Mode choice modelling using elements of MINDSPACE and structural equation modelling

by

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Declaration

I hereby declare that the work contained in this thesis is my own work and that it has not been previously accepted for the award of any degree or diploma. To the best of my knowledge and belief, it contains no material previously published or written by another person except where due reference has been made in the text.

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Abstract

The last two decades have witnessed a rising research interest in integrated choice and latent variable(ICLV) modelling, in direct response to the inability of the traditional choice models to adequately explain the over half a century growing trend of vehicular traffic in cities around the world. With little variations, several researchers in transport choice behaviour have suggested that the theory behind the traditional choice models do not sufficiently account for the heterogeneity of human behaviour and observed choice preferences. Literature is replete with evidence suggesting that attitudes and perceptions significantly influence decision-making. The challenge for researchers is understanding the attitude with the most significant impact to include in the hybrid choice models.

Interestingly, recent literature on consumer behaviour suggests that MINDSPACE have a significant impact on behaviour. MINDSPACE is the mnemonic for **M**essenger, **I**ncentive, **N**orms, **D**efault, **S**alience, **P**riming, **A**ffect, **C**ommitment, and **E**go, these behavioural effects are believed to offer robust way of analysing and influencing behaviour. This study, therefore, exploits the potential benefits of these two new research areas to develop MINDSPACE enriched ICLV model to explain the underlying transport mode choice behaviour of the population of Edinburgh using five hundred responses collected in a mail-back revealed preference survey. The proposed model integrates variables from the MINDSPACE framework as latent variables in the ICLV model. The study found strong evidence aside the socio-demographic and mode specific variables that Norm, Salience, and Affect have a significant influence on transport mode choice, among others. Overall, the ICLV model demonstrates considerable improvement over a reference logit model. The study could prompt policy development toward urban transportation because the findings have broader policy implication for public transport and travel behaviour change.

Keywords:

Travel mode choice; Behavioural economics; MINDSPACE; Structural equation modelling; Integrated choice and latent variable models; Norms; Affects; Emotions; Ego; Narcissism; Salience.

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Dedication

I dedicate this thesis to my uncle, Okrah Ababio, not only for raising and nurturing me but also for unselfishly funding my education since childhood.

I also dedicate this thesis to my lovely wife, Victoria. Her love and months of hard work in providing for me and our children; Phoebe, Michelle and Yiau made the completion of this work possible.

"... She is far more precious than jewels."
Proverbs 31:10

Above all, to the Almighty God for the grace and strength through it all.

Tables of contents

List of Tables

List of Figures

FIGURES **Page**

List of Abbreviations

CFA Confirmatory Factor Analysis

CSF Critical Success Factor

EFA Exploratory Factor Analysis

ICLV Integrated Choice and Latent Variable

LV Latent Variable

MINDSPACE Messenger, Incentive, Norms, Default, Salience, Priming, Affect, Commitment, Ego

NMT Non-motorised Transport

PT Public Transport

SEM Structural Equation Modelling

SIMD Scottish Index of Multiple Deprivation

TMA Tobacco Manufacturing Association

Part I

INTRODUCTION AND LITERATURE REVIEW

Chapter One

Introduction

1.1 Background

The traditional transport mode choice behaviour is a function of individual socio-economic characteristics, the attributes of the mode and the characteristics of the trips (Simon, 1955; Ben-Akiva and Lerman, 1985). However, the literature is replete with evidence suggesting that attitudes, perceptions and situational factors significantly influence decision-making (Simon, 1955; Ben-akiva and Bierlaire, 1999; Manski, 1973; Belgiawan et al., 2016; Liu et al., 2017; Samson, 2019; Halonen, 2020). With little variations, several researchers in transport choice behaviour suggested that the theory behind the traditional models is not entirely accurate in the prediction of individual choice preference (Ben-akiva and Bierlaire, 1999; Ben-Akiva and Boccara, 1995; Simon, 1982). The models do not adequately account for the heterogeneity of human behaviour and observed choice preferences (Manski, 1973). Consequently, choice models that incorporate attitudinal and behavioural variables as latent factors to account for the heterogeneity in human behaviour, which hitherto was absent in choice models have been proposed (Ben-Akiva and Boccara, 1995; Ben-Akiva et al., 2002). Recent studies incorporating attitudinal variables such as accessibility, reliability and comfort/safety in the choice models, found that accounting for the individual subjectivity enhanced the explanatory power of choice models, the resultant models were superior to the traditional choice models (Johansson and Heldt, 2006; Yáñez et al., 2010; Ardeshiri and

Vij, 2019).

However, since attitudes and perceptions are difficult to observe directly, they are treated as latent variables and observed indirectly with multiple indicator variables. These latent variables could then be integrated into the choice models utilising structural equation modelling (SEM), resulting in a hybrid or integrated choice and latent variable (ICLV) model (Atasoy et al., 2013). SEM provides a powerful tool to analyse and explain psychometric indicators and latent variables. Literature is replete with numerous studies involving the application of SEM in transportation, including frameworks for integrating latent variables into choice models in ICLV model (Ben-Akiva et al., 1999; Ben-Akiva et al., 2002; Yáñez et al., 2010; Vij et al., 2016; Temme et al., 2008a; Bhat and Dubey, 2014; Chae et al., 2018; Ardeshiri and Vij, 2019).

Numerous studies have developed hybrid choice models with different attitudinal variables to investigate their impact on individual choice preference. The difficulty for researchers is understanding the attitude to include in the hybrid choice mode.

Interestingly, recent literature in consumer behaviour have proposed a framework called MINDSPACE as a possible key for influencing human behaviour(MINDSPACE is a mnemonic for the following nine contextual effects; **M**essenger, **I**ncentive, **N**orms, **D**efault, **S**alience, **P**riming, **A**ffect, **C**ommitment and **E**go). It is suggested that MINDSPACE have a significant impact on behaviour and believed to offer a robust way of analysing and influencing behaviour, including travel behaviour (Avineri, 2012a; Avineri, 2012b). Readers are referred to 2.4.1 for detailed review. However, few studies have investigated the effect of MINDSPACE on travel behaviour and car ownership (Belgiawan et al., 2016). None of the existing literature in this area have studied the impact of MINDSPACE as latent variables in ICLV model (Temme et al., 2008b; Zhang et al., 2016; Belgiawan et al., 2016; Avineri, 2011; Juhász, 2013; Aczél and Markovits-somogyi, 2013).

Temme et al. (2008b) believes that integrating MINDSPACE as latent variables into the choice model could improve the explanatory power of choice models. Therefore, building on the hybrid choice models, this research investigates the impact of the components of MINDSPACE as latent variables in ICLV model on individual choice preference.

MINDSPACE have been applied in explaining, predicting and influencing behaviour in health and energy consumption (Johnson and Goldstein, 2003; Frederiks et al., 2015). There are several reported effects and influences of MINDSPACE in literature (Dolan et al., 2010; Samson, 2017; 2019), however, few of these studies have been in transport. The impact of MINDSPACE on travel choice decision-making remains to be fully explored. None of the existing studies considered the incorporation of MINDSPACE as latent variables to develop ICLV model (Avineri, 2012a). The challenge for transport planners and policy-makers is how to empirically evaluate the impact of MINDSPACE on transport schemes, which is the overall aim of this research.

1.2 Research Aim and Methodology

1.2.1 Research Aim and objectives

The overall research aim is to investigate whether the extended ICLV model incorporating latent variables from MINDSPACE could enhance the explanatory power of transport mode choice models and individual choice preference. The following specific objectives are developed to help achieve the overall aim of the study:

1. To investigate and provide insight into the importance of the components of MINDSPACE in choice decision-making.
2. Identify potential latent variables from MINDSPACE and develop psychometric indicators to measure them
3. Investigate the impact of the latent variables on the explanatory power of ICLV model and individual choice preference.

1.2.2 Research Methodology

The study adopts Revealed Preference(RP) survey methods with stratified random sampling technique and postal or mail-back survey method to collect data for the study. The RP approach allows the acquisition of information to understand the respondents' travel behaviour and the relative importance of the psychometric indicators and their impact on individual choices. EFA and CFA were performed on the psychometric indicators collected as part of the data. The extracted factors from the CFA together with the observed socio-demographic and transport characteristics variables were used to develop ICLV model.

1.3 Research Publications

The Following academic papers have been prepared and published in academic conferences during the course of the study.

Peer Reviewed Paper

- **Ababio-Donkor, A.**, Saleh, W. and Fonzone, A. (2020): The role of Personal Norm in the Choice of Transport Mode, *Research in Transportation Economics*
- **Ababio-Donkor, A.**, Saleh, W. and Fonzone, A. (2020):Understanding transport mode choice for commuting: The Role of Affect, *Transportation Planning and Technology*

Conference Paper

- **Ababio-Donkor, A.**, Saleh, W. and Fonzone, A. (2018): The Influence of Narcissism on Transport Mode Choice, In *IATBR2018: 15th International Conference on Travel Behavior Research. Santa Barbara, CA, United States, 15-20 July 2018.*
- **Ababio-Donkor, A.**, Saleh, W. and Fonzone, A. (2019a): Understanding transport mode choice for commuting: The role of Affect. In *UTSG 51st Annual Conference. Leeds, UK, 8-10 July 2019.*
- **Ababio-Donkor, A.**, Saleh, W. and Fonzone, A. (2019b): Augmenting narcissism: The role of car ownership and commuting mode choices. In *9TH International Symposium on Travel Demand Management, Edinburgh, UK, 19-21 June 2019.*
- **Ababio-Donkor, A.**, Saleh, W. and Fonzone, A. (2019c): The role of personal norms in the choice of mode for commuting. In *16th International Conference on COLPT. Singapore, 25-30 August 2019.*

1.4 Structure of the thesis

This thesis comprises of eight chapters written in four parts. Part one consists of the introduction of the study and literature review (written in two chapters). Part two consist of two chapters, involving Research methodology and the study area. Part three comprise of two chapters, involving the data collection process and statistical analysis of the sample data. The final part of the thesis titled, "conclusions and recommendations", covers the research conclusions and recommendations. A brief account of the content of each chapter is presented in the paragraphs below:

Chapter 1: Introduces the thesis and presents the background and objectives of the research, the main contribution of the study, and gives a brief outline of the thesis.

Chapters 2 and 3 presents a review of relevant existing literature on choice theories and transport mode choice modelling, respectively.

Chapter 2: Explains the rational choice theory, the notion of bounded rationality and choice overload. It argues that these concepts stimulated further research into choice models and contributed to the development of the recent latent/hybrid choice models. It further discusses the theory of MINDSPACE in recent behavioural economics research and how it reinforces the concept of bounded rationality and choice overload. It also explains the implication of MINDSPACE for transport studies and transport mode choice modelling based on existing literature. Moreover, the chapter explains how transport modellers and transport planners could leverage on the potential of MINDSPACE in understanding travel decision making and influencing travel behaviour change. The review in chapter two occasioned the need for conducting a further literature review of transport modelling and latent/hybrid transport mode choice modelling.

Chapter 3: Extends the literature and presents a review of the literature on transport modelling and provide a brief historical background to it. The main types of transport models, their characteristics, as well as their strengths and limitations, are similarly discussed. A brief overview of models developed in an attempt to address the reported limitations of the earlier models. Therefore, mode choice modelling and modal split models are reviewed and discussed in detail.

Chapter 4: Discusses the research methodology and explains the research instrument design and, the procedures for data collection and analysis. A critical review of all possible techniques and procedures are presented with the rationale behind the selection of any particular method or technique.

Chapter 5: Describes the study area, the demographics, as well as the statistical profiles of the study population. It further explains the rationale for the choice of the study area and the study population.

Chapter 6: Extends chapter 4 and further outlines the data collection process, including sample size estimation and sampling technique. The chapter also reports the descriptive statistics and preliminary analysis of the sample data including a brief discussion of the initial findings of the study.

Chapters 7: Statistical analysis of the sample data is discussed and presented in detail. The chapter further presents the Exploratory factor analysis and confirmatory factor analysis conducted in SPSS and AMOS software package, respectively, on the observed psychometric indicators. Finally, the development of a traditional discrete choice model and integrated choice and latent variable model using Biogeme are discussed in the chapter

Chapter 8: The conclusion of the research is summarised and presented in this chapter. The chapter also shows the link between the research findings and the research objectives outlined in the introductory chapter. The study's recommendation and the researcher's suggestion for future research direction closes this chapter and the thesis.

Chapter Two

Choice Theories

"What a piece of work is a man! How noble in reason, how infinite in faculty! In form and moving, how express and admirable! In action, how like an Angel! In apprehension, how like a god! The beauty of the world! The paragon of animals!..." (Shakespeare, 1603).

2.1 Introduction

The piece by William Shakespeare above is the view of human nature held mainly by neoclassical economists. This forms the basis for the neoclassical economic theory in the 18th and 19th century (Veblen, 1900). Traditional economic theory postulates a "Rational and economic man", one who is assumed to be rational and perfectly informed on the relevant aspects of his environment, which if not complete, is at least impressively clear and quite substantial. He is assumed to also have a well-organised and consistent system of preferences and computational skills. These qualities enable him/her to calculate and evaluate alternative courses of action that are available and consequently, select the option that will provide the highest attainable economic utility or satisfaction on his preference scale while trading off between costs and benefits(Ben-Akiva and Boccara, 1995). The following section discusses the rational choice theory and the limitations of the theory as presented by Simon Herbert. Additionally, the chapter presents behavioural economic theory, while explaining the MINDSPACE framework and the meaning and implication of the individual effects for transport. This chapter forms the basis of this study and the development of the survey instrument.

2.2 Rational Choice Theory

The rational choice theory suggests that consumer choice decisions result from a careful weighing of costs and benefits and always lead to optimal decisions making. Becker (1978) outlined a litany of ideas to buttress the "Rational Choice" theory, ranging from crime to marriage. The author believes that academic disciplines such as sociology could learn from the "rational man" assumption of neoclassical economics. This theory has been the basis for the development of consumer choice models, transport and travel demand models (such as discrete choice models). It provides the theoretical framework for the random utility theory (Ben-Akiva and Lerman, 1985; Ortuzar and Willumsen, 2011; Samson and Ariely, 2015).

Notwithstanding, literature suggest that this view is not entirely accurate (Simon, 1955; 1982; Ariely, 2008; Samson and Ariely, 2015). The human race has achieved many great feats, including building planes for air travel and defence systems, designed and built sophisticated structures and skyscrapers and most notably has stepped foot on the moon. However, we have failed from time to time, and the costs of these failures can be substantial. Think, for example, about smoking, alcohol/drug abuse, using the phone while driving, and drunk driving. People are very much aware of the devastating effects these have had on lives and society, including deaths, yet many are found culpable. These are consumer decisions and choices far from perfect rationality and a deviation from the rational man paradigm. Several policies and laws including drink driving laws (UK Government, 2006), the provision of health warning such as "Smoking kills-quit now" on tobacco products for smokers (UK Goverment, 2016) and the imposition of high taxes on tobacco products (in the range of 74% and 88% APR of retail price) (Action on Smoking and Health (ASH), 2015; Tobacco Manufacturing Association (TMA), 2016) are punitive measures to discourage these negative consumer behaviours, yet a substantial proportion of the population are still complicit. Statistics suggest that the percentage of UK population smoking has halved since 1974, having said that, 20% of the UK adult population remain active smokers (Action on Smoking and Health (ASH), 2016). These are substantial problems facing humanity, the crux of the matter is that people act in ways that are inconsistent with their long-term interests (Samson and Ariely, 2015).

Buttressing earlier claims by Kahneman et al. (1990) and Ariely (2008), Acker et al. (2010) explained that human behaviour is irrational with weakly linkable factors, which makes it challenging to predict deterministically. Acker et al. (2010) argued that studies like Gardner and Abraham (2008) explain why the utility maximisation theory does not entirely explain the motivation of human behaviour and suggest that "unreasoned behaviour" characterises people's travel behaviour. The author further suggested that a perfect predicting model of human behaviour was yet to be developed by researchers. Therefore, the understanding of people's travel behaviour and choices would involve the establishment of a more comprehensive framework, involving the combination and linkages of theories stemming from not only transport science and microeconomics but also from transport geography, social psychology and cognitive psychology. The following sections discuss some of the studies.

2.3 Bounded Rationality

Cognitive bias describes behaviour that reveals inconsistencies in the evaluation of choices; such as higher implied discount rates on purchase decisions relative to savings decisions, violation of transitive principles (i.e. rational preference axioms), and greater aversion to losses than the desire for gains (Ariely, 2008). The term "Bounded rationality" as coined by Simon Herbert describes decision-making based on imperfect information, including behaviours such as; procrastination, simplified decision-making heuristics, disproportionate weight to readily observable factors, and decisions resulting from incomplete information (Simon, 1955; 1982). This concept, according to Simon, challenges the notion of perfect human rationality. Humans are rationally bounded because there are limits to the human information processing capabilities, information availability and are mostly constraint by time (Kahneman, 2003; Simon, 1955; 1982). Bounded rationality also explains choice overload (Chernev et al., 2015). The higher the number of options presented to the decision-maker and their complexity, the more difficult decision making becomes for the decision-maker. The resultant effect is decision fatigue, reduction in self-control and eventually to satisficing or choice deferral (avoiding making a decision) (Simon, 1955; Chernev et al., 2015).

As a heuristic, satisficing result in consumers choosing options that meet their most basic decision criteria but not necessarily the option with the highest economic utility (Johnson and Goldstein, 2003; Schwartz, 1977; Baumeister et al., 2008; Samson, 2014). Similarly, it is suggested that the rationality of consumer decision depends on the structures found in the environment of the decision-maker (Gigerenzer and Goldstein, 1996; Simon, 1982). The section below presents a review on human behaviour.

2.4 Behavioural Economics

Behavioural economics is defined by the Oxford Dictionary as "*a method of economic analysis that applies psychological insights into human behaviour to explain economic decision-making*". Thus, behavioural economics involves the use of psychology to explain economics while maintaining the mathematical structure of economics. More specifically, this approach draws on psychology and behavioural sciences in assessing consumer behaviour; how cognitive, social and emotional variables impact choices.

In summary, behavioural economics is essentially a series of observations about how people behave (The Australian Government, 2013). This field of study has its foundations from the works of Herbert Simon in the mid-1950s (Simon, 1955). Simon (1955) found that contrary to the classical economic notion of the "rational man", the human had internal and external limitations that make them psychologically limited in rationality. For instance, Simon argued that limits on the human computational capacity and predictive ability were a significant constraint, particularly on processing a large amount of information when making decisions. Simon, therefore, defined human as a "choosing organism of limited knowledge and ability" (Simon, 1955, p. 114), thus raising serious doubts about the suitability of the model of economic man paradigm as the foundation to build the theory of rational consumers behaviour (Simon, 1955).

A model based on the psychological limitation dubbed "limited" rationality model commonly referred to as "bounded rationality" was proposed to replace the "global" rational man model to address the psychological and computational limitations of the decision-maker (Simon, 1955; 1982; Samson, 2014; 2019).

In the 1970s, two psychologists Daniel Kahneman and Amos Tversky also criticised the utility theory and demonstrated that people systematically violated the predictions of the expected utility theory (Kahneman and Tversky, 1979). Through a series of laboratory experiments, the authors proposed and developed an alternative model by incorporating risk attitudes called the "prospect theory". The foci of the new model were that people derive utility from "gains" and "losses" measured relative to a reference point. People were found to be loss averse; losses appear salient than gains of the same magnitude. It was also noticed that choice making was context dependent, framing of an offer could significantly influence the outcome of a choice decision (Kahneman and Tversky, 1979; Camerer, 1999).

Similarly, Becker (1978) argues that the traditional economic theory places so much emphasis on the monetary value of consumer products than it does for attitudinal and behavioural factors in decision-making. Becker (1978) argued that the absence of these subjective factors significantly limited the resultant choice models and further proposed the formulation of choice theory to include subjective factors absent in the traditional choice models since decision-makers maximise utility according to their attitudes (Becker, 1978; 1993; 2013).

Moreover, it is becoming increasingly clear from recent psychological and behavioural studies that decision-makers do not always seek to maximise their economic utility neither do consumer choices always satisfy the "rational man" axiom (Ariely, 2008). Ariely (2008) reinforced the findings of Simon (1982) and further suggested that although people's decisions are sometimes irrational, they can be predicted, and therefore described human behaviour as "predictably irrational" (Ariely, 2008). Halonen (2020) indicated that besides the influence of individuals characteristics such as gender, age, income and social class, every decision is also influenced by situational factors such as time pressure, cognitive load and social context experienced by the decision-maker Frederiks et al. (2015) argued that a wide gap exists between consumers values, their material interests and their observed behaviour. It has thus been established that consumers often act in ways that do not align with their knowledge, values, attitudes and intentions, which fall short of maximising their economic utility and material interest (Frederiks et al., 2015). Further to the above, it can be summarised from similar studies that people are not always self-interested, benefits maximising and costs minimising individuals with stable preferences. Human decision making is subject to insufficient knowledge and processing capability. This often involves uncertainty and affected by the context in which the decision is made. Most choices do not result from careful deliberation because people are influenced by readily available information in memory known as the salience effect; salient information in the environment and salient experiences. people also live in the moment; in that they tend to resist change and are poor predictors of future behaviour. People are subject to distorted memory and are affected by their physiological and emotional states. Finally, people are social animals with social preferences, such as those expressed in trust, reciprocity and fairness as well as susceptible to social norms (Simon, 1955; 1982; Kahneman and Tversky, 1979; Becker, 1993; Ariely, 2008; Avineri, 2012b; Metcalfe and Dolan, 2012a; Dolan et al., 2012; Samson, 2014; Aczel and Markovits-somogyi, 2013).

Aczél and Markovits-somogyi (2013) explained that people care about other people and value the opinion of people important to them; meaning the behaviour of others shape our norms and decision. Consequently, the attitudes of family members, peers and colleagues could largely influence one's travel behaviour. There has been much research about the cognitive limitation of consumers in the past decades and how consumers could be nudged to consume a particular goods and services (Avineri, 2009). The confluence of these behavioural inconsistencies is viewed by some researchers as the limitation of the existing travel behaviour models and possibly explain the market failure in the transport sector (Avineri, 2009). The findings of consumers economic

irrationality in the context above cannot be overlooked when seeking for clues in understanding travel behaviour (Frederiks et al., 2015; Beirao and Cabral, 2007).
The observed limitation of behavioural economics is that; there are now literally hundreds of different claimed effects and influences. However, nine of these effects of behavioural economics referred to as MINDSPACE have been suggested to have a profound effect on consumer behaviour; (Dolan et al., 2012; Metcalfe and Dolan, 2012; Aczél and Markovits-somogyi, 2013; Liu et al., 2017).

2.4.1 Mindspace

MINDSPACE is the mnemonic for nine contextual effects that can significantly influence human behaviours: Messengers, Incentives, Norms, Defaults, Salience, Prime, Affect, Commitment, and Ego (Dolan et al., 2012).
Mindspace framework provides tools to reframe the decision task to engage the system one thinking processes (Kahneman, 2013) to influence behaviour. The context for the decision task can be reframed using the Mindspace effects to influence decisions-making and overcome undesirable bias in behaviour. Several findings in the behavioural studies have demonstrated the effectiveness of MINDSPACE in public policy contexts across numerous domains, including health, finance, and climate change (Liu et al., 2017; Metcalfe and Dolan, 2012).
It has been suggested that Mindspace can be useful in understanding travel and influencing travel behaviour (Dolan et al., 2010; Metcalfe and Dolan, 2012; Aczél and Markovits-somogyi, 2013). This study, therefore, employs MINDSPACE to extend travel mode choice models in an integrated choice and latent variable model. MINDSPACE could improve the explanatory power of latent/hybrid choice models. These nine effects (elements) are investigated in the context of transport mode choice in this study. The study investigates the reasonable way to integrate these effects with the existing transport models, to enhance the understanding of travel behaviour and decision-making process. The sections below discuss the effects of the various elements of MINDSPACE in details.

2.4.1.1 Messenger

Researchers have established that the importance we attach to information depends to a large extent on the source, the content and most importantly the conveyor of the information (Dolan et al., 2010; 2012; Metcalfe and Dolan, 2012a; Sy, Horton and Riggio, 2018; Martin and Marks, 2019a; 2019b). Seethaler and Rose (2006) earlier suggested that people are most likely to follow a request brought forward by someone they admire. Similarly, Dolan et al. (2012) explained that information carries more weight when delivered by experts; the authority and respect commanded by the messenger can produce behaviour compliance. For instance, it was found that nurses complied bluntly with doctors' instructions even when the doctors were wrong (Hofling et al., 1966), the implication is that the messenger holds more influence than the message, in short, the Messenger rather than the Message holds the greater influence (Martin and Marks, 2019b; Sy et al., 2018). Similarly, Webb and Sheeran (2006) found that health interventions delivered by health professionals were more effective in changing behaviour compared with interventions delivered by other professionals.

According to Avineri (2012a), people are more likely to change behaviour when influenced by people in their social networks, and geographical and social proximity (such as neighbours, work colleagues, classmates). Durantini et al. (2006), earlier established that people from lower socio-economic groups are more sensitive to messengers from within their group (age, gender, ethnicity, social class/status, culture and profession). A similar study also indicated that people's emotional state towards the messenger because of prior experience or encounter could affect their effectiveness. For instance, people will mostly discard advice or information from people they dislike or distrust (Cialdini, 2007; Martin and Marks, 2019a),

The accuracy, reliability and consistency of information from a messenger also play an essential role in its acceptability and effectiveness. People use cognitive and rational processes to assess whether the messenger is convincing enough (Kelley, 1967). If people exhibit consistency and transitivity in their transport choices, then the framing and presentation of information (alternatives and attributes), the conveyor of that information, attitudes and beliefs, social norms and habits should be irrelevant to decision-making (Ben-Akiva and Lerman, 1985). However, there exist a plethora of theories in social psychology, suggesting that beliefs and attitudes determine behaviour rather than economic utilities (Ariely, 2008; Dolan et al., 2010; 2012; Metcalfe and Dolan, 2012a; Avineri, 2012b; The Australian Government, 2013; Liu et al., 2017; Samson, 2017; Sy, Horton and Riggio, 2018; Martin and Marks, 2019a). Therefore, the effectiveness of any policy or campaign for transport behaviour change will depend largely on the integrity of the individual or organisation providing and disseminating the information about travel behaviour and the benefits of changing our behaviours.

2.4.1.2 Incentives

The economic law of demand suggests that people are perfectly rational and seamlessly consider options and are sensitive to new information such as changes in prices and situations (Kreps, 1990; Uri, 2019). It is also suggested that behaviour change can be induced in people by offering them monetary incentives or disincentives (Marteau et al., 2009). Incentives can motivate people to create or break habits by negatively or positively altering the cost or benefit of an activity (Uri, 2019; Liu et al., 2017). Responses to incentives are shaped by mental shortcuts such as the desire to avoid losses (Ariely, 2008; Liu et al., 2017). Kahneman (2013) proposed that human have two systems of thinking; the automatic system (fast and shallow thinking mode) and the reflective system (slow and deep-thinking mode). The author further established that incentives are effective when people engage the slow and deep thinking process. Meanwhile, research has shown that many human decisions are made using the automatic system. People rely mostly on past experiences (salience effects), habits and norms but not on rationality. Therefore, monetary incentives do not always result in expected changes in behaviour. It is believed that when considered, these factors can assist researchers and policymakers to design more effective schemes (Dolan et al., 2012). The following effects summarise the main effects of incentives on behaviour. People are loss averse, uses anchors, overweigh small chances, think in discrete bundles, value right now very highly and inconsistently and care about other people (Dolan et al., 2012).

2.4.1.3 Norms

Social and cultural norms are the behavioural expectations or rules within a society or group (Dolan et al., 2012). Alternatively, norm is defined as "*a standard, customary or ideal form of behaviour to which individuals in a social group try to conform*" (Burke and Young, 2011). Norms also signal appropriate behaviour or acceptable actions by most people. People often take their understanding of social norms from the behaviour of others, although this may not be maximising their overall utility.

The influence exerted by neighbours on behaviour can be described as normative or informational (Aronson et al., 2005). Normative influence describes conformity to be accepted by a social group and informational influence occurs in situations where people look to others for cues when they are uncertain about the acceptable behaviour (Schroeder et al., 1983). Sunitiyoso et al. (2011a; 2011b) discovered the existence of strategic behaviours in social learning models such as confirmation (reinforcing behaviour if other group members have similar behaviour) and Normative/conformity (following the majority choice in a group). The author suggested that confirmation and conformity models may exist in real life whenever individuals have access to social information about other's behaviour (Sunitiyoso et al., 2011b; Marek, 2018; Zhang et al., 2019).

Avineri (2012b) believes these social learning models could be relevant in designing social interventions such as 'social nudges' to change travel behaviour. Hirshleifer (1993) observed that the presence of others causes people to change their behaviour and performed better on simple tasks. Avineri (2009) also demonstrated that people are motivated to continue in a behaviour if they believe they have the approval of peers (Liu et al., 2017; Martin and Marks, 2019b).

Some social norms have an automatic effect on behaviour and capable of influencing actions positively or negatively. The effectiveness of some social norms come from the social penalties for non-compliance or the social benefit of conformity. Social norms are also heavily related to herding behaviour and social pressure (DellaVigna, 2009). Cialdini et al. (1999) noted that giving people information about how others behave in a task or past behaviour significantly influences their behaviour and leads to greater compliance. Similarly, Bamberg et al. (2007) discovered that personal norms, among others, significantly influence people's intention to use public transportation.

Additionally, Sunitiyoso et al. (2011a) studied the effect of social information on travel choices by giving participants two scenarios to choose from; contributing to an employer-based demand management initiative meant to reduce employees' car-use or not. Two schemes of social information about other participants' behaviour were provided to the participants. The findings suggest that participants who received information about the contribution of other participants increase their level of contribution. The more widely a norm is followed by members of a social group, the more likely that everyone in the group will adopt it (Burke and Young, 2011). Therefore, presenting a desired social norm such as the use of greener transport modes to the target population, the more likely will it be adopted (Dolan et al., 2010; 2012; Metcalfe and Dolan, 2012a).

Norms also could refer to social norms, legal norms and personal norms. Schwartz (1977) described social norms as expectations, obligations, and sanctions currently associated with a reference group. Social norms are held in place by the reciprocal expectation and the fear of social penalties by the reference group (Bamberg et al., 2007; Mackie et al., 2015). Legal norms are formal rules backed by laws and are enforceable, while personal norm refers to individual values and principles. Personal norms are personalised or internalised social norms (Schwartz, 1977). Unlike social norms, personal norms are internally motivated (Schwartz, 1977; Mackie et al., 2015; Bamberg et al., 2007). It is argued that activated personal norms prompt behaviour and the most important moderating factor of pro-environmental behaviour (PEB)(Ferreira and Wijngaard, 2019).

Therefore, if several people are travelling by unsustainable transport modes within a population, suggesting to them that they are behaving outside of the norm could provoke a desirable behaviour change (Dolan et al., 2012). The idea that norms can influence behaviour is something difficult to explain in terms of 'perfect rationality' (Schroeder et al., 1983).

2.4.1.4 Defaults

Defaults are pre-selected options made for individuals when they fail to make an active choice. Avineri (2009c; 2012b) stated that "*people are influenced by 'defaults' set to them by choice architects*". Most of the routine decisions made by consumers and travellers have defaults options associated with them (Dolan et al., 2012). Default has a significant influence on consumer behaviour and can lead to habit formation (Avineri, 2009). It is argued that a default may be more persuasive in influencing decisions when the decision-makers care less about a particular choice or do not have a preferred option in mind (Jachimowicz et al., 2019).

Samson (2014) submitted that the more uncertain consumers are about their decision, the more likely they are to accept a default option, especially if it is explicitly presented as a recommended option. Default has been demonstrated to be effective in financial behaviour, car insurance choice behaviour (Johnson and Goldstein, 2003), car purchase behaviour, organ donation campaigns (Johnson and Goldstein, 2003) and pro-environmental behaviour. However, there are no noticeable parallels in travel behaviour context (Avineri, 2012b). Avineri (2009a; 2012c) proposed defaulting people into 'green defaults' such as clean vehicles and clean mode of travel as a means of encouraging greener travel. Presenting sustainable modes of transport such as walking, cycling or public transport as default options in journey planning apps and website could potentially influence travel behaviour and choices (Avineri, 2009a; 2012c).

2.4.1.5 Salience

Behaviour is greatly influenced by what comes to mind when options are being considered in choice making. For instance, most popular consumer brands have the highest probability of being remembered when making product choice (Kahneman, 2013). Therefore, any information that seems relevant to the decision-maker is more likely to affect his/her thinking and decision (Dolan et al., 2010). Salience is a form of anchoring, meaning consumers use some initial reference point in estimating the relative utility or disutility of an option in choice decision making (Ariely, 2008; Stewart, 2009; Kahneman, 2013). This has been shown to play a very significant role in decision making and assessing consumer value (Ariely, 2008). The human memory of experiences is said to be governed by most intense moments, as well as the final impression in a chain of events (Kahneman, 2013). Salience explains why unusual, extreme, or unexpected experiences loom larger to the consumer and stay in memories for long. The most prominent (pleasant or unpleasant) experience, such as any incidents of criminal activity or any undesirable social behaviour experienced by the decision-maker could have far-reaching consequences on future behaviour. Therefore, addressing customer complaints to their satisfaction could reverse the salience effect of such experience and reduce the potential negative impact of the experience on future decisions (Dobbie et al., 2010). Similarly, delays experienced by passengers which negatively affected them may have a disproportionate effect on their future travel behaviour. Such experience could potentially influence their future travel decision. Therefore, salience cost of transport experiences such as traffic delay, passenger annoyance, anti-social behaviour and criminal behaviours on a travel mode could influence future travel behaviour(Dolan et al., 2012).

Developing user satisfaction and experience survey for both users and non-users of the public transport services could unravel the salience effect of such experiences. To this end, user experience questionnaire is developed and included in the general survey instrument for measuring any lousy transport experience respondents are likely to encounter on PT and their impact on travel behaviour.

2.4.1.6 Priming

Research in social and cognitive psychology has proven that when people are exposed to certain stimuli (such as exposure to certain sights or sensation), memories associated with the stimuli are activated (Hertel and Fiedler, 1994; Liu et al., 2017). This process is observed to influence people's behaviour on subsequent tasks (Tulving et al., 1982). In other words, people behave differently if they are exposed to certain cues before a related task. After exposing people to words relating to the elderly stereotype such as wrinkles and poor vision, Dijksterhuis and Bargh found that the participants subsequently behaves as the elderly; they walked more slowly when leaving the room and had a poorer memory of the room (Dijksterhuis and Bargh, 2001).

There are no empirical studies yet on how priming would work for transport. However, the Dolan et al. (2012) believes that by priming travellers with images and words about peak oil, traffic congestion, smarter choices and sustainable transport, policy makers could influence decision-makers to opt for more sustainable transport mode for their journeys.

2.4.1.7 Affect

Baumeister and Bushman (2014) defined emotion as a "conscious state that includes an evaluative reaction to an event and "Affect" as an automatic response to a good or bad experience. "Affect" could refer to four different states Moods, Affective Styles, Sentiments, and Emotions (Davidson et al., 2009). All four of these affective constructs could have a transient or lasting effect on the decision-maker and can consciously or unconsciously influence decision-making and behaviour. Sentiment is an emotion an individual attaches to a target because of the subject's interaction with the target. This type of "Affect" is categorised either as positive valence (joy, satisfaction, pleasure) or negative valence (shame, embarrassment, anger, fear, frustration) (Resnick, 2012). If the sentiments attached to a target is intense, it would usually emerge whenever the individual is dealing with the target in question.

Similarly, it is believed that any sentiment associated with a travel mode could potentially affect behaviour towards that mode, most importantly, when the emotion provoked is intensely negative (Liz et al., 2016). Sentiments can be remarkably influential; it can cause overreactions and override rational course of action even in the presence of evidence suggesting alternative courses of action (Loewenstein, 2000; Loewenstein et al., 2001; Liu et al., 2017; Samson and Ariely, 2015; Dolan et al., 2012). Rozin et al. (1986) suggested that once a consumer attaches emotion to a decision targets, it influences the desirability of the target and become difficult to detach. Consumer's experiences with a particular product or service could create temporal or lasting emotional attachment or detachment towards the products or service, which could influence behaviour (Liz et al., 2016). Elster, suggests that aside from economic satisfaction, decision-makers also evaluate their choice sets emotionally and opt for the product with high perceived emotional and economic benefits (Elster, 1998).

2.4.1.8 Commitment

It has been established that individuals are susceptible to procrastination and mostly delay taking decisions that will serve their long-term interests (O'Donoghue and Rabin, 1999). To overcome this innate weakness, people use commitment devices such as goal setting to achieve behaviour change (Strecher et al., 1995). It has been shown that people are more likely to make and sustain a change in habitual behaviour if they make a verbal or written commitment and share this with others (Savage et al., 2011). This opinion supports an earlier finding by Cialdini (2007) that the act of writing a commitment down have the tendency to increase the probability of its fulfilment.

Similar to Ego, Cialdini (2008) opines that people like to maintain a positive and consistent self-image of themselves and so are motivated to keep commitments made publicly. Since breaking them will significantly damage that reputation (Festinger, 1957; Samson, 2019). There is a large potential to get people to commit to changing their travel behaviour to cleaner and sustainable mode of transport if these commitments are done publicly (Liu et al., 2017).

2.4.1.9 Ego

It has been suggested that people behave in ways that tend to support the impression of a positive and consistent self-image about themselves and are motivated to maintain that view about themselves to avoid reputational damage. People pat themselves when things go well with them and blame others or circumstances when things go awry. This effect is referred to as the "fundamental attribution error" (Miller and Ross, 1975). Millar and Tesser (1986) explained that people's desire for positive self-image often leave them with the tendency to compare themselves with others. This tends to give them a bias opinion about their performance. It is believed that this self-centred nature and gratification of one's own desires guides behaviour (Vazire et al., 2008; Holtzman et al., 2010). This tendency to behave in ways that tend to make us feel better about ourselves, according to (Tajfel and Turner, 1979) is what advertisers take advantage of when advertising a product. Dolan et al. (2012), therefore believe that the consumer's quest for respect, recognition and identity could lead to a change in their preference for certain goods and services and perhaps their travel behaviour. Therefore, manipulating people's Ego using saliency and nudges could result in a change in travel behaviour. Vazire et al. (2008), suggested that the obsession of narcissist of their reflection was due in part to their Ego, in other words, narcissism is driven by a strong but fragile ego (Vazire et al., 2008). Therefore, the terms "narcissism" and "ego" are used interchangeably in this study. Narcissism describes a person's obsession with oneself and one's physical appearance and/or public perception (Graves, 1968).

Research by social psychologists, behavioural scientists and behavioural economists on consumer behaviour have suggested a possible relationship between consumer choice behaviour and level of narcissism. The relationship between narcissism and consumer behaviour has been widely explored (Tian et al., 2001; Dunning, 2007; Sedikides et al., 2007; Campbell and Foster, 2007; Vazire et al., 2008; Gao et al., 2009; Horvath and Morf, 2009; Gregg et al., 2013). Most of these studies present a convincing argument about the role of narcissism in consumer decision making. Gregg et al. (2013) found that participants scoring high on the Narcissism Personality Inventory (NPI) scale were more likely to consume products with the potential of making them socially unique and distinguishable than those scoring lower. Narcissist deliberately flouts established norms in pursuit of distinctiveness relative to others. Gregg et al. (2013) further reinforced the findings of Gao et al. (2009), and Horvath and Morf (2009) on consumer behaviour and offered a plausible explanation that the narcissist effort to maintain this perceived positive view and social identity of themselves explains their consumer behaviour. Actions that threaten to damage this perceived view could trigger a reaction in the form of attitudinal or behaviour change (Samson, 2014). This attitudinal weakness gives an insight into human behaviour (Vazire et al., 2008; Holtzman et al., 2010), and what marketing experts exploit in advertising (Tajfel and Turner, 1979). Very little is known about the relationship between narcissistic traits and travel behaviour, this study, therefore, investigates whether the travel behaviour of narcissists reflect their personality.

2.5 Summary

This chapter discussed extant literature in behavioural economics relevant to consumer behaviour. It has been shown that consumer behaviours violate the rational choice theory. The review also has established the inconsistency in human behaviour and exposed the limitations that prevent humans from making a perfect rational decision. It has been established that humans are limited in our computational capabilities. People resort to mental shortcuts and heuristics in decision making.

The chapter has provided significant insight and implication of MINDSPACE in the transport sector, particularly, in explanation of consumer behaviour and how that could be translated into sustainable travel. It was established that people attach substantial importance to messenger than the message. The study has shown that people do not always listen to people because of the content or accuracy of their message; rather, people listen because they feel connected to the messenger. Therefore, the study submits that using high-status messengers in transport-related campaigns could be an effective means to achieve behaviour change and promote sustainable travel.

In contrast to the assertion that people are perfectly rational and sensitive to new information, such as changes in prices and situations, is has been shown that altering the cost or benefit of an activity through incentives could motivates behavioural change.

The review has established that personal norms also referred to as "own-action" responsibility are the most relevant moderating factor of pro-environmental behaviour (PEB), it refers to individual values or internalised social norms. It is found that when activated, personal norms induce the obligations to act.

It is also shown that the human memory of experience is governed by most intense moments. The review has explained that dissatisfying experiences loom larger to the consumer and stay much longer in memory. Lousy and negatively intense experiences could induce negative valence towards an alternative, this is because such dissatisfying incidences could have negative influence on passenger satisfaction and negatively affect its desirability of PT modes.

It is also demonstrated that people assess both the economic and emotional benefits of a product when making decision. Emotional associations can negatively or positively influence decisions and behaviour. Policy making must account for aspect of products and services because they can override a rational course of action even when alternative course of action is against the decision maker's economic interest. The study has demonstrated that individuals are motivated to maintain a consist and positive self-image of themselves, and less likely break their commitments to maintain a positive self-image. Hence, encouraging people to develop publish their travel plans could increase compliance and promote sustainable travel. Additionally. people are said to behave in ways that tend to make them feel better about themselves. This quest for approval and recognition leads to changes in preference for consumer goods. They will deliberately flout established norms to appear unique, this group of people uses consumer products to maintain a certain their identity.

Chapter Three

Transport Mode Choice Models

3.1 Introduction

Travelling is a demand derived from the need for activity participation (Ben-Akiva and Lerman, 1985). Activities that make up human existence such as working, schooling, shopping and recreation have geographical and time attributes (Pred, 1977; Hägerstraand, 1970). Participation in these activities, therefore, demands travelling from one geographical location to another through space and at a defined time (Miller, 1991). Once the need for activity participation remains exigent for human existence and survival, the demand for travel will inevitably remain, and the more so as cities keep growing spatially and economically. This need for activity participation has over the past decades resulted in unsustainable levels of demand for travel and the primary cause of the continuous rise in vehicular population globally (Millard-Ball and Schipper, 2011). According to Webster and Bly (1981), this increasing demand for activity participation occasioned by population and economic growth led to the rapid increase in car ownership and traffic congestion in the 1960s. Similarly, Millard-Ball and Schipper (2011) reported a similar trend for the period between the 1970s and early 2000. Net increase in activity participation and travel demand over the period has resulted in increasing demand for vehicles and seen the growth in vehicle ownership. This came with lots of road traffic accidents, traffic congestion, and transport-related externalities including but not limited to air pollutions, global warming and its attendant health issues as well as the fiscal cost of road construction (upgrading and expanding existing roads to accommodate the vehicular volumes) to the taxpayer in addition to the destruction of the natural and built environment. While some researchers may want to suggest that traffic congestion is a result of a failed transportation system, others suggest that it is a sign of having vibrant and prosperous economies and communities (Webster and Bly, 1982; Pred, 1977; Hägerstraand, 1970).

Moreover, Taylor (2002) argues that the increasing demand for travel reflects the level of economic and social activities participation of the population. Vibrant cities are those that promote/support social and economic activity participation amongst its inhabitants. Traffic congestion has negative economic consequences on society, however, redesigning cities and expanding road capacities to ameliorate this effect also have dire consequences on both the natural and built environment. The relationship between economic growth, activity participation and traffic congestion are well established in literature (Ecola and Wachs, 2012).
Notwithstanding, economic prosperity and high level of activity participation have been the bane of traffic flow. Most of the trips for activity participation are undertaken by private motorised modes, which has been the principal cause of traffic congestion in urban centres. It is believed that private motorised modes are largely used because car travel is hugely under-priced; users are not paying for the external cost of driving (such as air pollution, global warming, health hazards etc.) on the society and the environment (Taylor, 2002).

3.2 Transport Demand Management

Evidence suggests that the dramatic increase in car ownership witnessed in the twentieth century necessitated many traffic management and mitigation schemes. Notably, highway capacity expansion and change in land-use patterns to deal with the challenges (Buchanan, 1963). However, it was discovered that any added capacity quickly disappears soon after introduction. Meanwhile, the increasing scarcity and cost of space in urban centres for road expansion and the burgeoning cost of road expansion schemes make this demand and supply approach of tackling road congestion unsustainable (Ettema, 1996; Chien and Ioannou, 1992; Buchanan, 1963).

As discussed in the previous section, travel is a necessity for economic and social activity participation as well as for human survival and therefore, cannot be entirely substituted. The scale of which can only be managed and minimised through a combination of soft and hard measures such as land-use planning, teleworking et cetera. Meanwhile, it is conventionally accepted that the most efficient and sustainable way of addressing travel demand for activity participation is through the use of mass public transport system (Eboli and Mazzulla, 2012) and land-use planning (redesigning our cities into compact development) (Little and Edition, 2014; Litman, 2013; Taylor, 2002). However, Litman (2013) argued that land-use planning happens too slowly, and it might take decades to deliver any significant change capable of altering the dynamics at the trip nodes. Therefore, mass public transport remains the only option to get around this conundrum. Public transport is suggested to be of immense benefit to the society, the natural and the built environment not only in terms of congestion and constructional cost reduction but in the reduction of air pollution and the preservation of the natural and the built environment (Teicher et al., 2002; Friman, 2004; Eboli and Mazzulla, 2010; Cipriani et al., 2012). Several schemes have been proposed and implemented to promote public transport ridership, notably amongst them in the UK are high fuel tax, congestion and parking charges, park/kiss and ride schemes. After the reported "peak car" phenomenon in some major cities around the world (Puentes and Tomer, 2008; Newman and Kenworthy, 2011; Millard-Ball and Schipper, 2011; Goodwin and Dender, 2013), many developed cities around the world including cities in the UK continue to record rising trend of car traffic and declining public transport ridership numbers (TomTom International BV, 2016). In this regard, Matas (2004) proposed the use of active public transport policies based on low transport fares and improved public transport service quality to reverse the declining trend in public transport ridership. Beirao and Cabral (2007) also recommended the improvement of public transport service quality to the satisfaction of customers to attract potential users. There are a plethora of studies examining the effect of public transport service quality improvements on customer satisfaction (Friman, 2004; Eboli and Mazzulla, 2010). Startlingly, it has been observed that public transport service quality improvement has less impact on the level of customer satisfaction; this provokes calls for further studies to understand where efforts and resources should be directed to make the necessary impact (Honore et al., 2014). The main factors influencing travel mode choice decisions remain elusive. Consequently, attitudinal, social and psychological factors have been proposed by behavioural economist as the magic wand needed to unravel the decision-makers' "black box" (Beirao and Cabral, 2007; Martin et al., 2012). Martin et al. (2012) further added that improving the public transport system and level of service might not necessarily induce change from private car to public transport (Beirao and Cabral, 2007). It is against this backdrop that this research seeks to explore the effects of behavioural factors on transport mode choice.

3.3 Transport Modelling

The efficiency of transportation systems is a major driving force in the success of viable economics in history. To make informed planning decisions on transportation systems, planners and engineers borrowed from a variety of disciplines including statistics, physics, geography, economics and engineering in the early 1950s to quantifiably predict demand for proposed transportation facilities. The primary objective was to understand and predict the response of transportation demand to changes in the attributes of the transportation system and changes in the characteristics of the people using the transportation system (Beckmann et al., 1955). The result was the development of travel demand models that used mathematical relationships to predict travel characteristics for different socio-economic scenarios and land-use configurations (Beckmann et al., 1955). The decision on how, where and when to travel is influenced by individual characteristics such as income, gender, number of children, employment status and the attributes of the travel mode such as travel time and travel cost.

The four-step models (FSM), involving the following four sequence: trip generation, trip distribution, modal split and trip assignment was developed to study and predict demand (McNally, 2007). By the 1960s, the demand models advanced into the Trip-based models. The four-step model (FSM), is discussed briefly in the following sections. However, the modal split model; the third component of the four-step model, which forms the core of this study is discussed in greater details.

The trip-based models have advanced into the recent dynamic traffic assignment (DTA) models. The demand estimation components of the trip-based models have been developed into the current advanced form; the "Activity-Based Modelling." Transport models are essential because their output informs the transport planning process. The models are used to estimate the number of trips made on transportation systems at some future date. These estimates form the basis for transport plans and major transport investment analysis. The traditional "predict and provide" demand management approach has now switched to "predict and manage" (Ben-Akiva and Lerman, 1985; Ortuzar and Willumsen, 2011; McNally, 2007). As a result, a deeper appreciation of the triggers of demand is required for the introduction of effective control management measures. This requires the understanding and application of supply and demand theory of the travel. The traditional approach assumed that travellers would always make the best decision on their travel choices (McNally, 2007). However, contrarily to earlier theories, recent findings suggest that travellers do not always maximize their economic utility neither do they always have complete information about alternatives to make informed choices. This belies the traditional economic theory of perfect rationality. Decision-makers are limited in computational abilities (Simon, 1982), hence are not able to assess the full economic costs of their decisions. The resultant effect is a cost-benefit decision that is far from ideal economic utility but what could best be described as the amalgamation of economic, emotional and psychological utility (Simon, 1982). Therefore, to prevent undesirable outcomes, the transport systems cannot be allowed to evolve under the free and perfect market assumption; instead, it must be planned and controlled to produce the maximum overall benefit for society. The need to address the limitation of the traditional modelling approach and replace them with travel demand models which incorporates behavioural and psychological components is well acknowledged in the literature (Kahneman and Tversky, 1979; Simon, 1982; Ben-Akiva and Boccara, 1995; Ben-akiva and Boersch-supan, 2002; Temme et al., 2008b; Dolan et al., 2010; 2012; Avineri, 2012a; Metcalfe and Dolan, 2012a). The consequent limitations of the approach in evaluating demand management policies led to the development of the activity-based approach to demand analysis. This need is particularly acute today as the emphasis is shifting from evaluating long-term investment-based capital improvement strategies to understanding travel behaviour responses to shorter-term congestion management policies (Bhat and Koppelman, 1999). There has been an increasing realisation that the traditional statistically oriented trip-based modelling approach to travel demand analysis need to be replaced with a more behaviourally oriented activity-based modelling approach (Bhat and Koppelman, 1999).

