 illustrates the trip purpose distribution. Excluding the return-home trip, which accounted for about half of all the trip purposes, most trips were taken with the purpose of going to work and transfers, followed by school and shopping.

[6] The software can be found at: www.flowmap.geo.uu.nl and www.esri.com/en-us/arcgis/products/arcgis-online/overview

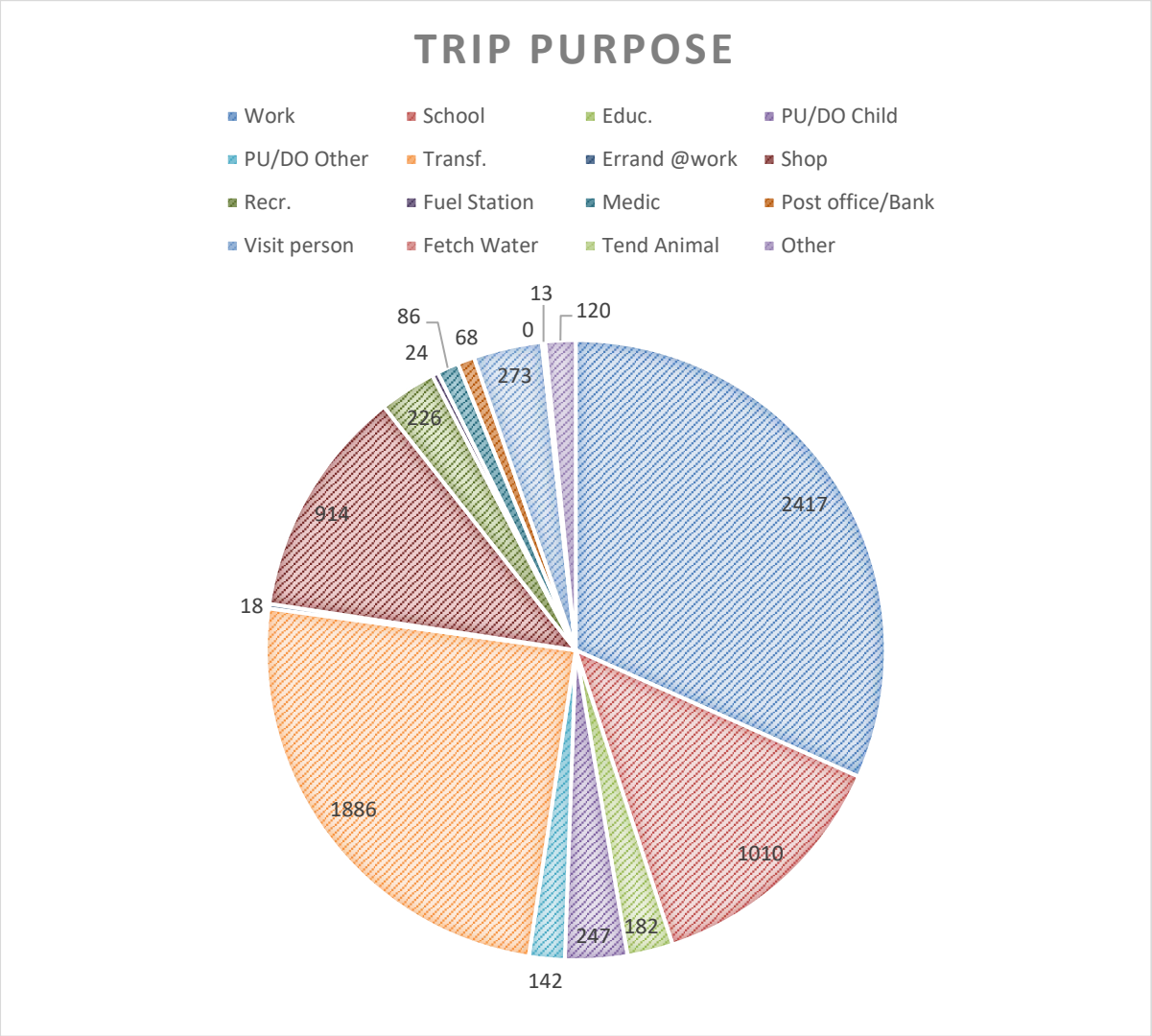


Figure 14: Trip purpose (Without 5289 Home trips)

Figure 15 illustrates the mode used for each trip. The importance of NMT is clear, with NMT accounting for 31 per cent of all trips. Private transport is also important, with 22 per cent indicating car as driver and 12 per cent car as passenger. Traditional public transport, including bus and train, only accounts for a combined 13 per cent for trip mode choice. Minibus taxis complete the major modes used with 17 per cent.

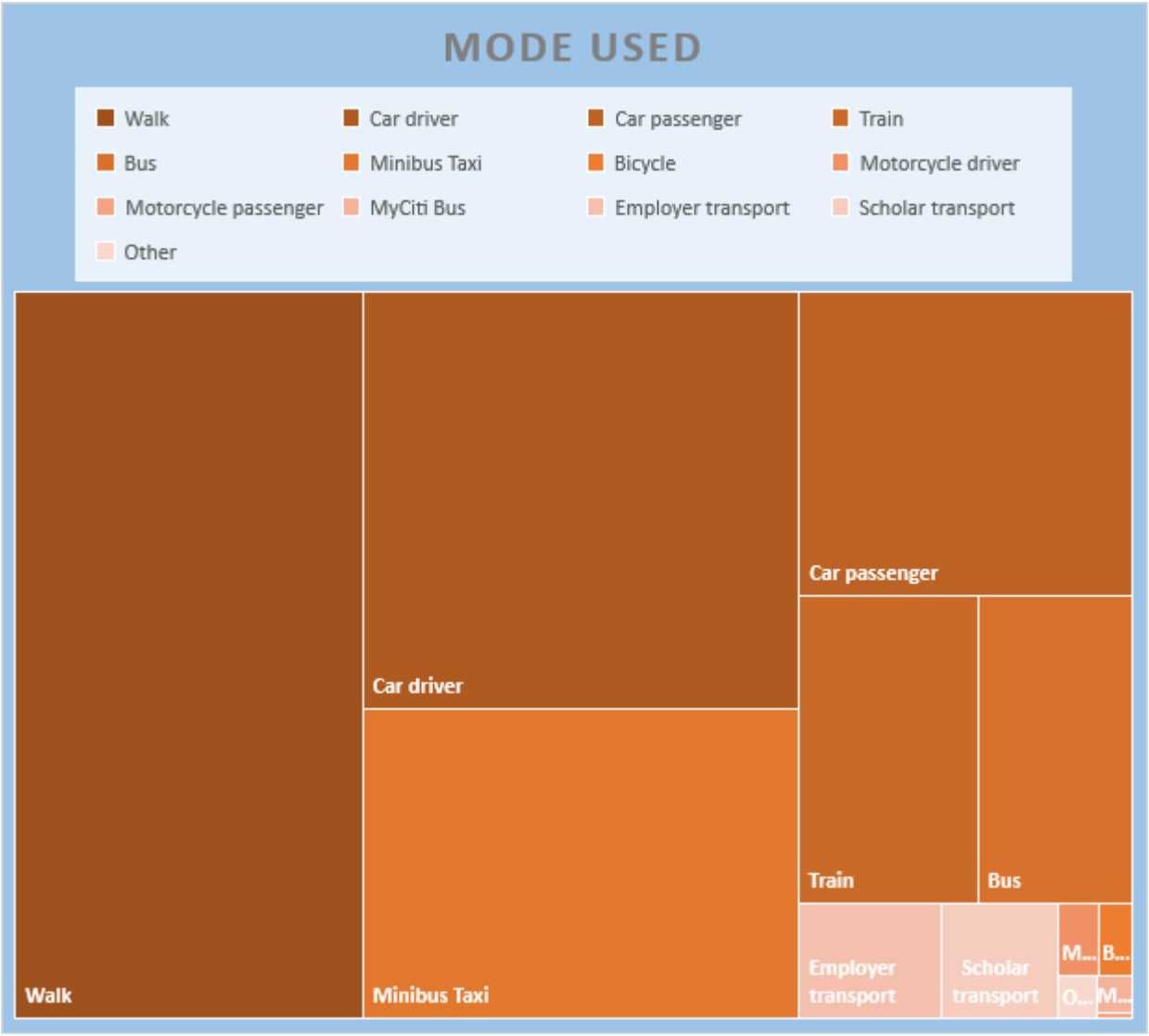
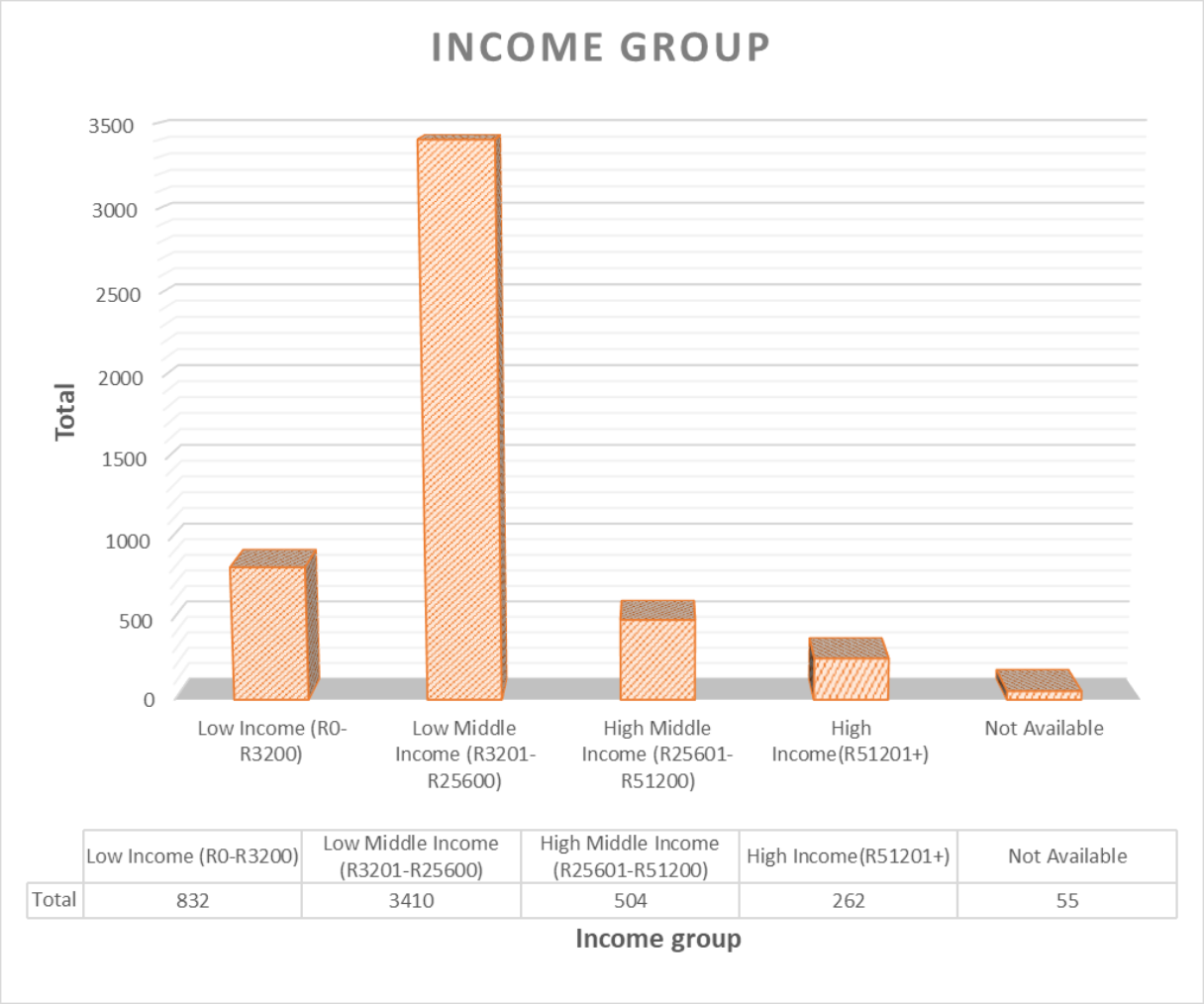


Figure 15: Mode used per trip

Only 3 797 of the trips had the number of occupants inside the vehicle recalled by the respondents, and 11 697 trips had no response. The low response rate is understandable as it is hard to recall the occupants in a vehicle the previous day and certain modes such as walking, which was responsible for 4 001 trips alone, do not require any occupants as there is no vehicle. Further responses included 1 595 trips made with one occupant inside the vehicle, 1 205 made with two, 514 with three and 316 with four occupants. A few trips were made with between five and 17 occupants, which most likely account for minibus taxis, while a few trips were made by bus or train with 30, 50 and 60 occupants.

The monthly household income was sorted according to the criteria of the 2011 census in the household survey data and the results could be cross-referenced and used in the trip diary because of the unique identifier used across all the household data sheets. Figure 16 illustrates the monthly household income of the respondents.



	Low Income (R0-R3200)	Low Middle Income (R3201-R25600)	High Middle Income (R25601-R51200)	High Income(R51201+)	Not Available
Total	832	3410	504	262	55

Figure 16: Monthly household income

3.4 How the variables were calculated

In this section, the methodology used to calculate the variables used to address the research objectives will be discussed.

The main mode was determined by measuring in which mode the person had the longest total trip time. The consultants for the City of Cape Town made use of the household travel survey data, and a hierarchy transport modes, to calculate the main mode used by the individual (City of Cape Town, 2013b). For example, if a person walked and took the bus, then bus would be

the main mode of transport. This method was used because trip duration could not be calculated because the consultancy team made use of the household travel survey data that only allowed for the time leaving for work and the time arriving at work, not the time spent travelling on each mode. This research considered the time on each mode as the factor that determines the main mode in a multimodal chain. This method could be used as the start and end time of each trip that was recorded in the trip (stage) diary. The results from the trip-time method were 98.5 percent similar to the hierarchy coded method for the 5 063 individuals who completed the trip diary. A similar method was used by Krygsman, Dijst and Arentze (2004) and Krygsman and Dijst (2001). In analysing multimodal trips in The Netherlands, the authors classified the main mode as the trip on which the longest distance was travelled. This method could not be implemented as the trip diary did not allow for the distance calculation of individuals modes in a trip chain.