3.3.1 Trip-based models

Trip-based models are commonly known as four-step models because they primarily involve four components. Trip-based modelling is the most common approach to forecasting traffic patterns in the transport planning process. The four-step model has been broadly applied in transport modelling due to its overarching design framework. As the name suggests, the model consist of the following four stages trip generation (how many trips will be made?); this first step involves the estimation of the number of home-based and non-home-based person-trips produced from or attracted to each zone in the study area. The second step is trip distribution (where will the trips go?); this step determines the trip-interchanges (i.e. number of trips from one zone to each other zone). The third step is the modal split (by what means, or modes will the trips be carried out?); this step splits the person-trips between each pair of zones by travel mode. Finally, the trip assignment step (what route or network will be taken?); this last step assigns the vehicle trips to the road network to determine link volumes and travel times and the person trips to the transit network. The figure below is the depiction of the stages

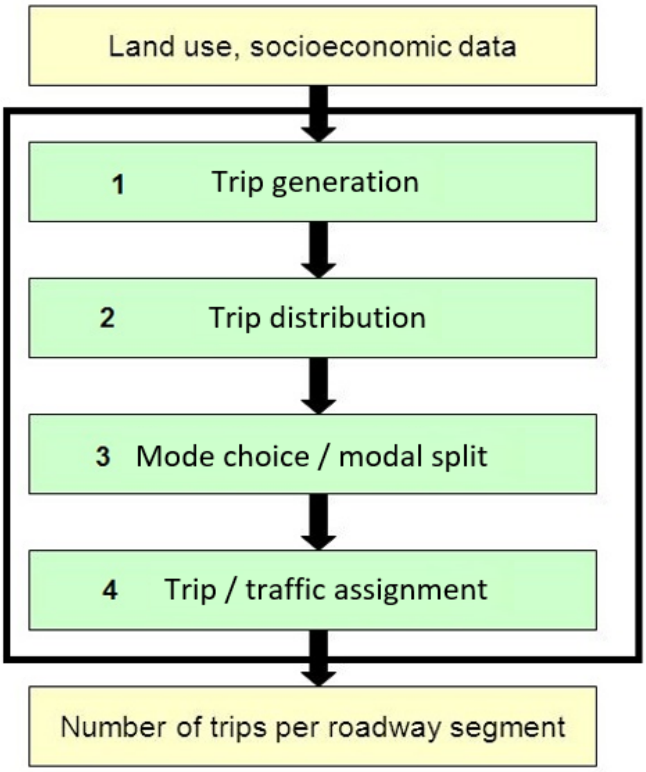

Figure 3.1: The four-step model [1]

3.3.1.1 Trip Generation

The objective of this first stage of the traditional four-stage process is to predict the total number of trips generated by each household and zone and attracted to each zone for various trip purposes. It aims to identify and measure the factors affecting the trip generation. In the trip generation model, trip rates are estimated separately for each trip purpose; this is because trips undertaken for different purposes often have different characteristics. For example, work trips are frequent trips, usually made during peak hours and normally with the same origin and destination (Ortuzar and Willumsen, 2011). The total number of trips within a region are essentially generated at this stage. The proportion of travel for different trip purposes varies significantly with the time of day, as such, trip generation is usually estimated separately for morning peak, afternoon off-peak, and evening peak periods. The factors that influence the number of trips generated by a household or zone includes household income, household car

[1] Source: adapted from Rosenbaum and Koenig (1997)

ownership, household size and structure, zonal value of land, zonal residential density and accessibility. Similarly, zonal trips attraction is influenced by a zone's roofed space available for industrial, commercial purposes, zonal employment and accessibility.

3.3.1.2 Trip Distribution

The trip distribution model is a destination choice model that generates the trip matrix table. It is commonly referred to as the origin-destination matrix (O-D Matrix). In other words, trip distribution links the trips generated by each zone to the attraction zones. This stage estimates the number of trips between pairs of zones and within zones in the study area. There are several methods for distributing trips between origins and destinations, including the growth factor models and gravity models.

3.3.1.3 Modal split

The purpose of modal split models or modal choice models is to forecast the proportion of the total number of predicted trips that would use the various transportation modes available. According to Hensher and Button (2007), Modal split models are mostly disaggregate models that are often estimated on separate choice-based samples and reflects the choice probabilities of individual trip makers. The issue of selecting the most appropriate travelling mode has always been a critical issue in travel behavioural modelling; it tells an individual about the most efficient travelling mode available. The quantification of this interaction in terms of mathematical relationships is known as modal split and travel demand models. Hence, modal split models assist a transport planner to assess the impact of each urban element on mode choice, and it also allows the evaluation of various transportation schemes.

3.3.1.4 Trip Assignment

Trip assignment is the last stage of the four-step model. The number of trips is estimated and loaded onto each link in the network (Ortuzar and Willumsen, 2011). The main objectives of this stage include: the estimation of traffic flow between zones (origin zone i to destination zone j); the estimation of travel time and cost between these zones and identify congested links while specifying the travel behaviour of the individual, and determining the preferred routes between any two zones (O-D pairs) (Khan, 2007; Ortuzar and Willumsen, 2011).

3.3.2 Activity-Based Models

The activity-based models were developed out of the need to address the limitations of the trip-based models. In an earlier study, Hägerstraand (1970) proposed the incorporation of a time-space framework in the trip-based models to make them realistic. The researcher noted that, people live in a time-space continuum and limited by time and space. People could not be physically present at different locations simultaneously and therefore, must trade time and cost to move between activity centres (Hägerstraand, 1970; Bowman, 2008). Changes in policy direction from long-term transport investment policies to short-term strategies in the 70s and the criticism of the traditional four-stage models (Hagerstraand, 1970; Ettema, 1996; Kitamura, 1996; Bhat and Koppelman, 1999a; 1999b; Castiglione et al., 2015a), led to the development of the activity-based models (Kitamura et al., 1995). The activity-based models were thus proposed to provide a consistent framework for analysing travel behaviour and transport demand. The theoretical framework of the activity-based models stems from the appreciation that the need to pursue activities at a different spatial location (home, work et cetera) generates trips (Kitamura, 1988; 1996; Kitamura et al., 1995). Activity-based approach views travel as a derived demand resulting from the need to undertake an activity at different spatial locations (Axhausen and Gärling, 1992).

3.3.2.1 Historical Perspective

The works of Hägerstraand (1970), Chapin (1974) and Fried et al. (1977), inspired research into activity-based travel analysis. This research area subsequently received appreciable research coverage and have seen considerable progress after these early studies. The time-space constraint theorised by Hägerstraand (1970) is one of the earlier activity-based pioneering studies and provided the foundation for research into activity-based modelling (Hägerstraand, 1970). The study theorised that the geographical distribution of activities (such as work, school, shopping, hospitals et cetera.) poses a major constraint as well as the "time budget" required for each activity. Hagerstraand's study laid the foundation for the emergence of what is generally referred to as the "space-time prism" (Hägerstraand, 1970).

The space-time or time-geographical framework offers a wide and useful perspective for analysing human behaviour and daily activity participation. Hägerstraand (1970) opines that individuals operate within a geographical and time limitations imposed on their behaviour. The main principle of the space-time framework is the concept that the daily activities individuals pursue have both spatial and time attributes (Hägerstraand, 1970; Pred, 1977). An individual can only directly participate in events at a single location in space at a particular time. For instance, recurring activities like working, schooling and shopping which an individual of necessity has to participate, all take place at discrete locations and within a limited time period (Miller, 1991). The need for individuals to return home daily for rest and personal maintenance after participating in out-of-home activities is another constraint people must contend with daily (Bowman, 1995).

In a broader view, space-time framework is concerned with the nature of the constraints limiting the ability to participate in events in space and time (Pred, 1977). Miller (1991) underscored the importance of the space-time prism and explained that the prism models the location(s) at which the individual must be at the beginning and end of any time interval, the time required for activity participation during that time interval and finally the rates at which the individual can trade time for space in movement (i.e. travel velocities) through the environment. Miller noted that, the prism models the accessibility of an individual within a particular geographic and time context and can offer a valuable measure of accessibility (Miller, 1991). The time-space framework can also be helpful in planning for the siting of infrastructure for activities (Hägerstraand, 1970; Pred, 1977).

Chapin (1971) argued that human need for activity is provoked by his inherent instinct for survival, need for social interactions, health and quest for living a satisfactory life. The researcher categorised the activities into two main groups namely, obligatory activities (such as work, sleep, eating et cetera.) and discretional activities (such as visits, movies). In an effort to understand travel behaviour and why individuals participate in activities, Fried et al. (1977) noted that, Individuals' travel behaviour directly relates to the nature of their participating activities and the spatially distribution of those activities. They further explained that social role, ethnicity, life cycle status, residential location, social norms, resource limitations, attitudes and perceptions of opportunities were major determinants of activity choice and travel patterns. Fried, Havens and Thall, submitted that the spatial distribution of activity largely relates to the differences in the urban form; residential densities, socio-demographic distribution and historical development. These spatial variations, the researchers believe, explains the travel and activity patterns of various niches of the population.

It is believed that, the consolidation of the works of Hagerstraand and Chapin led to a surge in research interest on the relationship between human activity and travel behaviour (Bowman, 2008). Activity-based models is premised on the often-quoted fundamental research finding that, travel is a derived demand, which is derived from people's need to participate in activities distributed in space (Hägerstraand, 1970; Jones, 1979; Jones et al., 1990; Axhausen and Gärling, 1992). Activity-based models are premised on behavioural theories and therefore, provide forecast for; when and where activities will take place as well as the length of time and the travel mode required to pursue the activity. Unlike trip-based models, Activity-based models simulate each individual's activities and travel choices across the entire day and assign to each individual traveller the various activities they participate in (Castiglione et al., 2015).

3.4 Modal Split Models

Modal choice models forecast the transport mode a traveller will select for a trip from the given choice set available for the same trip. Transport mode choice is argued to be the single most important element in transport planning and policy making since the 1970s (Ettema, 1996). It has overreaching impact on the efficiency of the urban transportation system and the amount of urban space devoted to transport facilities (Ortuzar and Willumsen, 2011). The transport mode choice model typically tends to predict an individual's travel mode choice when presented with a discrete set of travel options (alternatives). Models of this type are commonly referred to as "discrete choice models" (Ettema, 1996; Ben-Akiva and Lerman, 1985).

3.4.1 Theoretical foundation of choice modelling

The theoretical foundation of the choice model has been discussed in the previous section in details. According to Lancaster (1966), it is assumed that people select travel mode that maximises their perceived utility (Ben-Akiva and Lerman, 1985; Koppelman and Bhat, 2006). The utility of travel mode is defined by Khan (2007) as the attraction associated by an individual to a particular mode. The individual is assumed to select the mode having the maximum attraction using the attributes of the mode such as; access time, waiting time, in-vehicle travel time, travel fares, parking availability and cost of parking et cetera.

3.4.2 Factors affecting modal choice

To develop choice models, it is important to investigate the factors which influence travellers decisions making. Ortuzar and Willumsen (2011) categorised these factors into quantitative and qualitative factors. The quantitative factors influencing mode choice are further classified into three, namely; the characteristics of the decision maker, attributes of the transport system and attributes of the journey. The qualitative factors, however, are factors difficult to measure in practice and include; comfort and convenience, safety, security et cetera. Guiver (2007) and Beirao and Cabral (2007) found that travellers also consider comfort, convenience, safety and flexibility when making decision on travel choice and proposed the incorporation of same in transport mode choice models. Guiver (2007) suggested that the cost of travel mode was less important to bus users.

Similarly, car-users admitted that car travel was comparatively expensive than the bus. However, it was argued that the cost difference between the two modes was a better trade-off, when weighed against the level of convenience and flexibility that comes with a car (Guiver, 2007; Beirao and Cabral, 2007). Therefore, preference for convenience, safety, comfort, flexibility et cetera are factors that cannot be overlooked when trying to explain transport mode choice decision and must be incorporated in decision makers' utility function (Johansson and Heldt, 2006; Guiver, 2007; Temme et al., 2008b; Yáñez et al., 2010). Recently, behavioural economics have received some research attention and few researchers have investigated the role of "MINDSPACE" in consumer choice decision. It is also suggested to have impact on travel choice as well (Avineri, 2012a).

Recent research in cognitive psychology and behavioural economics indicates that behavioural elements such as the "MINDSPACE" significantly influence consumer behaviour and might also impact on travel behaviour (Avineri, 2012a). However, none of the existing studies have incorporated these elements of "MINDSPACE" as latent factors in modal split models to test their impact on travel behaviour. It is suggested that extending choice models with these elements of MINDSPACE as latent variables could improve our understanding of the travel behaviour (Temme et al., 2008b).

3.4.3 Discrete choice modelling

Discrete choice models are mathematical relationship that represent the travel behaviour of an individual when provided with distinct set of travel options. Essential to discrete choice analysis is the random utility model and the concept of generalised cost. The theory is based on the assumption that travellers when given accurate information about the available travel alternatives, they will evaluate and always makes travel choices that will maximise their utilities. Conversely, studies have shown that decision makers do not always have complete information about all available alternatives (Simon, 1955). Moreover, decision makers do not possess unlimited information processing and computational capabilities to enable them to assess all available alternatives for perfect decision making (Simon, 1955; 1982; Kahneman and Tversky, 1979; Ariely, 2008).

3.4.4 Classes of discrete choice modelling

3.4.4.1 Deterministic models

The utility maximization rule suggests that decision makers will rationally allocate their available resources to different goods such that their utility is maximized. This implies the decision maker of certainty will choose the highest ranked alternative under the observed choice conditions (Lancaster, 1966; Koppelman and Bhat, 2006). Utility models with such level of prediction certainty are called deterministic utility models. Koppelman and Bhat (2006), provided the following illustration to explain the application of deterministic utility model.

For instance, Figure 3.2 portrays a utility space in which the utilities of alternatives 1 (Public Transport PT) and 2 (Car) are plotted along the horizontal and vertical axes respectively, for each individual. The 45^0 line represents those points for which the utilities of the two alternatives are equal. Individuals A, D and E (above the equal-utility line) have higher utility for alternative 2 (Car) than for alternative 1 (PT) and are certain to choose alternative Car over PT. Similarly, individuals B, C, and F (below the line) have higher utility for alternative 1 (PT) and are certain to choose alternative PT over Car.

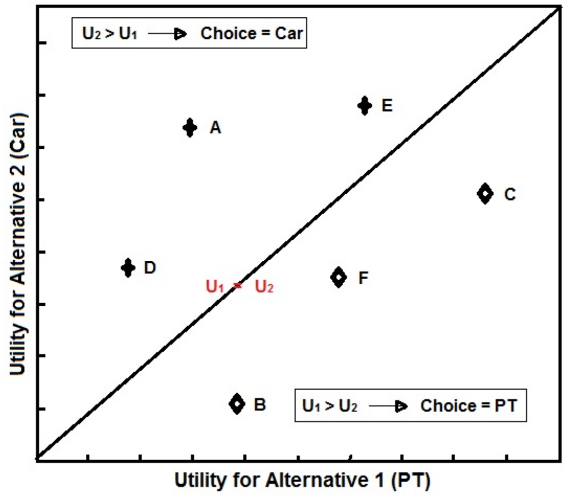

Figure 3.2: Illustration of deterministic choice models[2]

According to Luce (1959), given the values of the attributes, the utility derives from an alternative by an individual is fixed. That is, when faced with an identical alternative, an individual will always derive exactly the same utility from the alternatives. Thus, according to the deterministic utility models, when faced with an identical situation, an individual would be expected to make the same choice repeatedly. Similarly, individuals with similar socio-economic characteristics would be expected to make the same choice when confronted with identical set of alternatives. However, this is not the case in reality. When individuals with similar socio-economic characteristics are presented with identical choice sets, we observe variations in choice (Luce, 1959). These observations raise concerns about the appropriateness of deterministic utility models for modelling travel or other human behaviour. The challenge is to develop a model structure that provides a reasonable representation of these unexplained variations in travel behaviour. Three primary sources of error are found in the use of deterministic utility models.

First, people may have incomplete/inaccurate information and/or misperceptions about some attributes of the alternatives (Simon, 1955; Simon, 1982). As a result, individuals may have varied level of information or perceptions about alternatives, which is likely to result in dissimilar utilities on alternatives and consequently lead to different

[2]Source: adapted from Koppelman and Bhat (2006)

choices.

Second, the researcher/analyst may have different or incomplete information about the attributes relative to the decision maker or inadequate understanding of the utility function the decision maker uses to evaluate each alternative. For example, the analyst may not have a good measure of the reliability of a particular alternative. The likelihood of getting a seat at a specific time of day or the possibility of finding a parking space. However, regular users are likely to know these things, form opinion about them and may consider them and other factors oblivious to the analyst.

lastly, the analyst is unlikely to know or account for specific circumstances accounting for the individual's travel decision. For example, an individual's choice of mode for work trip may depend on whether another family member has a special travel need on a particular day or not. The failure of these models to account for the analyst lack of complete information results in the apparent behavioural inconsistencies. While human behaviour may be argued to be inconsistent (Kahneman and Tversky, 1979; Ariely, 2008), it can also be argued that the inconsistency can be attributed to the analyst's inability to fully appreciate and account for all the factors informing the decision making process (Koppelman and Bhat, 2006). This concerns led to the development of Probabilistic choice models (Koppelman and Bhat, 2006).

3.4.4.2 Probabilistic models

The concept of bounded rationality and cognitive bias in human decision making, flaws the fundamental assumption of the deterministic models. It has been shown that decision makers do lack complete information and understanding necessary for rational decision making (Kahneman and Tversky, 1979; Ariely, 2008). (Simon (1955; 1982), challenged the assumption of human perfect rationality and theorised that humans are rationally bounded and limited in thinking, information processing and computational capabilities. Therefore, the entire internal decision-making process and how the decision maker perceives available alternatives is not completely known. In light of the above limitations of the deterministic models, it was argued that choice models need to incorporate an error term to cater for the bias resulting from the incomplete understanding of the entire choice process.

Luce (1959), found that when decision makers are offered identical alternative, they will always derive the same utility from the alternative. Luce then proposed that the utility an individual derives from an alternative given the values of its attributes is fixed. Based on these utilities, the chance that an alternative is chosen is expressed as a probability p(i). Subsequently, Luce proposed a probability function in which the choice probability of an alternative is proportional to its utility and inversely proportional to the total utility of all alternatives in the choice set, as shown below:

$$p(i) = \frac{U_i}{\Sigma_j U_j} \tag{3.1}$$

Although, the probabilistic model proposed by Luce accounted for the inconsistency and transitivity of choice behaviour, it was however, based on the assumption of the deterministic utility function rather than random utility function (Luce, 1959; Ettema, 1996), neither was it based on the actual perception, preferences nor behaviour of the decision maker (Ettema, 1996).

Random Utility Models

The random utility theory is the theoretical framework for discrete-choice modelling, this was credited to the works of Thurstone (1927) and latter studies like Luce (1959); Block and Marschak (1960); Ben-Akiva and Lerman (1985), et cetera. The random utility theory uses the concept of utility maximization to represent the attractiveness of the alternatives. It assumes that when decision makers are presented with alternatives, they will always make choices to maximise their net personal utility. Similar to the Deterministic theory, random utility theory assumes that the decision maker will always choose an alternative with the highest utility. It further assumes utilities as random variables that cannot be precisely measured for the under listed reasons (Manski, 1973; Ettema, 1996; Walker, 2001; Koppelman and Bhat, 2006);

- measurement errors,

- instrumental errors,
- lack of complete information about the alternatives and
- the analyst's lack of complete understanding and information of the individual's choice making process.

Avineri (2012a) and Aczél and Markovits-somogyi (2013) also agreed with Manski (1973); Ettema (1996); Walker (2001); Koppelman and Bhat (2006) on the possible causes of the observed inconsistencies and violations. Avineri (2012a) and Aczél and Markovits-somogyi (2013) further suggested that the inconsistencies may be due to absence of the recently proposed behavioural characteristics in consumer behaviour such as "MINDSPACE" and/or the presence of errors in the utility function. Additionally, decision-makers' choices pattern is also observed to violate the assumption of transitivity of preferences (if **A** is preferred to **B** and **B** is preferred to **C**, then **A** should be preferred to **C**) (Walker, 2001; Ettema, 1996).

It is further suggested that human behaviour may be irrationally probabilistic. Meaning that even if all the relevant factors are perfectly measured and included, consumer behaviour cannot still be deterministically predicted. The utility U_i of the decision-maker is thus expressed in two distinct terms, the known or measurable component (deterministic term, v) and the unknown component, (random error term, ε), this is represented mathematically as;

$$U_{it} = V_{it} + \varepsilon_{it} \tag{3.2}$$

where

U_{it} is the utility of the alternative i to the decision-maker t

V_{it} is the deterministic or observable component of the utility estimated

ε_{it} is the unknown component of the random error term of the individual's utility.

The outputs of the models U_{it} represent the probabilities of an individual t selecting each alternative i. The utilities are assumed to be a function of the attributes of the alternatives and the characteristics of the decision-maker. The final component of the utility is a random error term. The aggregation of these individual probabilities produces the forecasts for the study population. The structure of the choice model depends on the assumptions of the distributions of the random error term and variance-covariance structure of the error term. Normally distributed error term lead to a probit model while Gumbel distributed error term results in Logit models (Walker, 2001; Khan, 2007; Ettema, 1996; Koppelman and Bhat, 2006).

3.5 Hybrid /Latent Choice Models

Ben-Akiva and Boccara (1995) proposed the hybrid discrete choice models to address the limitation and inconsistencies of the traditional travel choice models and the random utility models (Manski, 1973; Avineri, 2012a; Aczél and Markovits-somogyi, 2013). These choice models incorporated behavioural and attitudinal variables such as; happiness, convenience, comfort, flexibility and safety as latent variables in addition to factors unique to the decision-maker and alternative (Ben-Akiva and Boccara, 1995; Ben-Akiva et al., 1999; Ben-Akiva et al., 2002; Johansson et al., 2005; Johansson and Heldt, 2006; Raveau et al., 2012; Yáñez et al., 2010).

Two procedures were developed for the estimation of these models; the first approach called the sequential approach, construct the latent variables and incorporated them into the discrete choice model as a regular variable (Johansson et al., 2005; Raveau et al., 2012). The second method is referred to as the simultaneous approach; with this approach, the construction of the latent variables and the estimation of the discrete choice model are done simultaneously (Bolduc et al., 2008; Raveau et al., 2012). The latter has been argued to result in more efficient estimates of the parameters than the former (Ben-Akiva et al., 2002). Table 3.1 is a summary of some extant latent/hybrid choice studies.

3.5.1 ICLV model framework

This section presents the theoretical framework for incorporating the latent variables into choice models. The integrated choice and latent variable (ICLV) models are a

Table 3.1: Existing Latent/hybrid choice models

Study	Observed variables	Unobserved variables	Estimation Procedure	Software	Application
Walker and Ben-Akiva (2002)	Cost Travel time No. of Transfers Gender(Dummy) Business trip (Dummy)	Ride comfort Convenience	Simultaneous		Travel mode choice
Morikawa et al. (2002)	Cost Travel time Gender	Comfort Convenience	Sequential		Travel mode choice
Ashok et al. (2002)		Satisfaction Cost of switching Satisfaction with cost Satisfaction with coverage	Simultaneous	GAUSS	Propensity to switch- Television provider Customer satisfaction of- Health Care provider
Johansson et al. (2006)	Travel Time Cost Gender Age Kids Education Car Ownership/Availability	Flexibility Convenience Safety Comfort Environment	Sequential		Travel mode choice
Temme et al. (2008)	Travel time Distance to bus stop Age Gender Income Mode constant	Flexibility Convenience Comfort Safety Power Hedonism Security	CFA and Discrete choice modelling	M-Plus	Travel mode choice
Bolduc et al. (2008)	Age Income Gender Educational level Transit user Car pool user Capital cost Operational cost Driving alone	Environmental concerns Appreciation of new- car features (ACF)	SEM		
M.F. Yanez Patricio Mansilla and J. de D. Ortuzar (2009)	Cost Walking time waiting time Travel time	Accessibility Comfort Safety Reliability	Factor analysis		Choice
M.F. Yanez S. Raveau and J. de D. Ortuzar (2010)	Travel Time Cost Waiting time Number of cars Transfers	Accessibility Comfort Safety Reliability			Choice
S. Raveau M.F. Yanez and J. de D. Ortuzar (2012)	Income Age Children Education Level	Accessibility Comfort Safety Reliability			Choice
Kamargianni m. et al (2015)	Travel time Income Age Gender Parents's education status Travel cost Walking time to bus stop Weather Walking Facility	Safety Consciousness Physical Propensity Green Lifestyle	ICLV	GAUSS	Children's travel mode choice to school
Lavieri P.S. et al (2016)	Income Age Gender Parents' Education status Travel cost Walking time to bus stop Weather Walking Facility	Driver's risky behaviour Driver distraction/ careless behaviour	Generalized Heterogeneous Data Model		Accident severity

new generation of discrete choice models that expand on standard choice models and provides improved predictive power. ICLV models provide a mathematical framework for integrating discrete choice and latent variables models to account for the unobserved preference heterogeneity in the traditional discrete choice models and to test the influence of latent variables, such as values, perceptions and attitudes on observable behaviour (Ben-Akiva and Boccara, 1995; Vij and Walker, 2015; Vij et al., 2016). They allow the prediction of individual preferences and assess the impact of unobserved heterogeneity involved in the decision-making process by reflecting the difference in individual tastes, attitudes, perception and values, which are unaccounted for in the traditional discrete choice models (Bolduc and Alvarez-daziano, 2010; Mariel and Meyerhoff, 2016). In the general framework of the ICLV models, there are two separate sub-models: the discrete choice sub-model and a latent variable sub-model. Each of these two components consists of both structural and measurement models. The latent variable component of the ICLV allows a simultaneous relationship between the unobserved latent variables (psychometric indicators) and the observed exogenous variables (such as socio-demographics). The discrete component of the ICLV is consistent with the random utility maximisation theory and consist of the observed variables (characteristics of the decision-maker, attributes of the alternatives and the trip characteristics) and the unobserved latent variables reflecting the diversity in individual tastes, perception, values, and emotions. The reported gains or enhancement in the explanatory power of the ICLV models over the traditional discrete choice models is ascribed to the introduction of the unobserved individual heterogeneity in the specification of the ICLV models. I refer readers to Ben-Akiva and Boccara (1995); Ben-Akiva et al. (1999); Bierlaire (2016); Bierlaire (2018b); Bierlaire (2018c); Bolduc et al. (2008); Vij et al. (2016) for more details. The latent variables are not measured; they are linked with multiple indicators (questions in a survey) normally measured on a Likert-scale (Bolduc et al., 2008; Vij et al., 2016).

3.5.2 Model specification

Figure 3.3 is a graphical illustration of the ICLV Model. The framework consists of two components: a multinomial discrete choice sub-model and a latent variable sub-model. Each sub-model consists of two components, the structural equation and measurement equation. The structure of the full information simultaneous ICLV model will be discussed in brief. For more details refer to (McFadden, 1998; Ashok et al., 2002; Ben-Akiva et al., 2002; Temme et al., 2008b; Vij et al., 2016; Walker, 2001). The general framework of the model is represented below:

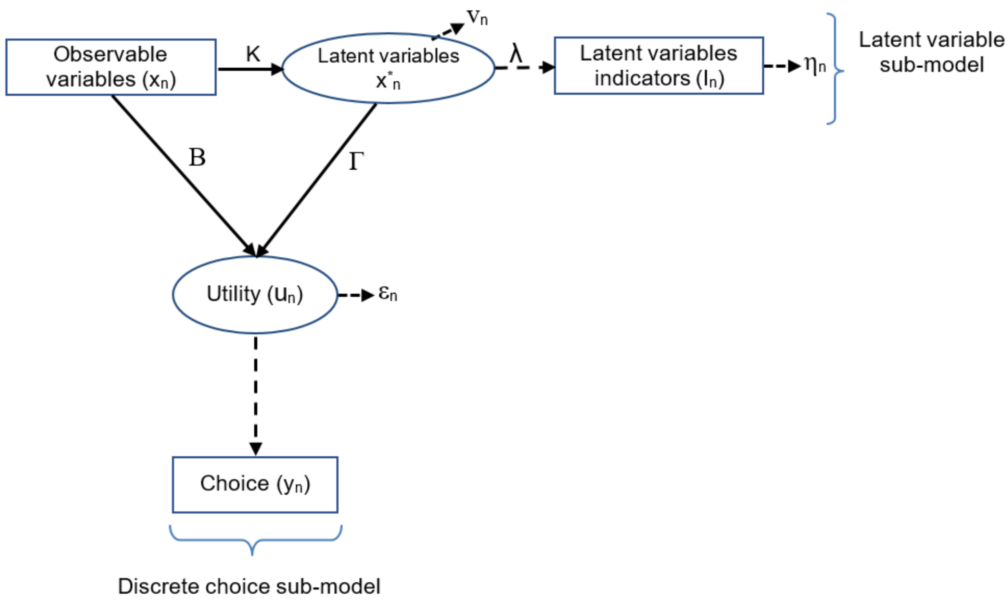

Figure 3.3: Framework for integrated latent variable and choice model[3]

3.5.2.1 *Latent Variable Sub-model*

The model identification of the latent variable component of the ICLV mostly requires that the unobserved latent variables (x_n^*) are defined by multiple indicator variables (I_n) such that the relationship between the unobserved latent variables and the indicators could be described by a linear factor model. The indicators of the latent variables and random disturbance term can be expressed as a linear function in measurement in

[3]The framework for the integrated choice and latent variable choice model is adapted from Ben-Akiva et al. (2002)

equation. However, since a latent construct typically have more than one indicator, it is a vector. From Figure 3.3, x_n^* represents the vector of latent exogenous variables with observed indicators I_n. The measurement model mapping the observed indicators into the latent variables for the latent variable sub-model is formulated as follows (Ashok et al., 2002):

$$\mathbf{I}_n = \boldsymbol{\alpha} + \boldsymbol{\lambda_n x_n^*} + \boldsymbol{\eta_n}, \ \boldsymbol{\eta_n} \sim N(0, \Sigma_{\boldsymbol{\eta_n}}) \tag{3.3}$$

Where $\boldsymbol{I_n}$ is a (P x 1) vector of observed scores of the latent variable indicators, α_n is the intercept for indicator n, $\boldsymbol{\lambda_n}$ is a (P x M) matrix of factor loading mapping indicator n to latent variable $\boldsymbol{x_n^*}$. $\boldsymbol{x_n^*}$ is the latent variable or a vector of socio-demographics underlying the latent factor and $\boldsymbol{\eta_n}$, is a vector of errors which are i.i.d. multivariate normally distributed error term with mean 0. The structural model of the latent variable model is shown in equation 3.4, the model describes the latent variables in terms of observables socio-demographic variables and links the latent variable and the indicators (Bolduc et al., 2008). The framework allows the integration of the latent variable model and the discrete choice model.

$$\boldsymbol{x_n^*} = K\boldsymbol{x_n} + \nu_n, \ \ \nu_n \sim N(0, \psi) \tag{3.4}$$

Where $\boldsymbol{x_n^*}$ is (L x 1) vector of latent variable L is the number of latent variables, $\boldsymbol{x_n}$ is (M x 1) vector of the observed socio-demographics underlying the latent factor and K is a matrix of unknown coefficients mapping the observed socio-demographics variables x_n to the latent factor.

3.5.2.2 Multinomial discrete choice sub-model

The discrete choice component of the ICLV model consists of structural and measurement sub-models which are based on the assumption that when individuals are presented with a finite set of mutually exclusive alternatives n, they will choose the alternative that maximises their utility (Ben-Akiva and Lerman, 1985). (Readers are referred to section 3.4.4 of this thesis for details on discrete choice models). The structural component (utility function) of the discrete choice sub-model consist of the systematic component V(.) and the random error component ε_n.

$$U_n = V(\boldsymbol{x_n}, \boldsymbol{x_n^*}; B, \Gamma) + \varepsilon_n \text{ or } A + B\boldsymbol{x_n} + \Gamma \boldsymbol{x_n^*} + \varepsilon_n,\ \varepsilon_n\ \sim N(0, \Sigma_{\varepsilon_n}) \tag{3.5}$$

Where U_n is the random utility of alternative n, $\boldsymbol{x_n}$ is a vector or observed variables, $\boldsymbol{x_n^*}$ is a vector of latent variables, A is an intercept for alternative n, B and Γ are the matrices of estimates mapping the observed and latent variables respectively to the alternative n, $\boldsymbol{\varepsilon_n}$ is a vector of random error term associated with the utility terms and Σ_{ε_n} is the covariance of the random error terms. The measurement equations or the choice model component of the discrete choice sub-model of the ICLV is denoted as follows:

$$y_{in} = \begin{cases} 1 & \text{if } U_{in} \geq U_{ij},\ \forall j \in C_n,\ j \neq i, \\ 0 & \text{otherwise.} \end{cases} \tag{3.6}$$

Where y_n is a choice indicator, which takes a value of 1 if alternative n is chosen and 0 otherwise and C_n denotes the choice set of individual i.

3.5.2.3 Integrated model

The integrated model comprises of equations 3.3 to 3.6, equations 3.3 and 3.4 are the latent variable sub-models and equations 3.5 and 3.6 are the discrete choice sub-model. Using equations 3.5 and 3.6 and the assumption that all the random error terms are independent of each other, we can integrate over the joint distribution of the latent variables, this produces a multidimensional integral because the number of latent variables defines the dimension of the joint likelihood function of the model (Ben-Akiva et al., 2002; Temme et al., 2008b; Kamargianni and Amalia, 2014).

3.5.2.4 Likelihood function

To begin with, the likelihood of an individual i observing a choice indicator y_n without latent variable can be expressed as:

$$P(y_i = 1|\boldsymbol{X}; B) = P(U_n \geq U_j);\ n \neq j,\ \forall j \in C;\ \text{where C is the choice set} \tag{3.7}$$

Moreover, because every respondent makes a single choice which is independent of each other, we can assume that the error terms (η, ν $\ and\ $ ε) of equations 3.3 to 3.5 are similarly independent of each other. This makes the situation less complicated and we can include the latent variables to equation 3.7. The likelihood function for observing a given choice indicator y_n, is then given by the joint probability of observing the choice indicators and the indicators of the latent attitude, this is expressed mathematically as follows:

$$f(y, \boldsymbol{I}|\boldsymbol{X}, \boldsymbol{X}^*; \boldsymbol{\alpha}, \boldsymbol{\lambda}, K, B, \Gamma; \Sigma_\varepsilon, \Sigma_\eta, \Sigma_\nu) = \int_{\boldsymbol{X}^*} P(y|\boldsymbol{X}, \boldsymbol{X}^*; B, \Gamma, \Sigma_\varepsilon) f_3(\boldsymbol{I}|\boldsymbol{X}, \boldsymbol{X}^*; \boldsymbol{\alpha}, \boldsymbol{\lambda}, \Sigma_\eta) f_1(\boldsymbol{X}|K, \Sigma_\nu) dX^* \tag{3.8}$$

The first term of the integrand relates to equation 3.5, while the second and third terms relate to the equations 3.3 and 3.4 respectively.

Assuming a linear function and a normally distributed error term for the choice model. The choice model component of the likelihood function takes the form of a standard choice model, with the utility being a function of the latent constructs. Deriving the probability function from equations 3.5 and 3.6 based on the assumption of i.i.d. error term $\boldsymbol{\varepsilon}$, standard Gumbel. The probability function takes the form of a logit model as follows (Ben-Akiva et al., 2002):

$$U_n = V_n + \boldsymbol{\varepsilon_n} \text{or } U_n = V_n(\boldsymbol{X}, \boldsymbol{X}^*; B, \Gamma), \; n \in C, \qquad \text{C is the choice set} \tag{3.9}$$

$$\begin{aligned} P(y_i = 1|\boldsymbol{X}, \boldsymbol{X}^*; B, \Gamma, \Sigma_\varepsilon) = & P(U_n \geq U_j), \;\; n \neq j, \;\; \forall j \in C \\ & P(V_n + \boldsymbol{\varepsilon_n} \geq V_j + \varepsilon_j), \;\; \forall j \in C \\ & P(\varepsilon_j - \varepsilon_n \leq V_n - V_j), \;\; \forall j \in C \\ & \frac{e^{V_n}}{\sum_{j \in C} e^{V_j}} \end{aligned} \tag{3.10}$$

Similarly, assuming we have typical uncorrelated latent factors, which are normally and independently distributed together with the indicators, then using equation (3.4) we can derive the form of the distribution of the latent variables. While that of the indicators can be derived from equation (3.3). Again, when we assume that the random error terms of the structural and measurement equations of the latent variable model are normally and independently distributed, then the densities can be written as:

$$f_1(\boldsymbol{X}^*|\boldsymbol{X}, \boldsymbol{X}^*; K, \sigma_\upsilon) = \prod_{l=1}^{L} \frac{1}{\sigma_{\upsilon_i}} \phi\left(\frac{X_l^* - h(X; K_l)}{\sigma_{\upsilon_l}}\right) \tag{3.11}$$

$$f_3(I|\boldsymbol{X},\boldsymbol{X}^*;\boldsymbol{\alpha},\boldsymbol{\lambda},\sigma_\eta) = \prod_{q=1}^{Q} \frac{1}{\sigma_{\upsilon_q}} \phi\left(\frac{I_q - g(X,X^*;\alpha_q,\lambda_q)}{\sigma_{\eta_q}}\right) \tag{3.12}$$

Where: σ_υ and σ_η are the standard deviations of the error terms of υ and η in that order,

ϕ is the standard normal density function

L is the number of latent variables and

Q is the number of indicators

(readers are referred to Ben-Akiva and Boccara (1995) and Ben-Akiva et al. (2002) for details).

The independent and identically distributed(iid) error terms assumption simplifies the model and provides a very convenient form for the choice probability; the normalization for scale is made simpler if the error terms are assumed to be iid. The popularity of the logit model is due to this convenience (Train, 2003). However, the drawbacks of this framework is that the iid assumption is restrictive and fails to take into account the correlation between alternatives ; the critical part of the iid assumption is that the unobserved factors are uncorrelated over alternatives, as well as having the same variance for all alternatives. The assumption of independence can be inappropriate in some situations. Unobserved factors related to one alternative might be similar to those related to another alternative. In many instances, it would be expected that unobserved factors that affect respondents' choices or scores on different psychological constructs are related rather than independent. For example, it can be seen from Figure 7.3 that the latent variables PerNorm and Affect are about 57% correlated; meaning a person who scores high on PerNorm might also score high on Affect. In such a situation, the unobserved factors affecting PerNorm and Affect are somehow correlated rather than independent.

3.5.2.5 Estimation methods

There are three methods for incorporating psychometric factors into discrete choice models, sequential, simultaneous and simulation approaches; The first approach is commonly referred to as the sequential approach; the researcher performs a factor analysis using the psychometric indicators. The resultant latent variables and their distributions are then incorporated in the utility function. To obtain consistent estimates, the researcher must integrate the choice probability over the latent variables. However, the estimates generated from this technique are not efficient (Ben-Akiva et al., 2002).

The second approach is usually called simultaneous approach, as the name connote, the researcher jointly estimate the latent variables with their indicators (latent variable sub-model) and the observed variables of the choice model (Discrete choice sub-model), using simultaneous maximum likelihood estimation method (Ben-Akiva et al., 2002). This procedure produces efficient and consistent models estimates. The model estimation requires multidimensional integral over the distribution of the latent variables, the dimensionality is determined by the number of latent constructs in the model (Kim et al., 2014).

The limitation of this approach is that, with more than three latent factors, the multidimensional integration of the likelihood function becomes unworkable because of its complexity (Ben-Akiva et al., 2002). In such circumstances, we use the third approach known as the simulation technique; this technique estimates the parameters simultaneously, however, a smooth simulator (simulated maximum likelihood estimation) replaces the numerical integration method (Bolduc and Alvarez-daziano, 2010). The simulated maximum likelihood estimation involves using random draws from the estimated distribution of the latent variables to obtain consistent and efficient estimates (Ashok et al., 2002; Ben-Akiva et al., 2002), the drawback of this approach is the amount of time required for computing the estimates (Kim et al., 2014).

Moreover, due to the number of latent variables involves in this study, the ML-based simulation approach with Monte Carlo integration method is deemed appropriate. The framework of the simultaneous approach and model specification of the integrated latent variable and discrete choice model are illustrated and discussed in the subsequent sections of this chapter.

3.5.2.6 Simulated maximum likelihood solution

The dimension of the integral increases as the number of latent variables increases; this renders numerical integration practically complex. The numerical integration method is thus replaced with the simulated methods. This method uses random draws of the latent variables from their probability distributions. The likelihood function is as follows:

$$L(\boldsymbol{\alpha}, B, \Gamma, K, \Sigma) = \prod_{n=1}^{N} \prod_{i \in C_n} P_n(iI|\boldsymbol{X_n} B\Gamma K\Sigma) \tag{3.13}$$

3.5.2.7 Model Application

In the estimation of integrated choice and latent variable model, the function of the measurement equation is used for the identification of the latent variables and to enhance the estimates of the structural equations. The focus is on predicting the probability $P(y|X;\alpha,B,\Gamma,\Sigma)$ of observing the choice indicator y_n when forecasting rather than the indicators of the latent variables (Kim et al., 2014). Hence, we integrate the likelihood over the indicators to create a final forecasting model as shown below:

$$P(y|\boldsymbol{X};\boldsymbol{\alpha}, B, \Gamma, K, \Sigma) = \int_{\boldsymbol{X}^*} P(y|\boldsymbol{X},\boldsymbol{X}^*; B, \Gamma, \Sigma_\varepsilon) f_1(\boldsymbol{X}^*|\boldsymbol{X}, K, \Sigma_\eta) d\boldsymbol{X}^* \tag{3.14}$$

Therefore, after the model estimation, we use equation 3.12 for forecasting without the latent variable and measurement models neither their indicators.

Demand Indicators

Transport demand defines and quantifies the type and amount of travel that people would choose under particular conditions (Litman, 2019). The factors that influence transport demand includes the perceived cost of the transport services, which may include monetary cost, travel time, risk, comfort to mention but a few. Changes in user attributes such as income, and alternative specific attributes (such as transport prices, travel time) can affect demand in the form of mode choice, trip frequency, destination choice, vehicle type and the parking location (Litman, 2019). To understand the result of the analysis and evaluate the sensitivity of users with respect to important user and alternatives attributes, the demand elasticities are estimated and reported in this thesis. The aggregate direct and cross elasticities for the base model and the ICLV model are computed for explanatory variables (such as travel times and costs, income, trip distance, trip frequency, car ownership, Education as well as personal Norms, Salience and Affect representing the latent variables) for the private motorised modes, public transport and active mode of transport to assess the impact of a change of the attribute(variable) of the same or another alternative on the demand of an alternative (Bierlaire, 2018a; Atasoy et al., 2013; Axhausen et al., 2008).Elasticity measures how much the amount and type of goods will change when the price of the goods change. In transportation, It provides a framework for assessing the extent to which consumers will react to changes in the price or other determinants of demand for transport services, For detail description of demand elasticities, the reader is referred to (Cowie and Ison., 2009; Litman, 2019).

Direct elasticity measures the impact of a change of an attribute of alternative i on the choice probability of the same alternative, whiles cross elasticity measures the effect of a change in the cost of one alternative on the demand for the services of another alternative in the choice set.

Given that x_{in} is a variable associated with individual n and alternative i. If we assume that x_{in} is continuous and the relative (infinitesimal) change of the variable x is the same for every individual n in the population p for alternative i, then;

$$\frac{\partial x_{in}}{x_{in}} = \frac{\partial x_{ip}}{x_{ip}} = \frac{\partial x_i}{x_i} \quad \text{where} \quad x_i = \frac{1}{N}\sum_{n=1}^{N} x_{in} \tag{3.15}$$

Thus, for individual n, the elasticity E for attribute x of alternative i is given by;

$$E^i_{x_n} = \frac{\partial P_n(i)}{\partial x_n}\frac{x_n}{P_n(i)} \tag{3.16}$$

where $E^i_{x_n}$ is disaggregate elasticity of alternative i for individual n for variations in attribute x. $P_n(i)$ is the probability that individual n chooses alternative i

The aggregate direct elasticity E^i_x of alternative i with respect to the attribute x_i is defined as;

$$E^i_x = \frac{\sum_{n=1}^{N} W_n P_n(i) E^i_{x_n}}{\sum_{n=1}^{N} W_n P_n(i)} \tag{3.17}$$

where W_n is the sample weight for individual n, Readers are referred to Bierlaire (2018a) for detail description of the mathematical formulations of Elasticities.

3.6 MINDSPACE and ICLV modelling

Transport Mode choice decision has been demonstrated not to only depend on objective criteria such as travel time, cost and income but subjective factors as well. Guiver (2007) found that while car-users admitted that car travel was comparatively expensive than a bus, bus users, on the other hand, were less concerned about the cost. Although car-users were concerned about the cost of driving, the authors argued that the cost difference between the two modes of transport was a better trade-off when weighed against the level of convenience and flexibility that comes with a car (Guiver, 2007; Beirao and Cabral, 2007). Therefore, preference for convenience, safety, comfort, flexibility, emotional satisfaction and similar subjective variables cannot be overlooked when investigating transport travel behaviour (Johansson and Heldt, 2006; Guiver, 2007; Temme et al., 2008b; Yáñez et al., 2010).

Researchers investigating consumer choice decision making believe that MINDSPACE could have a significant impact on travel behaviour (Avineri, 2012a; Avineri, 2012c). Moreover, few studies have explored the effect of some elements of MINDSPACE on travel behaviour and car ownership (Belgiawan et al., 2016). However, none of the existing studies has developed and tested ICLV models incorporating elements of MINDSPACE as a latent variables (Temme et al., 2008b; Zhang et al., 2016; Belgiawan et al., 2016). Temme et al. (2008b) suggested that extending choice models with elements of MINDSPACE as latent variables could provide higher explanatory power. Therefore building on the studies of hybrid choice models, this study, incorporates elements of MINDSPACE as latent variables in modelling an integrated choice and latent variable model (ICLV) while investigating the impact of MINDSPACE, on travel mode choice behaviour (Avineri, 2011; Juhász, 2013; Aczél and Markovits-somogyi, 2013).

3.7 Summary

The chapter reviews the literature on transport models and provides the theoretical background for the study. It was found that travel is a derived demand out of the need for activity participation; the level for activity participation rises with economic development and growth. Efficient transportation system is a necessity to achieve this end. Major cities have had to build roads and made changes to land-use patterns to deal with vehicular traffic for more than half a century. Building more roads to accommodate the increasing vehicular volumes have only resolved the situation temporarily; volumes always increase soon after the implementation of such schemes to fill any additional capacity introduced.

In order to make informed planning decisions, transport demand models (popularly called four-stage-models) were developed in the 1950s to understand and predict the response of transportation demand to changes in the attributes of the transportation system and the characteristics of the users of the transportation system. The results from these models formed the basis for major long-term transport capital and infrastructure investment strategies.

It is also shown that the emphasis has shifted from the capital investment strategies to understanding travel behaviour responses to shorter-term congestion management schemes. The realisation of the inefficiency of the capital investment strategies and traditional statistically-oriented modelling approach to travel demand analysis in resolving the conundrum has shifted the emphasis from the capital investment strategies to a more behaviourally-oriented modelling approach to understanding travel behaviour responses to congestion management strategies.

It has been argued from recent literature that travellers do not always maximise their economic utility neither do they always have complete information about alternatives to make informed choices as postulated by the economic theory of perfect rationality. The chapter has shown that subjective factors such as attitudes, behaviour and situational factors affect travel choices; decision-makers do not always assess the full economic costs of their decisions. It was further shown that several studies had proposed the inclusion of the subjective factor into the choice models to account for the heterogeneity in human behaviour. The chapter has also shown the framework for the development of such models, as well as examples of hybrid choice models developed to account for these subjective factors in literature.

Part II

RESEARCH METHODOLOGY AND DATA COLLECTION

Chapter Four

Research Methodology

4.1 Introduction

The theoretical framework for this study has been presented in chapters two and three. This chapter presents the overall research methodology adopted to address the research objectives and the overall research aim of empirically evaluating the impact of MINDSPACE on transport mode choice or individual choice preference. The existing literature, as shown in chapters 2 and 3 supports the incorporation of behavioural and attitudinal variables as latent variables to model and explain travellers' choice decision (Ben-Akiva and Lerman, 1985; Ben-akiva, 1997; Ben-Akiva et al., 1999; 2002; Ben-akiva and Boersch-supan, 2002; Johansson et al., 2005; Johansson and Heldt, 2006; Temme et al., 2008b; Yanez et al., 2010). Moreover, recent studies in cognitive psychology suggest that the application of behavioural economics, particularly MINDSPACE in explaining travel mode choice decision to enhance the understanding of travel mode choice decision (Avineri, 2012b; Metcalfe and Dolan, 2012; Aczél and Markovits-somogyi, 2013).

4.2 Research Approach

Guba and Lincoln (1994, p.107) defined research paradigm as "the basic belief system or world-view that guides the investigator ...". Hussey and Hussey (1997, p.47) also defined research paradigm as "the progress of scientific practice based on peoples' philosophies and assumptions about the world and the nature of knowledge". A research paradigm, therefore, is closely related to our belief system of how the real world is constructed (Ababio-Donkor, 2015). (Hussey and Hussey, 1997) further proposed two main research paradigms, namely; positivist and phenomenological. Sam (2011) agrees with the explanation of Hussey and Hussey (1997), which suggests that the type of methodology selected for a study should be influenced by the research paradigm adopted by the researcher. Sam (2011) expanded on the above to include time and cost availability for the research work. However, since the aim of this research is to apply MINDSPACE as latent variables in calibrating integrated choice and latent variable model (ICLV), numeric data was be required. Therefore, a questionnaire survey will be deployed for this purpose, and therefore quantitative approach was adopted for the study.

4.3 Research Design

Research design is defined as "a set of advance decisions that make up the master plan of the research work, specifying both the methods and procedures for collecting and analysing the needed information" (Robson, 1993; Burns and Bush, 2002; Yin, 2009). Yin (2009) expanded on the above definition to include "a logical sequence that links empirical data collection to research question, data analysis and conclusion". The author further asserted that the research design must be developed at the inception stage and kept in mind throughout the research work. The quality of any research work, therefore, depends on the formulation of the research design. Moreover, the quality and suitability of research design are essential in procuring information to answer the research question within resource constraint (Ghauri and Gronhaug, 1995; Sam, 2011).

4.4 Research methods

The methods for achieving the research objectives are discussed in two separate sections: data collection methods (literature review and revealed preference questionnaire survey) and data analysis methods (Exploratory and confirmatory factor analysis and latent variable choice modelling). The following sections discuss these in details.

4.4.1 Data Collection Methods

It is suggested that the scope and depth of a research influences to a greater extent the choice of research method to be adopted (Fellow and Liu, 2005). Richardson et al. (1995) argued that the choice of a survey method for transport research should be a trade-off between the objective of the survey and the resource available for the survey. Since the study involves transport modelling and behavioural economics (cognitive psychology), a combination of quantitative and qualitative research methods is deemed appropriate. The data collection involves a comprehensive review of relevant literature and a revealed preference questionnaire survey.

4.4.1.1 Documentary Survey

A comprehensive review of relevant literature was conducted for consolidating extant studies and literature by other practitioners and researchers in transport modelling and behaviour economics; this review is presented in chapters two and three of this thesis. Relevant studies and works from journal articles, conference papers, textbooks, research reports, working papers, Doctoral thesis and information from the internet were reviewed to establish the background of behavioural economics and transport mode choice modelling. The research framework for the study was developed through the review of existing literature, the current state of knowledge in transport choice modelling and MINDSPACE were explored to identify the best approach for the integration of the two areas of knowledge. This process provided a clear understanding of the type of information required in the survey and was quite helpful in the design of the data collection instrument (Richardson et al., 1995).

Chapter 2 presents the review of choice theories comprising, rational choice theory, bounded rationality and behavioural economics. The chapter further explains how behavioural economics or MINDSPACE could influence transport decision making as well as its potential application in transport. Materials from journal articles, conference papers, books, research reports, working papers, government policy document and information from the internet were reviewed for this exercise. Similarly, chapter 3 explored transport demand theories and transport modelling and also looked briefly at their historical development. The chapter also reviewed the types of choice models as well as their strengths and limitations. Additionally, published data from the National Travel Survey (NTS), the Scottish household survey (SHS) and census data provided useful background information on the demographic characteristics and travel behaviour of the study population.

4.4.1.2 Survey Instrument Design Methodology

Travel demand modelling requires data reflecting the travel behaviour of the targeted population, which could be acquired through a questionnaire survey. For the developed model to reflect and predict the travel behaviour accurately, the data must reflect the characteristics of the study population. Revealed preference survey, generally involves asking questions to acquire detailed accounts of the population actual travel behaviours, such as their previous travel decisions, i.e., frequency of travel, the purpose of the journey, chosen mode and other relevant attributes of their journeys. This approach is based basically on the respondents' past travel behaviour and hence overcomes the biases of stated preference approach. Stated preference survey, on the other hand, involves asking the respondents question about their future travel choices based on a hypothetical travel scenario, in which several travel modes are presented with different attributes. The respondents' choice indicates the relative importance of the attributes associated with their selected mode. Stated preference is superior to the revealed preference in terms of the flexibility it offers the researcher to explore the effects of significant variables efficiently as well as assessing the sensitivity of each variable in the model.

Mode choice data collection method

The previous section discussed the various methods of data collection for choice modelling. This section exploits the relative advantages offered by both approaches (Revealed and Stated preference) to overcome the limitations in using them separately by combining both revealed and stated preference type questionnaire in the data collection instrument. There are several methods for administering a survey questionnaire; this depends on the methods employed for the data collection and distribution of the questionnaire (Richardson et al., 1995). These formats include; postal survey (Mail back survey), computer-assisted survey, paper-and-pencil based, and telephone-based surveys. For this study, a combination of the first two methods was deployed for the data collection. These methods are described in the next section.

Postal Survey

Postal survey is a method of self-completion survey, which involves mailing the questionnaire to the respondent and asking them to mail back the completed questionnaire to the survey administrator. The presence or intervention of the researcher is not necessary in this case. According to Khan (2007), this approach requires less time. However, the postage fee and the provision of a self-addressed envelope for return postage by the researcher could make this method expensive (Walonick, 1993). Contrarily, Moser and Kalton (1979) and Scott (1961) in an earlier report argued that this method could lead to an increase in response rate since people might feel obliged to complete the survey because of the guilt of wasting the survey administrator's resources (the postage stamp)

Notwithstanding, postal survey is argued to be the most economical physical form of survey administration for population-based survey (Sinclair et al., 2012). The argument of cost raised by Walonick (1993) and McCrohan and Lowe (1981) was addressed by using Printed Postage Impressions (PPIs) self-addressed envelopes for return postage. This arrangement meant that postage fee is paid for only returned questionnaires, thus reducing the cost of the survey. The survey for the study was carried out between January 9th 2018 and July, 31st 2018. Four thousand one hundred and fifty-five (4,155) survey questionnaires and free-post PPIs self-addressed envelopes for return postage were packaged and distributed to the sampled addresses (in Edinburgh). Additionally, a web-link to the survey was included in the introductory letter accompanying the questionnaire for interested participants to complete the survey on-line.

Internet Survey

The internet-based survey is an inexpensive computer-assisted survey method for data collection. It is easier for respondents to answer and environmentally friendly. The internet-based approach has a quick turn-around time and saves considerable effort in data input and processing because the data is directly obtained in electronic form. Question branching is quite straightforward to implement in Internet-based surveys. Additionally, this method could only be administered to respondents already familiar with computers or have access to the internet and therefore, could produce a biased sample. However, to overcome sampling bias in the final dataset, the internet survey method was used as a supplementary method to the postal survey. A web-link to the on-line version of the survey was included in the introductory note of the postal survey questionnaire as an alternative option for respondents who prefer to answer the survey on-line.

4.4.2 Sampling Methods

This section discusses and compares the most commonly used approaches for selecting samples, together with their strengths and weaknesses. The sample selection process must be handled with care to ensure that the resultant sample is representative of the population. There are two general approaches to sample selection, namely:

1. Probability (Random) Sampling
2. Non-Probability Samples

4.4.2.1 Probability (Random) sampling

This section describes each of the probability sampling methods, indicating their advantages and disadvantages. In probability sampling, every unit in the target population has a chance greater than zero of being included in the sample. The probability of selecting any of the units can be mathematical determined (Richardson et al., 1995; Fife Research Co-ordinating Group, 2005; Chaturvedi, 2015). One advantage of probability sampling is the ability to calculate the extent to which a sample differs from the target population "sampling error", which is not possible in the case of non-probability sampling. The commonly known probability sampling methods include the under listed.

1. Simple random sample
2. Systematic random sample
3. Stratified random sample
4. Cluster sample
5. Multistage sample

Simple Random sampling

Simple random sampling is also known as random sampling without replacement. It is the simplest of all random sampling techniques and the basis of all other random sampling techniques. In this method, each unit in the sampling frame is assigned a unique identifier, and then these identifications are sampled at random to obtain the sample. Since the selection is made at random, each unit of the frame has an equal probability of being selected. A table of random numbers is used to determine which units should be selected. This method is applicable for generating small sample size from a small or homogeneous population. It is, however, impractical for larger population and sample sizes. Supposed we need to draw n units from a sampling frame containing N number of units, given that n ε N. Then the probability $_{N}P_{n}$ of generating n samples in n number of draws using simple random sample is given as:

$$_{N}P_{n} = \frac{n!(N-n)!}{N!} \tag{4.1}$$

Where:

$_{N}P_{n}$ is the probability of selecting n units from a sample frame of N units, such that n ε N.

Systematic random sampling

Systematic sampling is sometimes known as interval sampling, it is simpler than the simple random sampling and one of the widely known sampling techniques among transport researchers (Khan, 2007). In this method, the sampling frame is arranged in a systematic order. The researcher then draws units at regular intervals from the ordered frame. The first case is drawn at random, and then all subsequent selections are made at every kth interval from the first selection onwards. k is the ratio of the frame size and the sample size (Richardson et al., 1995; Chaturvedi, 2015). It is essential that the starting point is not automatically the first in the frame, but randomly selected between the 1st and kth unit in the frame. Although systematic sampling is very useful and straight forward, it has several limitations. Firstly, the sample may be biased if there is hidden periodicity in population which coincides with the interval of selection. Secondly, there is a scenario where the resulting sample may not adequately represent users of a particular mode in the case of a travel survey. Finally, it is difficult to assess the precision of the estimate from one survey.

Stratified random sampling

Stratified random sampling is a random sampling technique used for a population already subdivided into several distinct units such that the units within each subdivision (Stratum) are homogeneous with respect to the stratifying variable. The frame can be organised into separate "strata" where each stratum is treated as an independent sub-frame from which individual units can be randomly selected using the appropriate weightings. For studies as this, we can organise the strata based on the various transport modes, (i.e. public transport users and private car users) or based on demographics such as income-levels, education-level or age. Supposing N is the entire sampling frame then stratified random sampling can be done by dividing the frame into I number of distinct units (strata) such that;

$$N = N1 + N2 + N3 + \ldots + NI \tag{4.2}$$

Where:

N is the sampling frame

N1,2 . . . I are the number of units in the Ith stratum

This method of sampling has various advantages; firstly, every unit in a stratum has the same chance of being selected. Secondly, using the same sampling fraction for all strata ensures proportionate representation in the sample. Thirdly. It allows the use of different survey method for each stratum. Finally, it allows different sampling fractions to be applied in each stratum, also known as "Variable Fraction Stratified Random Sampling". Varying the sampling fractions between strata ensures adequate representation of minority subgroups of interest. Thus, the resulting sample will have the correct proportion of each stratum within the entire population while reducing the sampling error. The drawbacks of stratified sampling are that it is more time consuming than simple random sampling. Sampling frame of the entire population must be prepared separately for each stratum. Secondly, considerable prior information on the attributes of the population is required for subdividing the sampling frame into sub-frames.

Cluster sampling

Cluster sampling is a random sampling method where the sampling frame is first divided into clusters of sampling units, based on the characteristics of the population under investigation. Several clusters are then randomly drawn to represent the target population. However, depending on the size of the clusters, every unit in the selected clusters can be included to form the sample or units can be randomly selected from the selected clusters. This is a simple form of "multi-stage sampling". Cluster sampling is considerably economical than simple random sampling both in sample selection and in conducting the survey. However, cluster sampling is less efficient compared to simple random sampling; sampling error tends to be high for any given sample. Cluster and Stratified sampling both samples non-overlapping subsets of the population. However, they differ in several ways. Firstly, only a subset of clusters is in the sample. Conversely, all strata are represented in the sample. Secondly, with stratified sampling, the best survey results occur when elements within strata are internally homogeneous. However, with cluster sampling, the best results occur when elements within clusters are internally heterogeneous.

Multi-stage sampling

Multi-stage sampling is a random sampling technique for a study area with large populations. It is a complex form of cluster sampling based on the process of selecting samples in two or more (multi) stages (Fife Research Co-ordinating Group, 2005). A multi-stage survey for this study involves the following stages:

- Stage 1: Sub-divide the larger population by country and sample from the total population of countries.
- Stage 2: Sub-divide the selected country into council areas and sample from these council areas within each selected country in stage 1
- Stage 3: Sub-divide selected Council area into outward postcode (outcode) and sample from the outcode within each selected council area in stage 2
- Stage 4: Sub-divide selected outcode into streets or inward postcode (incode) and sample from the incodes within each selected outcode in stage 3
- Stage 5: Sub-divide selected incode into households and sample from the households within each selected incode in stage 4 to create the sample for the survey

This method is a multiple randomisations process; it essentially involves taking random samples of preceding random samples. At the end of this process, the individuals (units) selected at the final stage are surveyed.

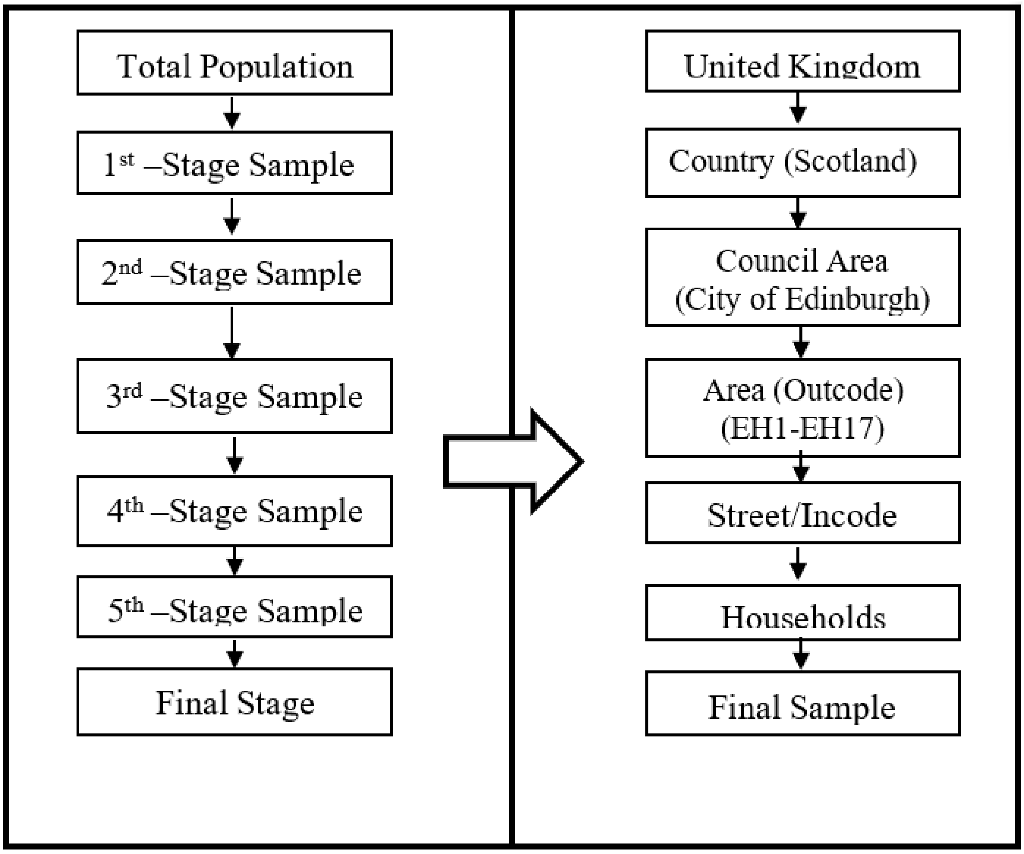

Figure 4.1: Multi-stage sampling

4.4.2.2 Non-probability sampling

The non-probability sampling method is any sampling technique where units are selected through a non-random process to form the sample. With this technique, some units of the population have no chance of selection. The selection criteria are based on the assumptions that the characteristics of the target population (such as age, income and education) are equally distributed. The non-probability nature of this sampling method makes it impossible to estimate the sampling errors; thus, this method is often used in the early stages of a survey. For example, in pilot surveys to test survey questions. Non-probability sampling methods are, therefore, not recommended for travel surveys. The most common methods used in non-probability sampling include:

1. Quota sampling
2. Convenience sampling
3. Purposive sampling

4. Volunteer sampling and
5. Judgement sampling

4.4.2.3 Summary of Sampling Methods

The generalisability of a study outcome to the larger population is achieved by minimising all potential errors and biases in the survey (Comrey and Lee, 1992; Richardson et al., 1995; Osborne and Costello, 2010; Field, 2013; Chaturvedi, 2015). Random sampling is one of such ways to reduce observational errors and biases (Porter, 2011; Richardson et al., 1995, p.75,). It is observed that non-random sampling methods, on the other hand, often produce biased sample estimates and therefore not recommended for transport surveys (Richardson et al., 1995; Chaturvedi, 2015). Consequently, all the non-probability sampling methods, including systematic sampling method, were deemed inappropriate on the above-stated grounds.

The major limitation of the simple random sampling method is its unsuitability for a larger population. The study target population is in excess of 507,000, according to The City of Edinburgh Council (2018). Therefore, considering the large size of the study population, simple random sampling method is considered unsuitable.

Although multi-stage and cluster sampling methods are suited for a large population, they tend to have higher sampling error and produce less accurate estimates (Fife Research Co-ordinating Group, 2005). Therefore, given the generalisability requirement of the study and the above limitations, multi-stage and cluster sampling methods were considered inappropriate for this research.

Stratified random sampling method is very laborious and time-consuming. Nevertheless, it generates a representative sample and consequently, produce better estimates (Fife Research Co-ordinating Group, 2005). Stratified random sampling also comes with an added advantage of making it possible to apply weights to each sub-frame or stratum to generate sample proportional to the size of each sub-frame. This characteristic enhances the representativeness of the sample and the generalizability of the survey results. Therefore, based on the above strengths, the stratified random sampling method was adopted for this study. This will generate a representative sample from the sampling frame and improve the generalisability of the study results.

4.4.3 Sample Size Estimation

The reliability of the results of structural equation modelling and factor analysis techniques depends on the sample size used. Larger sample size produces highly reliable results. However, at a higher cost to the study. On the other hand, too small sample will lead to large variations in the sample estimates and produce less reliable results. The adequacy of the sample size for a study is, therefore, a trade-off between the objective of the study and resource availability (cost and time) (Richardson et al., 1995; Hutcheson and Sofroniou, 1999). Several rules exist for the determination of sample size, including:

1. Simple rule of thump
2. Sample-to-variable Ratio
3. Central Limit Theorem

4.4.3.1 Simple rule of thump

A useful rule of thumb for estimating sample size adequacy for studies involving SEM is generally about 200 cases (Kline, 2011), this is more acceptable when using robust techniques like the Maximum Likelihood Estimator (MLE) (Kline, 2011; Zainudin, 2012; Bahaman, 2012; Arbuckle, 2017). Others have suggested factors specific to individual models or complex models sometimes may necessitate a threshold above 200 cases (Kline, 2011). Consequently, several researchers recommended a minimum of 300 cases as adequate for obtaining good results (Comrey and Lee, 1992) (Floyd and Widaman 1995; MacCallum, Widaman, Zhang, and Hong 1999). Comrey and Lee (1992), further suggested that where resources allow, sample size of 1000 cases was ideal for getting excellent results, while many researchers support this view, others suggest sample size of 500 cases and above is adequate to reduce sampling and inferential errors considerably and at the same time improves the generalisability of the results (Richardson et al., 1995;

Osborne and Costello, 2010; Tabachnick and Fidell, 2012) A threshold of 300 cases is adopted in this section for the following reasons;

1. 300 cases meet the minimum sample size requirement proposed by the two groups of researchers.
2. MLE is employed for the CFA and ICLV, 300 cases satisfy the sample requirement for using MLE (Bahaman, 2012; Arbuckle, 2017)

4.4.3.2 Sample-to-variable ratio

A general rule for estimating minimum sample size requirement for standard ordinary least squares multiple regression analysis is the Sample-to-variable ratio (N:p) rule, because of its ability to account for model complexity (Osborne and Costello, 2010; Kline, 2011; Field, 2013). This method estimates the sample size as a function of the number of variables. Sample-to-variable ratio (N:p) of 15:1 (15 responses to each variable) has been recommended for the estimation of sample size (Velicer et al., 1998; Osborne and Costello, 2010; Field, 2013). However, the sample size requirement for statistical techniques like the CFA is contestable because it requires large sample (Kline, 2011). Conversely, since SEM is closely related to multiple regression in some respects, 15 cases per measured variable is suggested as reasonable for obtaining reliable results (Loehlin 1992; Lehmann 1999). Kline (2011) proposed N:p ratio of 20:1 as ideal for analysis involving SEM.

Osborne and Costello (2010) recommend sample-to-variable ratio (N:p) of 30:1 for studies that seek to generalise the results to the study population. However, because the ML estimator is adopted for analysis in this study, sample-to-variable ratio (N:p) of 15:1 is adopted for estimating the minimum sample size requirement. Table 4.1 below shows the latent variables and the number of indicators developed to measurement each:

Table 4.1: Latent Variables

Variable	No. of Constructs
Norm	10
Ego/Narcissism	16
Affect	6
Total	**32**

From the table above, the highest number of constructs is 32; hence, we adopt 32 as the number of variables (p) for the estimation of the sample size. Using sample to variable ratio N:p of 15:1 Number of variables, $p = 32$ Cases/variable, $N = 15$ Sample size $(n) = Nxp$ Sample size $(n) = 15x32$ Sample size $(n) = 480$

4.4.3.3 Central Limit Theorem

Another technique for determining sample size is the Central Limit Theorem (Richardson et al., 1995). According to Richardson et al. (1995), minimum required sample size is estimated by solving for the standard error equation below:

$$s.e.(p) = \sqrt{(}\frac{(N-n)}{N} \times \frac{p(1-p)}{n}) \tag{4.3}$$

Solving the equation 4.3 above, the sample size (n') becomes

$$n^1 = \frac{p(1-p)}{s.e(p)^2} \tag{4.4}$$

The final sample size (n) is estimated by applying equation 4.5, population correction factor

$$n = \frac{n^1}{(1+\frac{n^1}{N})} \tag{4.5}$$

Where,

N = Population size

n^1 = unadjusted sample size

n = Final sample size

$\frac{(N-n)}{N}$ = Population correction factor

$s.e.(p)$ = Standard error

p = proportion of sample possessing a characteristic

The January 2018 edition of the Royal Mail address file contained 242,361 household addresses in Edinburgh. Additionally, according to National Records of Scotland (2013), 39.9% of households in Edinburgh did not own a car. Therefore, using the central limit theorem and the information above, the minimum sample size at 95% confidence level is estimated as follows:

$s.e.(\mu) = \frac{\text{confidence limit}}{\text{z}}$; $s.e.(\mu) = \frac{5}{1.96} = 2.55$

$n^1 = \frac{39.9(100-39.9)}{2.55^2} = \frac{2397.99}{6.5025} = 368.78$

applying population correction factor;

$n = \frac{n^1}{1+\frac{n^1}{N}}; = \frac{369}{1+\frac{368.78}{242.361}} = 368.22 \equiv 368$

Estimated minimum sample requirement according to the central limit theorem is 368.

4.4.3.4 Summary

Since the study seeks to understand the travel behaviour of the study population, we need sample size sufficient enough to make the results generalisable to the study population (Comrey and Lee, 1992; Richardson et al., 1995; Osborne and Costello, 2010; Field, 2013).The highest minimum sample size estimated among the three methods was 480 from the sample-to-variable ratio technique. This figure almost satisfies the recommendation of 500 to 1000 for minimising sampling and inferential errors and obtaining high generalisability (Richardson et al., 1995; Osborne and Costello, 2010; Field, 2013). Therefore, sample size of 500 is adopted as the minimum requirement for this study. Moreover, statistical techniques for measuring sample size adequacy such as Kaiser-Meyer-Olkin (KMO) test and Bartletts test of sphericity will be subsequently carried out after the survey to confirm the adequacy of the sample.

4.4.4 Sample Generation

Field (2013) defines a sample as "a smaller but hopefully representative collection of units from a population used to determine truth about that population" (Chaturvedi, 2015; Field, 2013). The purpose of sampling is thus, to select a small group of people from the population that have similar characteristics as the study population. This

makes it possible to draw conclusion or make inference about the population. This is necessary because of the realisation that we deal with very large population in transport studies of such nature (Richardson et al., 1995).
Similarly, there were 242,361 households in Edinburgh as at January 2018, according to the January 2018 release of the Royal Mail PAF address data. Surveying the entire population will not only be impossible but very expensive and time consuming (Chaturvedi, 2015). It is essential that the sample generated represent the characteristics of the study population, Bias sample can lead to biased estimates and skewed modelling results (Richardson et al., 1995).

4.4.4.1 Sampling units

The population for a survey is made up of several elements which may or may not be the same as the units of interest (Richardson et al., 1995). The Population of the survey is composed of residents of the city of Edinburgh above the age of 16. However, the selection of sample for this study was based on the sample units listed below:

1. EH1-EH17 geographical area of Edinburgh
2. Postcodes and Households

4.4.4.2 Sampling frame

The sampling frame is defined by Richardson et al. (1995) as "a base list or reference which properly identifies every sampling unit in the survey population". In other words, it is a universal database from which potential respondents are drawn from. It must be representative of the population (Chaturvedi, 2015). The sample frame is the universal set of all the sample units in the survey population. Therefore, having defined the population for the study and identified the sampling unit, it is necessary to define a sampling frame from which the sample will be drawn. The sampling frame for the survey includes:

1. PAF address data, January 2018 release.
2. Datazones - Scottish Index of Multiple Deprivation (SIMD) Postcode lookup table.

PAF address data

The PAF address data contains all households and business addresses in Scotland. We procured the January edition of the royal mail PAF address data of EH postcode area for the study. The EH PAF address data contains all households and business addresses within the EH postcode area from EH1 to EH99. Data from EH1 to EH17 constituting the jurisdiction of the city of Edinburgh council area was extracted for this research. Summary of the extracted addresses is shown in Table 4.2. The PAF address data contained a total of 252,393 addresses for EH1 to EH17 outwards postcodes. 10,034 business addresses were identified and deleted, leaving 242,359 household addresses for sampling.

Table 4.2: Outward Postcode Addresses

Outcode	**Addresses**	**Deleted Addresses**			**Household Addresses**	**Remarks**
		PO Box	**Organizations**	**Sub-Total**		
EH1	4,975	20	847	867	4,108	Business
EH2	1,808	23	840	863	945	Business
EH3	16,785	55	1,269	1,324	15,461	
EH4	26,905	41	406	447	26,458	
EH5	11,122	9	190	199	10,923	
EH6	24,841	16	1231	1247	23,594	
EH7	22,155	39	621	660	21,495	
EH8	13,817	8	515	523	13,294	
EH9	10,663	15	413	428	10,235	
EH10	15,809	26	489	515	15,294	
EH11	23,432	24	676	700	22,732	
EH12	20,126	94	775	869	19,257	
EH13	6,888	1	83	84	6,804	
EH14	18,743	20	380	400	18,343	
EH15	10,564	14	358	372	10,192	
EH16	14,930	31	403	434	14,496	
EH17	8,830	0	102	102	8,728	
Total	**252,393**	**393**	**9,598**	**10,034**	**242,359**	

Scottish Index of Multiple Deprivation (SIMD) postcode lookup table

The Scottish Government defines Scottish Index of Multiple Deprivation (SIMD) postcode lookup table as "a tool for identifying areas of deprivation (poverty and inequality) and the specific issues and challenges that these areas face". Deprivation as used in this context does not necessarily mean 'poor' or 'low income', but also people or areas with fewer resources and opportunities. For example access to health, education, services and transport (Scottish Government, 2016). The SIMD is used as a tool for statistical classification and as an indicator to target resources and policies to areas that need them most. The SIMD divide Scotland into 6,976 areas called 'data zones', using indicators like pupil performance, travel times to the GP, crime rate, unemployment rate and many others. Each data zone in the SIMD is ranked from 1 (most deprived) to 6,976 (least deprived). The SIMD further classify the 'data zones' into Percentile (100 groups), vigintile (20 groups), decile (10 groups) and Quintile (5 groups) based on the initial ranking (Scottish Government, 2016).

Using the postcode fields in SIMD postcode lookup table and the dataset extracted from the PAF address data, the two datasets were merged to create the sampling frame. The sampling frame was classified based on the definitions of SIMD vigintile (20 groups) for sampling purposes. Each vigintile contains 5% of the data zones and represents a stratum in our sampling frame. Table 4.3 shows the household addresses by outward postcode and vigintile. 2,212 records from the extracted PAF address file could not be found in the SIMD postcode lookup table and were consequently discarded from the sampling frame. Table 4.4 presents a summary of the reclassified sampling frame by strata (vigintile).

Table 4.3: Sampling frame

Vigintile (Stratum)	Rank		Avg Pop	No. of Postcodes	Av income	HH Addresses	Weight%
	Min	Max					
1	6	347	824	286	212	7862	3.27%
2	370	689	827	312	590	7162	2.98%
3	714	1045	859	428	907	9608	4.00%
4	1054	1384	826	431	1351	10196	4.25%
5	1398	1715	932	387	1632	8575	3.57%
6	1750	2059	876	317	2021	7370	3.07%
7	2111	2427	777	418	2361	8978	3.74%
8	2452	2781	888	570	2873	13532	5.63%
9	2822	3126	875	288	3210	7515	3.13%
10	3140	3488	910	398	3631	9484	3.95%
11	3490	3832	876	447	3579	11382	4.74%
12	3868	4183	940	335	3833	9463	3.94%
13	4190	4521	996	318	4237	8764	3.65%
14	4539	4872	837	429	4429	10160	4.23%
15	4904	5232	871	427	4815	8416	3.50%
16	5241	5578	808	540	5196	11116	4.63%
17	5597	5928	874	629	5457	12763	5.31%
18	5943	6273	846	557	5668	11520	4.80%
19	6279	6624	861	1176	6235	21896	9.12%
20	6629	6974	877	2581	6518	44385	18.48%
Total				11,274		240,147	

Table 4.4: reclassified sampling frame

Vigintile	EH1	EH2	EH3	EH4	EH5	EH6	EH7	EH8	EH9	EH10	EH11	EH12	EH13	EH14	EH15	EH16	EH17	Total
1				864		212	1419				541			1824	953	1629	420	7862
2				1165	1490	680	796				862			771	356	609	433	7162
3				2233	604	1021	427				1174		888	762	312	301	1886	9608
4				449	1564	1668	389	1231			1490			393	698	2312	2	10196
5	590			963	260	680	894	1465			1039			258		1295	1131	8575
6				1388			311	1141			1984		407	329	375	509	926	7370
7				1471	280	2182	1299			27	1067	46	417		429	1464	296	8978
8	1023	207		718	361	3587	372	1238			2666	534	218	931	291	770	616	13532
9			982	697		1073	1006	687			1221	1188	464	193		4		7515
10	1070		174		420	2455	1014	1063		440	481			1051	965		351	9484
11	533		1164		399	1282	1701	980	375		2264	699		1182	432	30	341	11382
12	94		2359	427	530	2047	576	440			505	929		841	183		532	9463
13			1023		1046	948	1419	509		735	622	1443	354	6	240	63	356	8764
14				64		1741	1640	623		1	1865	1148	306		1189	1583		10160
15	201	519	871	645		4	1588	771	422	53	359	824	340	769	297		753	8416
16	214		958	723	327	855	1630	244		344	247	2328	659	1152	318	560	557	11116
17			748	1201	1419	976	628	717	1204	1544		1201		927	1236	962		12763
18			641	1931	860	923	991	952	785	817	1179	2048				393		11520
19	209	195	1245	4192	469	742	1228	1100	2163	1698	1242	1334	968	3320	507	1238	46	21896
20	174	23	5190	7269	752	368	1715		5286	9540	1786	5284	1774	3365	1288	571		44385
Not found		1	106	58	142	150	452	133		95	138	251	9	269	123	203	82	2212
Total	**4108**	**945**	**15461**	**26458**	**10923**	**23594**	**21495**	**13294**	**10235**	**15294**	**22732**	**19257**	**6804**	**18343**	**10192**	**14496**	**8728**	**242359**

4.4.5 Questionnaire Design

One of the main objectives of this study is to analyse travel behaviour of the study population. The questionnaire consisted of several parts consisting of travel patterns in terms of past, present as well as their future travel mode choice (next two years). The latter was measured on a five-point Likert scale (very unlikely-very likely). The study also seeks to analyse the respondents travel behaviour in the context of behaviour economics particularly using elements of MINDSPACE as explanatory variables as such the questionnaire included constructs developed to measure the elements proposed for this study; norm, Affects, Narcissism, Salience. Additionally, questions on other possible factors affecting travel mode choice were asked, including socio-demographic characteristics et cetera. Each of which is expanded on below. Detail of the questionnaire is presented in Appendix A

4.4.5.1 Transport Characteristics

This section of the questionnaire aims to understand respondents' past and current mode of travel including walking, cycling, motorcycle car and public transport (bus, tram and rail) for daily trips such as working trips, shopping trips and leisure trips. The frequency of the trips as well as travel time, cost, car ownership and accessibility of public transport were also asked. Questions about respondents' ability to use PT for their daily trips and their perception about PT service quality and their overall satisfaction with the PT service available.

4.4.5.2 MINDSPACE Variables

This section discusses the development of indicators for measuring the individual variables of MINDSPACE for inclusions as latent variables in a hybrid choice model. Since the objective is to use the variables of MINDSPACE as latent variables in a hybrid choice model, it was necessary to consider variables that could be measured with indicators. The selection of variables to measure for the choice modelling was accordingly based on: i) the existence of a metric or indicators for measurement. ii) The possibility of measuring the variable with indicators, and iii) whether a variable could be measured in the context of transport. Four out of the nine variables of MINDSPACE, namely; Norms, Salience, Affect and Ego or Narcissism, were judged suitable based on the criteria above. The following sections expatiate on the four selected variables.

Norms

Several studies have indicated that Norms has significant impacts on overt behaviour (Schwartz, 1977; Cialdini et al., 1991; Bamberg et al., 2007). Cialdini et al. (1991) suggested that peer influence and approval from social group sustains behaviour and could lead to behaviour change (Avineri, 2009; Hirshleifer, 1993). Schwartz (1977) found that personal norms significantly influence behaviour than social norms. It is argued that people feel morally obligated to act when their personal norms are activated. Therefore to understand the influence of norms on travel behaviour (in the context of MINDSPACE), measurement indicators were developed to assess respondents' perceived social and personal norms.

The primary objective is to investigate the impact of norms on travel behaviour and whether personal norms and social norms are of comparative significance to objective factors (such as income, age, car ownership, travel time et cetera.) in transport choice models (Schwartz, 1977; Bamberg et al., 2007; Belgiawan et al., 2016; Cialdini et al., 1991; Avineri et al., 2009; Avineri, 2009). The questions included statements on the general perception of cars/PT in society. For example, *"Driving is perceived to illustrate a person's power, financial status in society and provide the driver/owner with a positive self-image"*.

Finally, to measure "personal norms", respondents were asked about their perception of cars/PT usage and their perceived expectation of others to use car/PT. For example, *"I think people should use public transport more for their work/educational journeys due to the increasing levels of traffic congestion and air pollution in the urban centres"*, and *"I feel morally obligated to use more of public transport due to the impact of our travel behaviour on health and the environment (global warming)"*. All the statements were measured on a five-point Likert scale (1= Strongly Disagree; 5= Strongly Agree). Some of the statements used were adapted from Bamberg et al. (2007) and Belgiawan et al. (2015). Question 23 in Appendix A shows the measurement scale designed to measure Norms.

Salience (PT User Experience)

The human memory of experiences is found to be governed by the most intense 'peak' moments and final impressions in a chain of events (Kahneman, 2013). Information that stands out and seems relevant affect human decision-making (Dolan et al., 2010). Human behaviour is thus influenced by what comes to mind when evaluating options in decisions making. The human memory of experiences is found to be governed by the most intense 'peak' moments and final impressions in a chain of events (Kahneman, 2013). Information that stands out and seems relevant affect human decision-making (Dolan et al., 2010). Human behaviour is thus influenced by what comes to mind when options are being considered for decision making.

Salience explains why unusual, extreme or unexpected experiences appear more significant to the consumer. So, the most prominent (desirable or undesirable) experience with a travel mode can have a disproportionate influence on behaviour.

The most remarkable experience, such as any incidents of passenger annoyance or anti-social behaviour experienced by a passenger on a bus could have a profound consequence on their future travel behaviour (Kahneman, 2013). Such undesirable experiences create negative valence (Resnick, 2012) and negatively reshape future travel decisions (Dobbie et al., 2010; Metcalfe and Dolan, 2012).

Therefore, this variable seeks to investigate the public transport user experience and its effects on ridership. A survey instrument is designed based on reported passenger experiences on public transport (Dobbie et al., 2010; Beirao and Cabral, 2007). The instrument is in two parts; in the first part, respondents were asked to indicate how discouraging they will be if they encounter the outlined experiences on public transport. Indicators for this effect are measured on a five-point Likert scale (1=Not Discouraging, 5=Very Discouraging). Whiles the second part requests respondents to evaluate the extent to which the experiences could affect or have affected their loyalty to public transport. This aspect of the tool is measured on a five-point Likert scale (1=Not at all, 5=Very much). The experiences investigated includes; *"Anti-social behaviour (drunk people et cetera)", "Poor hygiene (service uncleanliness and smell on the buses)", "Inaccurate bus and real-time information".* Question 20 in Appendix A presents the measurement instrument for this construct.

Affect

This section seeks to understand the role of Affect on respondents' travel choices. Affect is defined as "*an automatic response to a good or bad experience*". Affect is an omnibus term and refers to four different states; Sentiments, Moods, Emotions and Affective Styles (Davidson et al., 2009). These affective states could have a transient or lasting effect on the subject and can influence behaviour consciously and unconsciously. This discussion is limited to the affective state of sentiment and its influence on travel behaviour for this study.

Sentiment is an emotion an individual attaches to a product as a result of his/her interaction with the product. This could be described either as positive valence (such as satisfaction or joy) or negative valence (such as embarrassment, anger or frustration) (Resnick, 2012). Loewenstein (2000) suggest that intensely negative sentiments can be very influential and can overrule otherwise rational plan of action even in the presence of cognitive information that would suggest alternative courses of action (Loewenstein et al., 2001). Sentiment attached to a product becomes difficult to detach and influences the desirability of the product (Rozin et al., 1986). Elster (1998) found that decision-makers also evaluate their choice sets emotionally aside economic utility.

The study, therefore, hypotheses that the sentiments associated with public transport by users could impact its desirability or ridership negatively or positively. To this, the study developed a measurement scale to investigate public transport user sentiment and its impact on ridership. Inspired by the findings in Elster (1998) and Han and Lerner (2012), an instrument was designed to measure respondents sentiments towards PT. The measurement indicators include; *"I feel uncomfortable travelling in the local bus with strangers", "I am happy using public transport because I can use the travel time for* *other activities"*. Participants were requested to indicate the extent to which they agree or disagree with each of the statements on a five-point Likert scale with endpoints (1 = Strongly Disagree; 5 = Strongly Agree). Refer to question 21 in Appendix A for the full measurement tool.

Narcissism or Ego

Narcissism has recently attracted a lot of research attention. Several studies have investigated the impact of narcissism on consumer behaviour (Cisek et al., 2014; Morf and Rhodewalt, 2001; Graves, 1968). Literature suggests that the consumer behaviour of a narcissist is based on the symbolism of consumer products rather than utility maximisation (Cisek et al., 2014; Gregg et al., 2013; Sedikides et al., 2007). Therefore the study hypothesis that "narcissist will select transport modes that will enhance their social identity and sense of uniqueness." Raskin and Terry (1988) developed a 40-item Narcissism Personality Inventory (NPI-40)for measuring narcissism as a personality trait. NPI-40 scale consists of forty paired statements for respondents to select the statement they closely related to their feeling. NPI-40 was subsequently refined to a 16-item scale referred to as NPI-16 by Ames et al. (2006). The author developed the 16-item scale (NPI-16) out the original 40-item measurement scale.
However, very little is known about the relationship between narcissism or ego and travel behaviour (Metcalfe and Dolan, 2012; Aczél and Markovits-somogyi, 2013). Therefore, NPI-16 is adapted and included in the survey to measure the narcissism score of respondents and investigate its relationship with their travel behaviour. The NPI statements adapted include; *"I like having authority over people"*, *"I find it easy to manipulate others"* and *"I am apt to show off if I get the chance"*. All the statements were measured on a five-point Likert scale with the following defined endpoints; 1 = Strongly Disagree and 5 = Strongly Agree. Refer to question 24 of Appendix A for the NPI measurement scale.

4.4.5.3 Socio-Demographic Characteristics

The survey instrument was concluded with questions on respondent's demographics. This section seeks to acquire information necessary to understand respondent's socio-economic status. Demographic questions relating to the following information were posed to participants; gender, age, marital status, highest education level and annual income (household) as well as employment status and household size. This information is used in conjunction with other relevant factors to investigate travel mode choices.

4.4.6 Pilot Survey

Pilot surveys were conducted to assess the appropriateness of the survey instrument concerning clarity, logical sequence, length and to solicit experts' feedback before doing the main survey. The pilot survey was in two phases involving:

- Phase one: Solicit expert opinion and feedback on the suitability of the draft survey instrument discussed in the preceding section.
- Phase two: Collect sample data from a small sample among the study population after the expert review to assess respondents understanding of the questions, assess the adequacy, validity, and reliability of the constructs for measuring the behavioural variables.

4.4.6.1 Expert Interview

Before the pilot data collection, experts opinions were solicited on the suitability of the data acquisition instrument. One of the major concerns at the stage was the identification of qualified participants. Hence, a purposive sampling technique was applied for the selection of participants for this purpose. The main criteria for the selection were the theoretical perspective of the study and the knowledge and research area of the participants.

The purpose of the survey was to acquire participants opinion of the survey instrument and identify potential pitfalls and consequently, improvements in the wording and presentation of the questionnaire.

Four experts were selected and contacted to participate in the survey and interview, Four experts from the fields of Psychology, transport psychology, transport economics and transport planning participated in the survey and provided feedback on the various parts of the survey instrument. One of the expert participants highlighted and discouraged the use of double-barrelled questions, most notably among the psychometric indicators; consequently, some of the psychometric indicators were revised.

4.4.6.2 Pilot Data Collection

A simple pilot survey was conducted to test the survey instrument before the actual survey. The survey was intended to assess respondents understanding of the questions, to help improve the questionnaire and assess the validity and reliability of the constructs for measuring the behavioural variables. The survey was conducted among research students and staff of the Edinburgh Napier University, and friends in October 2017 using QuestionPro online survey software. A total of 60 people were selected at random and invited to take part in the survey.

Again, the purpose of this pilot survey was to acquire respondents' opinion about the survey instrument and to identify potential drawbacks in the survey instrument to improve the questionnaire. Additionally, to assess the validity and reliability of the survey instrument and to establish the duration for the survey.

4.4.6.3 Results of the Pilot Survey

In general, the pilot survey indicated that the respondents reasonably understood the questionnaire, the questionnaire was clear, logical, and the presentation was satisfactory. Out of the 60 invited people to participate in the survey, 45 participants representing 75% of the number contacted completed the survey. The finding of the pilot survey and the problems noted in the questionnaire are presented below.

Table 4.5: Descriptive statistics

Education	
None	2.2%
High School	18.7%
College	15.1%
Bachelors	36%
Masters	23.7%
PhD	3.6%

Employment Status	
Students	7%
Employed (FT)	51%
Employed (PT)	15%
Retired	22%
Unemployed	5%

Modal Share	
Walking	21%
Bicycle	9%
Car	31%
Public Transport	38%
Other	1%

Table 4.5 shows that 31% and 38% of respondents of the pilot survey were found to be car and PT users, respectively. The estimates did not deviate from similar statistics from the Transport Scotland statistics, which reports 29% for car users (Transport Scotland, 2017). Consequently, the Transport Scotland (2017) figures were adopted for estimating the minimum sample requirement for the study. Some respondents were concern about the length of some of the questions, the length of the instrument and the duration of the survey.

4.4.6.4 Final Questionnaire Design

After the pilot survey, it was observed that respondents understood the wording and layout of most of the questions. However, following the concerns about wordy questions and overall length of the survey, some of the questions were rephrased and other omitted to reduce length and time required for the survey. Moreover, respondents were noted be consistent in their responses to the psychometric indicators for measuring narcissism. Following this, it was decided to change the layout and format of this part of the survey instrument to better capture respondents' responses more accurately, this is presented the following paragraphs. The final version of the questionnaire is included as Appendix A.

1. **Age**: A text box was provided for respondents to supply their age instead of selecting from a predefined age band.

2. **Narcissism**: Respondents were presented with a list of 16 pairs of opposite statements, one in Column A and the opposite in Column B. respondents were then

asked to select statements from either column that best describe them (Ames et al., 2006). However, it was observed that almost all respondents selected the same answer, possibly due to the negative undertone of the statements (Sam, 2011). Consequently, this section of the measurement instrument was revised for respondents to indicate the extent to which they identify with each of the narcissistic statements on a five-point Likert scale (1= Strongly Disagree, 5= Strongly Agree).

4.5 Method of Data Analysis

4.5.1 Introduction

Statistical analysis is carried out on the sample data to explore the possible relationships among the variables. Kruskal-Wallis Test and Mann Whitney U-test were used to investigate the relationship between active travellers, cars users and public transport users. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted using SPSS statistical package and AMOS Structural equation modelling (SEM) software package, respectively. Additionally, Integrated choice and latent variable model (ICLV) was developed using Pandas Biogeme software (Bierlaire, 2018b; Bierlaire, 2018a). These statistical measures are briefly discussed below.

4.5.2 Kruskal-Wallis Test and Mann Whitney U-test

The Kruskal-Wallis Test and Mann-Whitney U test are non-parametric methods for comparing independent samples of equal or different sample sizes (McKight and Najab, 2010; Singh et al., 2013). A Mann-Whitney U test (sometimes referred to as Mann-Whitney-Wilcoxon test or the Wilcoxon rank-sum test) allows analysis to be run on non-normally distributed data (Singh et al., 2013). A Mann-Whitney U test puts everything in terms of rank rather than the raw values; this allows analysis to be run on non-normally distributed data (Chan, 2003). The test ranks everything, sums the ranks and ultimately produces a statistic which indicates whether the two (or more) sub-populations within the sample likely came from the same underlying population. The major difference between the Mann-Whitney U and the Kruskal-Wallis H is that the former can handle only two categories whiles the latter can accommodate more than two groups (Vargha and Delaney, 1998).

4.5.3 Factor Analysis

Factor analysis (FA) is a statistical technique for transforming a multivariate observation in a dataset into single or smaller variables or principal factors (latent variables). A latent variable is an unobserved underlying concept that influences the responses of two or more of the observed variables (Chong et al., 2014). The latent variables also account for the correlations between these observed variables (Brown and Moore, 2012). FA therefore assist in establishing the underlying relationship between the latent constructs and their observed multivariate variables. This produces a more manageable and understandable variables or factor capable of defining a psychological concept or behavioural traits (Richardson et al., 1995). Factor analysis provides a useful tool for investigating the reliability and validity of the measurement constructs used. It is quite robust in handling very complex sets of data and relationships involving psychological concepts and unobserved variables. For instance, a person's level of 'ego' or 'subjective norm' cannot be measured directly by a single indicator question. These concepts and others of similar nature can only be measured using multiple indicator questions. Factor analysis is required for confirming the questions measuring the latent constructs and establish their validity and reliability. There are two forms of factor analysis, namely Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) (Joreskog, 1969) cited in (Brown and Moore, 2012). It is a very useful tool for consolidating large number of variables into relatively fewer constructs capable of explaining complex phenomenon.

4.5.3.1 *Exploratory Factor Analysis*

Exploratory Factor Analysis (EFA) is a descriptive data reduction technique that is used in the development and validation of assessment instruments (Ruscio and Roche, 2012). EFA is thus used to explore the data to determine the number of dimensions present in the dataset and the extent of the relationship between the observed indicator variables and the unobserved underlying latent construct (Byrne et al., 2012). The main objective of EFA is to reduce of the number of dimensions in the original data (Baglin, 2014). However, the decision concerning the number of factors to retain in the factor analysis is arguably most important than the rotation and extraction method to adopt Zwick and Velicer, 1986. Evidence indicates that over-extraction or under-extraction can affect the measurement scale and significantly alter the factor solution and interpretations of the EFA results (Schönrock-adema et al., 2009; Velicer et al., 2000; Courtney, 2013). Therefore, the estimation of the number of factors to retain during EFA is of utmost importance and must be handled with care. There are several methods for estimating the number of factors to retain, the most popular methods include: eigenvalue greater than one rule (KI rule), the Scree test, Parallel Analysis, et cetera.

In general, the KI rule theorises that factors with eigenvalue greater than 1 should be retained and those with eigenvalue below 1 rejected (Kaiser, 1960). The KI rule is the default procedure for determining the number of factors to retain in EFA in most statistical softwares, notwithstanding, the approach has been criticised as being too restrictive for models with many variables. Additionally, the rationale for retaining a factor with eigenvalue of 1.01 as important and a factor with eigenvalue of 0.99 as insignificant is questioned (Courtney, 2013; Garrido et al., 2013).
Cattel's scree plot approach lists all eigenvalues in decreasing order and plot a graph of the eigenvalues on the y-axis and all the factors on the x-axis (Cattell, 1966). The rationale is to retain all factors above a point of inflexion or elbow. Since it is believed that a few major factors will account for the most variance, resulting in a "cliff", followed by a "scree" of minor factors with relatively small variance. Zwick and Velicer (1986)

found that this method performs better than the KI rule, but further alluded that the selection of the number of factors to retain can be subjective when there is no clearly defined inflection point especially when there is minimal variation in the estimated eigenvalues (Garrido et al., 2013; Courtney, 2013).