The number of trips undertaken per person was calculated by counting the number of trips undertaken the previous 24 hours for every person who completed the trip diary. A trip was defined a single movement between two points. Multi-stage trips were not aggregated into single tours or journeys between an origin and destination as it was important for the researcher to be able to distinguish between the total number of trips needed to complete a journey between the different income categories and main modes that were chosen.

The number of activities undertaken per day was calculated by sorting the trips undertaken by trip purpose. Trip purposes that constitutes activities include work, school, tertiary education, errand at work, shopping, recreation, fuel station, medical care, post office, bank, municipality, visit a person, fetch water, and tending to animals. A trip purpose was classified as not constituting an activity if it was for returning home, pick up/drop off a person, pick up/drop off children and a transfer. Picking up or dropping off a person was not classified as an activity as the trip was initiated for the completion of the passenger's activity at the destination. Picking up and dropping off individuals will only constitute an activity in this research if it formed part of the individuals' job as a driver, this will include Uber drivers and metered taxis.

The distance travelled was calculated by identifying the origin and destination transport zones of the trips undertaken by individuals. The origin was identified as the transport zone where the individual's residence was located, and the destination was identified as the zone where the individual performed the activity, or where the trip terminated. The centroid of each transport zone was determined using GIS (ArcMap). These centroids were connected to the road network using the shortest link. The travel distance between all the transport zones, centroid to centroid was determined. This origin-destination tables measured the distances between the various transport zones. As the trip dairy contained the origin – destination pairs

for all the trips, it was possible to link these trips to the O-D table with trip distances. This allowed the trip distances to be extracted for all the trips in the trip dairy. The aggregation of all the trip distances per day provided the daily travel distance.

Access to cars in each household was noted in the household survey by using the variable household car access. The results could be used in the trip diary by using the unique identifier across the surveys and identifying whether the individuals inside the household had access to a car.

The income group of each of the participants' household was calculated in the household survey data and could be transferred to the participants of the trip diary by means of the unique identifier. The income categories ranged between 1 and 4, from low to high income. The process and graph can be viewed in the data description and Figure 12.

The total travel time per person per day was calculated by adding together the time of every single trip taken by the individual in the investigated 24-hour period.

The total travel time per activity was calculated by dividing the total travel time by the number of activities for every individual in the trip diary. This would give an indication of the travel time needed to complete a single activity between the various categories investigated.

The total travel time per mode was calculated by adding up the travel times of all trips taken per mode in the 24-hour investigated period.

The total activity time was calculated by taking the time an individual arrived at a destination to perform an activity and measuring the time spent performing the activity until the individual started the next trip. This time was then added to all the activities performed by the individual in the investigated 24-hour period to record the total activity time per individual.

4 INVESTIGATING THE INFLUENCE OF THE ACTIVITIES PERFORMED, INCOME GROUP AND DISTANCE TRAVELLED ON THE MODAL CHOICE OF AN INDIVIDUAL

4.1 Introduction

The relationship between the number of activities and the mode choice of an individual was investigated by comparing the number of activities undertaken in a day with the main mode used by an individual. As the literature revealed, the more activities undertaken during the day, the higher the likelihood that the individual will use private transport. The assumption is therefore that an increase in daily activities will be associated with an increased reliance on private transport. The number of trips, income group, and whether the person had access to a car were investigated alongside the number of activities undertaken to further the understanding of what has an influence on mode choice for the user.

4.2 Methodology used to address the research objective

The relationship between the number of activities undertaken in a day and the modal choice of an individual was investigated with two methodologies. The first method was to make use of SPSS (Statistical Package for the Social Sciences) (IBM Corp, 2019), aggregate the data and draw conclusions from the descriptive statistics. The data was sorted by the main mode used and then the mean number of activities undertaken was compared between the modes. The standard deviation, standard error, minimum, maximum and median values are also given to give statistical validity to the numbers given. A one-way analysis of variance (ANOVA) was used to determine the statistical differences between the means. The ANOVA tables can be found in appendix B. All results in the section are statistically significant unless explicitly stated otherwise. The same method was used for the number of trips undertaken with the data aggregated by main mode chosen but with the mean trips undertaken per mode used to compare the different modes. The method was also used to compare the mean income group per mode and whether the individual had access to a car. Lastly, an investigation was undertaken into the type of activity undertaken and the modal choice of an individual to possibly identify any relationships present.

The second method was to further the descriptive statistics and undertake classification statistics. SPSS was used and a multinomial logit model was built. The modal choice of the individual was the dependent variable and the number of activities, along with the income group of the individual, gender and distance from work was used as the independent variables. Conclusions could be drawn from the regression outputs.

The Multinomial Logit Model (MNL) is used when there is a dependent variable with more than two categories or discrete outcomes that need to be assessed (Arentze and Molin, 2013). The model predicts the possible outcomes of a categorically distributed dependent variable, given a set of independent variables. The MNL model was used in this research to investigate the relationship between the number of activities undertaken in a day, distance travelled, and the income group of the individual on the main mode used by the individual.

The model specification started by building the functional form of the model and deciding what variables to include and exclude from the model. A visual representation of the functional form of the model can be seen in Figure 15. This was followed by running multiple iterations of the model and including and removing variables to identify irrelevant variables that does not have an impact on the modal decision of individuals. The Pseudo-R square test was mainly used for this exercise and the final results of the chosen model can be found in section 4.1.3.1 with the results of the model. The final assessment of the model was to make sure the model adhered to the assumptions all multinomial logit models have to adhere to for the results to be valid.

The dependent variable for the multinomial logit model is the main classification of mode used by the individual. The research made use of three main classifications of transport as can be seen in Table 2. The first class of transport used is non-motorised transport (NMT), which includes walking and cycling as a mode of transport. The second class of transport is private transport (PvT), which includes all privately-owned forms of transport such as a vehicle or a motorcycle. The third and final classification of main transport mode is public transport (Publ.), examples of which include train, bus and minibus taxis.

Table 2: Classification of transport modes for multinomial logit model

Non-Motorised Transport	Private Transport	Public Transport
Walk	Car Driver	Train
Bicycle	Car Passenger	Bus
	Motorcycle	Minibus
		MyCiti Bus
		Employer transport
		Scholar transport

Figure 17 is a visual representation of the functional form of the model. The main modal choice is the dependent variable as this is the investigated variable for the research objective. Private transport was selected as the reference category. The influence on modal decision of the three independent variables was tested on non-motorised transport in reference to private transport and on public transport in reference to private transport. The three independent variables are the number of activities performed in a day, the income group the individual's household falls in and the distance travelled on the investigated day.

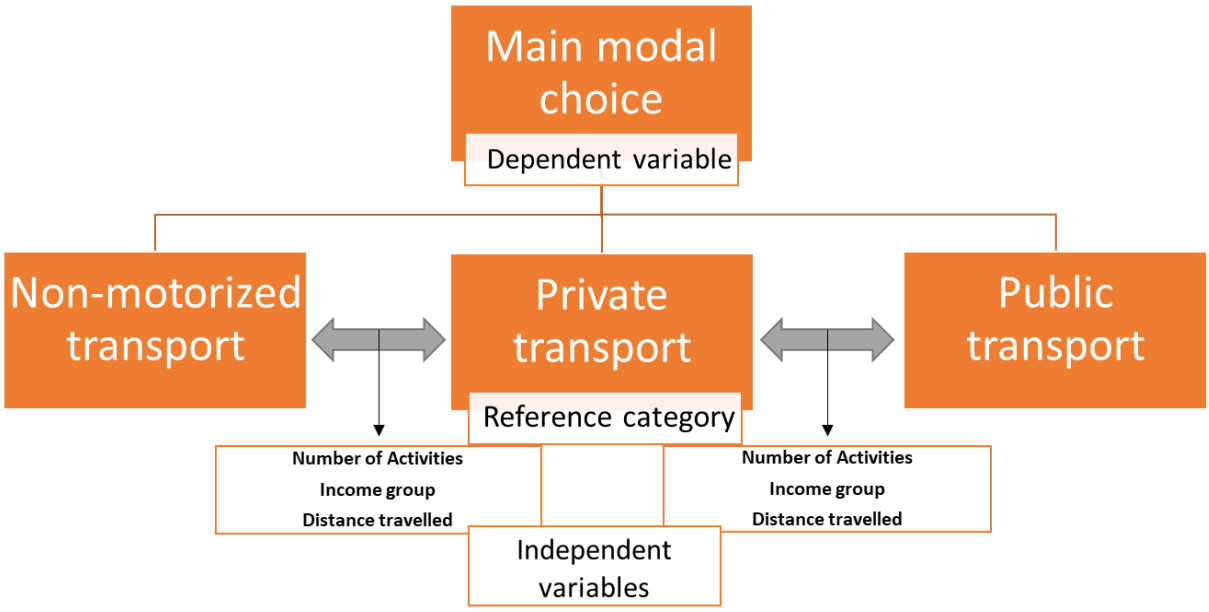


Figure 17: Multinomial logit model

There are six assumptions that must all be valid for the multinomial logit model to be useable (Kwak, Chanyeong; Clayton-Matthews, Alan, 2002). The first assumption is that the dependent variable should be measured at the nominal level. This means that the variable should not be able to be organised into a range or series from small to large. The second assumption is that there is one or more independent variable that is continuous, ordinal or nominal[7]. It is important to note that ordinal independent variables must be treated as continuous or categorical. SPSS cannot handle the independent variable if it is ordinal. The third assumption states that independence of observations should be present, and that the dependent variable should have mutually exclusive and exhaustive categories. This means that only one category can be true at a time, e.g. if A, then not B and if B, then not A. Assumption four states that there

[7] Nominal variables describe categories that does not have a specific order to them. Ordinal variables have two or more categories that can be ranked or ordered. Continuous variables are measured numerically and have an infinite number of values(reference).

should be no multicollinearity present between the independent variables. This is when there are two or more independent variables that are correlated to each other and make it hard to determine which of the variables is responsible for the change in the dependent variable. Assumption five states there must be a linear relationship between any continuous independent variable and the logit transformation of the dependent variable. This means that when the results of the dependant variable, in relation to the continuous independent variable, is plotted on a graph, it should form a relative straight line. The sixth and final assumption states that there should be no outliers, high leverage values or highly influential points.

To test the criteria of the six assumptions, a list was drawn up of the six assumptions and they were tested one by one. To meet the criteria of assumption 4, the number of trips was dropped as an independent variable as there was collinearity present between the number of trips and activities undertaken in a day.

To meet the criteria of assumption 6, some of the modes used had to be combined to ensure that no mode used could be seen as a highly influential point or outlier. To achieve this, the modes used were combined into three categories: non-motorised transport (NMT), private transport (PvT) and public transport (PT). Table 2 shows how the classification was done.

The criteria of all six of the assumptions were met by the data, which would indicate that the results of the multinomial logit regression are valid.

4.3 Results

4.3.1 Descriptive statistics

4.3.1.1 Mean activities undertaken per modal choice

The mean number of activities undertaken per main mode for all the modes in the data set is 1.05 activities per day. The highest number of activities per day was recorded for motorcycle at 1.29 activities per day. The lowest number of activities was recorded for walking at 0.97 and Employer transport at 1.03 activities per day.

It is possible to identify that there is no obvious relationship between the number of activities undertaken in a day and the main modal choice of an individual. This is what led to the investigation being taken further, with the type of activity and other factors investigated to help identify the reasons for the modal choice of an individual.

The standard deviation and standard error are both fairly low, indicating that a small deviation away from the mean indicates a significant result. The lowest mean activities undertaken were by individuals who used walking as a main modal choice. The highest mean number of

activities undertaken per day was by individuals who used the train as a main mode of transport. Second place was shared between individuals who utilised cars and busses as a main mode of transport. These results are not supported by literature regarding the mobility of individuals. Train is not supposed to give individuals more mobility to complete more activities than car. The literature does support walking as a mode being slow when compared to motorised forms of transport and thus does not allowing the individual to complete multiple activities per day (Mendiola, González and Cebollada, 2014).

The one outlier – motorcycle – is most likely the result of the small sample size with a total of 21 out of 5 063 individuals indicating that the main mode of transport was by motorcycle. If an alternative definition of an activity was used that included picking up and dropping off other individuals, it would have slightly lifted the number of activities undertaken by individuals making use of a car as main mode of transport. The definition used within this research follows the definition of activities as a continuous interaction with the physical environment, person or a service (Axhausen, 2006). According to this definition picking up or dropping off a person would only count as a trip for the driver of the vehicle and would be classified as an activity for the person being dropped off.

Table 3: Descriptive statistics for mean activities undertaken per mode

Descriptive Statistics						
Mean number of activities undertaken per mode						
Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Walk	1373	0,97	0,389	0,010	0,95	0,99
Car driver	1190	1,09	0,516	0,015	1,06	1,12
Car Passenger	735	1,07	0,380	0,014	1,05	1,10
Train	313	1,15	0,521	0,029	1,10	1,21
Bus	323	1,09	0,332	0,018	1,05	1,12
Minibus taxi	835	1,06	0,338	0,012	1,04	1,08
Motorcycle	21	1,29	0,561	0,122	1,03	1,54
Employer transport	118	1,03	0,243	0,022	0,98	1,07
Scholar transport	102	1,05	0,259	0,026	1,00	1,10
Total	5044	1,05	0,420	0,006	1,04	1,06

4.3.1.2 Mean trips undertaken per main mode

The highest mean number of trips undertaken in a day, as shown by Table 4, was by individuals making use of the train as the main mode of transport. This was followed by a bus and minibus-taxis. Individuals making use of a car as a passenger, scholar transport and walking undertook the least number of trips.

The results are supported by the literature that states the traditional public transport in developing countries, such as rail and bus, require the accompaniment of access and egress systems that help individuals get to the transport hubs where they can use the traditional public transport (Dissanayake and Morikawa, 2010). The access and egress stages that are classified as trips in this research highlights the users making use of traditional public transport that make more trips in a day than users making use of private transport and NMT like walking.

Table 4: Descriptive statistics for mean trips undertaken per mode

Descriptive Statistics						
Mean trips undertaken per mode						
Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Walk	1374	2,32	1,046	0,028	2,27	2,38
Car driver	1190	2,42	0,981	0,028	2,37	2,48
Car passenger	735	2,16	0,633	0,023	2,11	2,2
Train	313	4,04	1,971	0,111	3,82	4,25
Bus	323	3,23	1,485	0,083	3,06	3,39
Minibus taxi	835	2,64	1,233	0,043	2,56	2,72
Motorcycle driver	21	2,43	0,811	0,177	2,06	2,8
Employer transport	118	2,41	0,936	0,086	2,24	2,58
Scholar transport	102	2,18	0,57	0,056	2,06	2,29
Total	5045	2,54	1,211	0,017	2,51	2,57

4.3.1.3 Income group per mode used

Table 5 indicates the standard deviation and standard error for the results are low, indicating that a small deviation from the mean indicates a result. The individuals with the lowest mean income group made use of minibus-taxis, trains or walking as a main mode of transport. This was followed closely by individuals making use of the bus, employer transport and a bicycle.

Individuals making use of Motorcycles observed the highest income group. The next highest mean income group was observed by car drivers and passengers.

The results support the consensus that, in developing countries, private transport is seen as a status symbol and when an individual experiences a rise in income, the individual will become more reliant on private transport (Duffy, Simelane & Collins, 2018).

This leads to the conclusion that there is a relationship between the income level of an individual and the use of different forms of transport. Individuals in the lower income categories will make more use of public and NMT transport and individuals in a higher income group will make more use of private transport.

Table 5: Descriptive statistics of the mean income group per modal choice

Descriptive Statistics						
Mean income group per modal choice						
Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Walk	1344	1,83	0,57	0,016	1,8	1,86
Car driver	1157	2,41	0,791	0,023	2,36	2,45
Car passenger	717	2,29	0,704	0,026	2,23	2,34
Train	310	1,81	0,594	0,034	1,75	1,88
Bus	320	1,88	0,463	0,026	1,83	1,93
Minibus taxi	829	1,81	0,477	0,017	1,78	1,84
Motorcycle	21	2,57	0,676	0,148	2,26	2,88
Employer transport	116	1,89	0,601	0,056	1,78	2
Scholar transport	98	2,02	0,688	0,07	1,88	2,16
Total	4946	2,04	0,688	0,01	2,02	2,06

4.3.1.4 Car access and main mode chosen

The mean car access for individuals in the trip diary was 57 per cent. This means only 57 out of 100 individuals in the trip diary lived in a household with at least one car. The highest levels of access to a car were seen in individuals who made use of private transport. These include car as driver at 93 per cent and as passenger at 83 per cent. A surprise was discovered in the bus category with the subcategory, MyCiTi bus, had 89 per cent of individuals with access to a car using the service as the main mode of transport. The lowest levels of car access were seen in NMT with walking at 38 per cent car access and public transport with train at 31 per cent, bus at 43 per cent and minibus taxis at 34 per cent. Individuals making use of employer

transport also had a low level of car access of 39 per cent. The results can be viewed in table 6.

The transport modes used by individuals with the lowest car access were train, minibus-taxi, walking and employer transport. The main transport modes used by individuals with the highest level of car access were car, motorcycle, and car passengers.

The results were intriguing as traditionally individuals with access to a car made use of the car as the main mode of transport, especially in developing countries like South Africa. The results suggest that this is not necessarily the case, with 89 per cent of individuals who have access to a car making use of the MyCiti BRT system.

The rest of the results are as expected, with most individuals making use of private transport having access to a car and individuals making use of traditional public transport having a low level of car access in the household.

Table 6: Descriptive statistics for the mean car access per mode

Descriptive Statistics						
Mean car access per mode						
Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Walk	1344	0,38	0,486	0,013	0,35	0,41
Car driver	1157	0,93	0,254	0,007	0,92	0,95
Car passenger	717	0,83	0,375	0,014	0,8	0,86
Train	310	0,31	0,464	0,026	0,26	0,36
Bus	320	0,43	0,496	0,028	0,38	0,49
Minibus taxi	829	0,34	0,472	0,016	0,3	0,37
Motorcycle driver	21	0,81	0,402	0,088	0,63	0,99
Employer transport	116	0,39	0,489	0,045	0,3	0,48
Scholar transport	98	0,58	0,496	0,05	0,48	0,68
Total	4946	0,57	0,495	0,007	0,56	0,59

4.3.1.5 Type of activity undertaken per main mode chosen

The total number of activities undertaken was divided between the three main types of transport in Table 7. NMT had 1 316 total activities with 50 activities being done with the purpose of other. If other is ignored, then the lowest would be shopping and personal care with 187 activities. Individuals going to school, with 603 activities, undertook the most activities. A total of 2 033 activities was undertaken with private transport as the main type of

transport used. The activity done the least was other, with 90 activities, and the second lowest was school, with 228 activities. The most activities were done with the purpose of going to work with 917 activities. There were 1 777 individuals making use of public transport as a main mode of transport whilst completing an activity. The activity done the least was leisure, with 60 activities. The activity done the most was going to work, with 1 097 activities undertaken.

The activity performed most by individuals who used non-motorised transport was going to school or higher education. This was followed by individuals going to work. The activity performed least by individuals making use of NMT as a main type of transport was leisure and shopping and personal care.

The literature suggests that a great limitation of NMT is the lack of speed and inability to cover vast distances (Batty, Palacin and González-Gil, 2015). The results indicate that individuals who utilised NMT when performing an activity could mostly perform activities that did not require great distances to be covered.

Private transport is suited for the work trip and this reflected in the results. This was followed by shopping and personal care and the activity performed least by individuals making use of private transport was school and higher education and leisure activities.

Private transport allows transport users great flexibility and behavioural freedom (Calabrese *et al.*, 2013). Private transport had the highest number of individuals performing leisure, shopping and personal care activities. The results indicate that private transport users conduct a higher variety of activities compared to public and NMT users

Public transport was even more dominated by individuals going to work than private transport. Individuals going to school and shopping and personal care followed this. The activity performed least by individuals making use of public transport was leisure. Public transport allows for low levels

Table 7: Type of activity undertaken per main mode chosen

Main Mode Chosen	Type of Activity	Number of Activities	Percentage
NMT	Leisure	192	14,59%
	Other	50	3,80%
	School	***603***	***45,82%***
	Shopping & Pers. care	187	14,21%
	Work	284	21,58%
	Total	**1316**	100,00%
Private Transport	Leisure	230	11,31%
	Other	90	4,43%
	School	228	11,21%
	Shopping & Pers. care	568	27,94%*
	Work	***917***	***45,11%***
	Total	**2033**	100,00%
Public Transport	Leisure	60	3,38%
	Other	76	4,28%
	School	322	18,12%
	Shopping & Pers. care	222	12,49%
	Work	***1097***	***61,73%***
	Total	**1777**	100,00%

4.3.2 Multinomial logit model

4.3.2.1 Statistical significance of model

The model fitting information is used to gauge the overall measure of the model. The “Final” row in Table 8 represents whether the coefficients are statistically significant by comparing them to a model where all the coefficients are set to zero. From the Significance (Sig.) column it can be seen that *p*-value is 0.000, which is less than $p = 0.05$. A statistically significant result

is where *p* is less than 0.05. This indicates that the model is statistically significant in predicting the dependent variable.

Table 8: Model fitting information

Model Fitting Information				
Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	7299,901			
Final	5323,661	1976,239	6	0,000

The Pseudo R-Square summarizes the proportion of variance in the dependent variable associated with the independent variables. Larger R-square indicates that more variation is explained by the model. Numerous iterations of the model were run and variables were omitted if a lower combined Pseudo R-Square was realised with the inclusion of the variable. Table 9 represents the variance in modal choice as a result of the independent variables in the final model.

Table 9: Pseudo R-Square

Pseudo R-Square	
Cox and Snell	0,361
Nagelkerke	0,407
McFadden	0,206

The likelihood ratio tests show which of the independent variables are statistically significant. It is clear from the model that the distance in KM, number of activities and income group were statistically significant as *p* is equal to 0.000 for all three independent variables.

Table 9: Likelihood ratio test

Likelihood Ratio Tests				
Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	5866,730	543,068	2	0,000
Income group	5365,655	41,994	2	0,000
Number activities	5947,380	623,719	2	0,000
Distance in KM	6604,190	1280,529	2	0,000
The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.				

4.3.2.2 Interpretation of results

A positive B value would indicate a positive relationship, that is the independent variable or category is more likely to use the mode currently used compared to the reference category for a rise in the independent variable (Number of Activities, Income group or an additional KM). A negative B value indicates a category that is less likely to use the current main mode compared to the reference category for a rise in the independent variable. The MNL has negative and positive B values for the independent categories used, which indicates that the user is less and more likely to use the main mode of transport compared to the reference category.

The B value can be interpreted in more detail by using the exponential of B (also referred to as the odds ratio). The odds ratio is the ratio that a one value increase in the independent variable increases or decreases the probability of selecting the specific dependent variable compared to the reference dependent variable[8].

The independent variable used in the MNL include the number of activities, income group and distance travelled. The dependent variable is modal choice and the investigated independent

[8] *More detail on how to interpret and understand Multinomial Logit Models can be found by reading: Tabachnick, B. G., & Fidell, L. S. (2001). Using Multivariate Statistics (Vol. 4th). Allyn and Bacon*

variables are NMT and public transport. Private transport is set as the reference category for the dependent variable. The results of the MNL model is presented in Table 10.

The exponential of B makes it easier to quantify the results of the MNL. When using the number of activities undertaken in a day to investigate the relationship between the modal choices of an individual, it can be derived from the MNL that an increase of one activity per day will result in an individual being 57.3 per cent (1-0.427) less likely to use NMT compared to private transport. An individual making use of public transport will be 13.5 per cent (1-0.865) less likely to use public transport compared to private transport, when an increase of one additional activity per day is experienced. The result for the NMT is statistically significant, with a significance of 0.000 at a 95 per cent confidence interval. The result for public transport was not statistically significant at a significance of 0.155, where a result under 0.05 would indicate a statistically significant result.

When using the income group to investigate the main mode chosen, it can be derived that a rise of one income group will result in the individual being 74.8 per cent (1–0.252) less likely to make use of NMT, and 73.9 per cent (1–0.261) less likely to make use of public transport as a main mode of transport compared to private transport. Both results are statistically significant and supported by theory, where it is expected for individuals in higher income groups to make more use of private transport (Lansley, 2016).

Using the exponential of B to investigate the relationship between the distance travelled and modal choice yields two results that are statistically significant. With an increase of one additional kilometre travelled on a trip, the likelihood of an individual using NMT rather than private transport decreases with 20.9 per cent (1–0.791). This result is understandable as motorised transport increases the travel speed of individuals and if long distances need to be covered, NMT is not preferable. A one-kilometre increase for an individual using public transport increases the likelihood of using public transport compared to private transport by 2.4 per cent (1–1.024). This result is understandable, if one kilometre was made with public transport it is highly likely that an additional kilometre would also be made with public transport as public transport users in South Africa are usually captive transport users who does not have the choice of moving towards private transport (Teffo, Earl & Zuidgeest, 2019).

Table 10: MNL Parameter estimates

Parameter Estimates									
Main mode used		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
NMT	Intercept	4,735	0,242	383,210	1	0,000			
	Number activities	-0,850	0,142	35,844	1	0,000	0,427	0,324	0,565
	Income group	-1,377	0,083	273,658	1	0,000	0,252	0,214	0,297
	Distance in KM	-0,234	0,010	521,695	1	0,000	0,791	0,776	0,807
Publ.	Intercept	2,548	0,192	176,908	1	0,000			
	Number activities	-0,145	0,102	2,022	1	0,155	0,865	0,709	1,056
	Income group	-1,341	0,071	354,801	1	0,000	0,261	0,227	0,301
	Distance in KM	0,024	0,004	29,304	1	0,000	1,024	1,015	1,033
a. The reference category is: Private Transport									

4.4 Discussion

The purpose of this chapter was to investigate the influence of the activities performed, income group and distance travelled on the modal choice decision of an individual. Figure 18 is representing four variables and this helps to illustrate the results of the investigation. Individuals whom made the modal choice of using private transport are characterised by a higher mean income group and high levels of access to a car. Private transport users typically undertook less trips compared to public transport whilst completing the same number of activities. Public transport users could be characterised by undertaking more trips compared to NMT and private transport and falling in a lower income group.

Variables that could be identified to include in future transport planning and modelling would be the income group of the individual where high income individuals tend to make more use of private transport and lower income transport users more inclined to make use of public

transport. Another variable would be car access where individuals with household car access making use of private transport much more often than individuals without access to a car.