The Parallel Analysis (PA) method is developed based on the KI rule (Garrido et al., 2013; Horn, 1965). PA accounts for the proportion of variance resulting from sampling error. It is one of the highly recommended techniques for estimating the number of factors to retain in EFA (Horn, 1965; Zwick and Velicer, 1986; Courtney, 2013; Ruscio and Roche, 2012; Garrido et al., 2013). The PA method generates a large number of data matrices at random. Each matrix is generated with the same number of cases and variables as the sample data under investigation to estimate eigenvalues. Factors from the EFA with eigenvalues greater than the eigenvalues of the PA should be retained (Horn, 1965).

Total Variance Extracted is another selection method. The literature varies on how much variance should be explained before the number of factors is sufficient. While several researchers recommend factors to account for between 75 - 90% of the variance, others indicate a minimum of 50% is acceptable. The amount of variance explained by the extracted factors must adequately represent the data and theory (Beavers et al., 2013; Schönrock-adema et al., 2009). The following recommendations are adopted for the EFA:

- Extraction method: ML extraction
- Factor retention method: Combination of KI, PA and Total variance extracted methods
- Rotation: Oblique rotation (preferably Promax to generate correlated factors)

4.5.3.2 Measures of Sampling Adequacy

Several statistical test are required to establish the suitability and validity of the data for factor analysis before factor extraction is executed, Kaiser-Meyer-Olkin (KMO) test and

Bartletts test of Sphericity are the recommended statistical techniques for the task of assessing the adequacy and suitability of the data for factor analysis prior to extraction (Williams et al., 2010).

Kaiser-Meyer-Olkin Test: Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is based on the correlation matrix and tests the adequacy of the sample for factor analysis, it tells whether there are sufficient items for each factor regarding the partial correlations among the variables or distribution of the value for the application of factors analysis (Kaiser, 1970; Kaiser, 1974; Williams et al., 2010). Kaiser-Meyer-Olkin (KMO) index of factorial simplicity ranges between 0 and 1 with an index above 0.5 considered suitable for factor analysis (Kaiser, 1970; Williams et al., 2010). Kaiser (1974) defined the following levels of evaluation of KMO index of factorial simplicity as follows; index below 0.5 as unacceptable, index between 0.5-0.7 as mediocre, index between 0.7-0.8 as good, index between 0.8-0.9 as meritorious and index above 0.9 as excellent (Kaiser, 1974; Hutcheson and Sofroniou, 1999; Field, 2013). 0.5 is the boundary line of acceptability and so KMO index below 0.5 is unacceptable and suggest that the sum of the partial correlation among variables is very large relative to the sum of the correlations, suggesting diffusion in the pattern of the correlation and therefore factor analysis would not be valid, on the other hand, KMO index above 0.5 and approaching 1 suggests that the pattern correlation are compact, hence factor analysis would produce unique and reliable factors (Kaiser, 1974). KMO index of factorial simplicity of 0.7 (good) is adopted for this study.

Bartletts test of sphericity: The Bartlett's statistics test the sufficiency of the level of correlation of the original variables and determine whether the correlation matrix is significantly different from an identity matrix. Smaller p-value (i.e. $p < 0.05$) indicates that the data is adequate for factors analysis; thus, the test establishes the existence of correlation between the variables (Field, 2013). The success of the Bartlett's test of sphericity depends on the sample size.

4.5.4 Structural Equation Modelling

Structural equation modelling (SEM) is another name for Latent variable and path analysis, structural analysis, and causal modelling. SEM is a technique for testing hypothesis about the relationship between observed multivariate variables and the unobserved underlying concepts (latent variables) (Maruyama, 1998a; Miles, 2005). This method of modelling uses statistical techniques for investigating the relationship between unobserved (latent) variables or construct measured by multiple manifest (observed) indicators variables (Khine, 2013). SEM combines regression analysis and factor analysis to offer convenient means of studying complex patterns of relationship in data and simultaneously estimate both discrete choice and latent variable aspect of a model. SEM can also model the latent construct separately (Steenkamp and Baumgartner, 2000). The purpose of this modelling approach is to describe the structure of data and simplify it for easy understanding and interpretation, hence specifying the relationship between variables in a data (Muthén and Muthén, 2010). In behavioural science, researchers are often interested in studying hypothetical constructs that cannot be observed directly. These abstract phenomena are termed latent variables i.e. comfort, safety, flexibility, convenience, norms, ego commitment, affects et cetera. Since these variables cannot be measured directly with a single indicator variable, they are measured using multiple observable variables that explain them (Byrne et al., 2012). SEM also offers the researchers the opportunity to assess the validity and reliability of data under investigation.

4.5.4.1 Confirmatory factor analysis

Confirmatory factor analysis (CFA) is a technique for testing hypotheses based on the framework of structural equation modelling (SEM) (Bryne, 2012; Miles, 2005; Maruyama, 1998b; Hoyle, 1995). CFA is employed to confirm and validate the latent constructs specified during the EFA. The main advantage of using CFA is that the factor-solution is useful for further advanced analysis (Discrete choice modelling, et cetera.). Confirmatory factor analysis in AMOS program was used for confirming the latent constructs obtained during the initial EFA analysis. As discussed under section 6.7: Missing Data Treatment, Maximum Likelihood Estimator (MLE) available in SPSS and AMOS software packages was adopted for both the EFA, the CFA and the Choice Modelling (Muthén and Muthén, 2010; Temme et al., 2008b).

Evaluation of CFA and SEM: After the exploratory factor analysis, it is essential to establish the suitability of every variable and all latent constructs in the measurement model before undertaking any further analysis. The following assessments are done prior to the SEM or CFA operation; test of Unidimensionality, test of validity and the reliability test.

Unidimensionality: Unidimensionality refers to the situation where observed factors load satisfactorily on their respective latent construct. It is recommended for a newly developed item to have factor loading of 0.5 or higher and 0.6 or higher for an already established item. Any observed variable with factor loadings less than the threshold above must be deleted from the measurement model

Validity: Validity is the ability of an instrument to measure what it is designed to measure. This is established using CFA (Joreskog, 1969). CFA establishes the uniqueness of each latent construct and the extent to which each pair of latent constructs share their variance. Three procedures have been developed for assessing the overall validity of latent variables; convergent validity, divergent validity and construct validity, (Campbell and Fiske, 1959; Fornell and Larcker, 1981; Bagozzi, 1988; Shiu et al., 2011; Bahaman, 2012).

Convergent validity assesses the extent to which the indicator variables explain the variation in their latent construct. According to Fornell and Larcker (1981), convergent validity can be assessed by computing the Average Variance Extracted (AVE) for each latent construct. The AVE measures the average amount of variation a latent construct explains in its observed variables. In other words, AVE is the correlation between a latent construct and its observed variables. For instance, if a latent variable A is measured by variables x1, x2 and x3, then A should correlate with x1, x2 and x3. This correlation

(Li) between A and its observed variables is the factor loading. The square of each correlation explains the amount of variation in each observed variable that the latent construct accounts for. The AVE of the latent construct is thus, the average of all the sum of the squared correlation/factor loading measuring that construct (Fornell and Larcker, 1981; Farrell, 2010; Bahaman, 2012). Mathematically, AVE can be expressed as:

$$AVE = \frac{\Sigma Li^2}{n} \tag{4.6}$$

Where;

Li: Factor loading for every indicator variable

n: Number of variables in the latent constructs

Simply stated, variables used for measuring the same construct should strongly converge on the construct. To achieve convergent validity, the value of the AVE computed for each latent construct must be greater than 0.49 (Fornell and Larcker, 1981) and the factor loading for each indicator variable for the construct must also be greater than 0.50. The rationale behind the above condition is that, measurement error should not be greater than the variance explained by the latent construct (AVE less than 0.50) (Rourke and Hatcher, 2013).

Discriminant validity is analogous to testing for multicollinearity among independent variables in a multivariate analysis. It establishes the distinctiveness of each latent variable from other latent variables within a CFA model (Bahaman, 2012). It measures the inter-factor correlation in a pooled measurement model. The fundamental justification for this procedure is that every latent variable should be unique and not correlated highly with other latent constructs. Theoretically unrelated constructs should not correlate with each other in the measurement model (Fornell and Larcker, 1981; Shiu et al., 2011; Bahaman, 2012). A test displays discriminant validity when it can be demonstrated that it is not measuring a construct that it was not designed to measure. Indicators designed to assess one latent construct should not be measuring a different latent construct (Rourke and Hatcher, 2013). Three methods have been proposed and widely accepted for assessing divergent validity in CFA (Shiu et al., 2011).

The first procedure is the average variance extracted (AVE) versus shared variance test. According to Fornell and Larcker (1981), discriminant validity is assessed by comparing the average variance extracted (AVE) for every latent construct and its shared variance with other latent constructs in the measurement model. The AVE of each latent construct should be higher than the value of the squared correlation (shared variance) with any other latent constructs in the model (Fornell and Larcker, 1981; Shiu et al., 2011). The fundamental justification for this procedure is that every latent variable should be unique, having a strong correlation with its indicator variables than with any other latent variable in the model, also the correlation involving other latent variables should be smaller than 0.85 (Bahaman, 2012).

The second procedure, the paired constructs test, is attributed to Bagozzi and Phillips (1982) and Anderson and Gerbing (1988). The test compares the chi-square value between a constrained model (the parameter estimates for two factors is constrained to 1.0) and an unconstrained model (the parameter estimates are freely estimated) for each pair of constructs. Discriminant validity is achieved if the difference in chi-square value is more than 3.84 (Bagozzi and Phillips, 1982; Farrell, 2010; Shiu et al., 2011). The third procedure also proposed by Bagozzi et al. (1991), estimates the confidence interval for the correlations between the latent variables. If the 95% confidence interval for the correlation between a pair of latent variables contains zero but not unity, then the pair of latent variables are distinct and discriminant validity is achieved. The last two procedures consider sampling error in determining discriminant validity (Shiu et al., 2011).

A review by Shiu et al. (2011), on divergent validity found the Fornell-Larcker criterion for evaluating divergent validity (Fornell and Larcker, 1981) as the widely accepted and used procedure in literature (Henseler et al., 2014). Consequently, the first method is adopted for assessing the validity of the latent constructs in this study.

Construct validity is achieved when the Fitness Indexes for a construct achieves the required level.

Reliability: The reliability of an indicator variable is defined by Rourke and Hatcher (2013) as "the square of the correlation between a latent factor and its indicators or the percent of variation in the indicators that is explained by the factor it is supposed to measure". Thus, reliability measures the internal homogeneity of the measurement instrument (all indicators) used for measuring a construct. It evaluates how much of the variation in scores is attributable to random error. Similarly, an instrument is said to be reliable if it produces consistent scores upon repeated administration or by alternate forms. The following tools are used for assessing the reliability of construct and their indicator variables; Average Variance Extracted (AVE), Coefficient alpha (α) and Composite reliability (CR).

Average Variance Extracted: A measurement scale is reliable if the Average Variance Extracted (AVE) > 0.49. (for details; refer to the section under validity)

Coefficient alpha: The coefficient alpha (α) is the estimation of the internal consistency of a multiple-item scale and a measure of the reliability of the measurement scale (Cronbach, 1951). For internal reliability, coefficient alpha (α) (Cronbach's Alpha in SPSS) of 0.70 is an adequate indication of the internal consistency of the latent variable (Kline, 2011).

Composite reliability: The composite reliability index (CR) is comparable to the coefficient alpha and reflects the internal consistency of observed indicators measuring the latent construct. Composite reliability is achieved if CR ≥ 0.70. Composite reliability is estimated with the formula below:

$$CR = \frac{(\Sigma Li)^2}{[(\Sigma Li)^2 + \Sigma(1 - Li^2)]} \tag{4.7}$$

Where;

Li = Standardize Factor loading of every indicator variable

$1 - Li^2$ = error variance of every indicator variable Var(Ei)

Assumptions

The reliability of structural equation modelling like statistical procedures such as generalized least-squares estimation depend on the data satisfying some basic assumptions.

First of all, the sample size must be adequate. Secondly, the observations must be independent and finally, the data must meet multivariate normality assumption (Kline, 2011; Bahaman, 2012; Arbuckle, 2017).

Sample Size Adequacy: (Refer to sub-section 4.4.3 for details)

Multivariate normality: In many statistical procedures, such as linear regression and generalised least squares, the distribution assumption is that the residuals should be normally, identically and independently distributed (Kline, 2011; Arbuckle, 2017). This is necessary to produce valid estimates of the coefficients and p-values for the t-tests. Violation of this assumption will result in invalid estimates, biased coefficients and misleading results. This assumption also holds for CFA and structural equation modelling. The normality of the data needs to be evaluated after assessing the fit indexes during the CFA before conducting any further analysis (Kline, 2011; Arbuckle, 2017; Bahaman, 2012).

Normality is assessed by evaluating the skewness value for each item and the multivariate kurtosis statistic. Normality is achieved when the absolute value of skewness is not greater than 1.0. However, Maximum Likelihood Estimator (MLE) is robust to skewness and multivariate kurtosis statistic violation, if the sample size meets the minimum threshold (Bahaman, 2012). Thus, we could proceed with the CFA when the sample size is large enough, even when the data fails the normality test (refer to section 4.4.3) (Bahaman, 2012).

Assessing normality in Amos: One of the techniques useful for identifying outliers when multivariate normality assumption is violated is the Mahalanobis distance (Mahalanobis, 1936). Mahalanobis distance is the estimate of the deviation of each observation from the centroid of the dataset. The farthest observation from the centroid of the dataset defines potential outliers. Outliers are observation too far from the centroid compared to majority of cases in the dataset. We may delete any observation with Mahalanobis distance having a low p-value ($p < .001$) (Kline, 2011; Bahaman, 2012).

Extreme outliers are called influence because of the impact they have on the model estimates. Deleting influence in the dataset could substantially change the estimate of coefficients. Notwithstanding, we can retain outliers and influence and continue with the CFA if; 1) the method of estimation used is the Maximum Likelihood (ML) and 2) Bootstrapping is used to confirm and validate the results (Bahaman, 2012). Moreover, since ML is adopted for the model estimation, this condition is ignored.

Model Fit Statistics

Structural equation modelling and CFA, unlike traditional statistical methods, utilise several fitness statistics to evaluate how well the hypothetical model explains the data, known as model fit. These statistics examines whether the covariance matrix of the hypothetical model of the researcher is close enough to the covariance matrix of the data under investigation. Reasonable disparities might be attributed to sampling error. Otherwise, the researcher must explain the differences if they exceed a recommended threshold or the hypothetical model should be rejected for failing to explain the data (Kline, 2011).

The knowledge of which model fit indices to report and the thresholds to adopt is essential in the application of structural equation modelling. Model fit indices and threshold to report has stimulated debate among researchers in the field of structural equation modelling (Kenny and McCoach, 2003; Marsh et al, 2004). (Barrett, 2007). Hu and Bentler (1999) appraised the fit indices with their thresholds and recommended the following indices RMSEA, CFI, SRMR, NNFI and TLI.

A similar study by McDonald and Ho (2002) supported Hu and Bentler (1999) in part; the authors found CFI, GFI, NFI and NNFI were widely reported in the literature and recommended them. A review by Hooper et al. (2008) on fit indices also recommended the RMSEA, SRMR, CFI, one parsimony index like PNFI and the model chi-square with its degree of freedom and p-value. Hayduk et al (2007) and Kline (2011) support the assertion of Hooper et al. (2008) concerning the reporting of the chi-square statistics. However, (Kline, 2011) further explained that the chi-square statistics should only be reported if the Maximum Likelihood (ML) is not the estimation method used. Several authors, including Arbuckle (2017) recommend reporting the relative/normed chi-square statistic instead of the chi-square statistic because the latter is sensitive to sample size. However, Kline (2011) disagrees with Arbuckle (2017) on the reporting of relative/normed chi-square statistic. According to Kline (2011), chi-square sensitivity to sample size only applies to incorrect models.

The fit indices can be categorised into three main groups, namely, absolute fit indices, incremental fit indices and parsimonious fit indices. Hair et al. (2010) recommend reporting at least one index from each category because each give different information about the model. They provide a more reliable evaluation of model fit when used together (Brown and Moore, 2012). Because it is not practical to report every index reported by the Amos SEM software, it is reasonable to select indices based on the recommendations above, while ensuring representation from each of the three categories. Thus, we limit the scope of this review to the universally recommended indices for assessing model fit, namely, RMSEA, GFI, CFI, NFI, SRMR, PNFI and the Relative chi-square. The selected indices are less sensitive to sample size and parameter estimates. The chi-square statistics is not reported in the document because the estimation method is based on ML (Kline, 2011).

Absolute fit indices: Absolute fit indices measure the degree to which a model fits the data compared to no model at all (Jöreskog and Sörbom, 1993; Hair et al., 1998)[p.683]. These indices largely provide information on the proportions of the covariance matrix of the data accounted for by the researcher's hypothetical model (Kline, 2011). Absolute fit indices provide a fundamental indication of how well the proposed theory fits the data and demonstrate which proposed model has the most superior fit. Absolute fit indices included in this category are presented below. The frequently used and recommended indices in literature are shown in italics; Chi-square test, RMSEA, PClose GFI, AGFI, RMR and SRMR.

Model chi-square (x^2): The chi-square is another name for discrepancy function and likelihood ratio chi-square. However, it is called the minimum discrepancy (CMIN) in AMOS with maximum likelihood estimation (MLE). The Chi-Square value measures the overall model fit; it evaluates the level of discrepancy between the data and the fitted covariances matrices Hu and Bentler, 1999. A good model fit must be insignificant at 0.05 probability (Barrett, 2007; Rourke and Hatcher, 2013). The model perfectly fits the data if the chi-square (x^2) value equals zero (just-identified model) but this not so for models with degrees of freedom equals zero (Kline, 2011).
The chi-square test has several limitations, including the assumption of multivariate normality; the violation of this assumption may lead to model rejections (McIntosh, 2007). Secondly, the chi-square statistics is sensitive to sample size. Bentler (1990); Jöreskog and Sörbom (1993) found that larger sample size in most cases results in model rejection. Small sample size is similarly observed to produces unreliable statistics. Researchers are advised to ignore the chi-Square statistics if the sample size exceeds 200 threshold (Bahaman, 2012). As a rule of thumb, a good fit model should return a smaller chi-square value and large p-value (p-value >0.05); otherwise, the data does not support the model, and the null hypothesis of good fit is rejected (Rourke and Hatcher, 2013). Therefore, the chi-square (x^2) statistics is regarded unsuitable in this study on the advice of (Bahaman, 2012) because the sample size exceeds 200.

Root mean square error of approximation (RMSEA): RMSEA is a parsimony adjusted index with 90% confidence interval. It is one of the most informative and reported absolute fit indices in literature. RMSEA is related to residual in the model and sensitive to sample size and degree of freedom (Kline, 2011). RMSEA has an acceptable cut-off range of 0.0 to 0.06; zero indicates best fit and 0.06 the maximum threshold. RMSEA values below 0.06 suggestive of a better model fit. (Hu and Bentler, 1999; Kline, 2011). RMSEA is mathematically expressed as;

$$RMSEA = \sqrt{\frac{x_M^2 - df_M}{df_M(N-1)}} \tag{4.8}$$

Where;

x^2_M is the model chi-square

df_M is the model degree of freedom

N is the sample size

RMSEA = 0, if $x^2_M \leq df_M$. However, this does not always indicate perfect fits ($x^2_M = 0$). The denominator of the expression indicates that RMSEA decreases with increasing parsimony (larger degree of freedom) and increasing sample size. The effect of the parsimony correction factor disappears as the sample size gets larger (Kline, 2011). The estimation of the confidence interval around the RMSEA values provide an avenue for testing the null hypothesis more precisely (McQuitty, 2004).

PClose: PClose is based on the RMSEA; it is the calculation of the p-values for testing the null hypothesis that the population RMSEA ≤ 0.05 (Browne and Cudeck, 1993). The researchers found that RMSEA of 0.05 or less was suggestive of a good fit. They further proposed that PClose greater than 0.05 (not significant) indicates that the fit of the model is "close". Therefore, if PClose is less than 0.05, then the model is poorly fit (RMSEA > 0.05). Failure to reject the null hypothesis means the proposed model is well fit. However, like any significance test, the model's degree of freedom (df) and sample size are critical factors, the power of the test reduces with lower df Kline, 2011; Arbuckle, 2016.

Root mean square residual: The RMR is the square root of the average of the difference between the observed covariance matrix and the predicted covariance matrix of the evaluated model. RMR value of zero is indicative of a perfect fit but unbounded at the upper limit because RMR computation is based on the scale of each indicator. This makes it difficult to interpret (Hooper et al., 2008; Kline, 2011). The standardised RMR (SRMR) account for the limitation above and limit the maximum threshold to 1.0. The values of SRMR ranges from 0 to 1.0. SRMR should not exceed 0.08 for acceptable fit (Hu and Bentler, 1999). However, values not greater than 0.05 are preferable (Byrne et al., 2012).

Incremental fit indices: Incremental or Comparative fit indices do not measure model adequacy in any absolute terms but relatively. They indicate the relative fitness of the hypothetical model to the data compared with a statistical baseline model. The baseline model is usually a null model, which assumes that all latent variables are uncorrelated (McDonald and Ho, 2002; Kline, 2011). In simple words, incremental indices tell the performance of the proposed model compared with a statistical worst model. Comparative fit indices include the following frequently used and recommended indices in literature are shown in italics; Normed-fit index (NFI), Comparative fit index (CFI) and Tucker-Lewis Index (TLI).

Normed Fit Index: The Normed Fit Index measures the discrepancy between the model being evaluated and a baseline model (terribly fitting model). NFI compares the model's Chisq (x^2) value to the Chisq (x^2) value of the null model. The values of NFI ranges from 0 to 1. (Hu and Bentler, 1999) recommends a minimum threshold of 0.90. NFI is sensitive to sample size and less reliable when the sample size is less than 200 (Kline, 2011).

Comparative fit index (CFI): The Comparative Fit Index (CFI) is similar to the NFI and the most reported incremental index in literature. It was proposed by Bentler, 1990 to cater for the limitation of the NFI. CFI adjust for sample size and degree of freedom (Byrne et al., 2012). It returns reliable indices even with smaller sample size (Tabachnick and Fidell, 2007). The CFI, like all incremental indices, compares the sample covariance matrix with the statistical baseline model and assumes that all latent variables are uncorrelated (Kline, 2011). CFI ranges between 0.0 and 1.0 with values closer to 1.0, indicating better fit. CFI value of 0.90 or greater is indicative of a good mode fit. $CFI = 1$, if $x_M^2 \leq df_M$. However, this does not always mean perfect fits ($x_M^2 = 0$)

$$CFI = 1 - \frac{(x_M^2 - df_M)}{(x_B^2 - df_B)} \tag{4.9}$$

Where;

x^2_M is the chi-square of the default model

df_M is the degree of freedom of the default model

x^2_B is the chi-square of the baseline model

df_B is the degree of freedom of the baseline model

Tucker-Lewis Index (TLI): The Tucker-Lewis Index is also known as the Non-Normed Fit Index (NNFI). The TLI was developed to correct the limitation of the NFI. TLI is computed as follows:

$$TLI = \frac{\frac{x^2}{df_{(NullModel)}} - \frac{x^2}{df_{(ProposedModel)}}}{\frac{x^2}{df_{(NullModel)}} - 1} \tag{4.10}$$

The value of TLI index is set to one if it is greater than one and when $x^2 = df$, we assume perfect fit. Similar to the NFI, TLI value of 0.80 is acceptable for a good model fit. However, TLI value of 0.90 or larger is recommended.

Parsimony fit indices: Comparatively, models having fewer parameters and larger degrees of freedom are described as high in parsimony while models with more parameters and a small degree of freedom are said to be saturated or complex. The parsimony ratio (PRatio) was proposed to correct for model complexity in the absolute fit indices and incremental fit indices which failed to account for it (James et al., 1982; Arbuckle, 2017). The indices account for the model degree of freedom (df_M). Parsimony indices favour simpler models and penalise saturated models. Given two models with an acceptable model fit to the same data, parsimony fit index would favour the simpler model with a higher degree of freedom (Kline, 2011; Rourke and Hatcher, 2013). The parsimonious-adjusted indices include PNFI, PGFI and PCFI. The PRatio was expressed as;

$$PRatio = \frac{d}{d_b} \tag{4.11}$$

Where;

d is the degrees of freedom of the evaluated model

d_b is the degrees of freedom of the baseline model

Multiplying PRatio with NFI, GFI and CFI discussed above, gives the parsimony-adjusted indices PNFI, PGFI and PCFI et cetera.

Relative chi-square: The relative chi-square also called the normed chi-square, was proposed to account for the effect of sample size on the chi-square statistics discussed above. The relative chi-square statistics is computed by dividing the model chi-square (x^2_M) by its degree of freedom (df) (Wheaton et al., 1977). This makes the index less sensitive to sample size. This statistics is estimated by dividing the minimum discrepancy (CMIN) by the degree of freedom (df) in AMOS software package when using maximum likelihood estimation (MLE) (Arbuckle, 2017).

$$Relative\ chisq = \frac{x^2_M}{d_f}\ or\ \frac{CMIN}{d_f} \tag{4.12}$$

Wheaton et al. (1977) proposed an upper limit of 5.0 for a reasonable fit model. Researchers are split in opinions on the acceptable ratio for this statistic. While some researchers share the views of Wheaton et al. (1977), others recommend a ratio of 2.0 (Bryne, 2012). However, the majority seem to favour a ratio in the range of 1 and 3 as suggestive of acceptable fit between the evaluated model and the sample data (McIver and Carmines, 1981; Tabachnick and Fidell, 2007; Arbuckle, 2017)

Table 4.6: Summary of reporting indices and their threshold

Category	**Fitness Index**	**Threshold**
Parsimonious Fit Indices	Relative Chisq	< 3
	PNFI	≥ 0.90
Absolute Fit Indices	Chisq	> 0.05
	RMSEA	< 0.06
	PClose	≥ 0.05
Incremental Fit Indices	NFI	≥ 0.90
	CFI	≥ 0.90
	TLI	≥ 0.90

4.6 Mode Choice Model Estimation

The study aims at developing an integrated Choice and latent variable model (ICLV) by incorporating the measured latent variables (MINDSPACE elements) as latent factors. This section describes the method for estimating the Choice models. The latent or hybrid choice model will be developed using the observed variables comprising the trip characteristics, attributes of the alternatives, characteristics of the decision-maker and latent variables from the confirmatory factor analysis (CFA). The next sections describe the specification of the models.

4.6.1 Model specification

This section presents the specification of the proposed model. Two models are developed and evaluated. Multiple choice model between PT, Car and NMT is developed and used as a base model to evaluate the ICLV models. The second model is a latent or hybrid choice model which incorporates the latent variables from the CFA.

4.6.1.1 Base Model

multinomial logistic (MNL) regression model involving three alternatives (PT, Car and NMT) is estimated without the latent variables and used as a baseline model to evaluate the ICLV model. The model is based on the logit framework which assumes that the error terms ε_{PT}, ε_{Car} and ε_{NMT} are iid Gumbel distributed. The utilities for the three alternatives (PT, Car and NMT) are shown in Eq. 4.13 to 4.15. The first alternative (PT) was used as the reference alternative (the Alternative specific constant (ASC) was normalised to 0) in the estimation. The variables in the model are scaled slightly different from the scaling in the questionnaire, detailed definitions of the variables are presented in chapter six. The Public transport (PT) alternative includes bus, tram, and train, private motorised mode (Car) consist of taxi, car as driver and passenger and the active modes (NMT), similarly comprises of walking and cycling. The utilities of the alternatives are assumed to be based on utility maximisation and presented below:

$$U_{PT} = ASC_{PT} + \beta_{cost} * Cost + \beta_{TT} * TravelTime + \beta_{Income} * Income + \beta_{Age} * Age + \varepsilon_{PT} \quad (4.13)$$

$$\begin{aligned} U_{Car} =& ASC_{Car} + \beta_{TT} * TravelTime + \beta_{NCars} * Carvail + \beta_{WTime} * WalkingTime \\ &+ \beta_{Work} * WorkTrip + \beta_{Dist} * Distance + \beta_{TrFreq} * TripFreq + \beta_{Gender} * Gender + \varepsilon_{Car} \end{aligned} \quad (4.14)$$

$$U_{NMT} = ASC_{NMT} + \beta_{Age} * Age + \beta_{Dist} * Distance(km) + \beta_{Edu} * Education + \varepsilon_{NMT} \quad (4.15)$$

4.6.1.2 Integrated Choice and Latent variable model

ICLV models are a new generation of choice models that expand on the standard choice models. ICLV models provide a mathematical framework for integrating discrete choice and latent variables models to account for the absent unobserved preference heterogeneity in the traditional discrete choice models. They allow the prediction of individual preferences and assess the impact of the unobserved heterogeneity involved in the decision-making process which are absent in the traditional discrete choice models (Bolduc and Alvarez-daziano, 2010; Mariel and Meyerhoff, 2016). The integrated choice and latent variable model of this thesis is developed by integrating the latent variables (i.e. Personal Norm, Affect, Salience and Exhibitionism) developed from the CFA into the discrete choice model discussed in the preceding section. This will accounts for the unobserved individual heterogeneity in the perception of safety, values, emotions and taste using the framework in Figure 4.2 and equation 3.9 (Refer to section 3.5 for details).

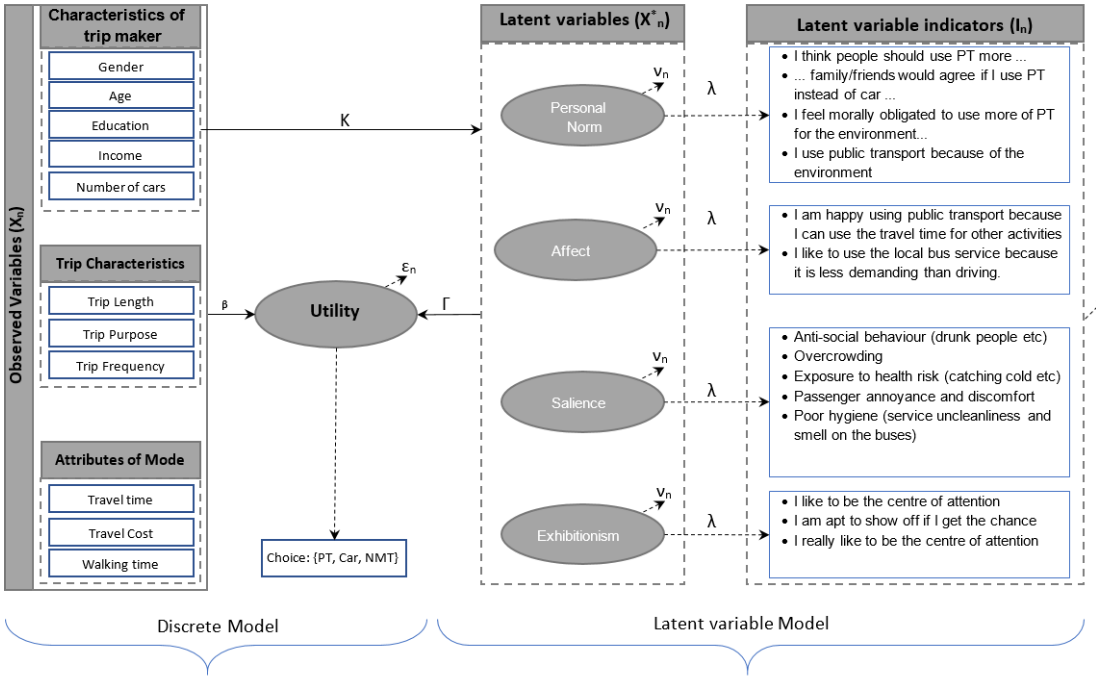

Figure 4.2: Integrated choice and latent variable model

Using the framework in equations 3.3 to 3.6 and the utility equations 4.13 to 4.15, The model can be written as:

$$\begin{aligned} U_{PT} = & ASC_{PT} + \beta_{cost} * Cost + \beta_{TT} * TravelTime + \beta_{Income} * Income + \beta_{Age} * Age \\ & + \Gamma_{Aff} * X^*_{Affect} + \Gamma_{Sal} * X^*_{Salience} + \varepsilon_{PT} \end{aligned} \tag{4.16}$$

$$\begin{aligned} U_{Car} = & ASC_{Car} + \beta_{TT} * TravelTime + \beta_{NCars} * Carvail + \beta_{WTime} * WalkingTime \\ & + \beta_{Work} * WorkTrip + \beta_{Dist} * Distance + \beta_{TrFreq} * TripFreq + \beta_{Gender} * Gender \\ & + \Gamma_{PNorm} * X^*_{PerNorm} + \varepsilon_{Car} \end{aligned} \tag{4.17}$$

$$U_{NMT} = ASC_{NMT} + \beta_{Age} * Age + \beta_{Dist} * Distance(km) + \beta_{Edu} * Education + \varepsilon_{NMT} \tag{4.18}$$

Equation 3.4 can be written as follows:

$$X^*_{PerNorm} = K_{PerNorm} X_{PerNorm} + \upsilon_{PerNorm} \tag{4.19}$$

$$X^*_{Aff} = K_{Aff} X_{Aff} + \upsilon_{Aff} \tag{4.20}$$

$$X^*_{Sal} = K_{Sal} X_{Sal} + \upsilon_{Sal} \tag{4.21}$$

$$X^*_{Exhib} = K_{Exhib} X_{Exhib} + \upsilon_{Exhib} \tag{4.22}$$

Note:The factor name abbreviations in the equations above denote: Personal Norm, Affect, Salience and Exhibitionism respectively. Similarly, from equation 3.3 the measurement model for the latent variables can be expressed as follows:

Personal Norm:

$$Nrm10 = X^*_{PerNorm} + \eta_1 \tag{4.24}$$

$$Nrm9 = \alpha_2 + \lambda_2 * X^*_{PerNorm} + \eta_2 \tag{4.25}$$

$$Nrm8 = \alpha_3 + \lambda_3 * X^*_{PerNorm} + \eta_3 \tag{4.26}$$

Affect:

$$Aff3 = X^*_{Affect} + \eta_4 \tag{4.27}$$

$$Aff4 = \alpha_5 + \lambda_5 * X^*_{Aff} + \eta_5 \tag{4.28}$$

$$Aff5 = \alpha_6 + \lambda_6 * X^*_{Aff} + \eta_6 \tag{4.29}$$

Salience:

$$PTExp5b = X^*_{Salience} + \eta_7 \tag{4.30}$$

$$PTExp4b = \alpha_8 + \lambda_8 * X^*_{Sal} + \eta_8 \tag{4.31}$$

$$PTExp3b = \alpha_9 + \lambda_9 * X^*_{Sal} + \eta_9 \tag{4.32}$$

$$PTExp2b = \alpha_{10} + \lambda_{10} * X^*_{Sal} + \eta_{10} \tag{4.33}$$

$$PTExp1b = \alpha_{11} + \lambda_{11} * X^*_{Sal} + \eta_{11} \tag{4.34}$$

$$PTExp8b = \alpha_{12} + \lambda_{12} * X^*_{Sal} + \eta_{12} \tag{4.35}$$

Exhibitionism:

$$Nar7 = X^*_{Exhib} + \eta_{13} \tag{4.36}$$

$$Nar2 = \alpha_{14} + \lambda_{14} * X^*_{Exhib} + \eta_{14} \tag{4.37}$$

$$Nar11 = \alpha_{15} + \lambda_{15} * X^*_{Exhib} + \eta_{15} \tag{4.38}$$

The error terms ε_n, η_n and υ_n are assumed to be independent. β, λ, K and α are unknown parameters to be estimated. Personal Norm, Affect, Salience and Exhibitionism latent variables are normalised by setting the intercept terms and the coefficients of the latent attitudes to zero(0) and one (1) respectively (see equations 4.24, 4.27, 4.30 and 4.36 in that order).

4.6.1.3 *Models Estimation*

The base model (equations 4.16 to 4.18) is estimated based on the likelihood function as equation 3.7. The ICLV model comprising equations 4.19 to 4.38 are estimated simultaneously based on the likelihood function in equation 3.8 using Biogeme software package (Bierlaire, 2018a; 2018b). The python script for the model estimation is presented in Appendix E.

4.6.1.4 *Assessing goodness of fit*

The indices for assessing model fit and discriminating between alternative models in Biogeme include; log-likelihood, the Rho-square (ρ^2), the adjusted Rho-square ($\bar{\rho}^2$), the likelihood ratio test, and the information criteria such as Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Biogeme also reports the t-statistics of all explanatory variables used in the model.

The log-likelihood is the log of the likelihood of observing an alternative given that individuals make a random selection. Considering that the choice set comprises of three alternatives (PT, Car and NMT), there is one-third ($\frac{1}{3}$) chance of an individual selecting either of the alternatives in the null or baseline model. The null log-likelihood ($LL(0)$ is thus automatically calculated based on the one-third ($\frac{1}{3}$)probability of observing each mode in every observation. Similarly, null log-likelihood of the ICLV model is given by the joint probability of observing of observing the three alternatives (PT, Car and NMT) and the indicators of the four latent variables(Personal Norm, Affect, Salience and Exhibitionism each measured on 5-point Likert scale. Hence, the null log-likelihood and final log-likelihood values of the ICLV model becomes significantly smaller compared to log-likelihood estimates of the base model which is estimated from only the alternatives (PT, Car and NMT). Therefore, the final log-likelihood values are estimated from the choice probabilities for the ICLV model to be comparable with the discrete model (base model) (Atasoy et al., 2013).

Thus, log-likelihood comparison of the base and ICLV models is not possible using this approach. However, the final log-likelihood values is estimated the simulated probabilities.

$$LL(0) = N * ln(\frac{1}{c}) \tag{4.39}$$

where: N is the number of observations

C is the number of alternatives in the choice set

The final log-likelihood $LL(\beta)$ is the simulated log-likelihood values of the final or unrestricted model.

$$LL(\beta) = \sum_{1}^{N} ln(\text{simulated probabilities}) \tag{4.40}$$

where: N is the number of observations

The likelihood ratio test $(-2(LL(0) - LL(\beta)))$, tests the hypothesis that the null and the final model are equivalent. The $(-2(LL(0) - LL(\beta)))$ must be large enough for the final model to be significantly better than the null model (Antolín, 2016). The statement above means that the $LL(\beta)$ should be remarkably different from LL(0) for a good model fit.

The $\bar{\rho}^2$ is not a statistical test but gives a general overview of model fit when comparing models. $\bar{\rho}^2$ takes into account the number of explanatory variables used in each model and normalises for their effect when comparing two or more models, and this makes it suitable for comparing models with different number of variables.

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{4.41}$$

and

$$\bar{\rho}^2 = 1 - \frac{LL(\beta) - p}{LL(0)} \tag{4.42}$$

where: p is the number of explanatory parameters in the estimated model

The likelihood of observing an alternative in the ICLV model is given by the joint probability of observing an alternative and the indicators of the latent variables (Norms, Salience, Affect and Exhibitionism). The log-likelihood values become significantly smaller with the incorporation of the latent variables in the ICLV model compared to a discrete choice model of similar specifications. Similarly, the AIC and the BIC increases substantially with the inclusion of latent variables; this renders these indices inappropriate for comparing discrete choice models and ICLV models. However, to discriminate or compare the base model and the ICLV model reported in this document, the final log-likelihood values are estimated from the simulated choice probabilities for the unrestricted models (final base model and final ICLV model) based on equations 3.13 and 4.41.

4.7 Summary

The chapter presents detail description of the research methods adopted for this study. Stratified random sampling method was considered appropriate for the study after a careful review of the strength and weaknesses of the most popular sampling techniques. The ability to apply weights to sub-frames when generating the sample is believed to enhance the representativeness of the sample and the generalisability of the survey results. A sample size of 500 was found adequate and recommended to ensure the generalisability of the results. Additionally, postal or mail-back survey method is selected as the primary mode for administering the survey and supplemented by on-line survey method. Moreover, the statistical methods for data analysis and choice model estimation methods are discussed and illustrated in detail including the detail specification for the development of ICLV model. The next chapter presents the study area and the population of the study.

Chapter Five

Case Study

5.1 Introduction

Defining the boundary of a study is necessary for contextualising results of a study and discussing the finding from a specific perspective. It also provides insight into the demographics and socio-economic characteristics of an area and gives the basis for comparison. This chapter defines the study area and presents the demographic and economic characteristics of the area. Additionally, a brief description of the strength and challenges of the transport system of the study area, as well as some measures adopted to mitigate the situation.

5.2 Profile of the Study Area

Study Area is a geographic boundary selected to define the geographic space of data collection and analysis for a study. This section and the next sections describe the boundaries of the study and the characteristics of the study population. Edinburgh is the administrative capital city of Scotland, in the United Kingdom (UK). It is UK's second-largest financial centre after London and the fastest-growing city (Arcadis, 2017). Edinburgh is geographically located at the central belt of Scotland, bounded by the Firth of Forth on the north and the Pentland Hills on the south. The population of Edinburgh is projected to be 518,100 in 2018 (National Records of Scotland, 2018a). This population lives on 263 square kilometres of land with a population density of

1,969 persons per square kilometre. Edinburgh is Scotland's second-highest populated city and the third city with the highest number of persons living on a square kilometre. Edinburgh's population is forecasted to increase to 575,143 by 2037 (Edinburgh City Council, 2016; National Records of Scotland, 2018a).

Edinburgh's population accounts for 9.5% of the total population of Scotland and has the highest proportion of young people between the ages of 16 and 44, which is 9.2% higher than the Scottish average of 37.1%. Similarly, the proportion of the aged population (people over 60 years) is well below the Scottish average: this implies Edinburgh has lots of young and active population (National Records of Scotland, 2018a). Edinburgh has been famous for its international festival, the Edinburgh International Festival (EIF), which dates back to 1947. The festival has since been successfully organised every August for over seven decades. The festival brings together performing artists and several cultural events including theatre, opera, music and dance from all over the world and tourist (Harvie, 2003).

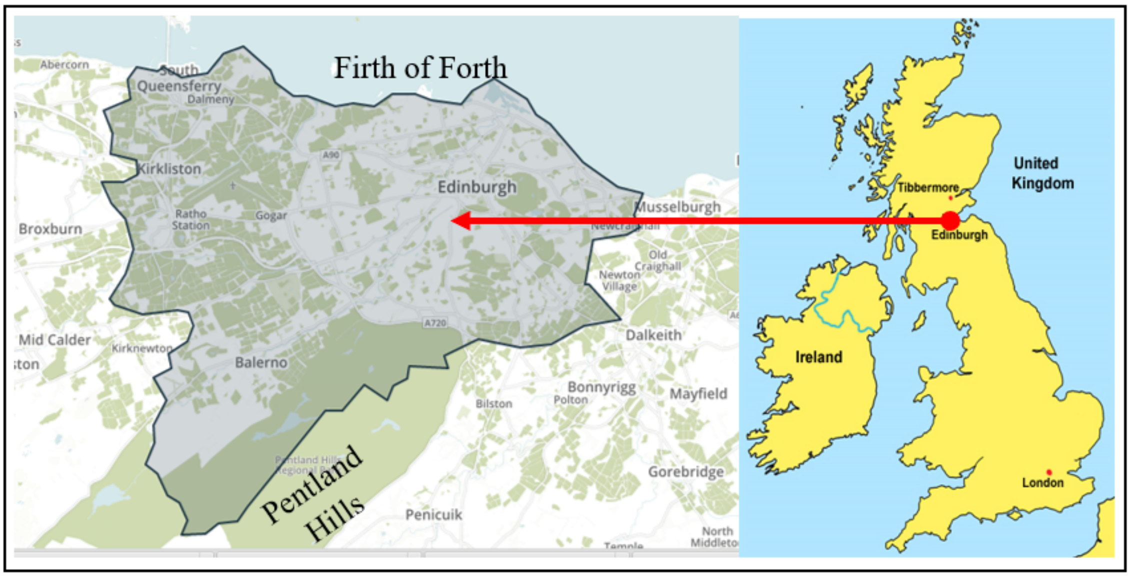

Figure 5.1: Map of the Study Area[1]

[1]Source: Google Map

5.3 Transport Characteristics of the Study Area

In 2014, 160,000 estimated vehicles drove into Edinburgh city centre each morning. This figure was projected to rise to 180,000 vehicles in 2016. Moreover, 233,370 households were recorded in 2017; this is forecasted to rise by 39 per cent by 2037 (Edinburgh City Council, 2016). The factors cited above contribute to the traffic situation in the city. Edinburgh constitutes a major transport hub in east-central Scotland and at the centre of a multi-modal transport network comprising road, rail and air. Transport for Edinburgh is the executive body of the City of Edinburgh Council and responsible for the development of all transport schemes and policies within the city (Transport for Edinburgh, 2013). Moreover, Edinburgh is one of the cities with extensive bus services in the United Kingdom with pervasive and efficient public transport services. The bus network covers almost all parts of the city (Arcadis, 2017). Nonetheless, according to Tomtom Traffic Index, Edinburgh is the most congested city in Scotland and performs better than only Belfast in the United Kingdom (TomTom International BV, 2016). Car traffic in Edinburgh has been on a rising trajectory since 2009 (TomTom International BV, 2016; Transport Scotland, 2018b), whereas bus passenger numbers have been declining since 2008 (Transport Scotland, 2018b). Between 2014 and 2015, the city's congestion level rose by eight percentage points to 37%; this means that travel time in the city has become 37 per cent longer on average than it would have been n free-flowing traffic. Travel time during the morning peak (7:30 am to 9:30 am) was 64% longer and that of the evening peak (4:00 pm and 6:00 pm) was 73% more for the same period (Shan and John, 2015; Edinburgh City Council, 2016; Alastair, 2013; TomTom International BV, 2016). Moreover, in 2016, the average travel time increased by 43 minutes a day due to congestion (TomTom International BV, 2016).

This is consistent with the findings in Transport Scotland (2015) and Transport Scotland (2018a). The reports indicate that 9.7%, 11.7% and 12.8% of all car journeys experienced a delay due to increasing traffic volume in 2015, 2016 and 2017 respectively. Figure 5.2 shows the modal share trend in Edinburgh, while Figure 5.3 shows the congestion level in Edinburgh.

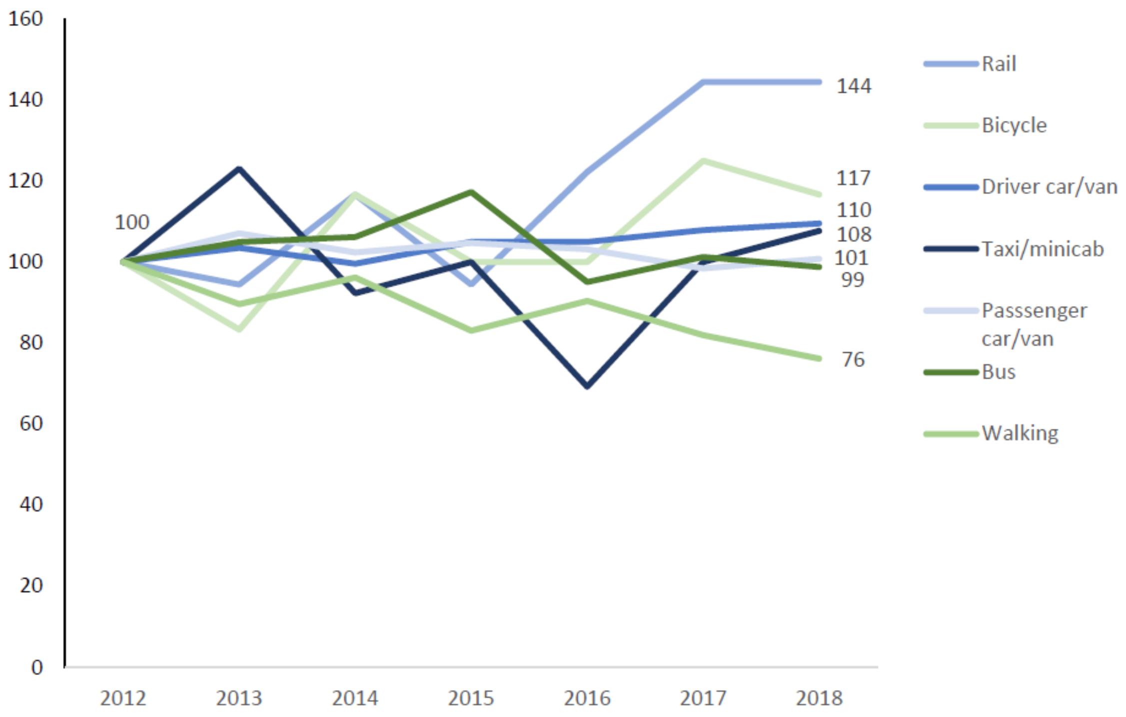

Figure 5.2: Modal share trend in Edinburgh[2]

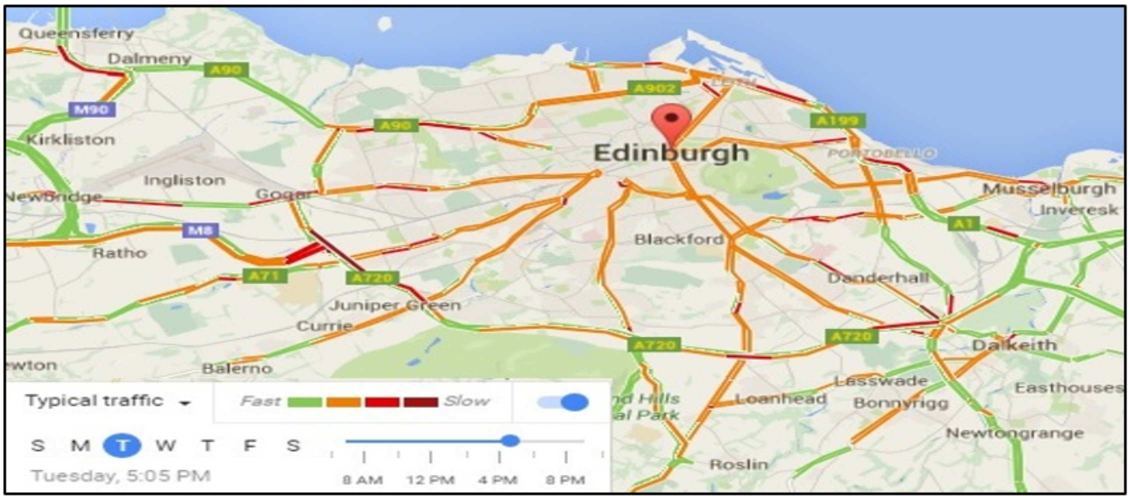

Figure 5.3: Typical weekday PM traffic in Edinburgh [3]

5.3.1 Congestion Reduction Measures

Several measures have been considered to mitigate the rising trend in congestion resulting from; increasing vehicular numbers, population growth, and changing population

[3]Source: google maps

demographics. The city authorities have promoted bus and rail-based Park and Ride ($P\&R$) schemes as a tool for reducing traffic congestion, air pollution while ensuring high levels of accessibility and sustainability (Hazel, 2000). Several $P\&R$ facilities have been built outside the city (notably; Ingliston near Edinburgh Airport, Hermiston gait on the Edinburgh City bypass, Newcraighall in the east of the city and Ferrytoll in Fife). Additionally, car-free zones to create safe zones for shoppers and reduce pollution; a scheme similar to the shared space design in Copenhagen (Maad and Ferguson, 2010), have been implemented in the city centre to remove vehicular traffic from the central business district (CBD). Moreover, traffic calming measures (such as narrowed roads, speed bumps) have been installed to restrict free-flow of traffic on some local roads to restrict the type of vehicle that can enter certain parts of the city. Furthermore, an increasing number of web-based car-sharing schemes run across the city. For example, Tripshare is funded by the Scottish Executive and supported by Edinburgh Council as part of the UK's National Liftshare network. The Edinburgh City Car Club has specific parking spaces in the city for members of the scheme to pick up a car or van locally when in need of one. Additionally, permit and parking prices across the city centre have been deliberately set high to deter drivers and motorist from driving into the city centre. The magnitude of the traffic situation led to the proposed congestion charging scheme by the City Council in 2003 (Saunders and Lewin, 2005). Although this scheme was unsuccessful due to lack of support, it was proposed to toll main routes entering the city centre and deter motorist from driving into the city centre. Several public transport improvement schemes have also been implemented to improve public transport services and promote ridership, notably, defining bus lanes, the Edinburgh tram project, and the provision of ubiquitous real-time bus information for public transport users. Notwithstanding the above schemes, the city continues to record increasing vehicular volumes and declining bus passenger numbers (Transport Scotland, 2018b; Hazel, 2000).