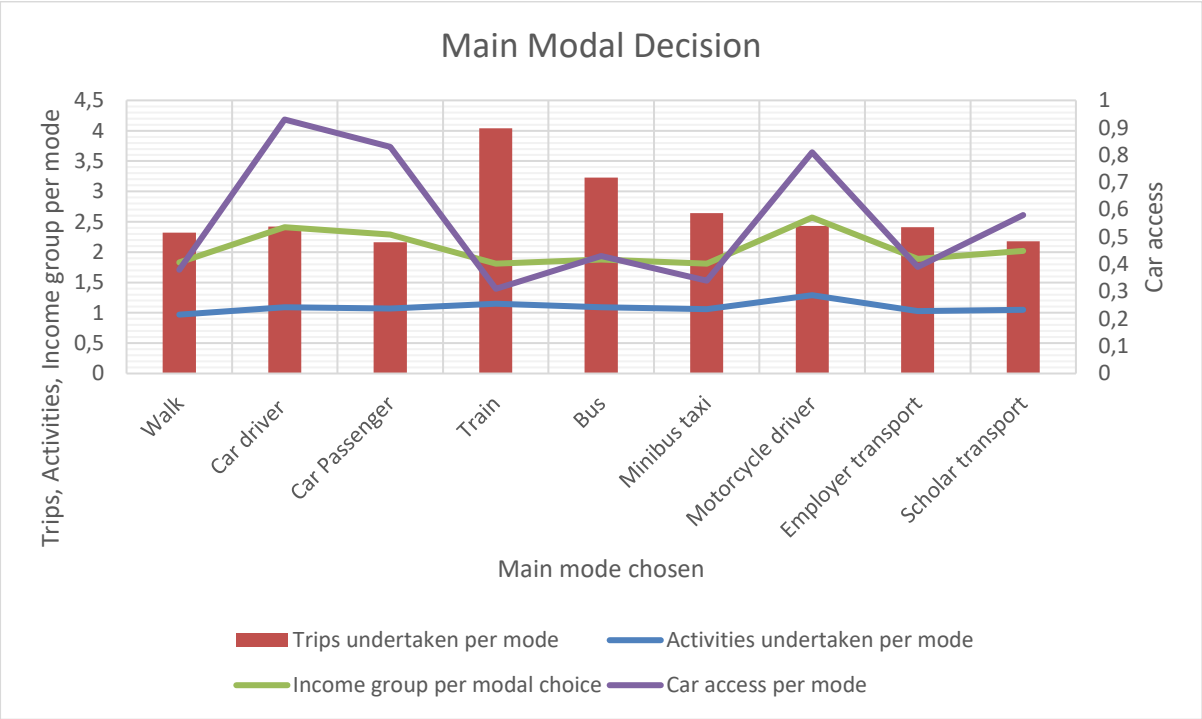
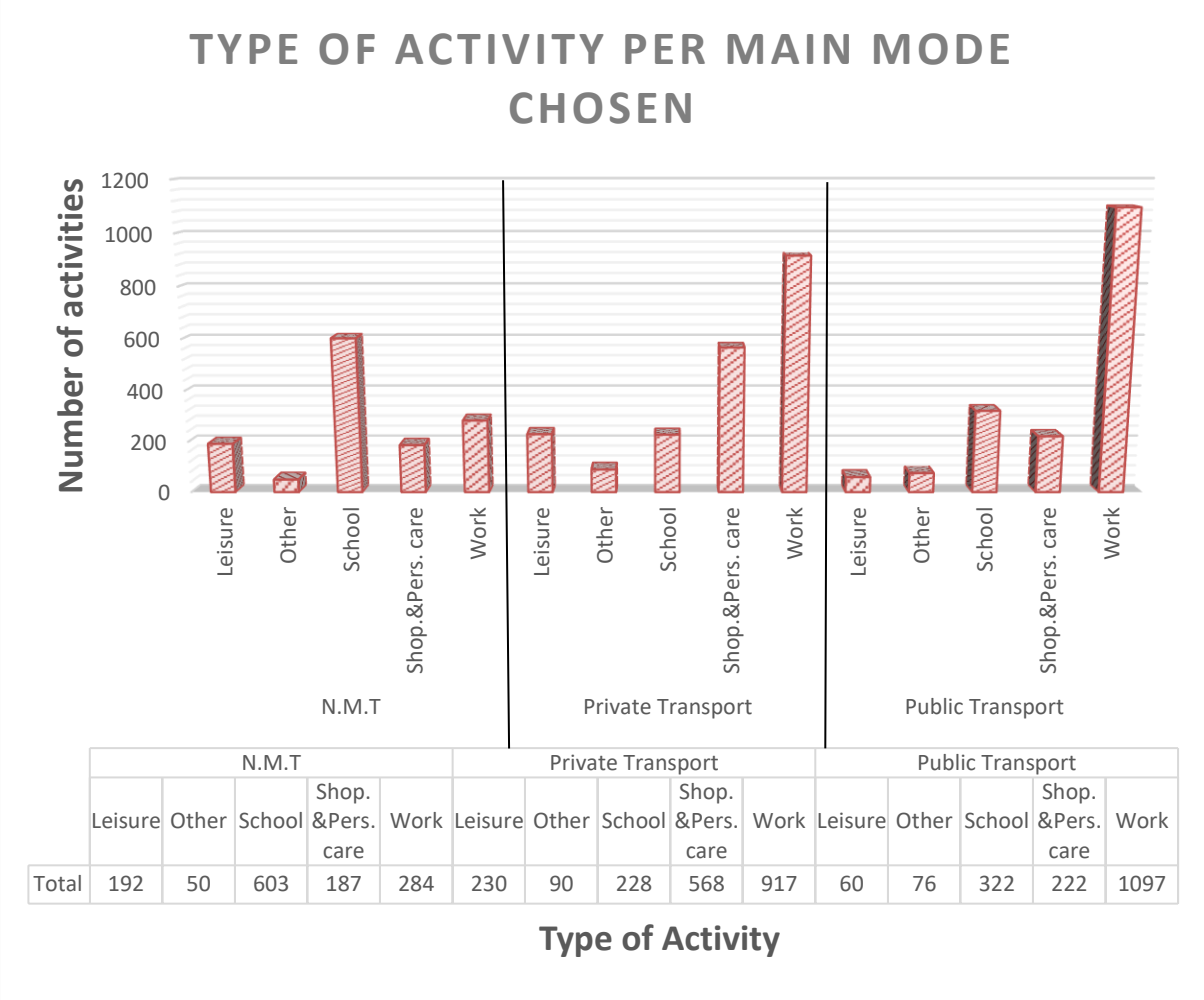


Figure 18: Main Model Decision

The influence of the type of activity performed on modal choice is illustrated in Figure 19. Findings from this include that when an individual is going to school, there is a high likelihood that the individual will be making use of N.M.T. If an individual is going to the shops there is a high probability that the individual would make use of private transport and if an individual was going to work then the individual would most likely make use of public transport or private transport if that was an option for the individual.

The type of activity performed by an individual would by a good candidate to include as a variable in a transport model when attempting to model the modal choice of an individual.



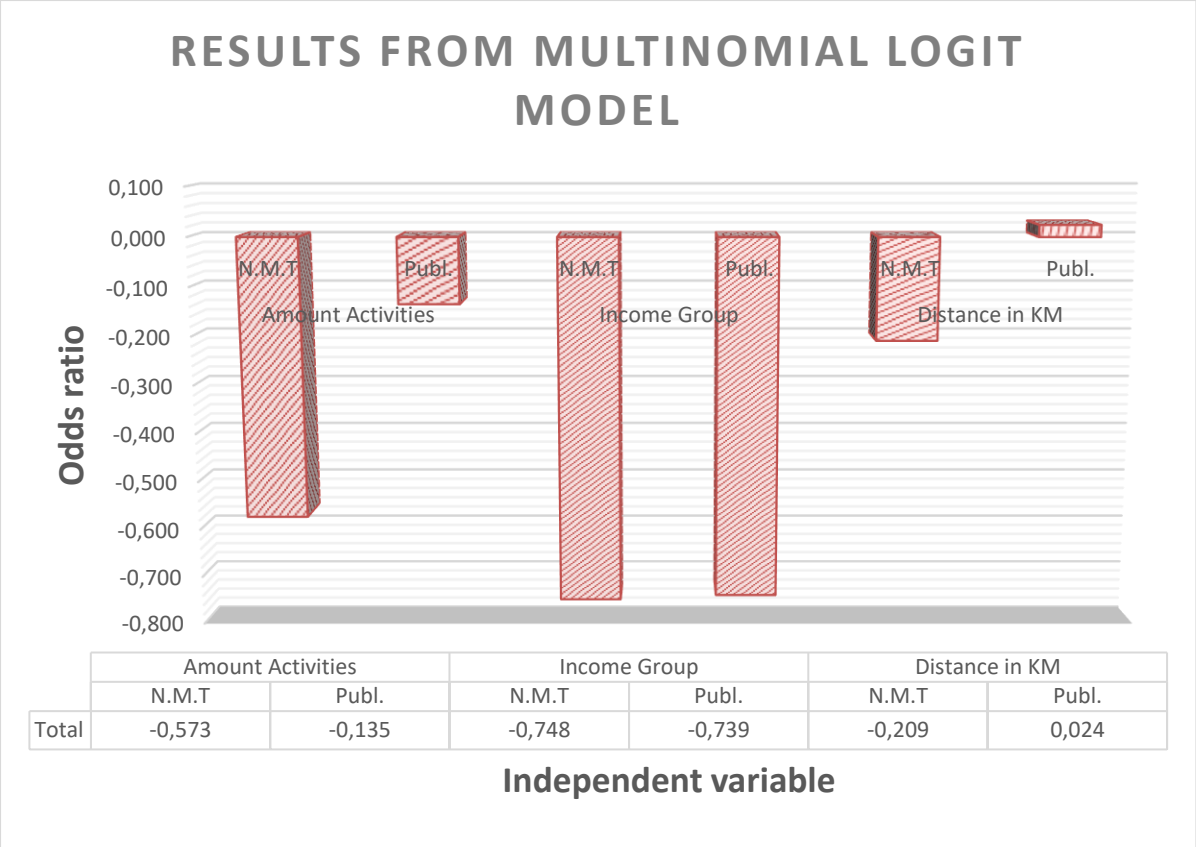
	N.M.T					Private Transport					Public Transport				
	Leisure	Other	School	Shop. &Pers. care	Work	Leisure	Other	School	Shop. &Pers. care	Work	Leisure	Other	School	Shop. &Pers. care	Work
Total	192	50	603	187	284	230	90	228	568	917	60	76	322	222	1097

Figure 19: Activity type per main mode chosen

The multinomial logit model investigated the likelihood of an individual to change the modal decision if a single unit rise in the independent variable was experienced. Figure 20 is a visual illustration of the likeliness to change of the individuals in the study.

Findings from the model include that an increase from one income category to the next highest would make the individual highly likely to change from either public transport or N.M.T to private transport. An increase in the number of activities completed in a day would make individuals making use of N.M.T more likely to partake in modal shift towards private transport than individuals making use of public transport. An increase in the distance travelled would entice users making use of N.M.T. more likely to shift to private transport whilst individuals making use of public transport would be more likely to keep using public transport, when compare to private transport.

The three independent variables had an impact on the modal decision of users in the study and would by good candidates to include in future transport planning models to increase the accuracy of modelling the modal decision making of transport users in the City of Cape Town.



	Amount Activities		Income Group		Distance in KM	
	N.M.T	Publ.	N.M.T	Publ.	N.M.T	Publ.
Total	-0,573	-0,135	-0,748	-0,739	-0,209	0,024

Figure 20: Results from Multinomial Logit Model

5 COMPARING THE RANGE OF ACTIVITIES IN THE DAILY SCHEDULE OF LOW-, LOWER-MIDDLE, HIGHER-MIDDLE AND HIGH-INCOME INDIVIDUALS.

5.1 Introduction

The daily range of activities was compared by means of an activity profile between the income classes. The activity profile was determined by calculating the mean number of activities per person and then compared between the different income groups. This was done to investigate how the number of activities differs between the income groups. The mean number of trips was calculated and compared between the income groups to help explain and support the results in the mean number of activities per person. The distance travelled was calculated and compared between the income groups to help compare the activity profile of low-income individuals with the activity profiles of high-income individuals.

The income groups were split into the three broad categories of transport found in Cape Town. The categories were non-motorised transport, private transport and public transport. This enabled the researcher to determine an activity profile of the different income groups.

5.2 Methodology

The data was aggregated in SPSS by sorting the population into four income categories, i.e. low income, lower-middle income, upper-middle income and high income.

The four income groups were compared by the mean number of activities undertaken. The standard deviation, standard error, minimum, 95 per cent confidence interval values were also given to aid in the statistical validity of the model. A one-way analysis of variance (ANOVA) was used to determine the statistical differences between the means. The ANOVA tables can be found in appendix B. All results in the section are statistically significant unless explicitly stated otherwise. The income groups were compared a second time, but this time the mean number of trips undertaken per person in each income group was used. This allowed the researcher to explain and differentiate between the number of trips undertaken and activities undertaken per income group.

Next, the main category of transport chosen was calculated and used to compare the mean number of trips and activities between the income groups. The mean number of trips and activities was calculated for each category of transport within each income group. This allows for the comparison of the number of trips and activities between the income groups for each of the categories of transport.

The distance travelled between the origin and destination zone of each individual was calculated for every activity undertaken in a day. The comparison of the distance travelled between the income categories and main modes used allowed for the comparison of the activity profiles of individuals.

5.3 Results

5.3.1.1 Activities per income group

The mean number of activities per income group is 1.05, with a standard deviation of 0.421, a standard error of 0.006 and a 95 per cent confidence interval that the mean would be between 1.04 and 1.06. The most activities per day were done by individuals in the high-income category and the least number of activities was done by individuals in the low-income category.

The mean number of activities increases gradually with the increase in income group of the individuals in the research.

The results are in line with the literature, which states that as the income group or financial freedom of an individual increases, the individual will experience more freedom to participate in more activities in a day (Del Mistro, Proctor and Moyo, 2017).

Table 11: Descriptive statistics for mean activities per income group

Descriptive Statistics						
Mean number of activities per income group						
Income group	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Low-income	832	1,02	0,373	0,013	1	1,05
Lower-middle income	3410	1,05	0,408	0,007	1,03	1,06
Upper-middle income	504	1,06	0,391	0,017	1,03	1,1
High-income	262	1,19	0,687	0,042	1,11	1,28
Total	5008	1,05	0,421	0,006	1,04	1,06

5.3.1.2 Number of activities per main type of mode chosen per income group

The mean number of activities undertaken for income group 1 is 1.02. Both NMT and private transport have a mean of 0.98 and public transport has a mean number of activities of 1.08 for income group 1. The mean number of activities for income group 2 is 1.05. The lowest mean number of activities was recorded by individuals making use of NMT as a main mode of transport and both private and public transport had a mean number of activities of 1.08 per day for income group 2. The mean number of activities for income group 3 was 1.06. The

lowest mean number of activities recorded per day was NMT with 0.98 activities per day, followed by private transport at 1.06 and public transport at 1.13 activities per day. The mean number of activities recorded for income group 4 was 1.20 activities per day. Individuals making use of NMT with 1.00 activities per day performed the lowest number of activities. This was followed by individuals making use of public transport with 1.09 activities per day and private transport at 1.23 activities per day.

Low income individuals relied mainly on public transport to engage in daily activities. NMT and public transport both had a daily number of activities performed below one. This can be an indication of how public transport allows low-income individuals less freedom to perform less activities than private transport, which would be expensive, and NMT, which would restrict mobility.

Interestingly, very few low-income individuals made use of private transport. Most low-income individuals made use of either NMT or public transport.

Lower-middle income transport users made less use of NMT when performing activities. Private and public transport were both used more than NMT with exactly the same mean number of activities performed. This represents the limitation imposed on individuals making use of NMT as a main mode of transport. Even when the individual is in a higher income group, the same number of activities is performed as a low-income individual.

The spread of individuals making use of a certain type of transport was evenly spread out across all three types of modal choices. This is the only income group with such an even spread between the modal choices, indicating a higher level of access to the three modal choices.

Upper-middle income transport users had the highest mean number of activities whilst using public transport. This was followed by private transport, and transport users making use of NMT performed the lowest mean number of activities. The low number of activities performed by individuals making use of NMT is another representation of the restriction on mobility imposed by using NMT as a main modal choice. When looking at the modal choice of individuals, upper-middle income individuals prefer to use private transport (79%) over NMT and public transport.

High-income transport users performed the most activities when private transport was the main modal choice. This was followed by public transport and NMT had the lowest number of activities performed. The low number of activities performed by low-income individuals is another representation of the mobility restrictions posed by NMT. High-income individuals

make use of the flexibility and mobility provided by private transport. This is reflected in the modal choice of high-income individuals, with 82 per cent of individuals making use of private transport as a main modal choice.

Table 20: Number of activities per main mode chosen per income group

Descriptive Statistics							
	Number of activities per main mode chosen per income group						
Income group	Main mode chosen	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
						Lower Bound	Upper Bound
Low-income	NMT	340	0.98	0.368	0.020	0.94	1.02
	PvT	121	0.98	0.437	0.040	0.90	1.05
	Publ.	368	1.08	0.349	0.018	1.04	1.11
	Total	829	1.02	0.374	0.013	1.00	1.05
Lower-middle income	NMT	957	0.97	0.395	0.013	0.94	0.99
	PvT	1201	1.08	0.440	0.013	1.05	1.10
	Publ.	1247	1.08	0.376	0.011	1.06	1.10
	Total	3405	1.05	0.408	0.007	1.03	1.06
Upper-middle income	NMT	49	0.98	0.478	0.068	0.84	1.12
	PvT	395	1.06	0.382	0.019	1.03	1.10
	Publ.	56	1.13	0.384	0.051	1.02	1.23
	Total	500	1.06	0.393	0.018	1.03	1.10
High-income	NMT	26	1.00	0.632	0.124	0.74	1.26
	PvT	213	1.23	0.719	0.049	1.13	1.33
	Publ.	22	1.09	0.294	0.063	0.96	1.22
	Total	261	1.20	0.688	0.043	1.11	1.28

5.3.1.3 Trips undertaken per income group

This most trips are undertaken by individuals in the lower-middle income category. This is followed by individuals in the low- and high-income categories and individuals in the upper-middle income category make the least number of trips per day.

The ANOVA table indicates that there is not a statistically significant variance between the means. This is understandable as the means are fairly close to each other with no noticeable trend forthcoming by looking at the means. This result forced the research to further the investigation into how the trips taken by lower income individuals compare to that of higher income individuals. The ANOVA table can be viewed in Appendix B.

Table 13: Trips undertaken per income group

Descriptive Statistics						
Mean trips per income group						
Income group	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Low-income	832	2,53	1,234	0,043	2,44	2,61
Lower-middle income	3410	2,58	1,243	0,021	2,53	2,62
Upper-middle income	504	2,35	0,981	0,044	2,26	2,43
High-income	262	2,53	1,157	0,071	2,39	2,68
Total	5008	2,54	1,215	0,017	2,51	2,58

5.3.1.4 Trips undertaken per main mode used per income group

The mean number of trips undertaken for income group 1 was 2.53 trips per day. The lowest number of trips undertaken was by individuals making use of private transport as a main mode of transport at 1.98 trips per day. This was followed by individuals making use of NMT at 2.24 trips per day and public transport at 2.98 trips per day. The mean number of trips undertaken by individuals in income group 2 was 2.58 trips per day. The lowest number was recorded by individuals making use of private transport. This was closely followed by individuals making use of NMT at 2.36 trips per day and public transport at 2.97 trips per day. The mean number of trips undertaken by individuals in income group 3 was 2.35 trips per day. The lowest number of trips recorded for income group 3 was by individuals who made use of NMT at 2.24 trips per day. This is closely followed by private transport at 2.26 trips per day and the most trips were made by individuals making use of public transport. The mean number of trips undertaken by individuals in income group 4 is 2.54 trips per day. The type of transport with the lowest number of trips is both NMT and public transport with 2.50 trips per day and is closely followed by private transport at 2.54 trips per day.

Low-income individuals made the most trips when public transport was the main mode of transport. This was followed by NMT and the modal type with the least number of trips undertaken for low-income individuals was private transport. The low number of trips performed by low-income individuals when using private transport can be explained by the high cost associated with private transport. The high number of trips undertaken by individuals making use of public transport can be explained by the access and egress stages required to access public transport. Access refers to the trips undertaken to gain entry to the public transport and egress is the trips undertaken to travel the last leg from the public transport to the destination (Hensher and Rose, 2007).

Lower-middle income transport users also made the most trips when public transport was the main modal choice. This was followed by both NMT and private transport whose mean number of trips undertaken differed with a mere 0.02 trips. The higher number of trips undertaken by individuals making use of public transport can be explained by the access and egress required.

Upper-middle income users also made the most trips when public transport was the main modal choice. This was again followed by NMT and private transport, whose mean number of trips undertaken differed with just 0.02 trips. The higher number of trips undertaken by individuals making use of public transport can be explained by the access and egress required.

The number of trips undertaken for high-income users was even between all three modes. This is interesting, as high-income individuals do 11.3 per cent more activities than high-income individuals using public transport and 18.6 per cent more than individuals using NMT. High-income individuals only make 0.02 per cent more trips than high-income individuals making use of public transport and NMT. This can be a result of the increased flexibility and accessibility afforded by private transport that allows individuals to participate in more activities whilst making fewer trips.

Table 14: Number of trips per main mode used per income group

Descriptive Statistics							
Number of trips per main mode used per income group							
Income group	Main mode used	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
						Lower Bound	Upper Bound
Low-income	NMT	340	2.24	0.957	0.052	2.14	2.34
	PvT	121	1.98	0.577	0.052	1.88	2.09
	Publ.	368	2.98	1.455	0.076	2.83	3.12
	Total	829	2.53	1.236	0.043	2.45	2.61
Lower-middle income	NMT	957	2.36	1.085	0.035	2.29	2.43
	PvT	1201	2.34	0.841	0.024	2.29	2.39
	Publ.	1247	2.97	1.541	0.044	2.88	3.05
	Total	3405	2.58	1.240	0.021	2.53	2.62
Upper-middle income	NMT	49	2.24	0.830	0.119	2.01	2.48
	PvT	395	2.26	0.849	0.043	2.18	2.34
	Publ.	56	3.05	1.566	0.209	2.63	3.47
	Total	500	2.35	0.984	0.044	2.26	2.43
High-income	NMT	26	2.50	1.334	0.262	1.96	3.04
	PvT	213	2.54	1.155	0.079	2.39	2.70
	Publ.	22	2.50	1.012	0.216	2.05	2.95
	Total	261	2.54	1.158	0.072	2.40	2.68

5.3.1.5 Distance travelled per income group

Table 15 indicates the mean distance travelled per trip by individuals was 9.23 km, with a standard deviation of 8.58 km and a standard error of 0.129 and a 95 per cent confidence interval that the mean would fall between 8.982 and 9.487. The lowest mean distance travelled was recorded by individuals in the low-income group and the highest distance travelled was recorded by individuals in the high-income category.

The distance travelled per trip gradually increases from the low-income group all the way up to the high-income group. There are various explanations for this occurrence. The first possible explanation could be the fact that high income individuals can afford to travel further distances in shorter times by making use of private transport to get to and from work. Another possible reason might be the fact that over 41 per cent of trips made by individuals in the low-income category were made by NMT whilst only ten per cent of trips made by high-income individuals were made using NMT. It is harder to cover longer distances when making use of NMT (Barros, Martínez and Viegas, 2015).

Table 15: Mean trip distance travelled per income group

Descriptive Statistics						
Mean distance travelled per income group						
Income group	N	Mean (KMs)	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Low-income	692	8,22	8,426	0,32	7,591	8,849
Lower-middle income	3045	9,22	8,526	0,155	8,917	9,523
Upper-middle income	467	9,691	8,581	0,397	8,91	10,471
High-income	226	11,59	9,209	0,613	10,383	12,797
Total	4430	9,234	8,577	0,129	8,982	9,487

5.3.1.6 Distance travelled per main mode chosen per income group

The mean distance travelled by individuals in the low-income category was 8.2 km, with a standard deviation of 8.42 km, a standard error of 0.321 km and a 95 per cent confidence interval that the mean would fall between 7.57 km and 8.83 km. The lowest distance travelled was recorded by individuals making use of NMT and the highest was recorded by individuals making use of public transport. The mean distance travelled by individuals in the lower-middle income category was 9.22 km, with a standard deviation of 8.53 km, a standard error of 0.16 km and a 95 per cent confidence interval that the mean would fall between 8.91 km and 9.52 km. The lowest distance travelled was undertaken by individuals making use of NMT and the

longest distance was undertaken by individuals making use of public transport. The mean distance travelled by upper-middle income individuals was 9.77 km, with a standard deviation of 8.58 km, a standard error of 0.4 km and a 95 per cent confidence interval that the mean would fall between 8.98 km and 10.55 km. The shortest distance travelled was by individuals making use of NMT and the longest distance travelled was by individuals making use of private transport. The mean distance travelled by high-income individuals was 11.6 km, with a standard deviation of 9.23 km, a standard error of 0.62 km and a 95 per cent confidence interval that the mean would fall between 10.39 and 12.81. The shortest distance was covered by individuals making use of NMT and the longest distance was travelled by individuals making use of public transport.

The shortest distance travelled by low-income individuals was when making use of NMT. Next was individuals making use of private transport and the longest trips were made by low-income individuals when making use of public transport. This is as expected, with low-income individuals using public transport to make the journey from home to work as this is the cheapest form of transport over longer distances (Eriksson and Forward, 2011).

Lower-middle income individuals made the shortest trip when making use of NMT. This was followed by private transport and lower-middle income individuals made the longest trips when making use of public transport. The lower-middle income users are also price sensitive like the low-income individuals and therefore also make use of public transport for longer journeys.

Upper-middle income individuals made the shortest trips when making use of NMT. This was followed by public transport and the longest trips were made using public transport. Upper-middle income individuals are less sensitive to price and more sensitive to time and therefore a shift is visible from public transport, which is cheaper and slower, towards private transport, which is faster and more expensive (Batty, Palacin and González-Gil, 2015).

High-income individuals made the shortest trips when making use of NMT. The NMT was followed by public transport and the longest trips were undertaken when making use of private transport. The high-income individuals making the longest trip by private transport is a continuation of the higher sensitivity to time shown by higher income individuals.

Table 16: Distance travelled per main mode used per income group

Descriptive Statistics							
Distance travelled per main mode used per income group							
Income group	**Main mode used**	**N**	**Mean (KMs)**	**Std. Deviation**	**Std. Error**	**95% Confidence Interval for Mean**	
						Lower Bound	Upper Bound
Low-income	NMT	281	3,068	3,948	0,236	2,605	3,532
	PvT	101	10,215	7,192	0,716	8,796	11,635
	Publ.	307	12,225	9,304	0,531	11,18	13,27
	Total	689	8,196	8,423	0,321	7,566	8,826
Lower-middle income	NMT	837	2,92	4,583	0,158	2,609	3,231
	PvT	1069	10,577	8,53	0,261	10,066	11,089
	Publ.	1135	12,58	8,281	0,246	12,098	13,063
	Total	3041	9,217	8,527	0,155	8,914	9,521
Upper-middle income	NMT	44	3,056	3,62	0,546	1,955	4,157
	PvT	364	10,494	8,708	0,456	9,596	11,391
	Publ.	55	10,317	8,311	1,121	8,07	12,563
	Total	463	9,766	8,58	0,399	8,982	10,549
High-income	NMT	20	5,12	4,483	1,002	3,022	7,218
	PvT	188	12,317	9,562	0,697	10,941	13,692
	Publ.	17	11,27	6,421	1,557	7,968	14,571
	Total	225	11,598	9,229	0,615	10,385	12,81

5.4 Discussion

This chapter set out to compare the range of activities in the daily schedule of low-income, lower-middle, upper-middle- and high-income individuals. Figure 21 illustrates higher income individuals partaking in more activities per day and covering more distance compared to lower income groups. This is done whilst completing the same number or even less trips than lower income individuals. This suggests that higher income individuals have a higher range of activities over a larger area by being less sensitive to distance whilst completing more activities.

This information can be used by future transport planners to help estimate the activity profiles of higher and lower income individuals in the City of Cape Town when building transport models.