5.3.2 Selection of the study Area

The challenges confronting transport planners, city planners and traffic engineers of the city of Edinburgh going into the next decade include increasing vehicular traffic and how to stem the tide (TomTom International BV, 2016; Transport Scotland, 2018b; Hazel, 2000; Saunders and Lewin, 2005). It is in this regard that this study is designed to investigate the travel behaviour of the population, particularly, the impact of subjective variables on their travel mode choices.

5.4 Summary

This chapter has described the geographic boundary of the study area and highlight the characteristics of the study population. It has been argued that given the transport characteristics of Edinburgh; the rising vehicular congestion in the city; and the travel behaviour of the study population, MINDSPACE could help explain the travel behavioural of the population. The population of Edinburgh and the proportion of younger population are projected to increase in the next two decades due to increasing urbanisation and net immigration. The population increase and the change in demographics are expected to exert pressure on the transport systems. Therefore, the need to acquire a clearer understanding of the factors driving the travel behaviour of the population for developing a workable solution to curb the traffic situation.

Chapter Six

Data collection and Analysis

6.1 Introduction

This chapter describes that data collection procedure and descriptive analysis of the sample data. In chapter 4, we discussed the research instrument design and the physical forms of survey administration adopted for the study. The sample size required for the study, as well as the various sample generation approaches, were presented. A sample size of 500 was recommended for the survey, and the sample was to be generated through a stratified random sampling technique. Additionally, postal and internet-based forms of survey administering were considered convenient and cost-effective for the study. Chapter 5 presented the study area selected for this research, along with household and travel characteristic of the population. Section 6.2 of the is chapter outlines the sample selection process. The survey administration and implementation process are covered under section 6.3. Section 6.4 considers the description of the sample data, while section 6.5 performs exploratory analysis of the sample data and finally 6.6 summaries the chapter.

6.2 Sample generation

In chapter 4, stratified random sampling technique was recommended for the selection of the sample. This method was regarded as the most suitable for generating a representative sample to guarantee the generalisability of the survey results.

6.2.1 Sample Selection

The population of the study comprise residents of Edinburgh living within outward postcode area EH1 to EH17. The population was divided into 20 strata (vigintile) using the 2016 Scottish Index of Multiple Deprivation (SIMD 16) datazones classification tables (see Table 4.2) and the household addresses within the geographical boundary of the study area (EH1 to EH17) from the royal mail PAF address data file (sampling frame). (see Table 4.3). Datazones are groups of census areas with average populations between 500 and 1000 household residents with similar socio-economic characteristics in Scotland. There are 6505 datazones for covering the entire of Scotland (Scottish Neighbourhood Statistics, 2003). The SIMD ranks the 6505 datazones most deprived (datazone 1) to least deprived (datazone 6505). For the purposed of sampling, the 6505 datazones are classified into 20 strata called vigintiles based on the SIMD rankings. Each vigintile comprises of 5% of the datazones, where vigintile or strata 1 represent 5% of the most deprived household residents while vigintile 20 represents 5% of the least deprived household residents (Scottish Neighbourhood Statistics, 2003; Scottish Government, 2016; Scottish Government, 2018). The sample was generated by drawing households at random from each stratum using the inward postcodes (incodes). The number of households drawn from each stratum was based on its respective weighting in the sampling frame. In other to secure the desired 500 responses, a total sample size of 4,155 household addresses were drawn from a total of 240,147 household addresses using stratified random sampling technique. A response rate 17% was assumed because of the low response rate that characterises postal or mail back surveys (Jobber and Reilly, 1998; Greer et al., 2000; David De Vaus, 2002; Sahlqvist et al., 2011; Larson and Poist, 2018). Table 6.1 presents a summary of the sample generated from each stratum. The sampled addresses were subsequently re-organised into outward postcode (outcode) areas for easy sorting and distribution, Table 6.2 shows the reclassified data.

Table 6.1: Sample by vigintile

Stratum	No. of Incodes	Average Pop	Average Income	No. of Household Addresses	Weight of Stratum (%)	Sample size
1	286	824	212	7,862	3.27%	183
2	312	827	590	7,162	2.98%	88
3	428	859	907	9,608	4.00%	233
4	431	826	1351	10,196	4.25%	212
5	387	932	1632	8,575	3.57%	233
6	317	876	2021	7,370	3.07%	220
7	418	777	2361	8,978	3.74%	142
8	570	888	2873	13,532	5.63%	264
9	288	875	3210	7,515	3.13%	162
10	398	910	3631	9,484	3.95%	219
11	447	876	3579	11,382	4.74%	236
12	335	940	3833	9,463	3.94%	155
13	318	996	4237	8,764	3.65%	137
14	429	837	4429	10,160	4.23%	144
15	427	871	4815	8,416	3.50%	161
16	540	808	5196	11,116	4.63%	122
17	629	874	5457	12,763	5.31%	176
18	557	846	5668	11,520	4.80%	140
19	1,176	861	6235	21,896	9.12%	288
20	2,581	877	6518	44,385	18.48%	640
Total	**11,274**			**240,147**		**4,155**

Table 6.2: Sample by Outward Postcode

Outcode Area	Household Addresses	No. of Incodes	Sample Size	Remarks
EH1	4,108	238	3	Predominantly business
EH2	944	115	15	Predominantly business
EH3	15,355	597	366	
EH4	26,400	1,539	607	
EH5	10,781	591	252	
EH6	23,444	873	444	
EH7	21,043	660	187	
EH8	13,161	514	340	
EH9	10,235	475	123	
EH10	15,199	823	319	
EH11	22,594	849	839	
EH12	19,006	1,022	76	
EH13	6,795	369	39	
EH14	18,074	949	37	
EH15	10,069	574	151	
EH16	14,293	730	139	
EH17	8,646	463	218	
Total	**240,147**	**11,381**	**4,155**	

6.3 Survey Implementation

The study adopted postal and online survey methods for administering the survey instrument, as discussed under sub-section 4.4.2.2. A team of three was formed to hand-deliver the questionnaires to the sampled addresses. In total, 4,155 questionnaires were packaged and dispatched for delivery to the sampled addresses between February 2nd, 2018 and June 30th, 2018. The delivery package comprised of a 6-page questionnaire and one PPI self-addressed envelope for return postage. These were enclosed in a C5 envelope and addressed to *"the occupier"* of the sampled household address (see Figure 6.1). A web-link (https://thissurvey.questionpro.com) to the online version of the survey was included in the introductory note of the questionnaire. Participants were advised to complete the survey using their preferred option among the two.

- Complete and return the paper-based questionnaire by post using the PPI self-addressed envelope enclosed.
- Complete the survey online by following the web-link provided in the introductory of the questionnaire

Assuming a minimum of 17% response rate and the fact that postage cost of £0.51 is charged by the postage company for every questionnaire receive through the mail, the survey was conducted in two phases to ensure the cost of the survey does not exceed the approved budget in the unlikely event of recording higher responses than anticipated. In phase one, 2,185 addresses were sampled and sent the survey package. This process lasted almost two months. At the end of this process, the sample data was analysed to investigate characteristics of respondents and the distribution of the responses by vigintile. Considering the results and distribution of the sample for the first phase of the survey, additional 1,970 addresses were sampled for the second phase of the survey, which also lasted two months. In total, 4,155 questionnaires were packaged and dispatched for distribution Table 6.3 shows the number of addresses sampled during each phase of the survey. However, 3,973 questionnaires were successfully delivered. One hundred and eighty-two (182) questionnaires representing 4.4% of the total sampled addresses, returned undelivered (either refused, non-existent address or vacant address).

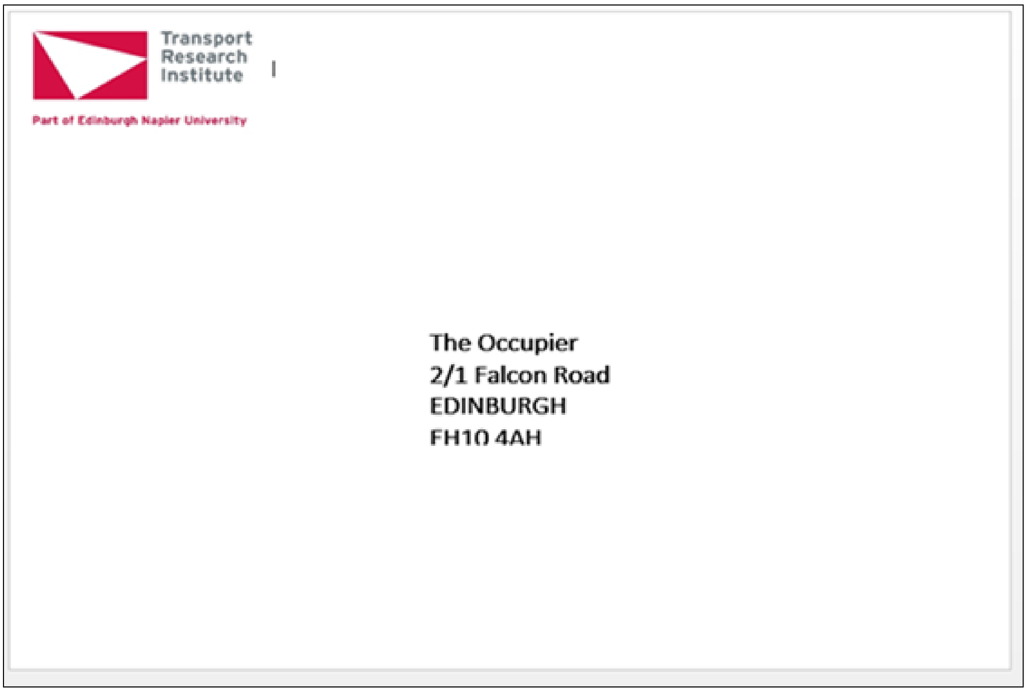

Figure 6.1: Envelope for questionnaire

An incentive package of £50 voucher each for four people was offered for participants of the survey. Participants interested in the voucher were advised to supply their contact addresses at the end of the survey to register their interest. The four winners were selected through a random draw at the close of the survey and contacted for their prize. No personally identifiable information was asked in the survey to ensure respondents identity was kept anonymous. However, the data provided by participants for the draw was maintained separately from the survey data and destroyed immediately after the winners were selected and contacted.

Table 6.3: Phases of Survey

Stratum	No of Incodes	Average Pop.	Average Income	Addresses	Weight of Stratum (%)	Sample 1	Sample 2	Total Sample
1	286	824	212	7,862	3.27	79	104	183
2	312	827	590	7,162	2.98	40	48	88
3	428	859	907	9,608	4.00	132	101	233
4	431	826	1,351	10,196	4.25	164	48	212
5	387	932	1,632	8,575	3.57	128	105	233
6	317	876	2,021	7,370	3.07	116	104	220
7	418	777	2,361	8,978	3.74	88	54	142
8	570	888	2,872	13,532	5.63	102	162	264
9	288	875	3,210	7,515	3.13	74	88	162
10	398	910	3,630	9,484	3.95	73	146	219
11	447	876	3,579	11,382	4.74	103	133	236
12	335	940	3,833	9,463	3.94	81	74	155
13	318	996	4,237	8,764	3.65	35	102	137
14	429	837	4,429	10,160	4.23	83	61	144
15	427	871	4,815	8,416	3.50	87	74	161
16	540	808	5,196	11,116	4.63	96	26	122
17	629	874	5,457	12,763	5.31	125	51	176
18	557	846	5,668	11,520	4.80	57	83	140
19	1,176	861	6,235	21,896	9.12	182	106	288
20	2,581	877	6,518	44,385	18.48	340	300	640
	11,274			**240,147**	**100%**	**2,185**	**1,970**	**4,155**

6.4 Characteristics of the Sample Data

In the previous section, we discussed the data collection process. This section presents the descriptive statistics of the sample data obtained. A total of 551 responses representing 13.9% of the households contacted completed and returned the questionnaire. 30 participants completed the survey online whilst 521 participants completed and mailed back the paper-based questionnaire using the enclosed self-addressed return enveloped. After the data entry, the dataset was systematically examined for data entry errors and for any unusual scores from participants. Table 6.4 presents a summary of the responses received, it is ordered by stratum. Detailed discussion on the sample data is provided in the subsequent sections.

Table 6.4: Received responses

Stratum	Incodes	Average Pop	Average Income	Household Addresses	Weight of Stratum (%)	Sample Generated	Responses	Responses (%)
1	286	824	212	7,862	3.27	183	14	2.58
2	312	827	590	7,162	2.98	88	8	1.48
3	428	859	907	9,608	4.00	233	13	2.40
4	431	826	1,351	10,196	4.25	212	17	3.14
5	387	932	1,632	8,575	3.57	233	14	2.58
6	317	876	2,021	7,370	3.07	220	16	2.95
7	418	777	2,361	8,978	3.74	142	16	2.95
8	570	888	2,872	13,532	5.63	264	41	7.56
9	288	875	3,210	7,515	3.13	162	17	3.14
10	398	910	3,630	9,484	3.95	219	17	3.14
11	447	876	3,579	11,382	4.74	236	32	5.90
12	335	940	3,833	9,463	3.94	155	18	3.32
13	318	996	4,237	8,764	3.65	137	24	4.43
14	429	837	4,429	10,160	4.23	144	22	4.06
15	427	871	4,815	8,416	3.50	161	18	3.32
16	540	808	5,196	11,116	4.63	122	23	4.24
17	629	874	5,457	12,763	5.31	176	34	6.27
18	557	846	5,668	11,520	4.80	140	33	6.09
19	1,176	861	6,235	21,896	9.12	288	43	7.93
20	2,581	877	6,518	44,385	18.48	640	122	22.51
Total	**11,274**			**240,147**	**100.00**	**4,155**	**542**	**13.0%**
chi-square test between Number of Household address (sampling frame) and Responses Received from each stratum = 28.44; p-value = 0.075 at 95% confidence level								

6.4.1 Missing data

Missing data (partial responses) is one of the ubiquitous statistical problems in research (Baraldi and Enders, 2010). This situation results when participants in a survey fail to respond to all the questions on the survey. It is caused by several factors such as stress, fatigue or lack of knowledge about a question and sometimes due to the sensitivity of the question(s), this is practically inevitable in questionnaire survey (Gyimah, 2001; Baraldi and Enders, 2010; Little and Edition, 2014; Newman, 2014; Arbuckle, 2017). The sample data discussed in the preceding section is consistent with the observations in Newman (2014); the pattern of the missing data observed in the sample data can be categorised into three levels, namely; item-level missing, construct-level missing and person-level missing (Newman, 2014). Item-level missing occurs when respondents fail to answer all the questions in the questionnaire. Construct-level missing occurs when a respondent answers some questions but skip others on a multi-item scale or skip an entire measurement scale. In contrast, person-level missing represents non-respondents (Gyimah, 2001; Newman, 2014). This section will primarily focus on the first two categories; the latter category is discussed under section 6.4.4 (Sample bias).

As indicated in Figure 6.2, the 500 valid cases comprised of 1,641 missing cells representing 4.0% of the total number of cells in the entire dataset. Seventy-one (71) cases representing 14.2% of the total respondents answered every question on the survey (full respondents). The remaining 85.8% failed to answer at least one question on the survey (partial respondents).

The high proportion of partial respondents is an indication of the variability of the response rate across the variables. Five variables out of the 82 variables were answered by all respondents, and the remaining 77 variables had at least one missing value. Table 6.5 presents a summary of variables with at least 5% missing values.

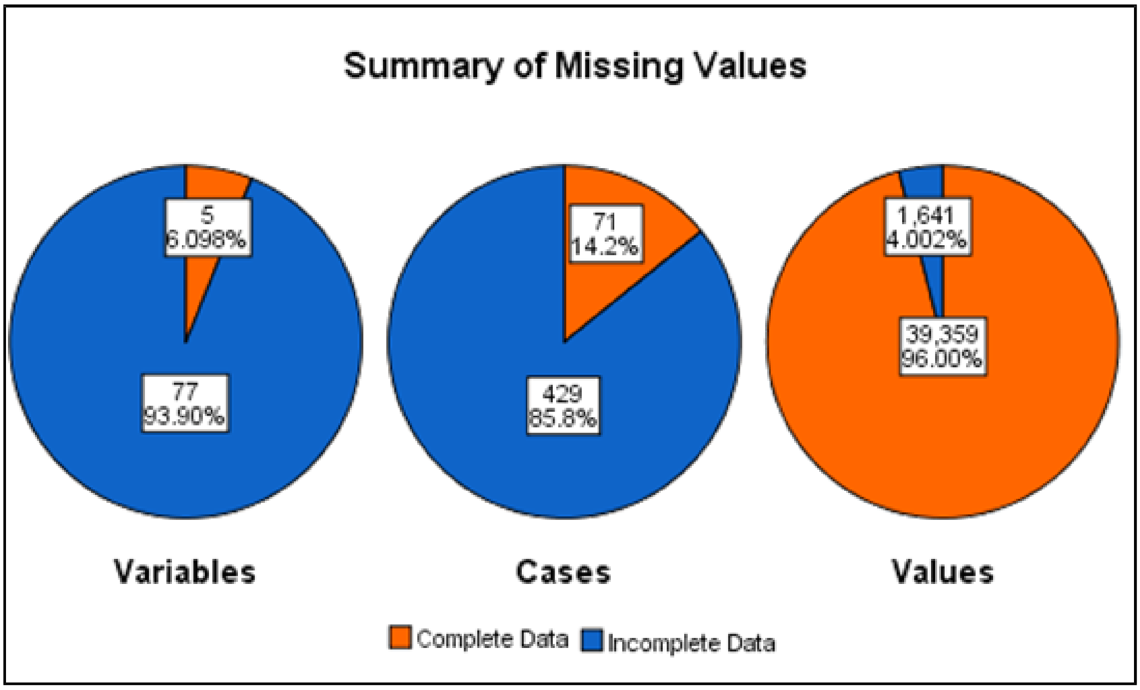

Figure 6.2: Summary of missing values

Table 6.5: Summary of variables

Item	Variable	Missing		Valid		Mean	Std. Deviation
		Count	Percent	Count	Percent		
1	SM_Cost:Alternative travel mode cost	334	60.6%	217	39.4%	51.56	65.821
2	Tr_Cost: Cost of travel mode	258	46.8%	293	53.2%	52.52	60.343
3	PT Usage:Difficulty of using PT	237	43.0%	314	57.0%	2.58	1.477
4	Tr_Time: Travel time of Primary travel mode	121	22.0%	430	78.0%	2.70	1.183
5	Nar13: I am going to be a great person	74	13.4%	477	86.6%	2.32	0.889
6	Nar5: I find it easy to manipulate others	70	12.7%	481	87.3%	2.00	0.725
7	Nar14: I can make anybody believe anything I want them to	69	12.5%	482	87.5%	1.93	0.641
8	Nar11: I really like to be the centre of attention	69	12.5%	482	87.5%	1.90	0.665
9	Nar9: Everybody likes to hear my stories	69	12.5%	482	87.5%	2.34	0.752
10	Nar12: People always seem to recognise my authority	68	12.3%	483	87.7%	2.13	0.81
11	Nar7: I am apt to show off if I get the chance	68	12.3%	483	87.7%	2.07	0.776
12	Nar1: I know that I am good because everybody keep ..	67	12.2%	484	87.8%	2.30	0.812
13	Nar16: I am an extraordinary person	66	12.0%	485	88.0%	2.10	0.785
14	Nar6: I insist upon getting the respect that is due me	66	12.0%	485	88.0%	2.24	0.847
15	Nar2: I like to be the centre of attention	66	12.0%	485	88.0%	2.01	0.67
16	Nar4: I like having authority over people	64	11.6%	487	88.4%	2.01	0.779
17	Nar8: I always know what I am doing	61	11.1%	490	88.9%	2.29	1.071
18	PTM: Travel mode 5 years ago	61	11.1%	490	88.9%	4.50	3.125
19	Nar3: I think I am a special person	60	10.9%	491	89.1%	2.26	0.877
20	Nar15: I am more capable than other people	57	10.3%	494	89.7%	2.18	0.852
21	Nar10: I expect a great deal from other people	56	10.2%	495	89.8%	2.38	0.882
22	R4ChaMode: Reason for changing travel mode	56	10.2%	495	89.8%	3.05	3.142
23	PTExp4b: Passenger annoyance and discomfort	43	7.8%	508	92.2%	2.94	1.193
24	PTExp8b: Safety issues (lack of seatbelt, ...	40	7.3%	511	92.7%	2.36	1.29
25	Nrm9: I believe most of the people important to me	38	6.9%	513	93.1%	3.53	0.986
26	PTExp7b: Long waiting and travel time	38	6.9%	513	93.1%	3.38	1.318
27	PTExp3b: Exposure to health risk (catching a cold etc)	37	6.7%	514	93.3%	2.68	1.325
28	PTExp5b: Poor hygiene (service uncleanliness and ...	35	6.4%	516	93.6%	3.34	1.302
29	PTExp2b: Overcrowding	35	6.4%	516	93.6%	3.13	1.269
30	Nrm7: If my family and friends change their ...	34	6.2%	517	93.8%	1.96	0.872
31	PTExp6b: Inaccurate bus and real-time information	34	6.2%	517	93.8%	3.07	1.25
32	PTExp4a:Passenger annoyance and discomfort	34	6.2%	517	93.8%	3.29	1.106
33	PTExp8a: Safety issues (lack of seatbelt, ...	32	5.8%	519	94.2%	2.61	1.318
34	PTExp1b: Anti-social behaviour (drunk people etc)	31	5.6%	520	94.4%	3.22	1.423
35	PTExp7a:Long waiting and travel time	30	5.4%	521	94.6%	3.66	1.209
36	Income: Household Annual Income	29	5.3%	522	94.7%	4.32	1.869
37	Nrm6: Most of my family and friends use public transport	29	5.3%	522	94.7%	2.91	1.105
38	Aff4: I like to use the local bus service because ...	29	5.3%	522	94.7%	3.45	1.172
39	PTSQl1: I feel personally safe and secure ...	29	5.3%	522	94.7%	3.78	0.92
40	Nrm10: I feel morally obligated to use more of ...	28	5.1%	523	94.9%	3.12	1.188
41	Nrm1: Driving is perceived to illustrate a person's power ...	28	5.1%	523	94.9%	2.44	1.162
42	PTExp3a:Exposure to health risk (catching a cold etc)	28	5.1%	523	94.9%	3.09	1.297

6.4.1.1 Missing Data Treatment

Several statistical methods are available for dealing with incomplete/partial dataset, notably, listwise deletion, pairwise deletion, single imputation, multiple and Maximum likelihood (Kim and Curry, 1977; Baraldi and Enders, 2010; Newman, 2014; Arbuckle, 2017). Listwise and pairwise deletion methods are the most basic techniques of the missing data treatment methods. Listwise deletion discards any observation with missing values; the advantage of this technique is that it produces dataset from only complete cases for analysis. However, handling partial respondents as person-level missing (non-respondents) and discarding the entire data from a respondent due to one or two missing values is a major drawback for this technique. This can affect the estimates and statistical power if the resultant sample size gets too small due to the exclusion of all usable data from partial respondents (Baraldi and Enders, 2010; Newman, 2014). Comparing the two deletion methods, Kim and Curry (1977), pointed out that the pairwise deletion method performs better than listwise deletion method. Although both deletion methods are available in most modern statistical software packages, researchers question their suitability; they argue that missing one or two values is not a reasonable justification for discarding all usable data from a participant. Furthermore, both techniques could lead to a considerable reduction in sample size, thereby affecting the validity of results. (Gyimah, 2001; Baraldi and Enders, 2010; Newman, 2014) Similarly, single imputation method involves replacing each missing value with a plausible estimate, such as the mean, median or a predicted value from a multiple regression equation from the observations. This technique is, however, noted for producing bias estimates and inaccurate standard errors (Gyimah, 2001; Newman, 2014). The advantages of this technique are that it is flexible and retains all usable data for analysis. However, it is argued that the imputed values may exaggerate the estimates and lead to type I or type II error. Hence this method is not recommended. (Gyimah, 2001; Baraldi and Enders, 2010; Newman, 2014). Multiple imputation method was developed to overcome the limitation of the single imputation; several single-imputation are performed and averaged (Baraldi and Enders, 2010; Newman, 2014). The sample variation between the different copies of the datasets achieved by allowing different values of the missing items to be imputed gives this technique advantage over the single imputation technique (Baraldi and Enders, 2010). This provides unbiased estimates and more accurate significance test. Multiple imputation procedure involves three stages; The first stage is the imputation stage, where several different copies of the datasets are created from the original dataset. A minimum of 40 different imputations is recommended at this stage for obtaining unbiased estimates (Graham, 2012). The second stage involves statistical analysis of each of the imputed datasets, and in the final stage, the researcher combines the estimates and their standard errors (SEs) from the analysis in the first two stages. This is achieved by simply averaging the estimates from all the imputed datasets for the final parameter estimates. The second advanced and highly recommended method for handling incomplete dataset is the Maximum likelihood estimation method. This technique assumes multivariate normality and scores missing at random (MAR). Maximum likelihood estimation uses the log-likelihood function and all the available dataset to estimate the population parameters that have the highest probability of producing the complete sample data (Baraldi and Enders, 2010; Newman, 2014). Restated, this technique does not impute any missing score; rather, it uses the available incomplete data to compute the value of the parameter that is most likely to have resulted in the observed data. The Maximum likelihood estimation technique and the multiple imputation techniques are the modern techniques for handling missing data. They are considered superior to the deletion techniques, and the single data imputation method and provides unbiased estimates than the traditional methods (Gyimah, 2001; Baraldi and Enders, 2010; Newman, 2014). Although several researchers favour MI and ML over the deletion and single imputation methods, Binder (1996, p.571) cited in Gyimah (2001), had this to say.

"none of the approaches is always right or always wrong, and it is important to understand the conditions under which each approach is preferred"

The crux of the matter is finding the most plausible replacement for any missing value. According to Newman (2014), maximum likelihood (EM or FIML) or multiple imputation (MI) techniques with auxiliary interaction variables should be used for treating missing data when partial respondents exceed 10% of the sample data. Mathematically expressed, if $\frac{Partial\ response\ rate}{Total\ response\ rate} > 0.1$, then ML or MI should be applied (Newman, 2014). From table 6.5:

$$\frac{Partial\ response\ rate}{Total\ response\ rate} = \frac{10.8}{12.6} = 0.86$$

As shown above, partial respondents account for 86% of the sample data, more than the 10% threshold proposed in Newman (2014). For this reason, maximum likelihood is adopted for missing data handling and for statistical analysis.

6.4.2 Data Cleaning

Descriptive analysis was conducted on the dataset and inspection carried out for data entry error or entry of unusual scores. Twenty (20) variables were found to contain unusual and implausible scores and accordingly corrected. Secondly, respondents' level of engagement when completing the survey was examined. Characteristically of behavioural survey (Gyimah, 2001), 32 respondents representing 5.8% of respondents skipped at least one entire behavioural construct. This may be due to the sensitive nature and/or the unusual wording of the questions for these measurement scales. In summary, 32 respondents skipped the "narcissism" measurement scale. 17 respondents skipped all items on "Norm" and "Affects", 16 respondents skipped all items on PT Experience, and finally, five respondents failed to answer any of the items on public transport service quality. Although these participants skipped these measurement scales yet answered the last part of the survey instrument on socio-demographics. This could be a reflection of the general sense of caginess or political correction when asked about sensitive social behaviours or attitudes (Gyimah, 2001). Although Gyimah (2001) believe there is no clear-cut rule for handling all categories of missing data cases, Newman (2014), suggested that.

"When conducting a construct-level analysis, if a participant responds to any items (even a single item) from a multi-item scale, then the participants' average response across the item(s) answered should be used to represent the participants' scale/construct score"

Having stated that, because the study seeks to investigate the impact of respondents' behaviour on their travel choices; it will be deleterious to retain cases with a substantial amount of behavioural data missing. Moreover, the heterogeneity of human behaviour makes it injurious to guess values for respondents skipping an entire measurement scale. Consequently, respondents skipping entire construct and respondents missing more than 25% of scores across all the behavioural constructs are dropped from the data. Overall, 51 cases representing 9.3% of the total responses received were discarded for non-engagement and various infractions; 35 participants representing 6.4% of respondents for failure to answer more than 25% of questions on the survey, at the same time skipping at least one entire behavioural measurement scale. 14 participants, representing 2.5% of respondents for not answering at least 25% of all items on the survey. Finally, two participants for skipping at least one entire behavioural measurement scale. This reduced the total valid responses to 500 cases for further analysis.

6.4.3 Response rate

A total of 551 participants making up 13.9% of the sample contacted completed and returned the survey. Respondents are aged between 18 and 90 ($\mu = 49.69, \sigma = 17.45$), Table 6.5 gives a brief overview of the sample data and the response rate. Table 6.4 summaries the responses received by stratum. The youngest respondent is aged 18, indicating that all respondents were eligible to drive in the study area. 51 partially completed responses and data from unengaged respondents were deleted from the dataset. This reduced the total valid responses for the analysis to 500 cases, aged between 18 and 90 ($\mu = 48.80, \sigma = 17.27$). Refer to Table 6.11 for the statistical profile of the respondents. The response rate is mathematically expressed as:

$$Response\ rate = \frac{Respondents}{Sample\ contacted} \times 100 \tag{6.1}$$

$$Full\ response\ rate = \frac{Full\ respondents}{Sample\ contacted} \times 100 \tag{6.2}$$

$$Partial\ response\ rate = \frac{Partial\ respondents}{Sample\ contacted} \times 100 \tag{6.3}$$

Table 6.6: Response rate

Description	Count
Total sample size sampled, (a)	4155
Undelivered questionnaire, (b)	182
Sample Contacted, (c) = (a)-(b)	3973
Total responses received, (d)	551
Invalid responses, (e)	51
Valid responses, (f) = (d)-(e)	500
Full Respondents (g)	71
Partial Respondents (h)	429
Response Rate (%)	
Unadjusted response rate = $\frac{d}{c}$	13.9
Total (adjusted) response rate = $\frac{f}{c}$	12.6
Full response rate = $\frac{g}{c}$	1.8
Partial response rate = $\frac{h}{c}$	10.8

6.4.4 Sample Bias

Characteristics of mail-back surveys, despite all the attempts to increase survey response rates, a substantial proportion of households contacted did not respond (David De Vaus, 2002). There exist a plethora of literature suggesting that exciting research topics (referred to as salience topics) tend to elicit more responses in a survey and vice versa (Zillmann et al., 2014). Even though transportation may well fall within the category of salient topics, the presence of the behavioural and psychological questions in the survey instrument may have annulled this effects; possibly due to how cagey people are when it comes to sensitive issues and undesirable social behaviour (Gyimah, 2001). Consequently, resulting in the observed low response rate, thus increasing the risk of non-response bias (Olson, 2006). However, this observation is consistent with Olson (2006) and Zillmann et al. (2014). The authors found an increasing refusal rate and declining response rate for household population surveys. Although Curtin et al. (2000) and Groves (2006) did not find any strong association between non-response rates and non-response bias, Zillmann et al. (2014) suggest it is a major concern when the characteristics of non-respondents systematically deviate from respondents (Richardson et al., 1995).

Thus, Richardson et al. (1995) and David De Vaus (2002) recommend the use of reminders to increase the response rate and minimise non-response bias in mail-back survey, unfortunately, the study could not adopt this recommendation due to budgetary constraint. Newman (2014) recommend undertaking missing data sensitivity analysis when response rate fall below 30% and then steps taken to account for the biasing effect of the non-respondents if established (Zillmann et al., 2014). The conventional method for assessing post-survey non-response bias is the estimates comparison method (Groves, 2006). This procedure compares the estimates of the sample data with estimates from a more trusted source (the Scottish Household Survey, SHS data is used in this study). Transportation Research Record 886 criticises this method of assessing non-response bias; according to the report, the measurement instrument may differ in both surveys. Besides, differences in measurement errors may influence the outcome of the comparison (Transportation Research Board, 1982). On the contrary, Groves (2006) recommends the use of this procedure if the researcher can source credible and independent estimates for the comparison and validation. Thus, this method was adopted to compare the distributions of gender, age (National Records of Scotland, 2018b) and modal share (Transport Scotland, 2018b) variables with those from the sample data. This method was adopted due to the quality and credibility of the data from the Scottish household survey and Transport Scotland. Additionally, the distributions of respondents from each stratum was compared with those from the sampling frame. Discussion on the comparison method is presented below.

6.4.4.1 Gender

The sample data indicates slightly more females than males; however, this is the characteristics of the study population. The percentage of males and females in the sample data is compared with similar estimates from the Scottish Household Survey (National Records of Scotland, 2018a). A chi-square test performed to examine gender representation between the sample data and the Scottish Household Survey yielded a chi-square value of $(x^2) = 0.003$, $p = 0.955$ at 95% confidence level. The test results do not provide sufficient statistical evidence to reject the null hypothesis that "the gender estimates of the sample data and that of the Scottish Household Survey data are similar" (refer to Table 6.7 for details). Hence gender distribution of the sample data is assumed representative of the study population.

Table 6.7: Gender Distribution

Gender	**Sample Data**		**SHS 2017***
	Count	**Percentage**	**Percentage**
Female	259	52.2	51.8
Male	237	47.8	48.2
Total	496		
Chi-square			0.003
p-value			0.955
df			1
Confidence level			95%
* Source:(National Records of Scotland, 2018b)			

6.4.4.2 *Age*

The distribution of the sample data by age is compared with similar estimates from the Scottish Household Survey (National Records of Scotland, 2018a) for ages 18 and above. In spite of combining mail-back and internet survey method to mitigate the effect of age-related differences in response (Gigliotti and Dietsch, 2014), the sample data was found consistent with mail-back surveys (lower response rate of younger (<45) respondents compared to the older respondents (>45)) (Gigliotti and Dietsch, 2014). The comparison of the age distribution of the sample data and that of the Scottish Household Survey data in Table 6.8 indicates that the sample data contains fewer young respondents and more old respondents compared to the Scottish Household Survey data. Chi-square test performed to investigate the level of deviations of the sample data, returned chi-square (x^2) value of = 7.09, p-value = 0.313 and df = 6 at 95% confidence level. The result is not statistically significant enough to justify the rejection of the null hypothesis (refer to Table 6.8 for details). Hence the distribution of the sample data by age is assumed representative of the study population.

Table 6.8: Comparison of Respondents by Age

Age Band	**Representation (%)**	
	Sample Data	**SHS 2017***
18 to 24 yrs	8.3	13.4
25 to 34 yrs	15.4	23.8
35 to 44 yrs	13.4	16.8
45 to 54 yrs	17.4	15.2
55 to 64 yrs	21.1	12.8
65 to 74 yrs	16.0	9.7
>= 75 yrs	8.3	8.4
Chi-square	7.09	
p-value	0.313	
df	6	
Confidence level	95%	
* Source:((National Records of Scotland, 2018a)		

6.4.4.3 Modal Share

The travel behaviour of respondents was similarly compared with the travel data of the Scottish Household Survey data (Transport Scotland, 2018b). A chi-square test performed to compare the modal share distribution of the sample data and that of the Scottish Household Survey data yielded a chi-square value (x^2) of = 2.59, p = 0.858, df =6 at 95% confidence level. the results suggest that the two estimates are not significantly different (refer to Table 6.9 for details). The test results do not provide enough statistical evidence to reject the null hypothesis. Hence the distribution of the sample data by modal share is assumed to characterise the study population, according to Transport Scotland (2018b)

Table 6.9: Comparison of Modal Share

Mode	**Proportion of Mode share**	
	Sample Data	**SHS 2017***
Walking	19.0	17.4
Cycle	8.2	9.8
Driver car/van	35.1	36.3
Passenger car/van	3.9	4.4
Bus/Tram	32.1	27.0
Rail	1.4	2.4
Taxi	0.4	2.6
Chi-square	2.59	
p-value	0.858	
df	6	
Confidence level	95%	
* Source:(Transport Scotland, 2018b, Table 1)		

6.4.4.4 Sampling Frame

The sampling frame of the study was divided into 20 sub-frames (strata). Samples were selected from each sub-frame based on its weightings in the sampling frame. A chi-square test to compare the number of responses received from each stratum and the population of the stratum indicates the sample data is not statistically different from the sampling frame at chi-square (x^2) value of 24.26 at a probability (p) value of 0.187 at 95% confidence level. It is an indication that the sample data adequately represent the sampling frame.

Table 6.10: Comparison by Stratum

Stratum (vigintile)	Proportion of Sample	
	Sample Data	Sampling Frame*
1	14	7862
2	8	7162
3	13	9608
4	17	10196
5	14	8575
6	16	7370
7	16	8978
8	41	13532
9	17	7515
10	17	9484
11	32	11382
12	18	9463
13	24	8764
14	22	10160
15	18	8416
16	23	11116
17	34	12763
18	33	11520
19	43	21896
20	122	44385
Chi-square	28.44	
p-value	0.075	
df	19	
Confidence level	95%	
* Source:(Table 6.9)		

Table 6.11: Summary Statistics

Characteristics	**Sample Estimates**		**Pop. Estimates**	**Chi-square test (95%)**	
	Frequency	**%**	**%**	x^2	**p-value**
Gender					
Female	259	52.2	51.8	0.003	0.955
Male	237	47.8	48.2		
Total	496				
Age			*		
18 to 24 years	41	8.3	13.4		
25 to 34 years	76	15.4	23.8		
35 to 44 years	66	13.4	16.8	7.090	0.313
45 to 54 years	86	17.4	15.2		
55 to 64 years	104	21.1	12.8		
65 to 74 years	79	16.0	9.7		
75 years or older	41	8.3	8.4		
Total	496				
Employment status			**		
Employed full-time	216	43.6	45.0		
Employed part-time	81	16.3	15.0	1.865	0.761
Student	40	8.1	13.0		
Retired	143	28.8	23.0		
Unemployed	16	3.2	3.0		
Total	496				
Educational Level					
No formal Education	5	1.0			
High School	85	17.1			
College	98	19.8			
Bachelor's degree	164	33.1			
Master's degree	117	23.6			
PhD	27	5.4			
Total	496				
Car Availability			***		
0	153	32.09	39.3		
1	231	46.58	42.2	1.644	0.650
2	92	17.39	15.7		
3+	20	3.93	2.9		
Total	496				
Income			**		
Less than 10000	52	10.5	12.0		
10000 to 20000	98	19.8	27.0		
20000 to 30000	93	18.8	22.0	2.984	0.560
30000 to 50000	113	22.8	16.0		
50000 +	140	28.2	24.0		
Total	496				
Households Characteristics			**		
1-Most deprived	48	9.9	15.0		
2	75	15.5	14.0	1.408	0.843
3	75	15.5	13.0		
4	78	16.1	17.0		
5-Least deprived	207	42.9	41.0		
Total	488				
* National Records of Scotland (2018), **Scottish Government (2018), *** Transport Scotland (2018b)					

6.4.4.5 *Summary*

Comparison of estimates from the sample data with those from the Scottish Household Survey data suggests the two sets of estimates are systematically similar. The estimates of the socio-demographic characteristics of the population such as gender, age, income, car availability and modal share were compared by t-test with the sample data. The results show no statistically significant differences between the estimates obtained by the surveys and the estimates of the population in terms of gender, age, income, car availability and modal share at 95% confidence level. Similarly, the representation of each stratum in the sample data was not significantly different from those from the sampling frame. Therefore, in the absence of enough statistical evidence to suggest non-response bias, it is concluded that the characteristics of respondents adequately represent the characteristics of the study population.

The findings did not provide enough statistical evidence to warrant the rejection of the null hypothesis that "the estimates of the sample data and the population estimates are similar". As a result, the characteristics of respondents is assumed to represent the characteristics of the study population, the sample data thus is appropriate to meet the study objectives.

6.5 Exploratory Data Analysis

6.5.1 Modal Split

The Modal share of the sample is as shown in Figure 6.3. The seven transport modes in Figure 6.3 are recoded into three transport modes as shown in figure 6.4. All active transport modes like cycling and walking are recoded into new value called "non-motorised transport mode (NMT)". Similarly, all public transport modes like the Bus/Tram and Rail are recoded to create a new value termed "public transport PT". Finally, all car related modes such as car/van either as driver, car sharing, and taxi are recoded into the value "Car". It is observed that 25% of respondents commute by non-motorised transport mode such as walking or cycling. 39% commute by car and last 35% commute by public transport. It was further found that respondents' choice of travel mode is influenced by several factors such as age, income and car ownership. Consequently, modal split is discussed under these factors (age, income and car ownership)

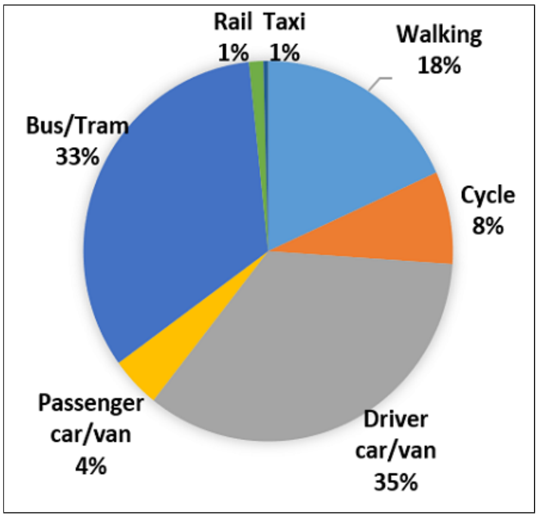

Figure 6.3: Original Modal Split

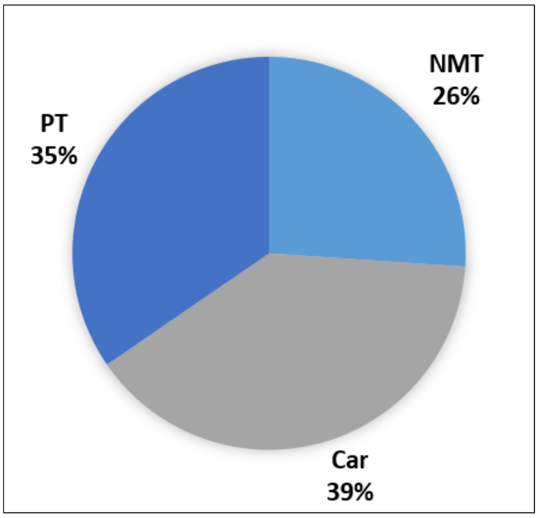

Figure 6.4: Modified Modal Split

6.5.1.1 Age

Respondents were categorised into seven age groups. Figure 6.5 shows the modal split by age. It is observed that respondents modal mix varies with age. The proportion of respondents using Non-motorised travel modes such as cycling and walking reduces as respondents advance in age. The highest proportion of non-motorised mode users are respondents between 25 and 34 years. Thus, according to Figure 6.5, it can be inferred that younger respondents walk and/or cycle more compared to older respondents. Additionally, Figure 6.5 shows that the proportion of car users increases as age increases, except for age band "45 to 54" (Generation-X). This age category also known as Generation-X (ONS, 2019) is observed to departs from the observed trend. A lesser proportion of respondents travel by car and higher proportion travel by public transport in this category compared to the adjoining age bands ("35 to 44" and "55 to 64"). Public transport, on the other hand, exhibits a mixed trend, the proportion of public transport users decreases with increasing age for respondents under 45 years and increases with age after 55 years. The highest proportion of public transport users are 55% and 42% for respondents under 25 years and over 74 years, respectively. Again, age band "45 to 54" departs from the observed trend. However, a careful inspection of this age band "45 to 54" in Figure 6.6, reveals that despite this age band belonging to the working-age group, it has high unemployment rate and more individuals in part-time employment with some few on retirement. This observation in parts could be due to the drug-related issues observed among the Generation-X by the Office for National statistics (ONS)(O'Connor, 2018; ONS, 2019). Further investigation of this observation is recommended for better appreciation of the issue.

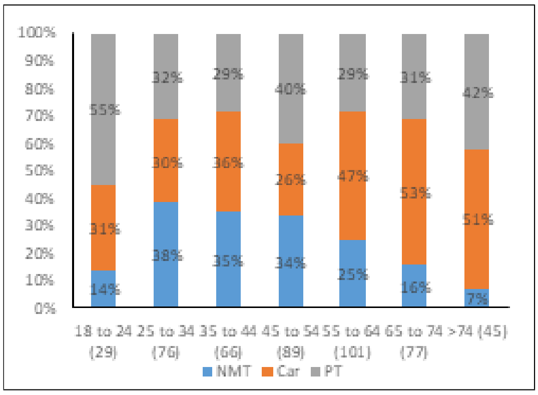

Figure 6.5: Modal Split by Age

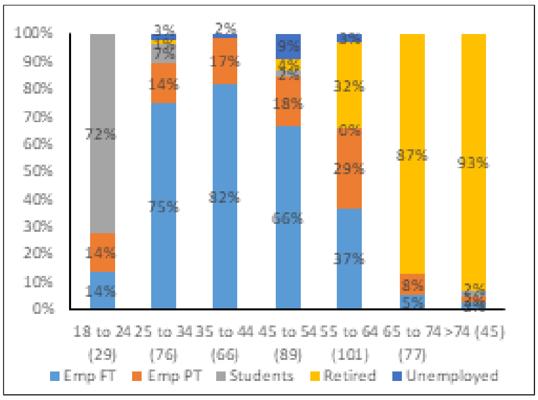

Figure 6.6: Employment status by age

6.5.1.2 *Income*

Modal choice of respondents is shown to depend on income. Participants were grouped into five categories based on their annual income, as shown in Figure 6.7. According to Figure 6.7, the modal share varies with increasing income. The percentage of public transport users is highest among respondents earning under £10,000 and declines with increasing household income. The share of car users increases with increasing income. However, the share of cars tends to plateau among respondents with annual income above £20,000. The modal share is similar for respondents earning more than £30,000 annually, what differs among respondents in this category is the number of cars per household. Similarly, Figure 6.8 shows the modal split of the dataset classified into five bands based on the Scottish Index of Multiple Deprivation (SIMD16). The modal share shows a similar trend to that shown in Figure 6.7. Public transport usage declines with decreasing deprivation whiles car travel increases.

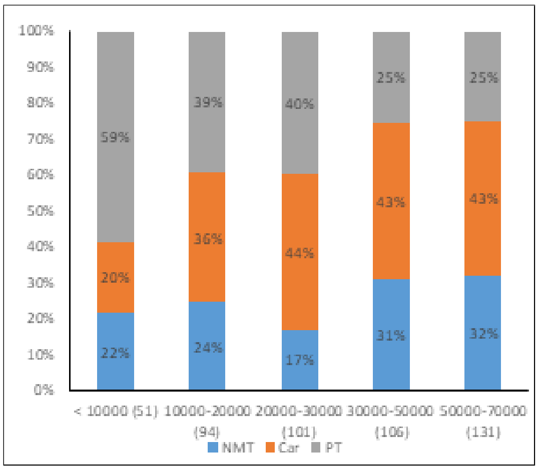

Figure 6.7: Modal split by Income

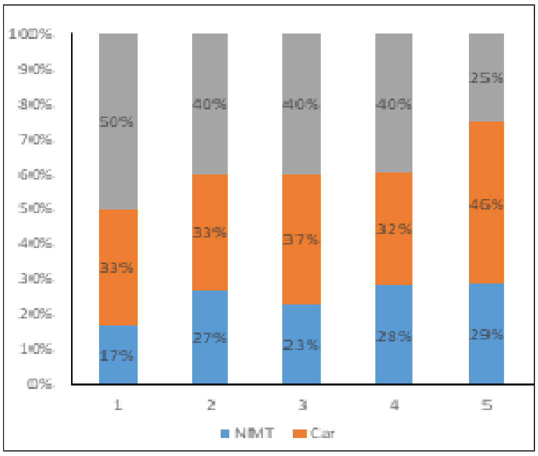

Figure 6.8: Modal Share by Quintile (SIMD16)

6.5.1.3 *Car Ownership*

Car ownership or availability is found to be a significant factor in the choice of travel mode. Figure 6.9 shows a reversed order relationship between car ownership/availability and non-car owners. The percentage of car owners increases with increasing income. Figure 6.10 demonstrate the effect of income on the number of cars owned by a household. It is clearly seen that not only does the percentage of car ownership increase with income, but the number of cars owned also increases as well.

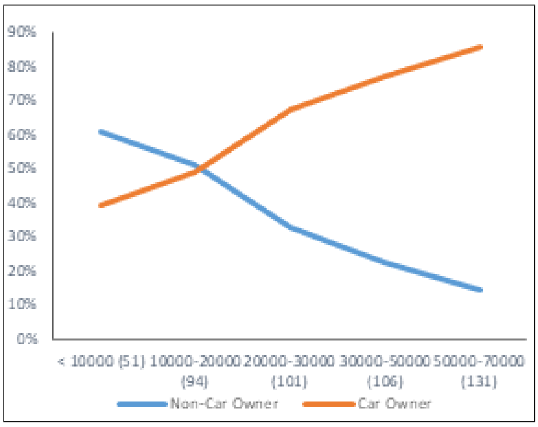

Figure 6.9: Car ownership by income

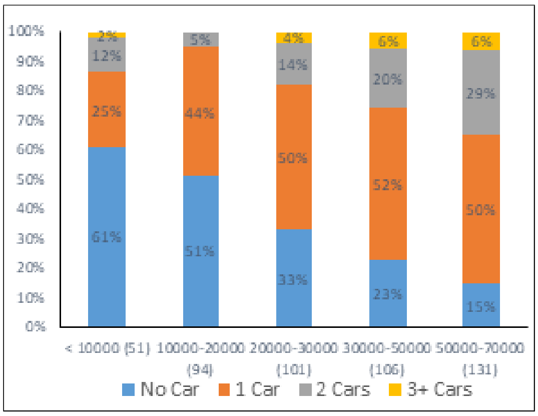

Figure 6.10: Number of cars by income

6.5.1.4 *Gender*

The data is made up of slightly more females than males, it comprised of 47.6% males and 52.4% females. Figures 6.11 and 6.12 show respondents' mode share and car ownership by gender, respectively. Even though, males and females do not differ significantly regarding car ownership, comparatively, greater percentage of females own or have car available for commuting than males. However, more males than females commute by driving. Females on the other hand commute more by PT and non-motorised transport mode than their male counterparts. Males were found statistically different from females in their choice of transport mode for commuting (chi-square value of 7.73 and p-value of 0.02) at 95% confidence level.

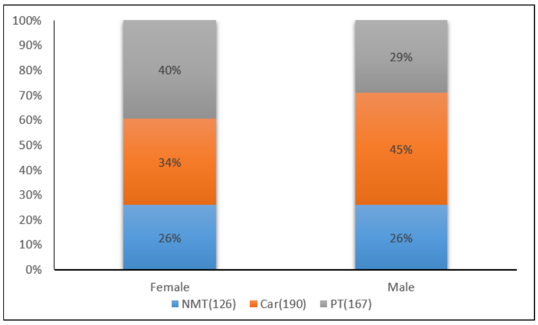

Figure 6.11: Mode share by gender

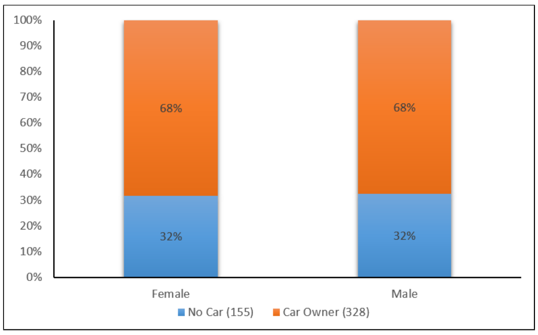

Figure 6.12: Car ownership by gender

6.5.2 MINDSPACE Variables

This section briefly analyses the behavioural variables measured in the survey. Respondents' responses to the behavioural statements and their transport choices are analysed to investigate the existence of any significant association between respondents' responses and their transport mode choices in the dataset. The behavioural dataset is ordinal and measured on a 5-point Likert scale. Respondents are categorised into three groups based on their transport choices for commuting (Non-motorised transport NMT, Car and Public transport PT). The groups are compared using Kruskal-Wallis test to investigate any similarities or difference between the three groups regarding their choice transport mode for commuting. The Kruskal-Wallis test is a non-parametric method for comparing independent samples of equal or different sample sizes. It extends the Mann-Whitney U test to allows the comparison of three or more sub-populations in a dataset.

6.5.2.1 Norm

Kruskal-Wallis test was performed to compare the responses on this measurement scale between respondents commuting by NMT, Car and by PT. Table 6.12 shows that respondents' answers statistically differ between the three groups. Six out of the ten variables used for measuring Norm significantly differ between the three groups at 99% confidence level; one variable significantly differs at 90% confidence level, and three of the variables do not show any significant difference. In general, the measurement instrument for measuring Norm can statistically explain the difference in mode choice. However, detailed analysis involving these statistically significant variables is presented in chapter 7.

Table 6.12: Norm differences between NMT, car and PT users

Variable	Mean	Std Deviation	Kruskal-Wallis Test				
			Mean Rank			Chi-Square	Sig
			NMT (N=126)	Car (N=190)	PT (N=167)		
1 : Driving is perceived to illustrate a person's power ...	2.44	1.191	201.69	266.80	241.00	19.991	0.000***
2 : PT is seen as a second best option in society	2.74	1.215	221.34	245.14	235.40	2.692	0.260
3 : PT is perceived to provide environmentally cleaner ...	3.92	0.870	210.72	249.02	244.79	10.702	0.005***
4 : PT is beneficial to the environment and our health.	3.99	0.821	216.84	242.01	243.25	5.637	0.060*
5 : Family/friends believe PT is beneficial to the ...	3.61	0.899	228.75	249.32	223.25	3.338	0.188
6 : Most of my family and friends use public transport	2.93	1.098	200.47	243.58	261.31	20.243	0.000***
7 : If my family and friends change their travel ...	1.97	0.903	232.39	238.57	227.69	0.537	0.764
8 : I think people should use PT more ...	3.91	1.009	194.64	254.78	259.09	27.691	0.000***
9 : ... family/friends would agree if I use PT ...	3.53	1.003	175.99	272.06	267.05	59.275	0.000***
10 : I feel morally obligated to use more of PT ...	3.14	1.199	197.27	257.75	253.56	22.394	0.000***

***: p<0.1, **: p<0.05, ***: p<0.01**

6.5.2.2 Affect

Table 6.13 shows the Kruskal-Wallis Test conducted to establish the similarities or difference in Affect between respondents commuting by NMT, by car and by PT. It can be seen from Table 6.13 that respondents differ significantly in Affect between the three groups. As can be seen three out of the six variables statistically differ significantly between the three groups at 99% confidence level; two statistically differ at 95% confidence level, and only one variable is not statistically different. In general, we assert that the measurement instrument for Affect statistically explains the difference in respondents' choice of transport mode for commuting. Further statistical analysis involving the significant variables is presented in chapter 7.

Table 6.13: Difference in Affect between NMT, car and PT users

Variable	Mean	Std Deviation	Kruskal-Wallis Test				
			Mean Rank			Chi-Square	Sig
			NMT (N=126)	Car (N=190)	PT (N=167)		
1 : I enjoy using PT ... I get to meet people	2.12	1.062	225.60	213.75	255.89	8.400	0.015**
2 : Travelling in PT is boring	2.41	0.949	230.65	244.23	225.14	1.729	0.421
3 : I can use travel time for other activities	3.34	1.028	198.25	250.03	258.68	22.316	0.000***
4 : Driving is demanding	3.48	1.166	204.50	235.51	263.11	17.572	0.000***
5 : I use PT for the Environment	3.23	1.179	204.75	257.10	245.27	14.395	0.001***
6 : Uncomfortable travelling with strangers	2.03	1.103	252.94	219.13	219.24	7.951	0.019**
***: p<0.1, **: p<0.050, ***: p<0.01**							

6.5.2.3 Salience (PT Experience)

Eight variables were used for understanding respondents' perception and experience with public transport and the impact that would have on the loyalty to public transport. Kruskal-Wallis Test conducted on this measurement tool to investigate any difference in respondents' responses in the following three categories; commuters by NMT, by car and by PT is shown in Table 6.14. As can be seen, respondents differ significantly in response across the three groups. Three variables statistically differ between the three groups at 99% confidence level; three statistically differ at 95% confidence level, whiles the remaining two variables were found statistically not different. We can infer from the results of the Kruskal-Wallis Test that people perception about certain experiences on public transport can shape their decision and affect their choice of transport for commuting. Further statistical analysis and discussion involving the significant variables are presented in chapters.

Table 6.14: PT Experience between NMT, Car and PT users

Variable	Mean	Std Deviation	Kruskal-Wallis Test				
			Mean Rank			Chi-Square	Sig
			NMT (N=126)	Car (N=190)	PT (N=167)		
9 : Anti-social behaviour	3.28	1.427	183.00	126.00	155.00	10.972	0.004***
10 : Overcrowding	3.13	1.268	257.46	216.08	216.38	6.401	0.041**
11 : Exposure to health risk	2.68	1.326	248.70	233.44	212.60	6.402	0.041**
12 : Passenger Annoyance and discomfort	2.96	1.208	251.20	216.43	223.48	13.817	0.001***
13 : Poor hygiene (uncleanliness and smell on bus)	3.35	1.291	257.27	230.98	204.49	10.892	0.004***
14 : Inaccurate bus and real-time information	3.07	1.277	254.61	231.06	207.57	4.211	0.122
15 : Long waiting and travel time	3.40	1.346	245.53	233.56	216.26	6.705	0.035**
16 : Safety issues (seatbelts, toilets et cetera.)	2.34	1.302	248.65	234.50	211.81	2.130	0.345
***: p<0.1, **: p<0.05, ***: p<0.01**							

6.5.2.4 Narcissism

16 variables were used for investigating respondents' level of narcissism and its impact on travel behaviour. It is observed that each of the 16 items impacted travel behaviour differently. Some items have a direct effect on the choice of mode, while others have an indirect effect.

Narcissism and Mode choice

Kruskal-Wallis Test conducted on the NPI-16 measurement scale to examine respondents' scores against their regular commuting mode (i.e. NMT, Car and PT) is shown in Table 6.15. As can be seen, the test shows a statistically significant difference between three of the narcissism items (2, 7 and 11) and travel mode. These three items define narcissistic trait of Exhibitionism according to Ames et al. (2006). The remaining 13 variables were found statistically, not different. We may infer from the above that the narcissistic trait of Exhibitionism could influence travel mode choice, indicating that exhibitionists are more likely to own and commute by car.

Table 6.15: Narcissism between NMT, Car and PT users

Variable	**Mean**	**Std Deviation**	**Kruskal-Wallis Test**				
			Mean Rank			**Chi-Square**	**Sig**
			NMT (N=128)	**Car** (N=188)	**PT** (N=168)		
1 : I know that I am good because everybody ...	2.53	0.998	233.52	237.84	237.33	0.094	0.954
2 : I like to be the centre of attention	2.12	0.906	248.80	246.70	219.9	4.912	0.086*
3 : I think I am a special person	2.47	1.031	251.25	229.81	245.86	2.298	0.317
4 : I like having authority over people	2.34	1.024	235.20	242.13	236.96	0.243	0.886
5 : I find it easy to manipulate others	2.16	1.004	238.52	233.72	236.64	0.108	0.947
6 : I insist upon getting the respect ...	2.32	1.035	240.14	226.72	247.82	2.294	0.318
7 : I am apt to show off if i get the chance	2.21	1.016	247.86	245.79	215.53	6.082	0.048**
8 : I always know what I am doing	2.85	1.157	234.28	246.27	237.34	0.701	0.704
9 : Everybody likes to hear my stories	2.36	0.962	233.66	226.16	250.45	3.119	0.210
10 : I expect a great deal from other ...	2.63	0.999	252.65	236.49	235.72	1.455	0.483
11 : I really like to be the centre of ...	2.06	0.946	249.26	247.98	212.40	8.346	0.015**
12 : People always seem to recognise my ...	2.49	1.022	239.99	230.19	240.95	0.712	0.700
13 : I am going to be a great person	2.50	1.026	236.35	227.45	239.59	0.817	0.665
14 : I can make anybody believe anything ...	2.16	0.953	244.81	244.34	221.13	3.465	0.177
15 : I am more capable than others	2.55	1.039	239.05	247.11	235.76	0.676	0.713
16 : I am an extraordinary person	2.35	0.987	245.30	238.14	230.79	0.888	0.642
***: p<0.1, **: p<0.05, ***: p<0.01**							

Further to the test above, Mann-Whitney U test conducted to confirm the relationship between car users and PT users. The test found significant difference between car users and PT users for five of the 16-item NPI scale and confirm that narcissistic trait of Exhibitionism significantly differentiates between car users and PT users. Table 6.16 indicates that the mean rank for Car users is significantly higher than that of PT users for all the three measurement items of Exhibitionism (2, 7 and 11). Thus, it can be concluded that car users exhibitionism score was statistically significantly higher than PT users score (U= 13469.50, 12846.0 and 12678.0 at p= 0.044, 0.025 and 0.008 respectively). The test indicates at probabilities of 1 in 23, 1 in 40 and 1 in 125; that the population of Narcissist (exhibitionist) will select different mode of travel from a population of non-narcissist.

Table 6.16: Narcissistic difference between car users and PT users

Mann-Whitney U test					
	Mean Rank				
Variable	**Car**	**PT**	**U**	**z-score**	**Exact Sig.**
	(N=188)	(N=167)			**(2-tailed)**
2: I like to be the centre of attention	185.08	164.63	13469.50	-2.012	0.044**
7: I am apt to show off if i get the chance	183.68	160.79	12846.00	-2.238	0.025**
9: Everybody likes to hear my stories	165.27	182.85	13389.50	-1.721	0.085*
11: I really like to be the centre of attention	186.60	159.78	12678.00	-2.632	0.008***
14: I can make anybody believe anything...	181.40	164.53	13450.50	-1.646	0.100*
*: p<0.1, **: p<0.05, ***: p<0.01					

Narcissism and Car Ownership

A similar test conducted between Narcissism and car ownership returned three statistically significant items. The Kruskal-Wallis Test showed that there is statistically significant difference in scores between Narcissism (component of exploitativeness, self-sufficiency and exhibitionism) and the level of car ownership. As indicated in Table 6.17, item 2 (component of exhibitionism) is significantly different between the three levels of car ownership at 95% confidence level. Similarly, item 9 (component of exploitativeness) is significantly different between the three levels of car ownership at 99% confidence level and finally, item 15 (component of self-sufficiency) is significantly different between the three levels of car ownership at 95% confidence level. The remaining 13 variables do not show any significant variation in car ownership.

Table 6.17: Narcissism and Car Ownership

Variable	Mean	Std Deviation	Kruskal-Wallis Test: Mean Rank No car (N=153)	1 car (N=223)	2+ cars (N=110)	Chi-Square	Sig
2 : I like to be the centre of attention	2.12	0.906	228.30	235.07	264.84	5.587	0.061**
9 : Everybody likes to hear my stories	2.36	0.962	264.59	216.69	247.50	12.505	0.002***
15 : I am more capable than others	2.55	1.039	234.26	235.38	272.82	6.755	0.034**

***: p<0.1, **: p<0.05, ***: p<0.01**

Mann-Whitney U test between the 16-item NPI scale and car ownership shows significant difference between car owners and non-car owners for three of the 16-item NPI scale. Table 6.18 shows that households having at least two cars available for commuting have significantly higher mean rank than respondents without a car, for items 2 and 15 (exhibitionism and self-sufficiency correspondingly according to Ames et al. (2006)) at 95% confidence level. This suggests that respondents exhibiting the narcissistic trait of exhibitionist and self-sufficiency are more likely to own multiple cars than those who are not. This is possibly because of the need to prop-up their lifestyle with those product (Cisek et al., 2014). It was further observed that the mean rank for non-car owners is significantly higher than that of car owners for measurement items 9 (a component of exploitativeness as defined by Ames et al. (2006)). The results suggest that respondents showing the trait of exploitativeness are less likely to drive nor own a car than non-exploitative (U= 12837.5, p= 0.001).

Table 6.18: Narcissistic difference between car owners and non car owners

Variable	Mann-Whitney U test: Mean Rank No Car (N=153)	1 Car (N=220)	2+ Cars (N=113)	U	z-score	Exact Sig (2-tailed)
2: I like to be the centre of attention	122.47		142.17	7099.50	-2.211	0.027**
9: Everybody likes to hear my stories	205.57	168.85		12837.50	3.434	0.001***
15: I am more capable than others	123.36		144.02	7092.50	-2.258	0.024**

*: p<0.1, **: p<0.05, ***: p<0.01

The results of the Kruskal-Wallis Test and Mann-Whitney U Test provide a possible explanation on how personal narcissism could influence choice of mode for commuting.

6.6 Summary

This chapter has discussed the data collection procedure and reports the descriptive statistics of the sample data. Although the response rate is below the expectation of the researcher, the sample data has been established to be representative of the study population.

A total number of 3973 households were given the questionnaire package to take part in the survey. 551 households representing 13.9% completed and returned the questionnaire.

The distribution of the sample data in by age, gender, income, employment, car ownership and modal share was compared with similar estimates from the Scottish Household Survey data (National Records of Scotland, 2018a) and travel data from the Transport of Scotland (Transport Scotland, 2018b, Table 1). This was done to investigate the representativeness of the sample data to the study population. It was necessary to know whether the study results and analysis could be generalised to the study population or not. The comparative test suggested that the characteristics of the sample data do not differ from the Scottish Household Survey data (National Records of Scotland, 2018a) and the Transport of Scotland travel data. This is an indication that both datasets come from the same population. Thus, it was found that the sample data was representative of the study population. Table 6.10 shows a summary of these estimates.

Exploratory analysis of the sample data indicates that participants' age, income, gender and car ownership significantly relate to their choice of mode for commuting. It was found that the proportion of car owners and car usage increases with increasing income and age. Male and females were found to differ in their choice of mode. While males predominately drive, females were found to commute more by public transportation modes. It was further found that the following MI**N**D**S**P**A**C**E** elements; Norms, Salience (experiences on public transport), Affect and Ego/Narcissism could have impact travel behaviour. The mean ranks of participants' responses to the indicators designed for measuring the selected MINDSPACE elements were found to significantly differ between Car, Public transport and Non-Motorised transport users. The next chapter presents detailed statistical analysis involving traditional discrete choice model and ICLV model which incorporates some effects of the MINDSPACE framework as latent variables.

Part III

STATISTICAL MODELLING AND CONCLUSIONS

Chapter Seven

Statistical Analysis and Model Development

7.1 Introduction

The travel behaviour of an individual is explained by modal attributes, trip characteristics and socio-economic characteristics. However, the literature suggests that these do not adequately account for the heterogeneity in observed preferences. It is well established that attitudes and perceptions play a significant role in the decision-making process (Ben-akiva and Bierlaire, 1999; Ortuzar and Willumsen, 2011; Kamargianni et al., 2015). Beyond the significance of attitudes and perception in the choice making, they are difficult to observe directly and are thus considered latent and measured with psychometric indicators. This chapter extends the analysis from chapter 6 and describes the systematic process of developing ICLV model by integrating a latent variable model into a discrete choice model. Section 7.2 of this chapter outlines the processes for extracting the latent variables from the psychometric indicators for the development of the latent variable structural model. The development of a traditional discrete choice model and ICLV model with the integration of the latent variable structural model is described in 7.3, and section 7.4 presents the results and covers the discussion of the results.

7.2 Construction of latent variables

The estimation of latent choice models or ICLV models requires a clear definition and construction of the latent variables as well as the theory behind them. Chapters 2 and 4 discuss the theoretical background of the latent variables (Variables of MINDSPACE). This section presents the formation of the latent variables from the sample data using the developed indicators. Section 7.2.1 describes the exploratory factor analysis performed to investigate the indicators in the sample data. Section 4.5.3 explains the theory and rationale behind the EFA and section 7.2.2 explains the CFA process. Figure 7.1 is a diagrammatic presentation of the processes involved in the analysis.

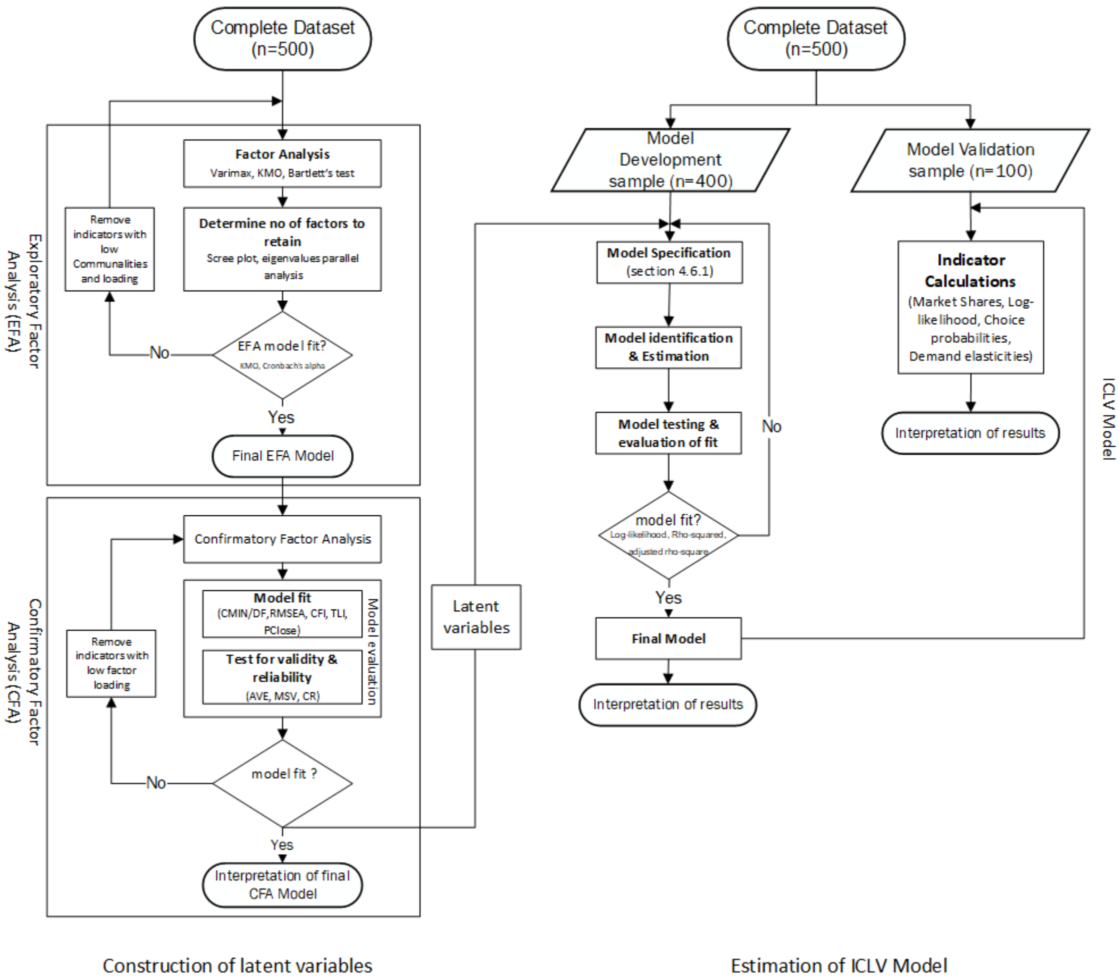

Figure 7.1: Conceptual Diagram for the Analysis

7.2.1 Exploratory factor analysis (EFA)

Since the measurement scale developed for measuring the selected MINDSPACE variables is being tested for the first time, EFA was performed to explore and reliability of the underlying dimensionality in the psychometric indicators. The EFA was performed with the indicators of the proposed MINDSPACE variables in the dataset. The normality of the indicators was tested using SPSS software package. According to the normality assumption, data is considered normal if the Skewness and Kurtosis are between ± 3.00 and ± 7.00 Tabachnick and Fidell, 2014. The results of the normality test indicate the 50 indicators had no normality issues (Bryne, 2012; Kline, 2011; Herman, 2016). The EFA was consequently performed using maximum likelihood (ML) estimation method in SPSS software package version 23.0 (Field, 2013). The robustness of ML method in handling normally distributed data, ordinal data, cases with missing data and the fact that AMOS software package uses ML for the CFA makes it most appropriate for the factor analysis (Bahaman, 2012; Arbuckle, 2017). Oblimin rotation method was adopted to allows some level of correlation between the factors.

7.2.1.1 Results and discussion of the EFA

Following the recommendations of Child (2006) and Tabachnick and Fidell (2014), eleven (11) indicators with communality score less than 0.2 were removed during the factor analysis. Additionally, items with factors loadings below 0.3 were also suppressed. Two variables "PTExp6b" and "PTExp7b" were found cross-load above o.40 on two factors. These two indicators were consequently removed from the analysis and the EFA reperformed, according to the recommendation in Schönrock-adema et al. (2009) (to remove variables cross-loading at least 0.40 on more than one construct). Figure 7.2 shows the scree plot of the eigenvalues of the final EFA and the eigenvalues of PA. According to the PA rule and Figure 7.2, five (5) factors must be retained. However, the 5-factor solution explains only 49% of the total variance, which is less than the minimum of 50% recommended by the total of variance extracted technique (Streiner, 1994).

On the other hand, according to the KI rule of "eigenvalue-greater-than-one", seven (7) factors explaining a total of 59.75% of the variance should be retained, this satisfies the total variance extracted rule. Therefore, the 7-factor solution is adopted for the analysis (Beavers et al., 2013); this follows the advice of Streiner (1994). The interpretability and comprehensibility of the factors were also considered in the factor retention decision. The rationale is to choose enough factors that adequately represent the data and theoretically relevant to the study (Beavers et al., 2013; Schönrock-adema et al., 2009).

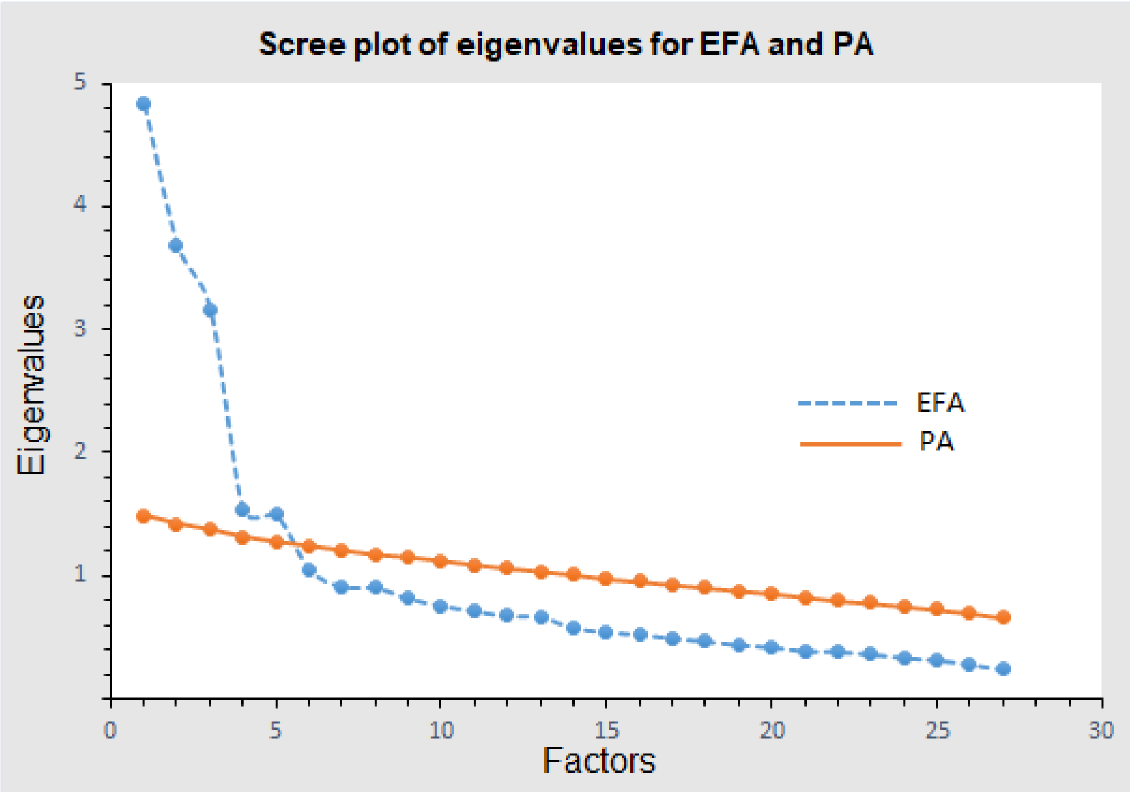

Figure 7.2: Scree plot of EFA and PA

Table 7.1 shows the results from the maximum likelihood factor analysis. Twenty-seven (27) observed indicator variables were analysed in the factor analysis, and these are categorised into seven latent constructs. Overall, five latent constructs have at least three indicators except for *Affect* and *symbolism* which have two indicators each. All factor loadings in the measurement equations are significant, except for three variables, which were borderline lower than the recommended absolute value of 0.4 (Schönrock-adema et al., 2009; Field, 2013). Largely all indicators contribute to the construction of the latent constructs. Alpha Cronbach's test has been conducted for the reliability of latent constructs extracted. Cronbach's alpha values for six of the seven retained constructs satisfied the 0.70 minimum requirements for reliability ($\alpha \geq 0.70$) (Cronbach, 1951). However, Cronbach alpha values for *Affect* ($\alpha = 0.664$) is marginally below the acceptable threshold. Meanwhile, according to Kline (2011), lower values of Cronbach's alpha can be tolerated in a latent variable analysis.

Consequently, *Affect* has been retained for further analysis due to its theoretical relevance to the study.

Additionally, any issue arising from individual heterogeneity could be controlled in the choice model (Beavers et al., 2013; Schönrock-adema et al., 2009; Streiner, 1994). Therefore, the extracted latent constructs are assumed to be reliable and acceptable; the sample size and the indicators are appropriate for testing the CFA.

Table 7.1: Exploratory Factor Analysis[1]

N = 500	Latent Construct						
MINDSPACE Elements	Norm			Salience	Affect	Narcissism/Ego	
Factor	PerNorm	SocNorm	Symb	Sal	Aff	Nar	Exhib
Cronbach's Alpha	0.785	0.772	0.721	0.859	0.664	0.852	0.762
Nrm10	0.847						
Aff5	0.651	0.331					
Nrm9	0.452						
Nrm8	0.445						
Nrm4		0.898					
Nrm3		0.763					
Nrm5		0.448					
Nrm2			0.902				
Nrm1			0.629				
PTExp4b				0.833			
PTExp5b				0.73			
PTExp3b				0.722			
PTExp1b				0.719			
PTExp2b				0.708			
PTExp8b				0.572			
Aff4					1.017		
Aff3					0.441		
Nar15						0.67	
Nar12						0.493	
Nar13						0.475	
Nar16						0.461	
Nar3						0.441	
Nar4						0.441	
Nar5						0.418	
Nar2							0.68
Nar11							0.534
Nar7							0.398

Nar = Narcissism; SocNorm = Social Norms; Aff = Affect; Exhib = Exhibitionism; PerNorm = Personal Norms

The Kaiser-Meyer-Olkin (KMO) Test verifies the adequacy of the sampling and whether

[1]For readability, factor loadings upto ± 0.3 has been suppressed, following the advice of Tabachnick and Fidell (2014)

the indicators are suitable for factor analysis whiles Bartlett's test of sphericity test the significance of the correlation between all the indicators in the EFA (Hair et al., 1998). Table 7.2 shows the results of the KMO and Bartletts test. From the results, the KMO value of 0.797 (KMO ≥ 0.70), satisfies the minimum requirement and indicate an adequate sample size for factor analysis. Similarly, Bartlett's Test value of 3492.347 is significant (P <0.01), also suggesting that the correlation between the indicators is adequate for factor analysis.

Table 7.2: Measure of sample Adequacy

Measure of Sample Adequacy		
Measure		**Value**
Bartlett's Test of Sphericity	x^2	3492.347
	df	351
	Sig.	0
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.797

7.2.1.2 Latent Constructs

Seven latent constructs/variables are extracted in the factor analysis, namely: Salience (Sal: 6 indicators), Social Norms (SocNorms : 3 indicators), Personal Norms (PerNorms: 4 indicators) Symbolism (Symb: 2 indicators), Narcissism (Nar: 6 indicators), Narcissistic trait of exhibitionism (Exh: 3 indicators) and Affect (Aff: 2 indicators).

Salience describes the participants' perception of negative experience on public transport (bus and tram services in Edinburgh). This variable reflects the assertion that negative experiences are exaggerated in human memory and mostly recalled in decision-making. The investigation seeks to examine the influence of salient PT experiences on decision making.

Three latent variables were extracted from the instrument designed for measuring *Norms*; the results of the factor analysis are consistent with Belgiawan et al. (2016). The latent variables comprise of Social Norms (SocNorm), Personal Norms (PerNorms) and social symbolism (Symb).

SocNorm describes the respondents' perception or understanding of societal beliefs and perception of cars, public transport and the environment.

PerNorm defines the individual views and perception of cars, public transport and their impact on the environment; this factor describes the internalised norms of the respondents.

Symb describes the perception of the social-symbolic value of driving and anti-status value of PT. *Symb* is constructed with two indicators, one describing the symbolic status of owning and driving a car and the second indicator depicting PT as anti-status symbol (Steg, 2005).

Affect could be explained in terms of positive or negative valence. The instrument designed for assessing this concept comprised of statements for measuring both aspects of *Affect*. The indicators for negative valence were suppressed and remove for having very low communalities and factor loadings. Therefore, the variable *Affect* describes positive valence and sentiments towards PT modes (Bus/Tram) resulting from the individual's experience of PT travel and driving.

Narcissism describes a personality type characterised by a sense of entitlement, specialness, a need for admiration and a lack of empathy. Narcissism comprises of seven (7) first-order subtypes namely, Superiority, Exhibitionism, Exploitativeness, Self-sufficiency, Authority, entitlement and Vanity (Raskin and Terry, 1988; Ames et al., 2006).

Two latent variables were extracted from the 16-item NPI scale developed for measuring. Narcissism; 4 indicators with very low communalities and factor loadings were removed or suppressed from the analysis.

Narcissism is the first factor, this construct was formed with six indicators comprising of indicators on Superiority, Exploitative, Self-sufficiency, Authority, entitlement (Raskin and Terry, 1988; Ames et al., 2006).

Exhibitionism; this is Narcissism trait of Exhibitionism (Raskin and Terry, 1988). This variable is characterised by Grandiosity personality traits and reflect an individual need for attention and admiration (Levesque, 2011).

7.2.2 Confirmatory factor analysis

This section is aimed at assessing the seven factors extracted in the EFA through Confirmatory Factor Analysis (CFA). This section tests the seven latent factors extracted during the EFA for validity and reliability. All the variables (exogenous and endogenous) are combined in the CFA analysis (pooled CFA) based on the findings in Chong et al. (2014) and Herman (2016). The threshold for validity, reliability and the goodness of fit indices are discussed under section 4.5.4.1 and summarised in Table 4.6. The latent variables are examined in a First Order pooled CFA using AMOS software package version 26.0.

7.2.2.1 Results and discussion of the CFA

The final CFA model as shown in Figure 7.3 comprise of 20 indicators categorised into six latent constructs namely; Salience, superiority, social Norms (SocNorms), Affect, Exhibitionism, Personal Norms (PerNorms). One indicator was dropped from the latent variable Salience and four indicators from the latent variable Narcissism (Table 7.1). The latent variable Narcissism (now with three indicators) is redefined as *Superiority narcissism (Superiority)* to reflect its indicators (Raskin and Terry, 1988). Superiority narcissism describes a situational narcissism where an individual believes they are superior to others and acts in ways that indicate they are not shy about discussing or flaunting their achievements.

Five of the 27 indicators from the EFA were found to have low loadings and subsequently dropped from the analysis (refer to Figure D.1 in Appendix D) (Field, 2013). The final CFA model had 22 indicators classed into seven latent constructs (refer to Figure D.2 in Appendix D). However, the latent construct, Symbolism was dropped for identification related issues; the standardised factor loading and squared multiple correlations of one of its indicators (Nrm1) exceeds unity (1.51 and 2.27 respectively)(Hair et al., 1998, pg.610), additionally, the critical ratio of Symbolism and Nrm1 of 1.286 and -0.719 are below the minimum threshold of ≥ 1.96. Researchers differ in opinion on the meaning and implication of having standardised coefficients greater than one in magnitude

(Hair et al., 1998; Jöreskog, 1999, pg.610). While Hair et al. (1998, pg.610) suggest the elimination of such constructs, Jöreskog (1999) believes this does not mean something is wrong, but an indication of high degree of multicollinearity (Jöreskog, 1999). Therefore, two CFA models were performed. The AIC and BIC estimates of the two CFA models were compared and the best fit CFA model adopted for the ICLV modelling. Table 7.3 below shows the fitness indices of the two measurements models, Model 1 with latent factor Symbolism and model 2 without Symbolism.

Table 7.3: CFA model comparison

Index	Model 1	Model 2
CMIN	357.864	328.809
DF	188	155
CMIN/DF	1.904	2.121
NFI	0.912	0.914
TLI	0.940	0.935
CFI	0.956	0.952
RMSEA	0.042	0.047
PClose	0.978	0.767
AIC	531.864	478.809
BIC	540.048	485.225
Δ_{AIC}	53.055	0
Δ_{BIC}	54.823	0

The final model satisfied all indices recommended for assessing goodness-of-fit (see Hu and Bentler, 1999; Kline, 2011), indicating that the measurement model sufficiently fits the sample data.

The results in Table 7.3 indicate that both models satisfied all indices recommended for assessing goodness-of-fit (see to 4.6) Hu and Bentler, 1999; Kline, 2011.

A comparison of the AIC and BIC estimates of the two models shows that model 2 has low AIC and BIC values compared to model 1.

The difference in AIC and BIC values between the two models (Δ_{AIC}= 53.055 and Δ_{BIC}=54.823) both provide strong evidence in favour of model 2 (Fabozzi et al., 2014). Therefore, model 2 is accepted and adopted in the study. Figure 7.3 below shows the graphical representation of the final CFA model. According to Figure 7.3, the final pooled first Order CFA has 20 indicators represented by six latent constructs.

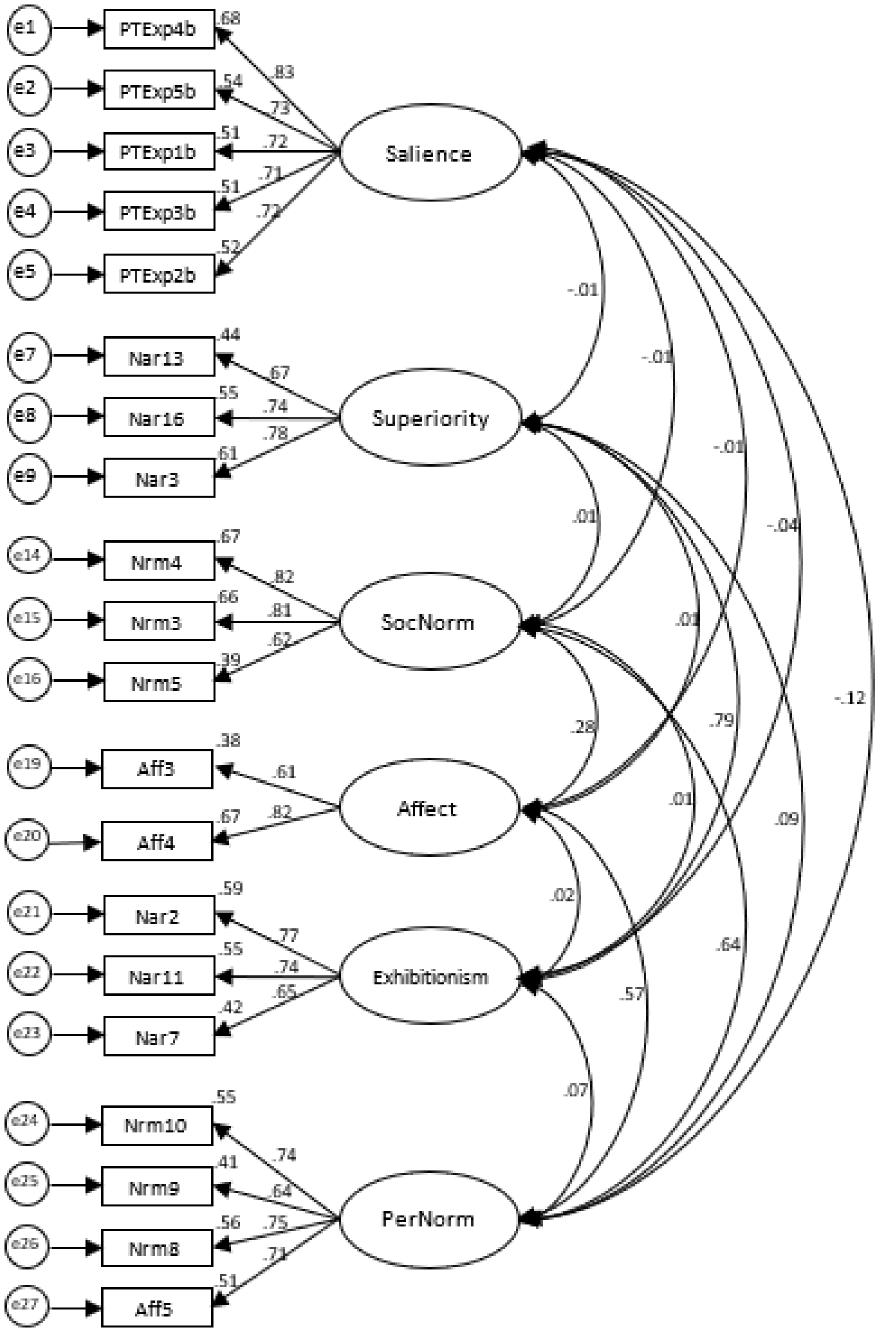

Figure 7.3: Final CFA Model: Standardised Estimates

Herman (2016) indicated that if one or two indicators have factor loadings below 0.70, the construct can still be accepted. However, according to Hair et al. (1998, pg.111), for a latent construct to account for at least 50% of the variance, the average of all its factor loadings must exceed 0.70, and the construct must satisfy fitness indices such as the CFI, TLI and RMSEA (Hair et al., 1998; Hu and Bentler, 1999, pg.111). According to Figure 7.3 and Table 7.4, all the 20 indicators achieved the minimum factor loading of 0.50 and the average of the factor loadings of each latent construct above 0.70. The Measurement model fitness indices presented in Table 7.6 show that there are no issues with the first order pooled CFA. In addition, Table 7.5 and Table 7.6 indicate that the CFA model achieved Convergent and Discriminant Validity, and reliability.

Table 7.4: Confirmatory Factor Analysis

N = 500	Latent Construct						
MINDSPACE Elements	Norm		Salience	Affect	Narcissism/Ego		Sig
Factor	PerNorm	SocNorm	Sal	Aff	Sup	Exhib	
Nrm8	0.748						***
Nrm9	0.641						***
Nrm10	0.741						***
Aff5	0.711						***
Nrm5		0.623					***
Nrm3		0.811					***
Nrm4		0.819					***
PTExp2b			0.718				***
PTExp1b			0.712				***
PTExp3b			0.717				***
PTExp5b			0.732				***
PTExp4b			0.825				***
Aff4				0.818			***
Aff3				0.613			***
Nar3					0.778		***
Nar16					0.739		***
Nar13					0.666		***
Nar7						0.648	***
Nar11						0.744	***
Nar2						0.765	***

PerNorm = Personal Norm; SocNorm = Social Norm ; Sup = Superiority Narcissism;
Exhib = Exhibitionism Narcissism; *** = P-value < 0.000

Table 7.5 shows the results of the validity and reliability test performed as part of the CFA. The CFA findings indicate that The CR values of all the constructs are ≥ 0.70, except Affect; which has CR value of 0.683. However, Affect is retained, following the suggestions of Fornell and Larcker (1981); Bagozzi (1988) that CR values greater than 0.60 can be considered adequate. Therefore, all the constructs are considered to have achieved CR. Moreover, all constructs satisfied the MaxR(H) test of reliability.

Similarly, the results show that there is no issue with convergent validity (AVE ≥ 0.50). All constructs but Superiority and Exhibitionism achieved Discriminant validity (MSV < AVE); this suggest a substantial level of correlation among the indicators of Superiority and Exhibitionism, which raises issues of multicollinearity. Bahaman (2012) recommended cut-off value of 0.85; meanwhile, the correlation between Superiority and

Exhibitionism is less than 0.85. Therefore, the CFA model has achieved Convergent and Discriminant validity, and reliability. In addition, the fitness indices of the measurement model presented in Table 7.6 show that there are no issues with the first order pooled CFA. The latent constructs from the CFA are accepted for the development of the ICLV model.

Table 7.5: CFA Validity and Reliability

Factor	CR	AVE	MSV	MaxR(H)
Salience	0.859	0.551	0.013	0.865
Superiority	0.772	0.532	0.619	0.779
Social Norm	0.798	0.572	0.412	0.821
Affect	0.683	0.524	0.320	0.728
Exhibitionism	0.764	0.520	0.619	0.771
Personal Norm	0.804	0.507	0.412	2.423
Level of Acceptance	≥ 0.70	≥ 0.50	MSV < AVE	≥ 0.70

CR=Composite reliability; AVE=Average value extracted; MSV=Maximum shared variance; MaxR(H)=McDonald Construct Reliability

Table 7.6: CFA model fitness

Measure	CMIN	DF	CMIN/DF	CFI	NFI	TLI	SRMR	RMSEA	PClose
Estimate	328.809	155	2.121	0.952	0.914	0.935	0.059	0.047	0.767
Level of Acceptance			<3.0	>0.90	>0.90	>0.90	<0.08	<0.06	>0.05

To better understand the characterisation of the latent factors, the latent factors were used as endogenous variables in estimating a linear regression model. Factors scores of the CFA latent variables were imputed using regression imputation in the AMOS Software after the CFA analysis and used as endogenous variables in the estimation of the linear regression model. Observed socio-demographic variables such as Age, Income, Gender and Education were used as exogenous variables to develop latent factor structural equations. This CFA linear regression model allows the prediction of the membership of the latent variables based on individual socio-demographic characteristics. Table 7.8 presents the results of the regression analysis. High_Income is a dummy variable 1 for respondents earning at least £50,000. High_Educ is a dummy variable 1 for respondents with a University degree and 0 otherwise. No_of_Cars represents the number of cars available in the household. Age_Sup represents three age bands: 1 for "18 to 24", 2 for "25 to 64" and 3 for respondents above 64 years. Age_Sal is a dummy variable, 1 for respondents aged "25 to 64" and 0 otherwise. Age_PerNorm is a dummy variable, 1 for respondents aged "18 to 24" and above 64 years and 0 for respondents aged "25 to 64. Gender is a dummy variable 1 for male and 0 for female.

Table 7.7: Specification of structural equation for the latent variable model

MINDSPACE Elements	Salience	Affect	Norms		Ego	
Variables			PerNorm	SocNorm	Exh	Sup
α_{Sal}	1	-	-	-	-	-
α_{Aff}	-	1	-	-	-	-
α_{PNorm}	-	-	1	-	-	-
α_{SNorm}	-	-	-	1	-	-
α_{Exh}	-	-	-	-	1	-
α_{Sup}	-	-	-	-	-	1
β_{Age_Sup}	-	-	-	-	-	Age
$\beta_{Ridacard}$	-	Ridacard	-	-	-	-
β_{NCars}	-	No_of_Cars	No_of_Cars	No_of_Cars	-	-
β_{Income}	-	-	High_Income	High_Income	-	-
β_{Educ}	-	-	High_Educ	High_Educ	-	-
β_{Age_Sal}	Age	-	-	-	-	-
$\beta_{Age\_PerNorm}$	-	-	Age	-	-	-
β_{gender}	-	-	-	-	Gender	-

Note: α = Constant; PerNorm = Personal Norms; SocNorm = Social Norms; Exh = Exhibitionism; Sup= Superiority

Table 7.8: Regression with CFA factors as dependent variables

Factor	Sal		Aff		PerNorm		SocNorm		Exh		Sup	
Variables	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Age_18-34											0.229***	0.073
Ridacard			0.211***	0.061								
No_Cars			-0.113***	0.043	0.295***	0.080	0.169***	0.059				
High_Income					0.313***	0.108	0.161**	0.079				
High_Educ					0.233***	0.077	0.206***	0.056				
Age_Sal	0.123***	0.093										
Age_PerNorm					0.247***	0.077						
Gender_Exh									0.10**	0.061		
R2	0.016		0.084		0.077		0.054		0.018		0.013	
Adj. R2	0.013		0.074		0.067		0.047		0.013		0.010	

Note: β = coefficients; SE = Standard errors; * = significant at 90%; ** = significant at 95%; *** = significant at 99%

Analysing the results of the regression analysis in Table 7.8, The following observations were made:

Salience: It is noticed that individuals of active working age between 25 and 64 are likely to belong to and affected by this factor; This implies that individuals within the active working-age group of the population are more likely to be affected by bad experience on public transport.

Affect: Individuals in this class are more positive about public transport. They are likely not to own a car and own a public transport season ticket, an indication of loyal riders of public transport and have high utility for PT in-vehicle travel time and disutility for driving. The likelihood to belong to this group decreases with an increasing number of household cars.

Norms: Two latent constructs were retained from this MINDSPACE Element in the CFA analysis named as "personal norm" and "social norms", these two constructs are discussed below:

Personal Norms: Individuals scoring high on this construct are likely to be either young or old and aged between 18 and 24 or above 64 years, respectively. The estimates indicate that members of this class are highly educated and have a university degree (at least have a first degree). They are likely to have a household income of at least £50,000 and may not have a car available for the household use.