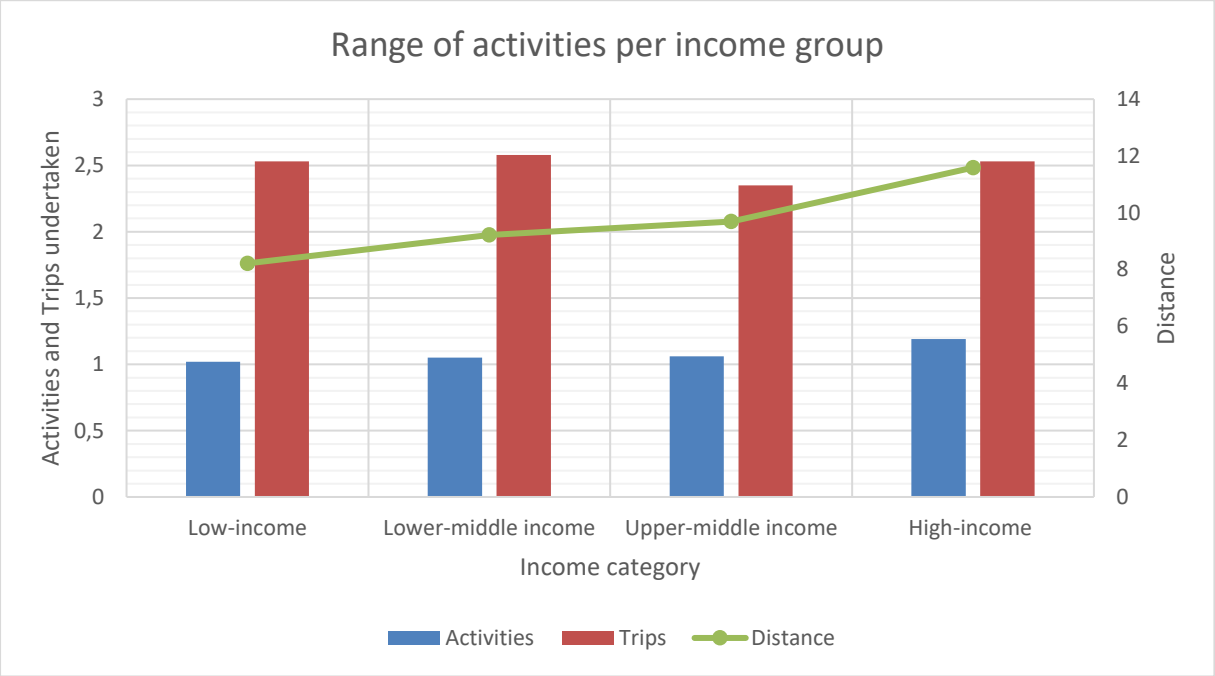


Figure 21: Range of activities per income group

Mode choice was introduced to further investigate why certain individuals experience a higher range of activities than others. Figure 20 is an illustration of the findings. Low-income individuals rarely make use of private transport whilst higher income individuals almost solely make use of private transport. Lower-middle income is balanced with the majority of individuals making use of public transport.

Private transport allows for a high range of influence or footprint of activities by having no set schedule or fixed infrastructure limiting the individual's ability to perform activities. This is supported by the findings where individuals making use of private transport are the individuals who are covering the most distance and performing the most activities. This information can be valuable to future transport planners in Cape Town where if an individual is in the higher income categories and is performing more activities than the mean number of activities, than the individual would most likely make use of private transport.

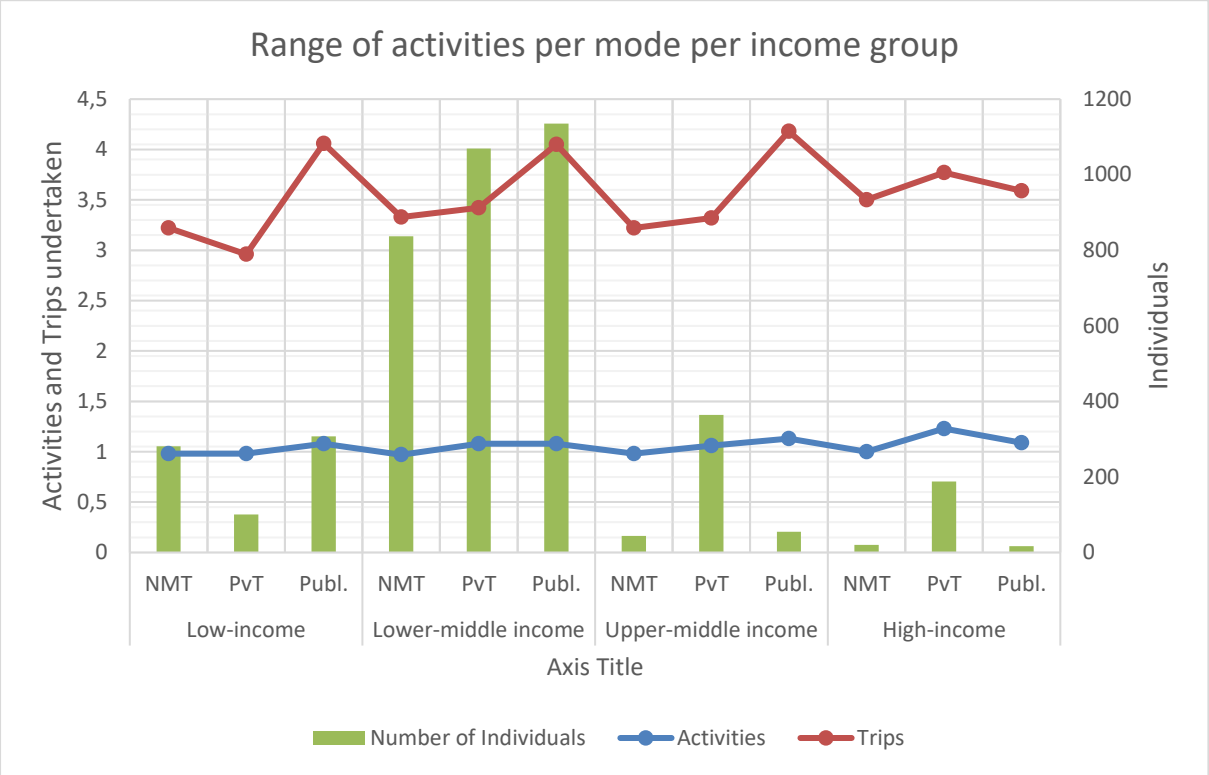


Figure 22: Range of activities per mode per income group

6 INVESTIGATING THE VALUE OF TIME BY COMPARING THE TOTAL TIME SPENT TRAVELLING PER MODE, ACTIVITY, INCOME GROUP AND DISTANCE TRAVELLED

6.1 Introduction

The value of time was investigated by comparing the daily time budgets between the income groups. The research compared the time spent performing out of home activities and the travel time of individuals in the four income groups. The value of time was investigated further by comparing the total travel time per activity to create a fairer comparison between the income groups.

6.2 Methodology

The data was aggregated using SPSS. The standard deviation, standard error, minimum, 95 per cent confidence intervals values were given to aid in the statistical validity of the model. A one-way analysis of variance (ANOVA) was used to determine the statistical differences between the means. The ANOVA tables can be found in appendix B. All results in the section are statistically significant unless explicitly stated otherwise. First the mean total travel time per mode was calculated to identify any differences in travel times between the modes in Cape Town. Next the mean total travel time was compared between the income categories to

identify whether there is a relationship between the income group and travel time of individuals. The mean travel time per activity was calculated and compared between the income groups to create a fairer comparison between the income groups, as high-income individuals can participate in more activities per day and this might have an effect on total travel times.

The total activity time per age group was investigated to reveal how much time is spent by each age group on activities per day. The activity time per income group was investigated to reveal how much time is spent on activities per day between the different income groups. Lastly, the activity time per main mode was calculated to reveal the amount of time individuals spent performing activities. This allowed a further comparison to be drawn between the total travel time and total activity time per mode. This revealed the total time spent away from home and how much time was left in a day for users of different modes.

6.3 Results

6.3.1.1 Total daily travel time per mode

Table 17 helps to paint an interesting picture, with the individuals making use of public transport spending more time in transit than the individuals making use of private transport. This can be attributed to the higher average speed of private transport and lower average speed of public transport. NMT has the lowest average speed, but NMT is mostly used for shorter trips (Joly, 2004). The discussion on how the total travel time per mode was calculated can be viewed in section 3.4.

The travel times of the individuals is higher when compared to the National Household Travel Survey (NHTS) (Schmidt, 2014). The reason for this variance was investigated and the research found that the NHTS only included individuals from the working class in terms of age. The total travel time per age group was investigated as the age of individuals included within the two surveys was not the same. If the young and older people are excluded from the data then the results resemble the findings of the NHTS. The daily travel times and modal share figures from the NHTS conducted in 2013 can be seen in Table 18.

Table 17: Descriptive statistics for mean total travel time per mode

Descriptive Statistics						
Total daily travel time per mode						
Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Walk	1874	35,97	28,65	0,662	34,67	37,26
Car driver	1222	71,42	47,197	1,35	68,78	74,07
Car passenger	826	47,72	38,549	1,341	45,09	50,35
Train	387	87,86	43,752	2,224	83,49	92,23
Bus	359	105,5	48,672	2,569	100,45	110,56
Minibus taxi	996	67,69	41,325	1,309	65,12	70,26
Motorcycle driver	21	59	32,444	7,08	44,23	73,77
Employer transport	128	91,5	45,029	3,98	83,62	99,38
Scholar transport	105	81,4	44,411	4,334	72,81	89,99
Total	5918	59,97	44,832	0,58	58,83	61,11

Table 18: NHTS Data *(Schmidt, 2014)*

Mode	Daily # of Users	Mean Daily travel time (minutes)
Train	262000	76
Bus	124000	75
Taxi	230000	53
Car/Bakkie/Truck/Company car driver	560000	43
Car/Bakkie/Truck Passenger	106000	46
Walk all the way	112000	29

6.3.1.2 Total daily travel time per income group

Table 19 indicates the income group with the highest mean total daily travel time is lower-middle income. This is followed by high-and low-income transport users and the lowest mean total travel time was recorded by upper-middle income individuals.

The results mirror the results found in Table 13, where the number of trips undertaken per income group was investigated. This was to be expected, with the number of trips and the total time spent travelling having a direct impact on one another. The results show that individuals in the lower income groups spend a lot of time travelling whilst individuals in the higher income groups spend less or the same amount of time travelling whilst completing more activities. The averages do not differ much. Also, this statement is not true as the low-income mean is lower than the high-income means.

Table 19: Descriptive statistics for mean total travel time per income group

Descriptive Statistics						
Mean total travel time per income group						
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Low-income	1004	59,24	41,765	1,318	56,65	61,82
Lower-middle income	4094	60,65	46,462	0,726	59,23	62,08
Upper-middle income	544	55,47	39,155	1,679	52,17	58,77
High-income	285	59,75	41,986	2,487	54,86	64,65
Total	5927	59,89	44,872	0,583	58,75	61,04

6.3.1.3 Travel time per activity for every income group

In Table 20 the mean total travel time per activity for every income group is 66.9 minutes. The standard deviation is 47.93 with a standard error of 0.69 that allows the researcher to predict with a 95 per cent confidence interval that the mean would be between 65.5 and 68.3 minutes. The lower income groups with 69.48 minutes for low income and 68.9 minutes for the lower-middle income group experienced the highest travel time per activity. The higher income groups with middle to high income at 54.8 minutes and high-income experienced much lower total travel times at 54.7 minutes.

Individuals in the low and lower-middle income groups recorded the highest mean travel time per activity. The individuals in upper-middle and high-income groups recorded the lowest mean travel time per activity.

By dividing the total travel time by the number of activities, the results make it clear that lower-income individuals spend more time travelling to accomplish the same number of activities as higher-income individuals. This can be a result of the remnants of apartheid spatial planning, removing previously disadvantaged individuals from economic opportunities and forcing the individuals to travel great distances to be economically active. This can also be the result of the poorly performing public transport system present in the City of Cape Town and lower income individuals being captive users that do not have alternatives to public transport. This forces the lower-income individuals to make use of the public transport system and spend more time travelling as this is less expensive than private transport.

Table 20: Descriptive statistics for mean travel time per activity for every income group

Descriptive Statistics						
Mean travel time per activity for every income group						
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Low-income	793	69,476	47,714	1,6944	66,15004	72,80204
Lower-middle income	3262	68,9989	49,8797	0,8733	67,28658	70,71127
Upper-middle income	489	54,8937	36,5745	1,654	51,64391	58,14342
High-income	248	54,7974	35,6464	2,2635	50,33906	59,2557
Total	4792	66,9035	47,937	0,6925	65,54594	68,26113

6.3.1.4 Mean total travel time per age group

The mean total travel time per age group is 71.86. Table 21 illustrates that individuals in the working class (25–65 years) spend the most time travelling at 81.75 minutes per day. This is followed closely by the student group of 19–24 years at 77.43 minutes per day. The young and old categories are both much lower, with 5–18 years at 49.07 minutes and the retired group (66+) at 46.48 minutes per day.

Individuals in the retirement age bracket recorded the lowest total travel time. This was followed by individuals in the school phase and individuals in the student and young working class who, along with the working class, had the highest total travel time.

The results indicate that individuals in the working-class age group spend the most time travelling, and this is most likely the result of the individuals having to commute to and from work every day. This corroborates the validity of the results, as the mean total travel time by the individuals in the trip diary can be perceived as low. The data from the travel diary can be compared to the national household travel survey conducted in 2013 (Schmidt, 2014). The results between the studies differ in that the NHTS only considered individuals of a working age. If the individuals in the NHTS, and the individuals of a working age from the travel diary are compared, then the results are similar.

Table 21: Descriptive statistics for mean total travel time per age group

Descriptive Statistics						
Mean total travel time per age group						
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
4-18	1125	49,07	40,487	1,207	46,7	51,44
19-24	574	77,43	48,082	2,007	73,49	81,37
25-65	2772	81,75	54,238	1,03	79,73	83,77
66+	157	46,48	31,288	2,497	41,55	51,42
N.A.	210	67,17	50,18	3,463	60,34	73,99
Total	4838	71,86	51,796	0,745	70,4	73,32

6.3.1.5 Travel time per activity per age group

Table 22 shows the mean total travel time per activity for every income group is 67.76 minutes per day. The results have a standard deviation of 48.01 and a standard error of 0.705, which allows the researcher to predict with a 95 per cent confidence interval that the mean would fall between 66.38 and 69.148. It is clear from the figure that individuals that fall within the working and student age spend more time travelling at 76.96 and 73.57 minutes respectively. People in the retired and minor age categories spend much less time travelling per day, with 43.179 minutes for retired individuals and 39.49 minutes for minors.

Individuals in the retirement age bracket recorded the lowest total travel time per activity. Individuals in the school phase and individuals in the student class followed this and young working class along with the working class had the highest total travel time per activity.

The total travel time per activity for every age group is similar to the total travel time per age group, indicating that there is not a great variance in the number of activities between the age groups.