Social Norms: Individuals scoring high on this latent construct have similar characteristics as those in the Personal norms group. The difference between these two constructs is that while personal norm is dependent on age, social norm is less affected by age.

Ego/Narcissism: Similar to Norms, two latent constructs were retained from Narcissism in the CFA analysis, namely, "Exhibitionism" and "Superiority".

Exhibitionism: This narcissistic trait is associated with the use of material goods to enhance social status. Members scoring high on this construct are observed to be single household males of all ages.

Superiority: This trait describes individuals with a delusional sense of superiority that leads them to believe they are unique from the average person. Respondents scoring high on this construct are observed to be young individuals aged between 18 and 34.

7.3 Mode Choice Modelling

The choice models were estimated on 80% of the sample data (400 cases randomly selected from the sample data). The estimated model is then applied to the other 20% of sample data for validating the developed model. The sections below discuss the model estimation and the model results.

7.3.1 The Baseline model

Multinomial logistic regression model has been estimated as the baseline model using the maximum likelihood estimator in Biogeme software package (Bierlaire, 2018b) based on the specification in section 4.6.1.1 and equations 4.13 to 4.15. The choice is assumed to be between; public transport (PT), which consists of bus, train and tram; private motorised modes (Car), which include car as a user and a passenger and taxi, and Non-motorised transport (NMT), representing walking and cycling. Utilities of the alternatives are presented in section 4.6.1 with explanatory variables of individual characteristics, modal attributes and trip characteristics.

There are several ways to decide on the variables to include in a model. The selection of variables allows for the construction of an optimal model. The selection limits the set of predictor variables to those that are necessary to account for as much of the variance in the data. The first consideration in the selection of variables included during the estimation of the base model was their theoretical relevance to the objective of the study according to the literature. Finally, statistical regression methods such as forward selection, backward elimination, stepwise selection were used in several trials to conclude on the final model.

7.3.2 Integrated Choice and Latent Variable model

The final integrated and latent variable (ICLV) model consisting of two components; the discrete choice model and a latent variable model was estimated using 10,000 Modified Latin Hypercube Sampling (MLHS) draws (Hess et al., 2006). The ICLV model has the same specification as the Baseline model but with the incorporation of the latent attitudes or psychometric constructs. The factors extracted during the EFA and validated in the CFA are used as latent variables in addition to the observed individual and trip characteristics, and modal attributes. The model estimation is done in the Biogeme software Bierlaire, 2018b. We estimate an integrated choice and latent variable model. Like the baseline model, the estimated model contains choices between PT, Car and NMT. The framework and detail specification of the integrated choice model is illustrated in Figure 4.2. (Readers are referred to the model specification in section 4.6.1) (Ben-Akiva and Boccara, 1995; Ben-akiva and Bierlaire, 1999; Bierlaire, 2018c) Modified Latin Hypercube Sampling (MLHS).

7.4 Results and Discussion

The results of the base model and the ICLV model are presented and discussed in the following sections.

7.4.1 Results

Table 7.9 reports the results of the ICLV model. The prediction rate of the ICLV model with the Base model for the validation sub-sample (20% of data). Overall correct prediction rate of 60% was obtained for the base model and 65% correct prediction rate for the ICLV model. This suggests that the latent variables succeeded in accounting for some existent heterogeneity of respondents' travel choices. In other to assess the validity and applicability of the estimated model on a similar dataset, the model was validated using the validation sample; the remaining 20% of the dataset. Table 7.10 presents the goodness of fit and the log-likelihood estimates for both models. The log-likelihood values for the ICLV and the base models are calculated from the simulated choice probabilities of both models from the validation sample for comparison. The ICLV model is observed to have the best goodness of fit statistics compared to the base model. Even though the ICLV model has more predictor variables compared to the base model, a comparison of the adjusted rho-square ($\bar{\rho}^2$) values indicates that the additional predictor variables in the ICLV model improved upon the base model more than would be expected by chance.

It can be seen from the results in Table 7.9 that the estimates of all the utility variables, i.e. travel time, cost, distance, age, education, income, walking time and number of cars have the expected signs. The estimates and the significance level for both the base and the ICLV models are similar and consistent with results from similar studies (Ben-akiva and Bierlaire, 1999; Dannewald et al., 2008; Ortuzar and Willumsen, 2011; Temme et al., 2008b; Yáñez et al., 2010; Kamargianni et al., 2015). Almost all variables are significant at 95% confidence level and have the expected signs. The estimate for the cost of PT has the expected sign but insignificant in both models. Gender is significant at 90% in the base and the ICLV models.

Table 7.9: Modelling Results

Variable	Base Model			Latent Choice Model		
	Estimate	t-test	p-value	Estimate	t-test	p-value
ASC_{Car}	-4.15	-4.49	0.000	-4.35	-4.21	0.00
ASC_{NMT}	-3.84	-4.42	0.000	-4.00	-4.13	0.000
β_{Age_NMT}	-0.22	-2.41	0.016	-0.25	-2.66	0.008
β_{Age_PT}	-0.53	-2.01	0.044	-0.80	-2.56	0.010
β_{Cost_Car}						
β_{Cost_PT}	-0.29	-2.36	0.018	-0.31	-2.40	0.017
β_{Dist_NMT}	-0.18	-3.58	0.000	-0.18	-3.47	0.000
β_{Educ_NMT}	0.48	3.88	0.000	0.45	3.51	0.000
β_{Gender_Car}	0.55	2.03	0.042	0.59	2.11	0.035
β_{Income_PT}	-0.18	-2.03	0.042	-0.19	-2.01	0.044
β_{NCar_Car}	1.83	8.92	0.000	1.75	7.95	0.000
β_{TT_car}	-0.41	-2.51	0.012	-0.39	-2.29	0.022
β_{TT_PT}	-0.20	-2.09	0.036	-0.21	-2.07	0.039
β_{Tr_Freq}	-0.25	-2.43	0.015	-0.29	-2.65	0.008
$\beta_{WTime\_To\_BS}$	0.36	3.60	0.000	0.34	3.36	0.000
β_{Work_Trip}	-0.80	-2.16	0.030	-0.80	-2.08	0.037
$\beta_{PerNorm\_Car}$				-0.35	-2.74	0.006
β_{Aff_PT}				0.50	2.22	0.026
β_{Sal_PT}				-0.27	-2.57	0.010
Latent Variable Structural Model						
α_{Aff}				0.40	3.16	0.002
α_{Sal}				0.00	0.00	0.000
$\beta_{Age\_PerNorm}$				0.55	3.28	0.001
β_{Age_Sal}				0.55	5.11	0.000
$\beta_{CarAvail\_Aff}$				-0.20	-2.57	0.010
$\beta_{CarAvail\_PerNorm}$				-0.44	-4.21	0.000
$\beta_{HighEdu\_PerNorm}$				0.61	4.16	0.000
$\beta_{HighIncome\_PerNorm}$				0.66	3.15	0.001
$\beta_{Ridacard\_Aff}$				0.54	3.68	0.000

Note: ASC = Alternative specific constant; α = Attitude specific constant;
Exh = Exhibitionism; Sal = Salience; Aff = Affect; PerNorm = Personal Norm

Table 7.10: Model fit

Index	Base Model	ICLV Model
Null Log-likelihood (LL(0))	435.1	
Final Log-likelihood (LLβ)	311.6	305.7
ρ^2	0.284	0.384
$\bar{\rho}^2$	0.249	0.377

Table 7.11: Classification table

Observed	Predicted							
	Base Model				ICLV Model			
	PT	Car	NMT	% Correct	PT	Car	NMT	% Correct
PT	22	7	9	57.9%	23	8	7	60.5%
Car	10	20	5	57.1%	5	26	4	74.3%
NMT	7	4	16	59.3%	6	5	16	59.3%
Market Shares	39.0%	31.0%	30.0%	58.0%	34.0%	39.0%	27.0%	65.0%

Table 7.12: Demand elasticities

Mode	Parameter	Base Model		ICLV Model	
		Direct Elast	Cross Elast	Direct Elast	Cross Elast
PT	Cost	-0.60		-0.65	
	Time	-0.39	0.27	-0.42	0.27
	Income	-0.54		-0.61	
	Age	-0.78		-1.23	
	Car Ownership	-1.58		-1.65	
	Affect			0.13	
	Salience			-0.09	
Car	Time	-0.45	0.24	-0.41	0.25
	Trip Frequency	-0.98		-1.13	
	Personal Norms			-0.18	
NMT	Distance	-2.79		-2.39	
	Age	-0.58		-0.48	
	Education	1.75		1.82	

Elast = Elasticity

7.4.2 Discussion

The travel time for PT and private motorised mode are observed to lower the likelihood of observing either mode of travel, which is intuitive and consistent with similar studies (Johansson and Heldt, 2006; Temme et al., 2008b; Yáñez et al., 2010). Mode-specific coefficients of travel time used for PT and private motorised modes both have the expected negative signs and significant at 95% confidence level (Kamargianni et al., 2015). The direct demand elasticities shown in Table 7.12 highlights this point and indicate that an increase in the travel time of either PT or Car mode will result in the reduction of demand of either alternative. Similarly, the positive signs of the cross elasticity of demand of both alternatives suggest that Car and PT are substitute goods; hence, increasing the travel time of either alternative will increases the demand of the other alternative. However, the disutility of travel time for Private motorised modes is found higher than that of PT. Thus, Private motorised users are more sensitive to variations in travel time than PT users; this effect is evident in the variation of the estimates of the direct elasticities of the two modes.

Mode-specific coefficients for cost were estimated for PT and private motorised modes. Both have the expected negative signs (Kamargianni et al., 2015). The estimate for PT cost is significant at 95% confidence level. However, that of the private motorised mode was insignificant, therefore, it was removed from the final model. It is noted that the dataset was disproportionally represented by older individuals (aged above 60 years) most of whom make fewer trips in a month and are entitled to free or subsidised travel on most public transport services in Scotland (Audit Scotland, 2010). Most respondents in this category either reported zero or very small figures as monthly travel cost, which could affect the estimate. The estimates for direct and cross elasticities of travel cost reveals variations in travel cost sensitivities across the two modes. The cost sensitivity for the PT is the highest for both the base and ICLV model.

Intuitively, the results also indicate that trip length impact the choice of travel mode. The average of the approximated walking and cycling distance based on the reported trip origin and destination postcodes produced walking and cycling distances of 3.4km and 5.6km respectively and 12.6km and 10.7km for private motorised mode and PT respectively. The finding reveals that respondents are willing to walk or cycle for shorter distances; however, active travel becomes less attractive and eventually impossible with increasing trip distance, in which case either private motorised mode or PT becomes the reasonable option.

Respondents making work-related trips are found to have high disutility for private motorised modes; the frequent nature of such trips makes this observation intuitive. The repetitive and routine nature of such trips means they are less likely to vary from day-to-day, hence reducing the risk of uncertainty. The estimate for the trip characteristic (trip frequency) support this argument; increasing the frequency of a trip reduces the utility of private motorised mode. It was further observed that the unemployed and the retired who make fewer and less frequent trips behave differently, possibly due to their low level of distant activity participation.

The results also show that the age of an individual has a significant impact on their travel mode choice. It was observed that younger (25-64) respondents are more likely to walk or cycle. The proportion of active travellers is highest among individuals of age group 25-34 years. Older respondents (>54 years) have high utility for private motorised mode and high disutility for active travelling, possibly due to age-related mobility challenges. Figure 7.4 reports that after age 54, individuals rely more on private motorised mode and PT to meet their mobility needs, it is seen that the proportion of respondents travelling by active mode steeply declines after age 64. Private motorised modes have the highest share of respondents aged above 54 years, even though most individuals in this category may qualify for subsidised bus fares or free bus travel. The Generation-X respondents are noticed to have the lowest proportion of private motorised mode users among all age groups (ONS, 2019; O'Connor, 2018). It is not clear why the Generation-X respondents differ in travel behaviour, car ownership and employment status from the other age groups. However, it is strongly believed that the reported drug use among individuals in this age group account for their low employment and car ownership rate as reported in section 6.5.1 and Figure 6.5, which consequently affect their travel behaviour.

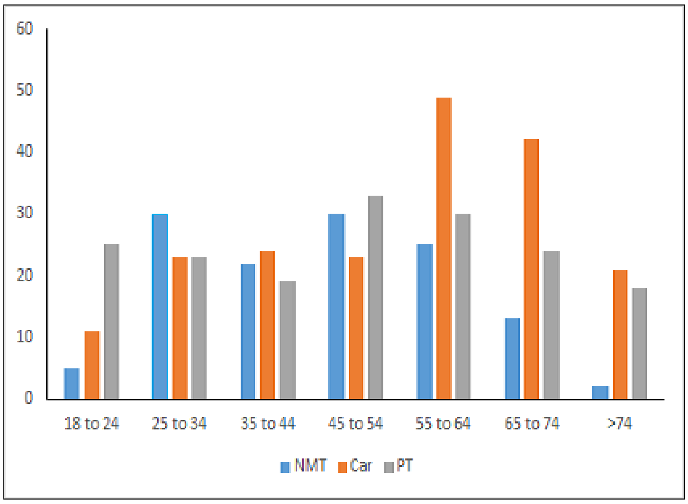

Figure 7.4: Modal share by age group

Furthermore, the results are consistent with the findings in Atasoy et al. (2013); the educational level of respondents was found to have a significant influence on mode choice preference. The results show that, comparatively, highly educated individuals are likely to travel more by active mode of transport. The higher the educational qualification of an individual, the more likely they are to choose an active mode of transport. The educational level of individuals in this class meant they are more likely to be well informed about the carbon footprints of transport. Embarking on public sensitisation on the environmental impact of behaviour could help promote green lifestyle

The relationship between household income and car availability has been established in the literature (Ben-akiva and Bierlaire, 1999). A similar relationship is observed in this study. We found that the likelihood of observing PT reduces with increasing level of income; this is consistent with the findings in section 6.5.1 and the research findings linking household income and car availability (Ben-akiva and Bierlaire, 1999; Dannewald et al., 2008; Kamargianni et al., 2015; Ortuzar and Willumsen, 2011; Temme et al., 2008b; Yáñez et al., 2010). Figures 6.9 and 6.10 indicate that the level of car ownership increases with increasing level of household income. Similarly, the estimate of car availability shows that car ownership directly increases the utility for private motorised modes and the likelihood of travelling by car.

Longer walking distance for trips involving PT modes is observed to increase the utility for private motorised mode significantly. The results show that the combined walking distance for PT trips; comprising the walking distance to the origin bus stop and the walking distance from the destination bus stop has a significant positive impact on the likelihood of observing private motorised mode. This effect is significant in both the base model and the ICLV model and consistent with finding in (Yáñez et al., 2010). Therefore, locating bus stops closer to trip generation and trip attraction sites could help reduce the combined walking time for PT trips, which potentially could attract car users to use PT.

The number of cars available in the household for individual use increases the utility of private motorised modes. This effect is significant at 99% in both the base and ICLV models.

Intensely negative sentiments can override otherwise rational course of action even when cognitive information suggest alternative courses of action (Loewenstein et al., 2001). The results support the statement above, the negative sign of the estimate of Salience indicates that such experiences increase the disutility of PT and hurt PT ridership. Unusual, extreme or unexpected experiences loom more significant to the consumer and stays in memories much longer. The results reveal that unpleasant experiences such as anti-social behaviour, passenger annoyance and overcrowding on a bus appear to evoke negative valence (feeling of anger, embarrassment, fear and frustration). Such undesirable experiences could have far-reaching consequences on individual travel behaviour (Kahneman, 2013). This observation is evident in individuals in active working-age between 25 and 64 years. These results give credence to the findings in the field of psychology that suggest that human memory of experiences is governed by most intense moments and the final impressions in a chain of events (Redelmeier et al., 1993). Preventing or deterring such experiences and addressing similar complaints could lessen the effects of such experiences and the associated negative valence (Resnick, 2012). That could also reduce the potential negative impact of such experiences on future travel decisions (Dobbie et al., 2010; Metcalfe and Dolan, 2012; Ababio-donkor et al., 2020)

It is evident from the estimates in Table 7.9 that attitude, Affect or pro-PT attitude increases the utility of public transport. Individuals in this class have high utility for the in-vehicle travel time for PT and a positive attitude towards the PT. This attitude is profound in individuals without a car; it decreases with an increasing number of cars in the household. Individuals with positive valence towards public transport (high level of satisfaction for public transport services) have high utility for public transport in-vehicle travel time (Resnick, 2012). The results buttress the report in Elster (1998) and indicate that decision-makers evaluate alternatives emotionally alongside economic utility. The findings further confirm the initial hypotheses and indicate that the sentiments associated with public transport by users could influence PT desirability or ridership. Therefore, user satisfaction and experience with PT services could evoke positive valence towards PT and influence loyalty (Resnick, 2012).

Individuals with a high level of pro-environmental attitudes (Personal environmental norms) have high disutility for private motorised modes; this effect is noted to be high for individuals with high education (university degree) and household income of at least £50,000. Individuals in this category are between the ages of 18 and 24 or above 64 years. It is also shown that highly educated individuals are likely to be more sensitive to environmental issues and therefore, mindful of their carbon footprint (Atasoy et al., 2013), which possible inform the environmentally friendly lifestyle. The results also confirm the finding of the descriptive analysis reported in section 6.5.2; a significant difference was found in responses among PT riders, Car users and Active travellers. Both results demonstrate that individuals holding high pro-environmental attitudes tend to be decisive and care deeply about their environmental behaviours (Jachimowicz et al., 2019). The results also corroborate the findings in Belgiawan et al. (2016) and Ababio-Donkor et al. (2019), it supports the assertion by Schwartz (1977) and suggests that "in the absence of personal norms, social norms alone did not add to the predictive

power already provided in the base model. Neither did social norms add to the predictive power already provided in the model by the personal norm when both variables were incorporated into the ICLV model" (Cialdini et al., 1991, p. 16).
In conclusion, it can be inferred from the results that personal norms, which describes individual internalised social norms, have a significant influence on individual behaviour. Persons with a high level of pro-environmental attitude are likely to adopt environmentally friendly modes of travel. It is believed that individuals with pro-environmental attitudes may be more likely to switch to travel options that offset the carbon emissions of their behaviour compared to individuals with anti-environmental attitudes Jachimowicz et al. (2019). The differences in behaviour observed between individuals scoring high on personal norms and social norms apparently confirm the suggestions that activated norms influence overt behaviour by inducing a sense of moral obligations to act (Schwartz, 1977; Cialdini et al., 1991; Bamberg et al., 2007).

Interesting to note is that the latent factors of Ego or Narcissism are shown to impact the utility of PT modes negatively. The estimate of Exhibitionism had a negative sign in the utility equation of PT, confirming the findings of the preliminary analysis; however, this effect is insignificant in the utility equation for PT. This is believed to result from the sensitivity of the indicators for measuring narcissism and respondents' low level of scores, consequently, this variable was removed from the final model.

7.5 Summary of Factors Influencing Mode Choice

The previous section discusses the estimates of the utility parameters in the models and highlights the nature of their influence on the decision-making process of the study population. The variables in the functions of the traditional discrete choice model and the ICLV model are all significant and have the expected signs. This observation is consistent with the outcomes of similar studies in the literature. The latent variables Personal norms, Salience and Affect have plausible estimates and significant. Personal norms and Salience are significant at 99% level, while Affect is significant at 95% confidence level. The magnitude of the standardised coefficients of Salience, Personal norms, and Affect indicates the level of importance of these variables in their respective utility functions. This is a clear indication that these MINDSPACE variables play a significant role in the decision-making process involving transport mode choice. The results loudly emphasise the significance of the included personality traits and establish their comparative significance to objective variables such as income, age, car ownership and travel time in the utility functions and by extension, the decision-making process of the study population. The incorporation of these MINDSPACE variables into the ICLV model also shows that socio-demographics could be used to define and explain personality traits or attitudes. For instance, the finding indicates that individuals with a university degree, aged 18-24 and above 64 are likely to be environmentally friendly and have high personal environmental norms. Additionally, the ICLV model has shown the effects of Personal norms, Salience and Affect on the choice of PT and private motorised mode. The findings of the analysis are summarised below and presented under the following two categories.

Subjective Factor influencing Mode Choice

- Salient experiences on the PT evokes negative valence and sentiments in individuals and increases the aversion and disutility of PT modes.
- User satisfaction and positive user experience induce positive valence which in effect increases the utility of PT modes
- Pro-environmental attitude activates one's internalised norms and increases the aversion and disutility of private motorised modes. This effect is high in individuals with at least a university degree.

Objective Factors Influencing Mode Choice

- Increasing in travel time and cost increases the disutility of travel mode.
- Active mode users are very sensitive to increase in trip length; trip length is directly proportional to the utility of active travel mode.
- Frequent and work-related trips increase the disutility of private motorised modes.
- Working aged adults between 25 and 54 are more likely to adopt active modes of travel than younger (<25) and older (>54) individuals

- Longer walking distance in a PT trip increases the utility of private motorised modes.
- The number of household cars available for individual use significantly increases the utility of private motorised modes.

Chapter Eight

Conclusions and Future Research Direction

8.1 Introduction

This concluding chapter of the thesis presents a summary of the research. Section 8.2 summarises the thesis and highlight the research objectives. Sections 8.3 explains the contribution of the research and the policy implication of the research findings. Section 8.4 closes the chapter with the research recommendation and give direction for future research.

8.2 Conclusion

The preceding chapters present the different aspects of the research work. Chapter 1 provides a general overview of the study and introduces the research work. Relevant literature to the study is reviewed in chapters 2 and 3, while chapter 4 extends the literature into the general methodology and the various methods and techniques for sampling, data collection, and the framework for empirical data analysis. Chapter 5 introduces the study population and the study area, and chapter 6 reports the data collection method, the sample data and exploratory analysis of the sample data. Chapter 7 presents the empirical data analysis involving transport choice modelling, presents and discuss the results of the analysis and the findings. Finally, this chapter concludes the study by outlining the findings, contribution and limitations of the study in addition to the recommendations for future research direction.

Several researchers have studied transport mode choice behaviour and made numerous contributions to the field, including the development of hybrid or ICLV models. However, very few studies have focused on MINDSPACE and transport mode choice, particularly, the integration of MINDSPACE in ICLV models.
The overall research aim is "to investigate whether the extended ICLV model incorporating latent variables from MINDSPACE could enhance the power of transport mode choice models and individual choice preference". The following specific objectives are developed to help achieve the overall aim of the study:

1. To investigate and provide insight into the importance of the variables of MINDSPACE in choice decision-making.

2. Identify potential latent variables from MINDSPACE and develop psychometric indicators to measure them

3. Investigate the impact of the latent variables on the explanatory power of ICLV model and individual choice preference.

8.2.1 Overview of the Research Objectives

This section presents a summary of the methods adopted to achieve each objective and the outcome of each objectives.

8.2.1.1 Objective 1

To investigate and provide insight into the importance of the variables of MINDSPACE in choice decision-making.

Comprehensive literature review of MINDSPACE was conducted in chapter 2. Each of the nine variables of MINDSPACE has been discussed in detailed citing relevant literature and practical application of each variable in literature and industry, including applications in transport where applicable.

It was demonstrated that the rational choice theory is not entirely accurate in explaining travel decision task; observed choice preference of individuals violates this fundamental theory underlying the random utility theory. It has been shown that observed choices do not only depend on socio-demographic factors such as age, gender and income, but also on personality traits, attitudes and situational factors. This observation seems to suggest that people do not always seek to maximise economic benefit but emotional and psychological benefits as well.

The study has demonstrated that situational factors such as time pressure, cognitive load and the situational context for the decision task experienced by the decision-maker at time of decision making could significantly sway a decision. It is indicated that the limitations of the traditional choice models are the failure to account for these subjective factors.

Recent studies have tried to bridge this knowledge gap by exploring the impact of several subjective variables on decision-making. However, what matters is the effectiveness of a subjective variable in explaining behaviour. Review of consumer behaviour literature revealed nine behavioural effects named MINDSPACE for convenience; these nine effects are believed to have a significant impact on behaviour and are consequently explore in the context of travel choice behaviour. The findings in the literature about the nine MINDSPACE effects are summarised below:

Messenger:

It was established that the importance people attach to information depends to a large extent on the conveyor of the information rather than the content of the information. The study has found that people do not always listen to people because of the content or accuracy of their message; rather, people listen because they feel connected to the messenger. The study proposed that using high-status messengers in transport-related campaigns could offer an effective means to achieve behaviour change.

Incentive:

The economic law of demand suggests that people are perfectly rational and sensitive to new information, such as changes in prices and situations. The review has shown that Incentives could have a positive effect on decision-making and can motivates people to create or break habits by negatively or positively altering the cost or benefit of an activity. In other words, incentives could cause people to adjust their behaviour

Norms:

Norm describes appropriate behaviour or acceptable behaviour by a majority of people. It is found that people are motivated to continue in a behaviour if they believe they have the approval of their reference group. Norm could refer to social norms, legal norms and personal norms. Social norm describes a subject's belief about what the society or reference group accept. Social norms are held in place by the reciprocal expectation and the fear of social penalties by the reference group. Personal norms or personal attitude (own-action responsibility) on the other hand, refers to individual values and principles or internalised social norms. It is found that activated personal norms induce the obligations to act. The literature also suggests that personal norms are the most relevant moderating factor of pro-environmental behaviour (PEB).

Defaults:

People will go with the flow when pre-set options are made for them in choice design. This can have a significant impact on behaviour, even in an unrestricted choice framework. It is found that defaulting to pre-set options could influence decisions when the decision-makers do not have a preferred option in mind and important for prompt behaviour change.

Salience:

It is found that the human memory of experience is governed by most intense moments and the final impression in a chain of events. The review revealed that unusual and extreme experiences loom larger to the consumer and stay much longer in memory.

Lousy and negatively intense experiences could induce negative valence towards a product affect its desirability.

Prime:

The literature demonstrates that subconscious stimuli in the form of words, sounds, sights, and smells in the environment influence behaviour. Literature suggests that priming explains some otherwise irrational consumer behaviour. The knowledge and correct application of priming can help policy-makers influence behaviour.

Affect:

"Affect" is as an automatic response to a good or bad experience. "Affect" could refer to four different states; Moods, Affective Styles, Sentiments, and Emotions and all the states could influence behaviour. Emotional associations can remarkably influence decisions and behaviour. Emotional attachments can lead to overreactions and override a rational course of action even when alternative course of action is not in one's own interest.

Commitment:

It is noted that people lack the inertia and the will power to achieve behaviour change or break bad behaviour. Individuals seek to be consistent with their public promises; literature suggests that public commitment reduces procrastination by increasing the cost of failure. The study argued that individuals are motivated to maintain a consist and positive self-image of themselves and are more likely to keep commitments to avoid reputational damage. Therefore, encouraging people to develop and make public their travel plans could increase compliance.

Ego:

People behave in ways that tend to make them feel better about themselves. This quest for approval and recognition leads to changes in preference for consumer goods behaviour. Experts suggest narcissism is due in part high ego; in other words, narcissism is driven by ego. Therefore, the study uses narcissism to explain and describe people with a high ego. Narcissism describes a person's obsession with oneself and the public perception of themselves. The study argued that narcissism plays a dominant role in consumer decision making. The literature demonstrates that individuals scoring high on the Narcissism Personality Inventory (NPI) scale were more likely to consume products likely to make them socially unique. They will deliberately flout established norms in pursuit of distinctiveness. The narcissists use consumer products to maintain the perceived social identity of themselves. It is also indicated that actions that threaten to damage this perceived view could trigger behaviour change.

8.2.1.2 Objective 2

Identify potential latent variables from MINDSPACE and develop psychometric indicators to measure them

Section 4.4.5.2 of chapter 4 explains the process of deciding on which MINDSPACE variable to select as a latent variable and the development of indicators for measuring the selected variables of MINDSPACE for inclusions as latent variables in the ICLV model. The decision concerning which variable to include as a latent variable in the ICLV model was based on:

- the possibility of measuring the variable with psychometric indicators
- the existence of indicators for measurement.
- whether a variable could be measured in the context of transport.

Overall, four of the nine variables of MINDSPACE, namely, Norms, Salience, Affect and Ego or Narcissism, satisfied the criteria above and were adopted for the study. Refer section 4.4.5.2 for details on the development of the indicators. The MINDSPACE effects adopted are discussed below:

Norms:

It is argued that Norms has significant impacts on overt behaviour and people feel morally obligated to act when their personal norms are activated. Ten measurement indicators were developed to assess respondents' perceived social and personal norms to investigate the influence of their perceived norms on their behaviour. Question 23 in Appendix A covers the measurement indicators for this MINDSPACE effect.

Salience:

The study argues that human behaviour is influenced by what comes to mind when making decisions. It is suggested that the most prominent (desirable or undesirable) experience with a travel mode can have disproportionate sway on behaviour. The review of relevant literature reveals that experience, such as any incidents of passenger annoyance or anti-social behaviour experienced by a passenger on public transport could have a profound consequence on their future travel behaviour. Therefore, measurement indicators were developed based on passenger experiences reported in the existing literature to investigate the effect of public transport user experience on ridership.

Affect:

The study hypotheses that the sentiments associated with a transport mode could impact its desirability. Inspired by the study of Han and Lerner (2012), measurement indicators were developed to investigate user sentiment and its impact on ridership. The indicators assess respondents' perception of cars and PT.

Ego/Narcissism:

The general hypothesis for this MINDSPACE effect is that "narcissist will likely travel by car to enhance their social identity and sense of uniqueness". This hypothesis is tested by adapting 16-item Narcissism Personality Inventory (NPI-16) developed by Ames et al. (2006) from the original 40-item scale to measure the NPI scores of respondents to investigate the relationship NPI score and travel behaviour.

8.2.1.3 Objective 3

Investigate the impact of the latent variables on the explanatory power of ICLV model and individual choice preference.

Chapter 3 presented a comprehensively review of the literature on transport and ICLV models; the review discussed existing ICLV models. Chapter 4 extended the literature in chapter 3 and discussed the specifications of the reference and the ICLV models. The construction of the latent variables from the psychometric indicators and the estimation of the reference and the ICLV model is performed to address objective 3. Sections 7.3 and 7.4 explain the model development process and covers the results of the choice modelling.

The results indicate that all variables are significant and have the expected signs. The MINDSPACE effects incorporated as latent variables in the ICLV model all have the expected signs in their respective utility functions. Personal Norm, Salience and Affect are significant at 1% level. Narcissistic trait of exhibitionism had the expected sign but was insignificant. To investigate the impact and significance of the MINDSPACE variables in the ICLV model, a reference choice model with similar specifications as the ICLV model but without any of the latent variables was estimated and compared with the ICLV model. Table 7.10 presents the goodness of fit and the log-likelihood estimates for both models. The indices show that the ICLV model has the best goodness of fitness values. The market shares estimates from both models confirm the finding and indicate that the ICLV model is superior to the reference model.

Based on the results and discussion, it can be concluded that the ICLV model outperforms the traditional discrete choice model. The ICLV model provides insight into the importance of attitudes in transport mode choice. The incorporation of the MINDSPACE variables improved the explanatory power of the choice model. Modal travel time, travel cost, number of cars available, household income and walking time to bus stop are all significant in the base, and ICLV models, pro-environmental attitudes (personal environmental norms), pro-PT attitude (Affect) and salience (negative PT user experience) are equally significant and found to influence travel behaviour.

Individuals with high pro-environmental attitudes show much concern about the environmental impact of their behaviour and they are likely to travel with modes that offset their carbon footprint. Individuals with a university degree and aged 18-24 or more than 64 years are likely to belong to this class.

Similarly, salient public transport user experiences such as passenger annoyance and overcrowding are likely to negatively impact the utility of PT modes, individuals in 25-64 age-band are likely to be influenced most by this MINDSPACE effect.

Pro-PT attitudes or positive sentiments increases the utility of PT modes; the study found that individuals who find in-vehicle travel time of PT useful are more likely to be loyal riders. The findings imply that Improving the in-vehicle experiences for PT riders could impact PT loyalty. The results support the assertion about the implication of MINDSPACE for the transport sector (Aczél and Markovits-somogyi, 2013) and demonstrate the implications of MINDSPACE for travel behaviour. The incorporation of MINDSPACE has made it possible to explain the observed heterogeneity in the respondents' travel choices from several behavioural perspectives. MINDSPACE have a significant impact on travel decision-making and enhance the explanatory power of the choice model. A better appreciation of these effects and their influence in the decision-making process by transportation planners and policy-makers could serve a useful guide for designing and developing effective transportation policies. The findings of the study can be group into the following two broad categories;

MINDSPACE Variables

The findings support existing literature in behavioural economics and demonstrate that people assess both the economic and emotional cost of an alternative when making transport mode choice decision. The results of the analysis show that three of the four MINDSPACE variables investigated in the study have a significant impact on transport mode choice. The presence of the three MINDSPACE variables (personal norm, salience and affect) accounts for individual heterogeneity and reflect individual values, perception of safety and improved the understanding of travel behaviour and enhanced predictive power of the final model. The finding addresses the overall research aim and indicates that the extended ICLV model incorporating latent variables from MINDSPACE enhances the explanatory power of transport mode choice models and individual choice preference. The main findings under this category are summarised below, the following section expatiate and presents the implications of the findings.

- Salient experiences on PT induces negative valence and sentiments and increases the disutility of PT modes.
- User satisfaction and positive user experience induce positive valence, which increases the utility of PT modes
- Pro-environmental attitudes increase the disutility of private motorised modes.

Alternative Specific and Socio-economic Variables

The findings of the study are consistent with results from similar studies and extant literature. The estimates of all the utility variables are plausible and significant for both the base and the ICLV models. The key finding from this category are itemised below.

- Increasing in travel time and cost increases the disutility of travel mode.
- Active mode users are susceptible to increases in trip length
- Frequent and work-related trips increase the disutility of private motorised modes.
- Working aged adults between 25 and 54 are more likely to adopt active modes of travel.
- Longer walking distance for PT trips increases the utility of private motorised modes.
- The number of household cars available for individual use significantly increases the utility of private motorised modes.

The findings of the study are relevant and useful for public transport delivery in the study area (Edinburgh) and could provide useful policy directions for public transport and travel behaviour change.

8.3 Contribution and Implication of the Research

The study has made a significant contribution to travel behaviour, and choice modelling literature. The findings have significant implications for transport planning and would be influential and valuable to transport policymakers and transport planners of the study area (Edinburgh).

The novelty of this study is the provision of key indicators, CFS and drivers of individual choice preference beyond the traditional objective characteristics and socio-demographic variables through a systematic process. The study has gone beyond the existing studies by incorporating and investigating four variables from the MINDSPACE framework in a single model.

The findings have great implication for transport in the study area; the results explain the observed rising trend of vehicular traffic and PT ridership decline in Edinburgh. Salient experiences by PT riders is shown to impact the choice of PT negatively and explains the observed trend.

The results indicate that pro-environmental attitudes reduce the utility of private motorised modes and can induce behaviour change, thus increasing public education on environmental issues could help promote these attitudes and consequently affect travel behaviour of the population. The main findings of the study are summarised below:

The study has also demonstrated that incorporation of personal norms, affect (user emotional satisfaction) and salient user experience (perception of safety) as latent variables in the ICLV framework provides comparatively better predictive power than the traditional discrete choice counterparts. The presence of the three latent variables accounted for individual heterogeneity and improved the understanding of travel behaviour. The model reflects individual values, perception of safety, and emotions. The framework has indicated that user satisfaction is moderated by the perception of safety and user perception of service quality. These are influenced by user experience and objective factors, such as the socio-economic characteristics of the decision-maker. The framework adopted in this study has shown that transport mode choice depends on how individuals perceive alternative specific and service attributes. The perception about alternative attributes is a measure of the individual evaluation of an alternative and attitudes towards an alternative is a measure of the significance accorded to the various attributes of alternatives.

The results of the study indicate that individuals with pro-environmental attitudes have high disutility for private motorised modes. This effect is observed to be high for individuals with high education (university degree). This observation has great implication for public policy. The results have shown that highly educated individuals are well informed about the environment and mindful of their carbon footprint. Therefore, developing an educational curriculum on the environmental impact of behaviour and taught in schools could sensitise more young people about the environment. Bear in mind that individuals of 18 to 24 age group already belong to this group and represent the future.

The study has established key attitudinal factors influencing individual transport choice preference. The results are consistent with findings in similar travel behaviour literature. This study extends the findings in previous literature and has established that personality trait, perceptions and attitudes significantly inform choices. It is also found that activated societal beliefs, also referred to as personal norms significantly determine an individuals choice preference.

In addition, the study has shown that positive user experience and user satisfaction can create positive valence and sentiments in users towards the target object; this is revealed to increase the utility of PT modes. The findings have outlined the indicators underlying this observation and indicate that the perceived utility of public transport in-vehicle travel-time considerably affect overall user satisfaction, user loyalty and lead to sustainable travel. The finding has implication for the design and manufacturing of PT coaches. It is suggested for service operators and planners to design and provides comfortable and utility coaches and services to improve PT travel experience while enabling environment for the productive use of the in-vehicle travel time.

Behavioural economics literature suggests that unusual and undesirable experience stays longer in human memory and looms more significant to the subject. Such experiences create intensely negative sentiments which could override rational choice preference (Loewenstein et al., 2001; Kahneman, 2013). The study has established that undesirable user experience on PT appears to induce negative valence in users, which is observed to impact the utility of PT modes adversely. The study has defined key indicators (critical success factors CSF) behinds these attitudinal variables first through EFA and validated in CFA. The underlying indicators of these attitudes wield significant influence on individual choice preference and decision-making.

These confirmed and validated CSFs are likely to activate behaviour when triggered. The following recommendations are suggested to translate the finding contained in this thesis into a useful application:

- The CSFs of the three latent variables must be critically examined and addressed through policy to improve PT user experience and loyalty. Facilities and services necessary to improve the perception of in-vehicle travel time utility for PT riders should be provided.
- Incidence likely to create intensely negative valence towards PT services must be severely sanctioned and published to discourage offenders and build public confidence. Similar reported cases should be addressed satisfactorily to maintain customer loyalty. For instance: Refusing to admit heavily drunk individuals on PT carriages, introducing high capacity coaches during peak hours to prevent overcrowding and keeping the interior of PT coaches clean and tidy at all times for customers.

The study has provided and demonstrated variables that can influence users' perceptions, the so-called critical success factors (CFS) defined as encounters that are particularly satisfying or discouraging for the user. The concept is not limited to rating the PT service attributes but user perception about on-board safety and negative encounters because customers who experience the salience CFS are less likely to forget the encounter, which in most cases can influence user loyalty (Dolan et al., 2012; Dobbie et al., 2010). However, since the salience experiences (CFS) are subjective, they may be beyond the control of the Service providers. It is therefore, suggested that the handling of the CFS incidences and experiences on PT services through public policy may be a

critical and logical approach for policy-makers and PT service providers to influence the overall user satisfaction, the perception of service quality and loyalty of PT users. Policies and services that eliminates user dissatisfaction, improve user perception of safety and emotional satisfaction will engender the perception of improved service quality and ultimately promote and lead to sustainable travel.
Total walking time for a PT journey correlate with the utility of private motorised modes. However, walking is an inevitable part of every journey but mostly with trips involving PT modes than private motorised modes, this leg of the journey is even more punitive in inclement weather. The study recommends increasing the density of bus stops within trip generation and attraction sites to reduce the total walking time for PT trips to minimise the effects of distance on PT ridership.

8.4 Recommendation for Future Research

The novelty of this study is the provision of key indicators and drivers of individual choice preference beyond the traditional objective and socio-demographic variables through a systematic process. The study has gone beyond the existing studies, which considers one effect/ variable at a time by incorporating and investigating four variables from the MINDSPACE framework in a single model. Notwithstanding, several limitations and inconclusive observations were noticed during the study. The following recommendations for future research could address the observed limitations. Similar methodology could be applied to build on the useful findings of the investigated MINDSPACE variables in addition to those MINDSPACE variables not considered in this study.

The validation of the data shows the sample data is representative of the study population; as a result, the finding could be viewed as a reflection of the study population's travel behaviour. However, readers should be cognizant of the fact that the study was carried out in urban travel context in one city in the United Kingdom. The study area has a very extensive and efficient public transport system which might have influenced the results. Literature also suggests that decision-making is influenced by culture (Halonen, 2020). Therefore, it is innocuous to assume that the culture of the study area could have influenced the outcome of the study. The results, therefore, may not necessarily apply in different contexts such as cities with less efficient public transport system or different form of public transport services. It is recommended for future research to explore the identified CSFs in different cities and context and investigate further the indicators dropped during the CFA for having low loadings.

This research only explored the MINDSPACE variables in the context of transport mode choice. A similar study is recommended to explore the impact of the MINDSPACE variables in other travel behaviour context. For instance, in route choice, departure time choice, et cetera.

It is also noticed that most of the observed psychometric indicators for the latent variables had very low factor loadings or did not correlate sufficient enough with other indicators. For instance, six indicators were developed to measure Affect; however, the final latent construct had only two indicators with sufficient factor loadings. Although it is difficult to get the right psychometric indicators for measuring psychological construct, it is recommended for future research to carefully design or adopt indicators with adequate validity and reliability in capturing their target construct.

The transport characteristics and travel behaviour of individuals of within Generation-X age band were observed to deviate from any observed trend. Further research is recommended to explore the transport characteristics and travel behaviour of individuals within this age band.

Considerable effort was made to identify and address potential limitations of the survey instrument. However, the quality of final data collected and the ensuing analysis indicated that the failure to pilot the final survey instrument after revising some aspect of the instrument after the pilot data collection and before the actual data collection (section 4.4.6.4) had considerable impact on the level of engagement of most respondents on the narcissism measurement scale and the related analysis.

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Appendix A

Survey Instrument

Introduction

You are kindly invited to participate in our survey on travel behaviour studies by the Transport Research Institute of Edinburgh Napier University for a PhD Study. The study seeks to investigate the effects of experiences, perceptions and personality on travel choices; as such, some questions may appear unrelated to transport. Your kindness in answering all questions is very important for us. The survey will take approximately 10 minutes to complete. Your participation in this study is completely voluntary. However, there are no foreseeable risks associated with this project. Your survey responses will be coded and stored under the University's Data Protection Policy until PhD project is finished. The findings will be used for writing a PhD thesis and academic articles. In order to ensure anonymity, no personally identifiable information will be associated with your response. We, therefore, entreat you to kindly complete and return the questionnaire by 20th of June using the enclosed prepaid enveloped. Alternatively, you may complete the survey online at "https://thissurvey.questionpro.com". Please, you may contact Augustus at augustus.ababio-donkor@live.napier.ac.uk if you have any questions about the survey or the procedures. Thank you very much for your time and support.

Transport Characteristics

1. Which of these applies to you?

- ◻ Currently hold a valid full driving licence (car or motorcycle) (78.4%)
- ◻ Currently hold a provisional UK licence (4.4%)
- ◻ Currently disqualified from driving (0.0%)
- ◻ Never held a UK driving licence (13.5%)
- ◻ Surrendered licence - given up driving (3.4%)

2. Which of the following do you have?

- ◻ A concessionary Travel Card (38.3%)
- ◻ A season Bus Ticket (9.5%)
- ◻ A season Train ticket (1.0%)
- ◻ Other travel card (8.9%)
- ◻ Not applicable (41.7%)

3. In total, how many cars or vans are owned or are available for private use by members of your household? (*Include any company cars or vans available for private use*)

- ◻ None (30.8%)
- ◻ One (46.6%)
- ◻ Two (18.5%)
- ◻ Three and above (4.0%)

4. Which of these applies to you?

- ◻ Employed full-time (43.5%)
- ◻ Employed part-time (16.3%)
- ◻ Student (8.1%)
- ◻ Retired (28.8%)
- ◻ Unemployed (3.2%)

5. Which of these is the purpose of your most regular journey in a week?

□ Work (54.8%)

□ Education (7.5%)

□ Shopping (23.0%)

□ Other (Leisure, Spots, Tourism) (14.7%)

6. How often do you make this trip in an average week?

□ Once (6.3%)

□ Twice(11.3%)

□ Three times (15.1%)

□ Four time (15.9%)

□ Five times (38.1%)

□ Everyday (13.1%)

7. Please indicate the postcode of the destination of the selected trip above

....

8. How do you usually make the journey above?

□ Walking..................... [GOTO QUESTION 12] (18.3%)

□ Bicycle......................... [GOTO QUESTION 12] (7.9%)

□ Motorcycle/moped .... [GOTO QUESTION 9] (0.0%)

□ Driver car/van .... [GOTO QUESTION 9] (33.5%)

□ Passenger car/van .... [GOTO QUESTION 12] (3.4%)

□ Car Sharing .... [GOTO QUESTION 9] (1.0%)

□ Bus/Tram service .... [GOTO QUESTION 10] (32.7%)

□ Work/School bus .... [GOTO QUESTION 12] (0.0%)

□ Rail .... [GOTO QUESTION 10] (1.8%)

□ Taxi/minicab .... [GOTO QUESTION 9] (0.2%)

9. How difficult would it be to undertake the journey above using public transport

(Bus/tram)?

- ☐ Not difficult (19.2%)
- ☐ A little difficult (10.7%)
- ☐ Moderately difficult (9.3%)
- ☐ Quite difficult (8.3%)
- ☐ Very difficult (8.3%)

10. Thinking about the journey above, what is the travel time including in-vehicle and walking time on an average day?

- ☐ 0 to 15 minutes (11.3%)
- ☐ 16 to 30 minutes (26.6%)
- ☐ 31 to 45 minutes (20.8%)
- ☐ 46 to 60 minutes (10.5%)
- ☐ More than 60 minutes (8.3%)

11. Referring to the journeys above, how much do you spend averagely in a month (£)?

(only fuel cost for car/van users)

....

12. Referring to the trip above, which other means of transport can you use regularly instead of the above-selected means of transport?

- ☐ None (17.7%)
- ☐ Walking (19.4%)
- ☐ Driver car/van (11.7%)
- ☐ Passenger car/van (4.4%)
- ☐ Motorcycle/moped (0.6%)
- ☐ Bicycle (3.2%)
- ☐ Work/School bus (2.2%)
- ☐ Bus/Tram service (33.1%)
- ☐ Rail (2.8%)

☐ Taxi/minicab (2.6%)

13. Thinking about the above-selected means of transport, how much would it cost for your trip in a month, if at all? (*only fuel cost for car/van users*)

....