Table 22: Descriptive statistics for mean travel time per activity per age group

Descriptive Statistics						
Mean travel time per activity per age group						
	N	Mean (minutes)	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
4-18	1106	47,884	39,493	1,188	45,554	50,214
19-24	550	73,568	46,764	1,994	69,651	77,485
25-65	2624	76,69	49,271	0,962	74,804	78,576
66+	145	43,179	30,031	2,494	38,25	48,109
N.A.	208	62,692	49,013	3,398	55,992	69,392
Total	4633	67,765	48,01	0,705	66,383	69,148

6.3.1.6 Total activity time per age group

Table 23 shows the mean total activity time per age group is 5:57:51 hours. The total activity time per age group indicates that the individuals of a working age spend the most time doing activities per day with six hours and 11 minutes. This is followed by individuals in the student age with five hours and 50 minutes and this is closely followed by individuals of school-going age at five hours and 41 minutes. The individuals of retirement age spend considerably less time per day doing activities, with a mean time of two hours and 56 minutes per day.

The results are understandable and as expected, with individuals of a working age spending the most time performing activities in a day, as work is considered an activity. It is also expected that older individuals spend less time performing activities as the older individuals most likely do not have to work 9 to 5 jobs every day and will most likely be retired.

Table 23: Descriptive statistics for total activity time per age group

Descriptive Statistics						
Total activity time per age group						
Age group	N	Mean Hours: Minutes: Seconds	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
4-18	1125	5:41:56.32	2:26:19.107	0:04:21.742	5:33:22.76	5:50:29.88
19-24	574	5:50:12.13	3:37:50.081	0:09:05.535	5:32:20.63	6:08:03.62
25-65	2773	6:11:59.18	3:53:19.239	0:04:25.846	6:03:17.90	6:20:40.45
66+	157	2:56:48.54	2:41:59.846	0:12:55.728	2:31:16.25	3:22:20.82
N. A.	210	6:53:00.86	3:18:59.570	0:13:43.909	6:25:56.62	7:20:05.09
Total	4839	5:57:51.88	3:33:49.091	0:03:04.424	5:51:50.32	6:03:53.43

6.3.1.7 Activity time per income group

Table 24 shows the mean activity time per income group is 5:58:44.55 hours. The income group with the most time spent on activities per day is the low-income group at six hours and 31 minutes. This is followed by lower-middle income at five hours and 58 minutes and high income at five hours and 59 minutes. Upper-middle income individuals have the least amount of time spent on activities per day.

This result is interesting as it shows low-income individuals spend more time on activities than higher income individuals. This can be partly explained by low-income individuals working in labour intensive jobs that usually require long working hours compared to higher income individuals whom typically have more time for at home activities like child care and leisure (Manville and Goldman, 2018).

Table 24: Mean total activity time per income group

Descriptive Statistics						
Activity time per income group						
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Low-income	817	6:31:33.86	3:27:10.515	0:07:14.889	6:17:20.22	6:45:47.49
Lower-middle income	3378	5:58:16.34	3:30:49.147	0:03:37.636	5:51:09.63	6:05:23.05
Upper-middle income	493	5:07:22.27	3:44:17.153	0:10:06.080	4:47:31.45	5:27:13.10
High-income	259	5:59:07.41	3:42:33.004	0:13:49.715	5:31:53.54	6:26:21.29
Total	4947	5:58:44.55	3:33:12.201	0:03:01.876	5:52:47.99	6:04:41.10

6.3.1.8 Total activity time per main mode chosen

Table 25 shows the mean total activity time per main mode chosen was 5:59:55. The modes with the lowest activity time were chosen by individuals who used walking and a car as a passenger as a main form of transport.

The mean total travel and activity times can be combined to create an understanding of how much time individuals making use of a mode of transport spend on travel and activities. This will give an indication of how sensitive transport users are to time as a modal choice indicator. The modes with the lowest activity times are walking and a car as a passenger were the modes with the lowest total travel time. This can be attributed to walking being used for short trips and car passengers not having behavioural freedom or flexibility to perform additional trips and activities. Next, car as driver was looked at. Car as driver had a low mean total activity

time whilst having a relatively larger mean total travel time. This high total travel time experienced by the car can be attributed to the high levels of congestion present on roads in Cape Town. The three modes with the highest mean activity time of the individuals were train, bus and employer transport. These were also the three modes with the highest mean total trip time. This can be an indication of not being sensitive enough to time to be able to pay for a faster means of transport.

Table 25: Activity time per main mode used

Descriptive statistics						
Activity time per main mode used						
Main mode used	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Walk	1357	4:57:19.06	3:15:30.83	0:05:18.45	4:46:54.35	5:07:43.76
Car driver	1169	5:54:48.71	3:50:03.30	0:06:43.72	5:41:36.62	6:08:00.80
Car passenger	722	4:49:58.50	3:33:58.69	0:07:57.81	4:34:20.45	5:05:36.56
Train	311	8:05:13.12	2:52:13.89	0:09:45.98	7:46:00.12	8:24:26.12
Bus	320	8:13:33.56	2:17:29.25	0:07:41.15	7:58:26.29	8:28:40.84
Minibus taxi	833	6:32:49.05	3:20:49.71	0:06:57.50	6:19:09.58	6:46:28.52
Motorcycle driver	21	7:33:08.57	2:29:33.55	0:32:38.19	6:25:03.86	8:41:13.28
Employer transport	116	8:59:38.28	3:11:26.68	0:17:46.51	8:24:25.72	9:34:50.83
Scholar transport	100	6:53:56.40	1:11:16.56	0:07:07.66	6:39:47.84	7:08:04.96
Total	4983	5:59:55.89	3:33:12.24	0:03:01.22	5:54:00.63	6:05:51.16

6.4 Discussion

The section investigated the value of time by comparing the total time spent travelling per mode, activity, and income group. Every individual has 24 hours in a day that the individual can spend on performing activities, traveling or at home/leisure and childcare time.

Figure 23 illustrates individuals making use of Train bus and employer transport experiencing high mean activity and total daily travel times. This results in individuals having less personal at home time for leisure and child care. Individuals making use of private transport experience less activity and daily travel time and have more personal time at home for social, leisure and child care.

This will help future transport planners better understand the daily time budgets of individuals making use of the different transport modes

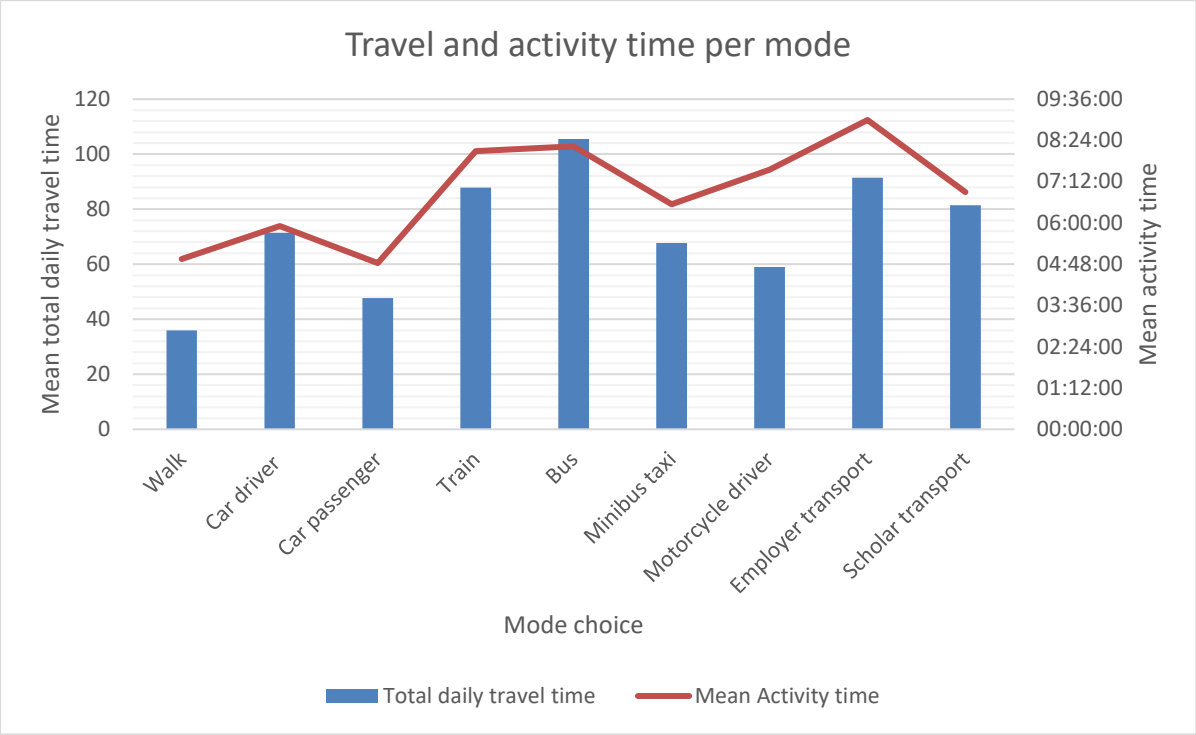


Figure 23: Travel and activity time per mode

Figure 22 illustrates how total daily travel time is mostly even between income groups. This changes when the number of activities is taken into account and it starts to become clear that higher income individuals spend less time travelling per activity than lower income individuals. This is possibly as a result of higher income individuals being more sensitive to time and would spend more on private transport to save a small amount of travel time.

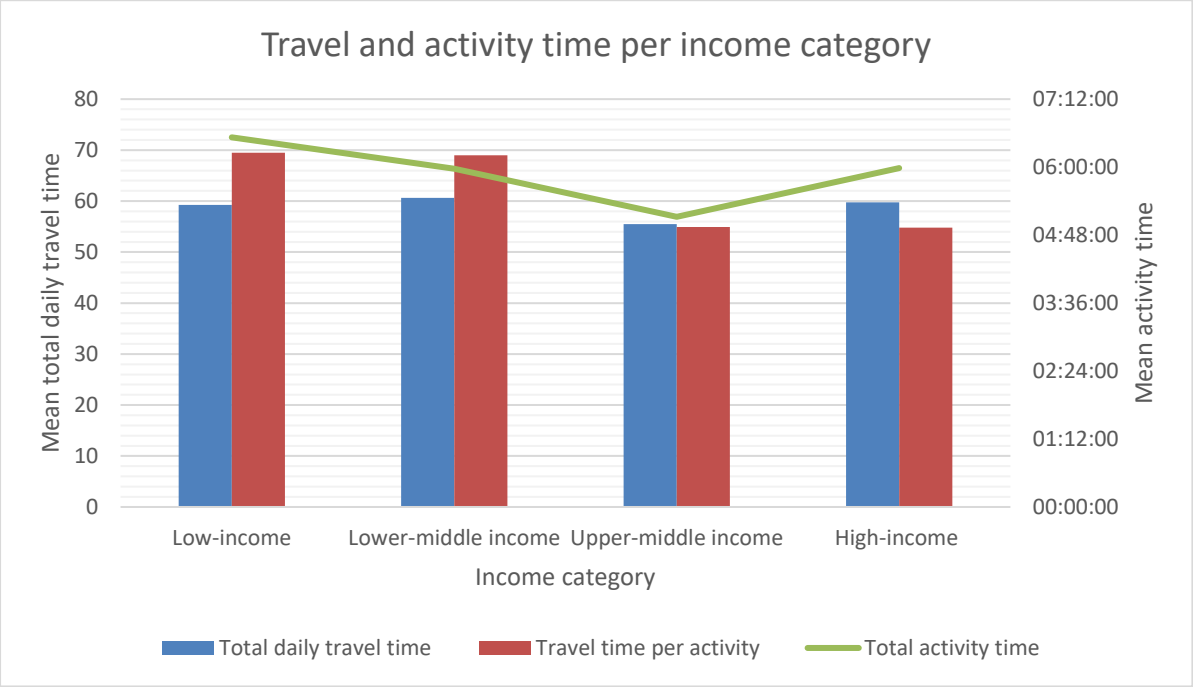


Figure 24: Travel and activity time per income category

Figure 23 illustrates how individuals of a working age spend much more time performing activities and travelling than retirement aged individuals. Children aged 4 to 18 have a high mean activity time as this is mostly spent at school whilst spending as much time travelling as individuals of a retired age.

This result can help transport planners better understand the daily time budgets of the various age categories.

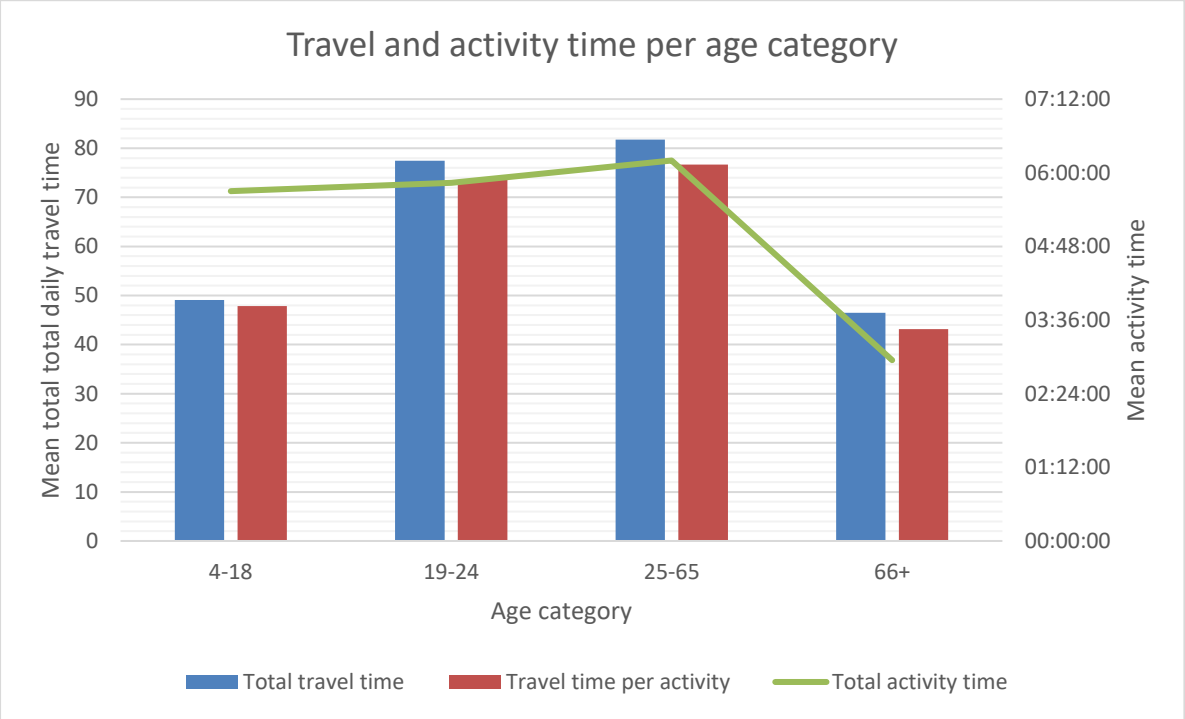


Figure 25: Travel and activity time per age category

7 FINAL CONCLUSIONS AND RECOMMENDATIONS

7.1 Final conclusions

This dissertation investigated the current planning and modelling process used by the City of Cape Town. Specific attention was given to how the planning and modelling process is used as a decision-making tool to inform and support decisions regarding transport projects and the policies that regulate transport.

The City of Cape Town has adopted a trip-based modelling approach to determine transport network, specifically, road capacity demands. As the literature review indicate, while the trip-based approach has several benefits, relying on this method does pose problems when considering softer travel demand management measures or quantifying the implications of implementing public transport. As the trip-based approach do not explicitly consider activities or the intrinsic relationship between activities and travel demand, need was identified to consider how the activity profile of individuals and households will influence their mode choice decisions, and vice versa, how the activity demands of households and individuals, influence their mode choice.

The research was divided into three sections to provide insight into what variables could help better understand how individuals make transport decisions. The first section investigated what variables have a direct influence on the model choice of an individual. The following section compared the activity profiles of individuals to identify any relationship between the activity profiles of individuals and the modal choice of individuals, and the final section investigated the daily time budgets of individuals to identify whether the composition of individuals' income-group has an effect on their daily time budget and modal choice.

Income of individuals had an impact on modal choice, with higher income individuals preferring private transport whilst lower income transport users preferring public transport and NMT. The number of activities completed in a day had an influence on modal choice, where individuals who perform multiple activities in a day being more likely to make use of private transport than any other mode.

The type of activity completed had an effect on the modal choice of the individual. If an individual was going to school there was a high likelihood that the individual would make use of N.M.T. If an individual went shopping there is a high likelihood that the individual would be making use of Private transport and if the individual was going to work then the individual would likely use public or private transport depending on the individual's household income.

Higher income individuals would make use of private transport and lower income individuals would make use of public transport.

The MNL model helped to illustrate that a rise in the income level of an individual making use of either N.M.T or public transport would most probably result in that individual making a modal shift towards private transport. This is also true for a rise in the number of activities performed with individuals making use of N.M.T. or public transport being more likely to make use of private transport if an additional activity is performed in a day.

To answer research hypothesis 1, stating that the number of activities in a day has an impact on mode choice with more activities leading to fewer trips undertaken with public transport. This was proven to not be false with a rise in the number of activities performed being accompanied with less reliance on public transport. The number and type of activities performed in a day along with the income group of an individual would be good candidates as variables to include in future transport planning models to help build accurate modal choice models.

The investigation into the range of activities of individuals in different income groups had interesting results. A rise in income led to individuals completing more activities whilst covering further distances and making more use of private transport. This was done whilst completing less trips than lower income individuals. Lower income individuals made more trips than higher income individuals and partake in less activities. Lower income individuals made more use of public transport.

Research hypothesis 2 has been proven not to be false. Complex transport chains involving more stages and transfers such as public transport that requires an access and egress stage leads to fewer activities completed in a day. This result can help transport planners when assigning modes to individuals. Individuals with complex activity profiles would tend to use private transport whilst individuals with simple activity profiles and complex transport chains would tend to use public transport.

Investigating the value of time for individuals found that private transport users spend less time travelling and performing activities than individuals making use of public transport. This results in individuals making use of private transport having more time to spend on social, leisure and at home activities like child care. Individuals making use of public transport spend substantially more time travelling per day and have a higher mean activity-time per day. This results in individuals having less time at home to spend on social or leisure activities or tend to children.

High-income transport users spend less time travelling per activity than lower income transport users. This indicates that high-income users are more sensitive to time and would spend more money on transport to save a small amount of travel time. Lower income transport users are less sensitive to time and would rather spend extra time travelling than spend more money to save time when commuting. This proves research hypothesis 3 to not be false. An inverse relationship exists between the income group of an individual and the travel time per activity completed of the individual.

This result can help transport planners better understand a transport users' sensitivity towards time and how this would influence the modal decision of the individual with time-sensitive individuals preferring private transport and less sensitive individuals preferring public transport.

The research provides insight on what activity-based variables could deepen the understanding of how individuals make decisions regarding transport. The type of activity, distance travelled, and number of activities had an influence on the modal choice of individuals. The research found that the activity profile of low-income individuals differs from those of high-income individuals and this had an influence on the transport behaviour of individuals. High-income individuals could participate in more activities per day and lower-income individuals made more use of public transport. The research also found when comparing daily time budgets that high-income individuals were more sensitive to time and would spend more money to save time whilst low-income individuals were less sensitive to time and would prefer lower cost transport that maybe took a little longer to reach a destination.

The results obtained in this research can help improve the accuracy and behavioural realism of transport decision modelling of the modal choice in the City of Cape Town. That would lead to more accurate transport models that can assist transport infrastructure planning and the drafting of new transport policy to obtain the goals of local and national government in the City of Cape Town.

7.2 Limitations

The researcher acknowledges the limitations of this study. The research made use of trip diaries to extract activity-behaviour data. This meant that extensive analysis had to be done to the data to formulate the variables needed to conclude the research. Specifically, activities had to be extracted and multistage and multimodal trips identified and classified. In instances where individuals undertook various activities at a single location, the trip diary did not record these activities. It may also be that the trip diary underestimated the total out of home activities.

The Trip Diary was conducted in 2012. This is 8 years ago and the implementation of the next phases of MyCiTi BRT and other transport projects might have changed the transport infrastructure environment individuals encounter in The City of Cape Town. Personal interviews could not be arranged with the relevant modellers from the City of Cape Town to understand why the modelling was done in the way it was.

The data was collected from a sample of the population in Cape Town. This narrows the findings to only be representative of, and applicable on, individuals in Cape Town and the survey population.

7.3 Recommendations

The research suggests it may benefit the accuracy transport models if activities are included in the modelling approach. It may provide a more realistic outcome for modal decision of the transport user.

Transport planners would be able to estimate more accurate and realistic transport models in terms of activity behaviour. If transport planners can estimate more accurate models, then transport planning would improve and more accurate scenarios would be able to be presented to the decisionmakers regarding new transport infrastructure and transport policy. If more accurate scenarios are presented, better decisions would be made regarding new transport projects and policy. The implementation of better transport projects and policy would lead to less congestion on the roads and less demand for additional infrastructure projects.

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APPENDICES

Appendix A:
City of Cape Town: Household Travel Survey (2012)

Metadata

INFORMATION ON HOUSEHOLDS AND HOUSING

All questions in this section of the questionnaire were asked of the responsible person, preferably the head or acting head of the household or institution.

Original input file

Contains **the n**ame of the input file from which the original input data were copied from.

Unique number

(Derived variable)

Notes to users

This is a unique identification code derived from the input person (Input_person) number and the input questionnaire number (Input_Q_number). This can be used to merge all the different files. The questionnaire number (Q_RN), the interviewer number (Interview_person) and the interviewer questionnaire number (Interview_Q_number) are also listed.

Universe

All households (Household Travel Survey).

Final code list

INTO1029/01 to INTO1029/1146

INTO1037/001 to INTO1037/2116

INTO1098/1 to INTO1098/222

INTO1099/1 to INTO1099/590

INTO1100/01 to INTO1100/129

INTO1101/1 to INTO1101/874

INTO1102/1 to INTO1102/111

INTO1104/01 to INTO1104/1245

INTO1106/1 to INTO1106/501

INTO1107/1 to INTO1107/452

INTO1109/1 to INTO1109/462

INTO1110/1 to INTO1110/2877

INTO1111/1 to INTO1111/656

INTO1112/1 to INTO1112/593

INTO1113/1 to INTO1113/321

INTO1117/1 to INTO1117/188

INTO1118/01 to INTO1118/70

INTO1119/1 to INTO1119/170

INTO1122/1 to INTO1122/124

NVTS0001 to NVTS000752

RTSC/1 to RTSC/1173

RTSE/062 to RTSE/2855

RTSL/1 to RTSL/287

RTSM/1 to RTSM/2792

RTSMB/1 to RTSMB/1055.

Transport zone

(Input variable)

Notes to users

This is the transport zone of the place of residence of the household (also seen as the transport zone the person travels from).

EA number

(Input variable)

Notes to users

The Enumerator area.

Q_EA_no

(Input variable)

Notes to users

Questionnaire number in this EA.

Date_travel_day

(Input variable)

Notes to users

Date of travel (previous day)

Day_travel

(Input variable)

Notes to users

Day of travel.

PERSON_id

(Input variable)

Notes to users

The Person Form includes everyone who usually lives at this address, even if they are not currently present on the day of the survey. Only persons are included who stayed in the household for at least 4 nights per week during a four week period. Permanent domestic workers living at the residence are included. Members of the household who are 5 years or younger, are excluded.

The Person_ID variable gives a unique number to each qualifying member of the household. In this case the person_number is the same as on the Person Form.

TD_start_time

(Input variables)

Notes to users

Interview start time.

TD_end_time

(Input variables)

Notes to users

Interview end time.

No_errands

(Input variables)

Notes to users

Check if trips were taken.

1=no trips taken (interview stops)

2=trips taken (interview proceeds)

TD_travel_for_work

(Input variables)

Notes to users

A question was asked: “Did you travel for work?” (such as newspaper deliveries, etc.)

1=yes (do not proceed with interview)

2=no (proceed with interview)

Where_start_travel_day

(Input variables)

Notes to users

Question: “Where were you at 4am on this travel day?”

1=same address as survey address

2=at work

3=somewhere else

TD_building_no, TD_building_name, TD_street_name, TD_suburb, TD_Zone

(Input variables)

Notes to users

If a person is not at home, therefore at work or somewhere else, provide the address.

Trip_no

(Input variables)

Note to users

The trip number for the current person in the household..

Trip_start_time, Trip_end_time

(Input variables)

Notes to users

The Trip_start_time (Trip_start_timex is in numeric format, Trip_start_time in character format) and Trip_end_time (Trip_end_timex is in numeric format, Trip_end_time in character format) provide the beginning and ending times of a single trip.

Dest_building_no, dest_building_name, dest_street_name, dest_suburb, dest_zone

(Input variables)

Notes to users

The destination address of the trip.

TD_Trip_purpose

(Input variables)

Notes to users

The purpose of the trip is recorded.

1=home

2=work

3=school

4=tertiary education

5=pick up / drop off of children

6=pick up / drop off of other person

7=transfer

8=errand at work

9=shopping

10=recreation

11=fuel station

12=medicare

13=post office/bank/municipality, etc.

14=visit a person

15=fetch water

16=tend to animals

17=other (1)

18=other(2)

TD_Mode_used

(Input variables)

Notes to users

Trip mode as follows:

1=walk

2=car as driver

3=car as passenger

4=train

5=bus

6=minibus taxi

7=bicycle

8=motorcycle as driver

9=motorcycle as passenger

10=MyCiti bus

11=employer transport

12=scholar transport

13=other

TD_payment_method

(Input variables)

Notes to users

The question: “How do you pay for the modes above?” Payment_code1 will correspond with Mode_1, etc. The payment codes are:

1=single ticket

2=return ticket

3=daily ticket

4=multiple trip

5=weekly ticket

6=monthly ticket

7=other

TD_cost

(Input variables)

Notes to users

Fare / parking cost in Rand value.

TD_occupants

(Input variables)

Notes to users

The number of persons in the car, including the person interviewed.

Comment1, Comment2

(Input variables)

Notes to users

Comments entered by the interviewers.

Checked

(Input variable)

Notes to users

If the checked-field is blank, the record was not checked; otherwise the electronic checker left a code in this field.

New_Income_grp1

(Derived variable)

Notes to users

The income groups were calculated in the Household data.

Appendix B: ANOVA tables

ANOVA tables for research objective 1

ANOVA					
Amount_Activities					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	17,255	12	1,438	8,292	0,000
Within Groups	872,446	5031	0,173		
Total	889,701	5043			

ANOVA					
Amount_Trips					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1066,920	12	88,910	70,625	0,000
Within Groups	6334,754	5032	1,259		
Total	7401,674	5044			

ANOVA					
Income_group					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	339,042	12	28,253	69,710	0,000
Within Groups	1999,349	4933	0,405		
Total	2338,391	4945			

ANOVA					
Car_Access_Binary					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	326,071	12	27,173	151,744	0,000
Within Groups	883,345	4933	0,179		
Total	1209,416	4945			

ANOVA tables for research objective 2

ANOVA					
Amount_Activities					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6,137	3	2,046	11,602	0,000
Within Groups	882,364	5004	0,176		
Total	888,502	5007			

ANOVA					
Amount_Trips					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	23,763	3	7,921	5,382	0,001
Within Groups	7365,007	5004	1,472		
Total	7388,770	5007			

ANOVA tables for research objective 3

ANOVA					
ftime_dif					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2655325,789	12	221277,149	141,134	0,000
Within Groups	9331837,902	5952	1567,849		
Total	11987163,691	5964			

ANOVA					
ftime_dif					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	13453,000	3	4484,333	2,229	0,083
Within Groups	11918501,304	5923	2012,241		
Total	11931954,305	5926			

ANOVA

Time per activity					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	126448,830	3	42149,610	18,544	0,000
Within Groups	10883045,670	4788	2272,984		
Total	11009494,500	4791			

ANOVA					
Time per activity					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	757661,978	4	189415,494	88,379	0,000
Within Groups	9918810,446	4628	2143,217		
Total	10676472,424	4632			

ANOVA					
Time_diff_sum					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	979345,239	4	244836,310	98,627	0,000
Within Groups	11997647,803	4833	2482,443		
Total	12976993,043	4837			

ANOVA					
Activity time					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	23966619518,659	4	5991654879,665	37,503	0,000
Within Groups	772298373705,891	4834	159763834,031		
Total	796264993224,550	4838			