14. How did you make similar journeys 5 years ago, if different from your current means of transport?

☐ Walking (14.5%)

☐ Driver car/van (28.5%)

☐ Passenger car/van (5.4%)

☐ Motorcycle/moped (0.2%)

☐ Bicycle (5.8%)

☐ Work/School bus (1.0%)

☐ Local Bus service (21.4%)

☐ Tram/Rail (1.4%)

☐ Taxi/minicab (0.0%)

☐ Not Applicable (not in Scotland) (12.1%)

15. Why did you change your means of travel to your current means of travel, if you have?

☐ Not applicable (not changed) (51.4%)

☐ I Changed job (8.1%)

☐ I live within walking distance (3.6%)

☐ I moved home (7.7%)

☐ I bought a car / I got a company car (3.6%)

☐ I lost my job (1.0%)

☐ I lost my licence (0.0%)

☐ I drop off/pick up children on the way (1.0%)

☐ Health reasons (6.7%)

☐ Other (please indicate) ...... (7.7%)

16. How long would it take to walk to the nearest bus-stop from your home?

□ 5 minutes walk or less (77.6%)

□ Within 6-10 minutes walk (19.0%)

□ Within 11-20 minutes walk (2.6%)

□ Within 21-30 minutes walk (0.2%)

□ More than 30 minutes walk (0.2%)

□ Don't know (0.2%)

17. How long would it take to walk to the nearest bus-stop from your trip destination?

□ 5 minutes walk or less (65.9%)

□ Within 6-10 minutes walk (20.2%)

□ Within 11-20 minutes walk (6.9%)

□ Within 21-30 minutes walk (1.6%)

□ More than 30 minutes walk (2.0%)

□ Don't know (3.2%)

MINDSPACE Variables

18. Please indicate how much you agree with each of the following statements or how true is it about you?

Statement	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
I feel personally safe and secure on the local bus during the night	□ (2.8%)	□ (6.5%)	□ (16.3%)	□ (54.0%)	□ (17.5%)
The buses and stops are accessible	□ (1.1%)	□ (1.2%)	□ (3.4%)	□ (55.6%)	□ (38.1%)
The cleanliness of the buses interior, seats and bus stops are acceptable	□ (1.4%)	□(6.0%)	□(8.5%)	□(66.9%)	□(16.9%)
The noise level in buses is acceptable	□(2.2%)	□(8.5%)	□(13.1%)	□(61.3%)	□(14.1%)
The buses are comfortable and spacious	□(2.2%)	□(10.3%)	□(14.5%)	□(55.4%)	□(16.9%)
I am satisfied with the bus travel time	□(3.6%)	□(9.1%)	□(13.7%)	□(55.8%)	□(16.7%)
The service is stable and reliable (arrives on time and according to the scheduled timetable)	□(2.2%)	□(9.3%)	□(14.1%)	□(56.0%)	□(18.1%)
The fares are good value	□(3.0%)	□(11.9%)	□(20.8%)	□(44.8%)	□(17.3%)
Real-time travel information (route and timetable) is readily available and easy to access	□(1.4%)	□(7.1%)	□(9.9%)	□(57.5%)	□(23.8%)
Frequency of service is acceptable	□(2.0%)	□(7.3%)	□(8.5%)	□(58.7%)	□(23.4%)

19. Overall how satisfied are you with the bus services in Edinburgh?

- ☐ Very Dissatisfied (4.0%)
- ☐ Not Satisfied (3.4%)
- ☐ Neutral (10.3%)
- ☐ Satisfied (47.2%)
- ☐ Very Satisfied (33.2%)

20. Based on the definition on the left-hand side of the table below;

20a. Please indicate how you would feel about the experiences on a public bus or tram

	How discouraging would you find each of the following experiences on a bus or tram? [1=Not Discouraging, 5=Very Discouraging]				
	1	**2**	**3**	**4**	**5**
Anti-social behaviour (drunk people etc)	☐(3.4%)	☐(6.5%)	☐(16.1%)	☐(28.6%)	☐(44.6%)
Overcrowding	☐(6.9%)	☐(14.1%)	☐(29.2%)	☐(29.6%)	☐(19.4%)
Exposure to health risk (catching a cold etc)	☐(15.7%)	☐(16.3%)	☐(26.4%)	☐(24.6%)	☐(15.5%)
Passenger annoyance and discomfort	☐(6.5%)	☐(14.7%)	☐(35.1%)	☐(26.4%)	☐(14.9%)
Poor hygiene (service uncleanliness and smell on the buses)	☐(6.5%)	☐(8.7%)	☐(17.1%)	☐(35.3%)	☐(31.9%)
Inaccurate bus and real-time information	☐(10.5%)	☐(15.9%)	☐(24.6%)	☐(27.8%)	☐(20.0%)
Long waiting and travel time	☐(7.1%)	☐(10.3%)	☐(19.8%)	☐(32.1%)	☐(29.4%)
Safety issues (lack of seatbelt, toilets on board or conductor etc)	☐(27.2%)	☐(21.4%)	☐(25.6%)	☐(13.1%)	☐(10.5%)

20b. Evaluate the extent to which you think the experiences would affect or have affected your usage of the public bus or tram services

	To what extent would these experiences affect your regular usage of the bus or tram? [1=Not at all, 5=Very much]				
	1	**2**	**3**	**4**	**5**
Anti-social behaviour (drunk people etc)	☐(15.7%)	☐(17.5%)	☐(20.6%)	☐(19.2%)	☐(25.8%)
Overcrowding	☐(12.5%)	☐(18.5%)	☐(26.6%)	☐(24.0%)	☐(16.3%)
Exposure to health risk (catching a cold etc)	☐(25.0%)	☐(19.4%)	☐(27.4%)	☐(13.7%)	☐(12.1%)
Passenger annoyance and discomfort	☐(14.1%)	☐(18.5%)	☐(32.9%)	☐(20.8%)	☐(10.7%)
Poor hygiene (service uncleanliness and smell on the buses)	☐(11.1%)	☐(14.5%)	☐(23.6%)	☐(26.4%)	☐(22.8%)
Inaccurate bus and real-time information	☐(12.9%)	☐(19.6%)	☐(27.8%)	☐(22.6%)	☐(%)
Long waiting and travel time	☐(11.1%)	☐(15.3%)	☐(21.0%)	☐(24.2%)	☐(26.0%)
Safety issues (lack of seatbelt, toilets on board or conductor etc)	☐(33.9%)	☐(23.8%)	☐(21.0%)	☐(9.5%)	☐(8.9%)

21. Please to what extent do you agree or disagree with each of the following statements?

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
I enjoy using public transport because I get to meet people and make friends	□(34.3%)	□(33.7%)	□(18.3%)	□(12.1%)	□(1.0%)
It is boring travelling on the bus	□(12.1%)	□(49.6%)	□(20.0%)	□(15.1%)	□(2.2%)
I am happy using public transport because I can use the travel time for other activities	□(3.4%)	□(20.2%)	□(22.2%)	□(44.8%)	□(8.3%)
I like to use the local bus service because it is less demanding than driving.	□(6.9%)	□(16.3%)	□(17.1%)	□(40.1%)	□(17.3%)
I use public transport because of the environment	□(7.1%)	□(23.6%)	□(20.6%)	□(33.7%)	□(13.9%)
I feel uncomfortable travelling on the local bus with strangers	□(36.9%)	□(38.7%)	□(8.9%)	□(11.9%)	□(3.0%)

22. How likely are you to change your means of transport, if at all, for your regular journeys in the next two years?

□ Very Unlikely (51.2%)

□ Unlikely (27.8%)

□ Not Sure (10.3%)

□ Likely (6.7%)

□ Very Likely (2.4%)

23. Please to what extent do you agree or disagree with each of the following statements?

	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Driving is perceived to illustrate a person's power, financial status in society and provide the driver/ owner with a positive self-image	□(24.2%)	□(35.1%)	□(14.3%)	□(22.4%)	□(3.2%)
Public transport mode (i.e. local bus service) is seen as a second-best option in society	□(15.7%)	□(35.1%)	□(10.7%)	□(34.1%)	□(4.4%)
Public transport is generally perceived to provide an environmentally cleaner choice of transport than a car	□(2.4%)	□(5.2%)	□(9.1%)	□(62.3%)	□(21.0%)
There is a general belief that adopting public transport instead of car/van for work/educational journeys is beneficial to the environment and our health.	□(2.0%)	□(4.0%)	□(8.1%)	□(63.7%)	□(22.2%)
I believe most of my family and friends share the perception about the benefit of adopting public transport on the environment and our health	□(1.4%)	□(10.3%)	□(25.4%)	□(50.0%)	□(12.9%)
Most of my family and friends use public transport for their work/educational journeys	□(7.5%)	□(36.9%)	□(17.3%)	□(31.5%)	□(6.3%)
If my family and friends change their travel choices, then, maybe I would do the same	□(30.2%)	□(48.8%)	□(13.5%)	□(5.0%)	□(1.4%)
I think people should use public transport more for their work/educational journeys due to the increasing levels of traffic congestion and air pollution in urban centres.	□(2.6%)	□(8.3%)	□(13.1%)	□(46.8%)	□(29.2%)
I believe most of the people important to me (family/friends etc) would agree if I use public transport instead of a private car for my normal trips	□(2.6%)	□(12.1%)	□(28.2%)	□(41.7%)	□(15.3%)
I feel morally obligated to use more of public transport due to the impact of our travel behaviour on health and the environment (global warming)	□(8.1%)	□(18.6%)	□(18.8%)	□(31.7%)	□(12.9%)

24. Please to what extent do you identify with each of the following statements?

	Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
I know that I am good because everybody keep telling me so	□(16.7%)	□(26.6%)	□(40.7%)	□(7.9%)	□(3.6%)
I like to be the centre of attention	□(25.8%)	□(39.9%)	□(25.4%)	□(3.0%)	□(1.8%)
I think I am a special person	□(18.3%)	□(31.9%)	□(33.7%)	□(9.5%)	□(3.8%)
I like having authority over people	□(21.8%)	□(34.9%)	□(26.6%)	□(10.7%)	□(2.4%)
I find it easy to manipulate others	□(28.2%)	□(34.7%)	□(24.6%)	□(4.6%)	□(3.0%)
I insist upon getting the respect that is due me	□(23.6%)	□(33.5%)	□(25.4%)	□(11.5%)	□(1.8%)
I am apt to show off if I get the chance	□(26.6%)	□(35.3%)	□(23.2%)	□(8.1%)	□(2.2%)
I always know what I am doing	□(13.1%)	□(26.2%)	□(28.2%)	□(21.6%)	□(7.7%)
Everybody likes to hear my stories	□(22.0%)	□(27.0%)	□(38.1%)	□(6.9%)	□(1.4%)
I expect a great deal from other people	□(13.1%)	□(31.5%)	□(35.1%)	□(14.5%)	□(3.0%)
I really like to be the centre of attention	□(31.0%)	□(34.7%)	□(25.0%)	□(2.2%)	□(2.2%)
People always seem to recognise my authority	□(19.2%)	□(26.6%)	□(36.7%)	□(10.3%)	□(2.6%)
I am going to be a great person	□(19.6%)	□(23.4%)	□(38.1%)	□(10.9%)	□(2.4%)
I can make anybody believe anything I want them to	□(19.6%)	□(23.4%)	□(38.1%)	□(10.9%)	□(2.4%)
I am more capable than other people	□(16.7%)	□(29.8%)	□(34.7%)	□(12.3%)	□(3.8%)
I am an extraordinary person	□(20.8%)	□(33.7%)	□(31.9%)	□(6.9%)	□(2.8%)

Demographics

25. What is your gender?

- ☐ Female (52.2%)
- ☐ Male (47.8%)

26. What is your age? ....

27. What is your Marital Status?

- ☐ Married (including Civil Partnership) (46.8%)
- ☐ Unmarried (46.2%)
- ☐ Divorced/Separated (7.1%)

28. Please, what is the size of your household including yourself and children?

- ☐ 1 (32.9%)
- ☐ 2 (40.9%)
- ☐ 3 (12.1%)
- ☐ More than 3 (14.1%)

29. Please, could you indicate the highest educational qualifications you have?

- ☐ No formal education (1.0%)
- ☐ Primary (0.0%)
- ☐ Secondary (17.1%)
- ☐ College (19.8%)
- ☐ Bachelor's degree (33.1%)
- ☐ Master's degree (23.6%)
- ☐ PhD (5.4%)

30. Which of these best represent your household annual income before tax?

- ☐ Less than £10,000 (9.9%)
- ☐ £10,000 to £15,000 (9.7%)

- ◻ £15,000 to £20,000 (10.7%)
- ◻ £20,000 to £30,000 (18.8%)
- ◻ £30,000 to £50,000 (22.8%)
- ◻ £50,000 to £70,000 (13.5%)
- ◻ Over £70,000 (14.7%)

31. Comments/Suggestions about the survey

....

....

Appendix B

Ethical Approval

SEBE RESEARCH INTEGRITY PROCEDURE
ETHICS APPROVAL FORM FOR STUDENT USE

Please complete sections 1 and 2 and sign in section 3, confirming whether you are self-certifying (in which case simply retain a copy of this form with your research materials) or referring the matter to the school academic lead on Research Integrity.

Section 1 – Research details	
Student name and number	Augustus Ababio-Donkor 40178349
Supervisor	Professor Wafaa Saleh
Module leader	Dr Achille Fonzone
Module number and name	Research project

Title of project: Applying behavioural economics in modelling and analysing the demand for public transport the MINDSPACE approach

Aim of Research

The main aim of this research is to investigate whether the extended model of Behavioural Economics using MINDSPACE can enhance our understanding of transport mode choice models.

Details of the research methods to be used. Please consider all of the following in your response:

a. The data will be collected by postal survey method. Questionnaire will be sent to sampled households in Edinburgh

b. Data will also be collected online using online survey tool (QuestionPro).

c. Students and friends will be appointed to distribute the questionnaire to the sampled addresses

d. The population will be stratified into data zones and households selected at random from each strata.

e. Residents of postcode areas EH1 to EH17 in the city of Edinburgh are the participant for this survey

f. The survey data will be tasted in terms of completion of questions

g. if applicable, please attach a copy of the questionnaire/interview questions (for student researchers, please include notification of approval of the questionnaire from your supervisor)
A questionnaire along with the supervisors' approval have been attached

Who/what will be the research subjects in the research? : a. The residents of City of Edinburgh 16 years and above will be the research subjects.

Section 2 – Research Subject Details
Will participants be free NOT to take part if they choose? a. Yes, participation in the survey is voluntary.
Explain how informed consent will be achieved. N/A
If you plan to use assumed consent rather than informed consent please outline why this is necessary. N/A
Will any individual be identifiable in the findings? The survey will be anonymous; therefore, the participants will not be identifiable.
How will the findings be disseminated? The findings will be used for writing academic articles.
Is there any possibility of any harm (social, psychological, professional, economic, etc.) to participants who take part or do not take part? If so, give details of the potential harm and the mitigation strategies you have adopted. There is no potential harm if anyone takes or does not take part in the survey.
How / where will data be stored? Who will have access to it? Will it be secure? How long will the data be kept? What will be done with the data at the end of the project: The data will be stored on online as well as in the computer. The supervisors will have online access as well. The data will be kept until PhD project is finished.
If payment or reward will be made to participants please justify that the amount and type are appropriate. We are proposing rewarding £50 each to two participants as a form of motivation to: a. Increase the response rate b. Improve data quality in terms of accuracy and completeness c. to thank respondents for their time
Any other information in support of your application.

Approved Jan 2018 p2 of 4

Section 3 – Self-certification (to be signed by both student and module leader or dissertation supervisor)		
Delete as appropriate: I confirm that I have completed the self-certification checklist and have not identified any ethical issues requiring approval. OR I refer this research to the school lead on Research Integrity (give reason).		
	Student	Module leader or dissertation supervisor
Signature	[redacted]	[redacted]
Name	Augustus Ababio-Donkor	Prof. Wafaa Saleh
Date	11-01-2018	15-01-2018

If you have self-certified that best practice has been followed and no ethical issues have been identified, please sign the form and retain with your research materials.

If you need to refer the matter to the school lead on Research Integrity, please sign and email to Dr Andrew Smith: a.smith7@napier.ac.uk. In most cases Andrew will be able to provide guidance and approve the research, but in some cases he may need to take the matter to the next meeting of the school Research and Innovation Committee. Exceptionally, the matter may be referred to the University Research Integrity Committee.

Approved Jan 2018 p3 of 4

Section 4 – Approval by school lead on Research Integrity (if applicable)	
Delete as appropriate: I approve this research OR ~~I refer this research to the School Research and Innovation Committee (give reason)~~	
Signature	signed
Name	Andrew Smith
Date	19-01-2018

Section 5 – School Research and Innovation Committee Approval (if applicable)
SRIC decision
Does this issue need to be referred to the URIC? If YES Secretary to forward to URIC Secretary for referral with any appropriate paperwork Date actioned
Reason for referral
Signature of Convener of SRIC Name Date
Date researcher informed of SRIC's decision

Approved Jan 2018 p4 of 4

Appendix C

Sample Map

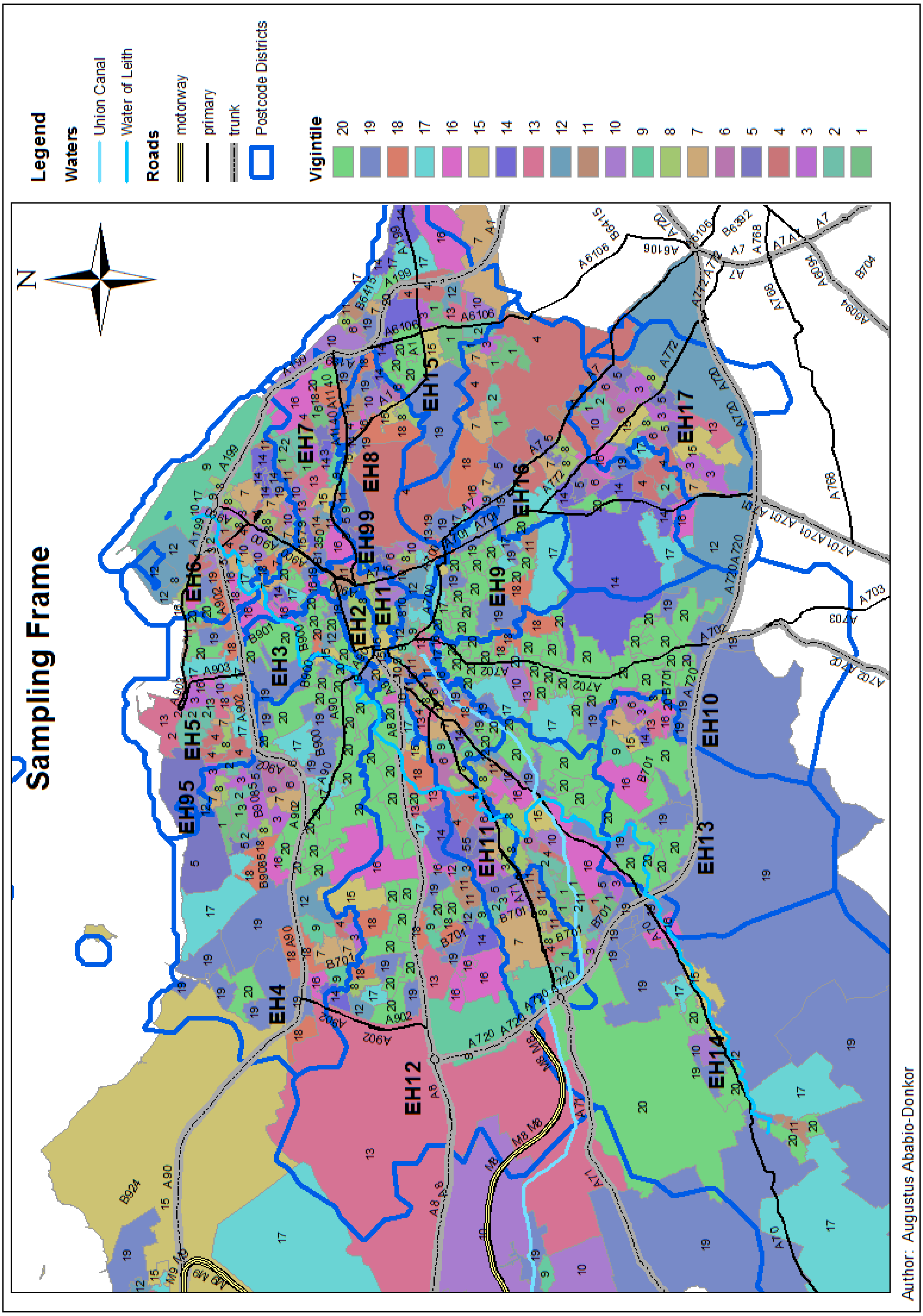

Figure C.1: Map of the Study Area by OutCode and Vigintile

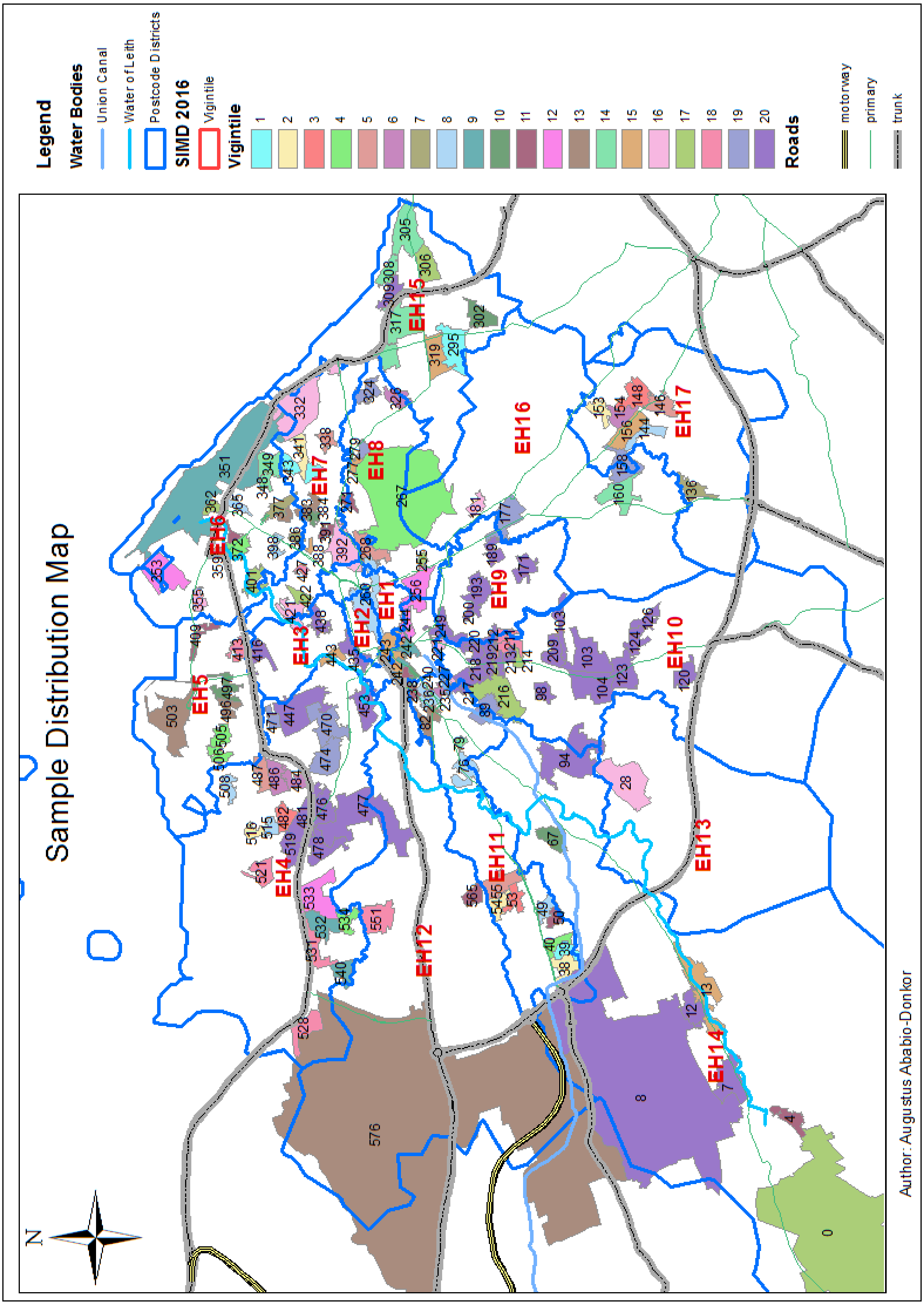

Figure C.2: Sample distribution by Outcode and Vigintile

Appendix D

Exploratory and Confirmatory Factor Analysis

Table D.1: List of Variables

Variable	Label/Description	Mean	SD
Licence	Driving licence	1.6	1.225
Tr_Pass	Travel card (Ridacard)	3.01	1.849
Ncars	Number of cars	1.96	0.818
Emp_Status	Employment status	2.36	1.377
Tr_Pur	Trip purpose	2	1.164
Trp_Freq	Trip frequency	4.03	1.466
Trp_Dest	Trip destination		
Tr_Mode	Primary mode of travel	4.49	2.298
PtDiff	Difficulty in using PT	2.54	1.47
Tr_Time	Travel time in minutes	2.72	1.189
Tr_Cost	Monthly travel cost	52.8	61.122
Alt_Mode	Alternative mode of travel	4.65	3.065
Tr_Cost_AltMode	Alt-mode per month	50.69	64.233
PTM	Travel mode 5yrs ago	4.5	3.143
R4ChaMode	If Travel mode has been changed in the last 5 yrs	3.08	3.149
DistToBS_Orig	Distance to Bus Stop from trip origin in minutes	1.26	0.549
DistToBS_Des	Distance to Bus Stop from trip destination in minutes	1.65	1.196
Gender	Gender	1.49	0.504
Age	Age	49.54	17.439
M_Status	Marital Status	1.59	0.622
HH_size	Household size	2.08	1.011
Educ	Education level	4.74	1.25
Income	Household income	4.37	1.862
Postcode	Address (postcode) of respondent		
PT_SS	Level of satisfaction with PT Services	4.03	0.972
ChMode	Possbility of changing travel mode in the next 2 years	1.79	1.03

Table C.1: List of Variables

Target Construct	Indicators	Label/Description	Mean	SD
Psychometric Constructs				
Please to what extent do you agree or disagree with each of the following statements?				
Norms	Nrm1	Driving is perceived to illustrate a person's power, financial status in society and provide the driver/owner with a positive self-image	2.45	1.177
	Nrm2	Public transport mode (i.e. local bus service) is seen as a second best option in society	2.76	1.202
	Nrm3	Public transport is generally perceived to provide environmentally cleaner choice of transport than a car	3.94	0.852
	Nrm4	There is a general belief that adopting public transport instead of car/van for work/educational journeys is beneficial to the environment and our health.	4.00	0.804
	Nrm5	I believe most of my family and friends share the perception about the benefit of adopting public transport on the environment and our health	3.63	0.885
	Nrm6	Most of my family and friends use public transport for their work/educational journeys	2.92	1.112
	Nrm7	If my family and friends change their travel choices, then, maybe I would do same	1.98	0.88
	Nrm8	I think people should use public transport more for their work/educational journeys due to the increasing levels of traffic congestion and air pollution in the urban centres.	3.92	0.993
	Nrm9	I believe most of the people important to me (family/friends etc) would agree if I use public transport instead of a private car for my normal trips	3.55	0.977
	Nrm10	I feel morally obligated to use more of public transport due to the impact of our travel behaviour on health and the environment (global warming)	3.13	1.195
To what extent would these experiences affect your regular usage of the bus or tram?				
Salience	PTExp1b	Anti-social behaviour (drunk people etc)	3.13	1.264
	PTExp2b	Overcrowding	2.95	1.195
	PTExp3b	Exposure to health risk (catching cold etc)	3.36	1.291
	PTExp4b	Passenger annoyance and discomfort	3.08	1.255
	PTExp5b	Poor hygiene (service uncleanliness and smell on the buses)	3.4	1.331
	PTExp6b	Inaccurate bus and real-time information	2.34	1.292
	PTExp7b	Long waiting and travel time	3.22	1.417
	PTExp8b	Safety issues (lack of seatbelt, toilets on board or conductor etc)	2.68	1.326
Please to what extent do you agree or disagree with each of the following statements?				
Affect	Aff1	I enjoy using public transport because I get to meet people and make friends	2.11	1.047
	Aff2	It is boring travelling in the bus	2.45	0.966
	Aff3	I am happy using public transport because I can use the travel time for other activities	3.35	1.006
	Aff4	I like to use the local bus service because it is less demanding than driving.	3.46	1.166
	Aff5	I use public transport because of the environment	3.24	1.172
	Aff6	I feel uncomfortable travelling in the local bus with strangers	2.05	1.101

Table C.1: List of Variables

Psychometric Constructs				
Target Construct	**Indicators**	**Label/Description**	**Mean**	**SD**
Please indicate how much you agree with each of the following statements or how true is it about you?				
PT Service Quality	PTSQ1	I feel personally safe and secure on the local bus during the night	3.79	0.913
	PTSQ2	The buses and stops are accessible	4.29	0.687
	PTSQ3	The cleanliness of the buses interior, seats and bus stops are acceptable	3.92	0.787
	PTSQ4	The noise level in buses is acceptable	3.77	0.876
	PTSQ5	The buses are comfortable and spacious	3.75	0.933
	PTSQ6	I am satisfied with the bus travel time	3.74	0.968
	PTSQ7	The service is stable and reliable (arrives on time and according to the scheduled timetable)	3.79	0.922
	PTSQ8	The fares are good value	3.63	1.009
	PTSQ9	Real-time travel information (route and timetable) is readily available and easy to access	3.96	0.865
	PTSQ10	Frequency of service is acceptable	3.94	0.889
Please to what extent do you identify with each of the following statements?				
Narcissism	Nar1	I know that I am good because everybody keep telling me so	2.53	0.997
	Nar2	I like to be the centre of attention	2.12	0.905
	Nar3	I think I am a special person	2.47	1.03
	Nar4	I like having authority over people	2.35	1.026
	Nar5	I find it easy to manipulate others	2.15	1.007
	Nar6	I insist upon getting the respect that is due me	2.32	1.032
	Nar7	I am apt to show off if I get the chance	2.2	1.015
	Nar8	I always know what I am doing	2.84	1.153
	Nar9	Everybody likes to hear my stories	2.36	0.962
	Nar10	I expect a great deal from other people	2.62	0.997
	Nar11	I really like to be the centre of attention	2.05	0.944
	Nar12	People always seems to recognise my authority	2.48	1.017
	Nar13	I am going to be a great person	2.5	1.025
	Nar14	I can make anybody believe anything I want them to	2.16	0.956
	Nar15	I am more capable than other people	2.55	1.04
	Nar16	I am an extraordinary person	2.35	0.99

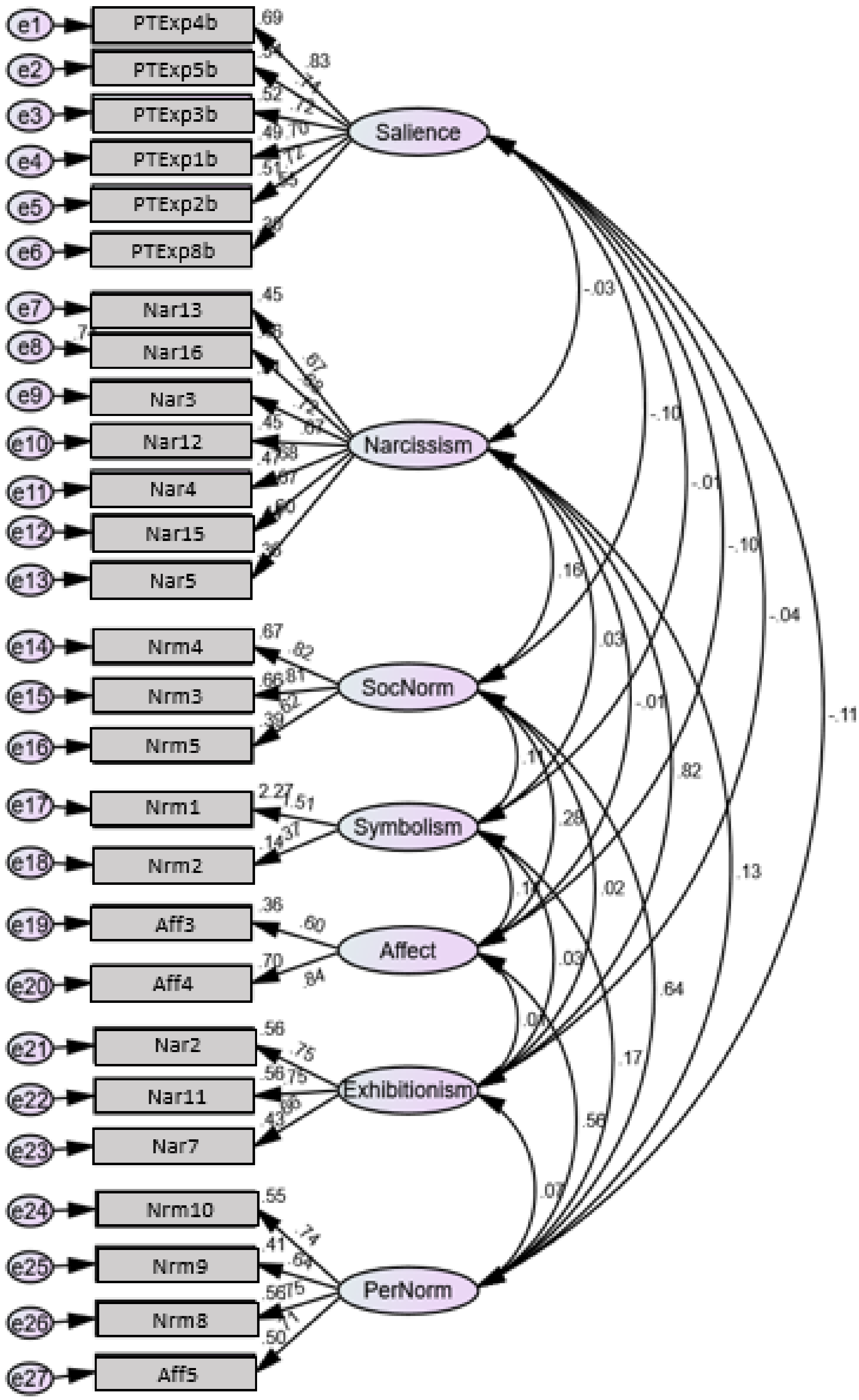

Figure D.1: Initial Confirmatory Factor Analysis

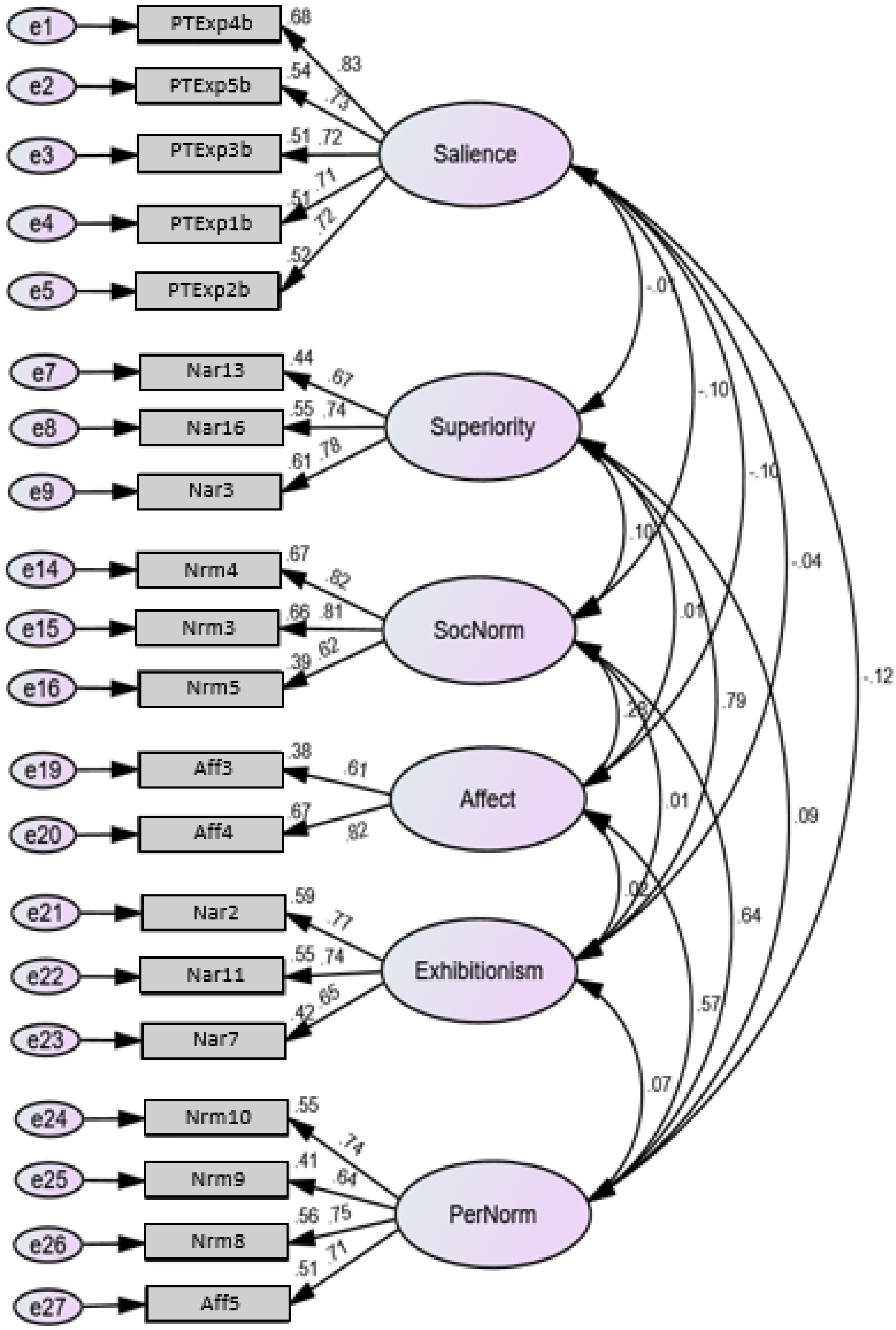

Figure D.2: Final Confirmatory Factor Analysis

Appendix E

Biogeme Script for Model Estimation

Base Model Estimation

```
[ ]: import pandas as pd
import numpy as np
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.models as models
import biogeme.distributions as dist
import biogeme.results as res

"Read Data"
pandas = pd.read_csv('Data-80.csv')
database=db.Database('Data-80',pandas)
database.missingData = -1
from headers import *
exclude = ( Choice == -1 )
database.remove(exclude)

"Coefficient Definition"
ASC_Car = Beta('ASC_Car',0,-10000,10000,0)
ASC_PT = Beta('ASC_PT',0,-10000,10000,1)
ASC_NMT = Beta('ASC_NMT',0,-10000,10000,0)
B_Dist_NMT = Beta('B_Dist_NMT',0.0,-10000,10000,0)
B_TT_Car = Beta('B_TT_Car',0,-10000,10000,0)
B_TT_PT = Beta('B_TT_PT',0,-10000,10000,0)
B_Work = Beta('B_Work',0,-10000,10000,0)
B_Age_Car = Beta('B_Age_Car',0,-10000,10000,0)
B_Age_NMT = Beta('B_Age_NMT',0,-10000,10000,0)
B_WalkingTime = Beta('B_WalkingTime',0,-10000,10000,0)
B_NCar_Car = Beta('B_NCar_Car',0,-10000,10000,0)
B_Edu_NMT = Beta('B_Edu_NMT',0,-10000,10000,0)
B_Cost_PT= Beta('B_Cost_PT',0,None,None,0)
B_Cost_Car= Beta('B_Cost_Car',0,-10000,10000,0)
B_Age_PT = Beta('B_Age_PT',0,None,None,0)
B_TrFreq = Beta('B_TrFreq',0,None,None,0)
B_INC_PT = Beta('B_INC_PT',0,None,None,0)
B_Gender_Car = Beta('B_Gender_Car',0,-10000,10000,0)

"Define Variables"
NoOfCars =  DefineVariable('NoOfCars',Cars * (Cars!=-1),database)
WkTrip =  DefineVariable('WkTrip', Tr_Pur * ( Tr_Pur  == 1) ,database)
Distance_km = DefineVariable('Distance_km', TripLength_km * (TripLength_km !=␣
↪-1), database)
HighEducation =  DefineVariable('HighEducation', Education * ((Education== 5) \
                               + (Education  == 6) + (Education  == 7)) ,database)

"Utilities Equations"
        V_PT = ASC_PT +\
               B_TT_PT * TimePT_1 + \
               B_Cost_PT * CostPT_1 +\
               B_INC_PT * Income_band  +\
               B_Age_PT * Age_group

        V_Car = ASC_Car  +\
                B_TT_Car * TimeCar_1  + \
                B_NCar_Car * NoOfCars +\
                B_WalkingTime * (DistToBS_Des + DistToBS_Orig) +\
                B_Work * WkTrip +\
                B_Gender_Car * Gender +\
                B_TrFreq * TripFreq #+\
                #B_Cost_Car * Car_Cost

        V_NMT = ASC_NMT +\
                B_Dist_NMT * Distance_km +\
```

```
                B_Age_NMT * Age_band +\
                B_Edu_NMT * Education

"Associate utility functions with the numbering of alternatives"
V = {0: V_PT,
     1: V_Car,
     2: V_NMT}

av = {0: 1,
      1: 1,
      2: 1}

"The choice model is a logit, with availability conditions"
logprob = models.logit(V,av,Choice)
loglike = log((logprob))
biogeme = bio.BIOGEME(database,loglike)

"Save results as HTML and Pickle File"
#biogeme.generatePickle = False
#biogeme.generateHtml = False

biogeme.modelName = "Discrete Choice"
results = biogeme.estimate()
print("Estimated betas: {}".format(len(results.data.betaValues)))
print("Results=",results)
```

ICLV Model Estimation

[ ]:

```
In [1]: import pandas as pd
        import numpy as np
        import biogeme.database as db
        import biogeme.biogeme as bio
        import biogeme.loglikelihood as ll
        import biogeme.models as models
        import biogeme.distributions as dist
        import biogeme.results as res

        pandas = pd.read_csv("Data-80.csv")
        database=db.Database("Data-80",pandas)
        from headers import *
        exclude = ( MChoice_3== -1 )
        database.remove(exclude)
        omega_PNorm = bioDraws('omega_PNorm','NORMAL_MLHS')
        omega_aff = bioDraws('omega_aff','NORMAL_MLHS')
        omega_sal = bioDraws('omega_sal','NORMAL_MLHS')
        omega_exh = bioDraws('omega_exh','NORMAL_MLHS')
        sigma_PNorm = Beta('sigma_PNorm',0,None,None,0)
        sigma_aff = Beta('sigma_aff',0,None,None,0)
        sigma_sal = Beta('sigma_sal',0,None,None,0)
        sigma_exh = Beta('sigma_exh',0,None,None,0)

        """Latent variable 1: Salience"""
        ### Coefficients
        coef_ASC_sal = Beta('coef_ASC_sal',0,None,None,1 )
        coef_Age_sal = Beta('coef_Age_sal',0.0,None,None,0 )

        ## Define Variables
        NCar =  DefineVariable('NCar',CarAvail * ( CarAvail >= 1),database)
        """
        1. Members of this class are mostly car users (46%), 25% PT users and␣
↪28% NMT Users
        2. They are either in full time employment or retired
        3. 51% own a ridacard indicating frequent users
        4. 62% of members of this class own at least
        5. Likely to be women
        """
        Salience = \
        coef_ASC_sal + \
        coef_Age_sal * Age +\
        sigma_sal * omega_sal

        ### Measurement Equations
        #B^m_0i
        INTER_PTExp1b = Beta ('INTER_PTExp1b',0.0,None,None,0)
        INTER_PTExp2b = Beta ('INTER_PTExp2b',0.0,None,None,0 )
        INTER_PTExp3b = Beta ('INTER_PTExp3b',0.0,None,None,0 )
        INTER_PTExp4b = Beta ('INTER_PTExp4b',0,None,None,0)
        INTER_PTExp5b = Beta ('INTER_PTExp5b',0,None,None,1 )

        #B^m_i
        B_PTExp1b_F1 = Beta ('B_PTExp1b_F1',0.0,None,None,0)
        B_PTExp2b_F1 = Beta ('B_PTExp2b_F1',0.0,None,None,0 )
        B_PTExp3b_F1 = Beta ('B_PTExp3b_F1',0.0,None,None,0 )
        B_PTExp4b_F1 = Beta ('B_PTExp4b_F1',0.0,None,None,0)
        B_PTExp5b_F1 = Beta ('B_PTExp5b_F1',1,None,None,1 )

        # B^m_0i + B^m_i.x
        MODEL_PTExp1b = INTER_PTExp1b + B_PTExp1b_F1*Salience
        MODEL_PTExp2b = INTER_PTExp2b + B_PTExp2b_F1*Salience
        MODEL_PTExp3b = INTER_PTExp3b + B_PTExp3b_F1*Salience
        MODEL_PTExp4b = INTER_PTExp4b + B_PTExp4b_F1*Salience
        MODEL_PTExp5b = INTER_PTExp5b + B_PTExp5b_F1*Salience

        # SIGMA_STAR = z^*_i
        SIGMA_STAR_PTExp1b = Beta ('SIGMA_STAR_PTExp1b',1.0,None,None,0)
        SIGMA_STAR_PTExp2b = Beta ('SIGMA_STAR_PTExp2b',1.0,None,None,0 )
        SIGMA_STAR_PTExp3b = Beta ('SIGMA_STAR_PTExp3b',1.0,None,None,0 )
        SIGMA_STAR_PTExp4b = Beta ('SIGMA_STAR_PTExp4b',1.0,None,None,0)
        SIGMA_STAR_PTExp5b = Beta ('SIGMA_STAR_PTExp5b',1,None,None,1 )

        sal_delta_1 = Beta('sal_delta_1',0.1,0,10,0 )
        sal_delta_2 = Beta('sal_delta_2',0.2,0,10,0 )
        sal_tau_1 = -sal_delta_1 - sal_delta_2
        sal_tau_2 = -sal_delta_1
        sal_tau_3 = sal_delta_1
        sal_tau_4 = sal_delta_1 + sal_delta_2

        PTExp1b_tau_1 = (sal_tau_1-MODEL_PTExp1b) / SIGMA_STAR_PTExp1b
        PTExp1b_tau_2 = (sal_tau_2-MODEL_PTExp1b) / SIGMA_STAR_PTExp1b
        PTExp1b_tau_3 = (sal_tau_3-MODEL_PTExp1b) / SIGMA_STAR_PTExp1b
```

```
        PTExp1b_tau_4 = (sal_tau_4-MODEL_PTExp1b) / SIGMA_STAR_PTExp1b
        IndPTExp1b = {
            1 : bioNormalCdf(PTExp1b_tau_1),
            2 : bioNormalCdf(PTExp1b_tau_2)-bioNormalCdf(PTExp1b_tau_1),
            3 : bioNormalCdf(PTExp1b_tau_3)-bioNormalCdf(PTExp1b_tau_2),
            4 : bioNormalCdf(PTExp1b_tau_4)-bioNormalCdf(PTExp1b_tau_3),
            5 : 1-bioNormalCdf(PTExp1b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp1b = Elem(IndPTExp1b,PTExp1b)

        PTExp2b_tau_1 = (sal_tau_1-MODEL_PTExp2b) / SIGMA_STAR_PTExp2b
        PTExp2b_tau_2 = (sal_tau_2-MODEL_PTExp2b) / SIGMA_STAR_PTExp2b
        PTExp2b_tau_3 = (sal_tau_3-MODEL_PTExp2b) / SIGMA_STAR_PTExp2b
        PTExp2b_tau_4 = (sal_tau_4-MODEL_PTExp2b) / SIGMA_STAR_PTExp2b
        IndPTExp2b = {
            1 : bioNormalCdf(PTExp2b_tau_1),
            2 : bioNormalCdf(PTExp2b_tau_2)-bioNormalCdf(PTExp2b_tau_1),
            3 : bioNormalCdf(PTExp2b_tau_3)-bioNormalCdf(PTExp2b_tau_2),
            4 : bioNormalCdf(PTExp2b_tau_4)-bioNormalCdf(PTExp2b_tau_3),
            5 : 1-bioNormalCdf(PTExp2b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp2b = Elem(IndPTExp2b,PTExp2b)

        PTExp3b_tau_1 = (sal_tau_1-MODEL_PTExp3b) / SIGMA_STAR_PTExp3b
        PTExp3b_tau_2 = (sal_tau_2-MODEL_PTExp3b) / SIGMA_STAR_PTExp3b
        PTExp3b_tau_3 = (sal_tau_3-MODEL_PTExp3b) / SIGMA_STAR_PTExp3b
        PTExp3b_tau_4 = (sal_tau_4-MODEL_PTExp3b) / SIGMA_STAR_PTExp3b
        IndPTExp3b = {
            1 : bioNormalCdf(PTExp3b_tau_1),
            2 : bioNormalCdf(PTExp3b_tau_2)-bioNormalCdf(PTExp3b_tau_1),
            3 : bioNormalCdf(PTExp3b_tau_3)-bioNormalCdf(PTExp3b_tau_2),
            4 : bioNormalCdf(PTExp3b_tau_4)-bioNormalCdf(PTExp3b_tau_3),
            5 : 1-bioNormalCdf(PTExp3b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp3b = Elem(IndPTExp3b,PTExp3b)

        PTExp4b_tau_1 = (sal_tau_1-MODEL_PTExp4b) / SIGMA_STAR_PTExp4b
        PTExp4b_tau_2 = (sal_tau_2-MODEL_PTExp4b) / SIGMA_STAR_PTExp4b
        PTExp4b_tau_3 = (sal_tau_3-MODEL_PTExp4b) / SIGMA_STAR_PTExp4b
        PTExp4b_tau_4 = (sal_tau_4-MODEL_PTExp4b) / SIGMA_STAR_PTExp4b
        IndPTExp4b = {
            1 : bioNormalCdf(PTExp4b_tau_1),
            2 : bioNormalCdf(PTExp4b_tau_2)-bioNormalCdf(PTExp4b_tau_1),
            3 : bioNormalCdf(PTExp4b_tau_3)-bioNormalCdf(PTExp4b_tau_2),
            4 : bioNormalCdf(PTExp4b_tau_4)-bioNormalCdf(PTExp4b_tau_3),
            5 : 1-bioNormalCdf(PTExp4b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp4b = Elem(IndPTExp4b,PTExp4b)

        PTExp5b_tau_1 = (sal_tau_1-MODEL_PTExp5b) / SIGMA_STAR_PTExp5b
        PTExp5b_tau_2 = (sal_tau_2-MODEL_PTExp5b) / SIGMA_STAR_PTExp5b
        PTExp5b_tau_3 = (sal_tau_3-MODEL_PTExp5b) / SIGMA_STAR_PTExp5b
        PTExp5b_tau_4 = (sal_tau_4-MODEL_PTExp5b) / SIGMA_STAR_PTExp5b
        IndPTExp5b = {
            1 : bioNormalCdf(PTExp5b_tau_1),
            2 : bioNormalCdf(PTExp5b_tau_2)-bioNormalCdf(PTExp5b_tau_1),
            3 : bioNormalCdf(PTExp5b_tau_3)-bioNormalCdf(PTExp5b_tau_2),
            4 : bioNormalCdf(PTExp5b_tau_4)-bioNormalCdf(PTExp5b_tau_3),
            5 : 1-bioNormalCdf(PTExp5b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp5b = Elem(IndPTExp5b,PTExp5b)
        """Latent variable 2: Affect"""
        ### Coefficients
        coef_ASC_aff = Beta('coef_ASC_aff',0.0,None,None,0 )
        coef_Ridacard_aff = Beta('coef_Ridacard_aff',0.0,None,None,0 )
        coef_CarAvail_aff = Beta('coef_CarAvail_aff',0.0,None,None,0 )

        ###Define Variables
        #HighEducation =  DefineVariable('HighEducation', Education *
↪((Education  == 5) +\
        #                                       (Education  == 6) + (Education
↪== 7)) ,database)
        """
```

```
        1. Likely to be people aged 54 years and below
        2. without a car or own one car
        3. Single
        4. in full time employment or student
             (possibly people who make frequent and routine trips)
        """

        Affect = \
        coef_ASC_aff +\
        coef_CarAvail_aff * Car +\
        coef_Ridacard_aff * Tr_Pass +\
        sigma_aff * omega_aff

        ### Measurement Equations
        #B^m_0i
        INTER_Aff3 = Beta ('INTER_Aff3',0,None,None,1)
        INTER_Aff4 = Beta ('INTER_Aff4',0.0,None,None,0 )

        #B^m_i
        B_Aff3_F2 = Beta ('B_Aff3_F2',1,None,None,1)
        B_Aff4_F2 = Beta ('B_Aff4_F2',0.0,None,None,0 )

        # B^m_0i + B^m_i.x
        MODEL_Aff3 = INTER_Aff3 + B_Aff3_F2*Affect
        MODEL_Aff4 = INTER_Aff4 + B_Aff4_F2*Affect

        # SIGMA_STAR = z^*_i#
        SIGMA_STAR_Aff4 = Beta ('SIGMA_STAR_Aff4',1.0,None,None,0 )
        SIGMA_STAR_Aff3 = Beta ('SIGMA_STAR_Aff3',1,None,None,1 )

        Aff_delta_1 = Beta('Aff_delta_1',0.1,0,10,0 )
        Aff_delta_2 = Beta('Aff_delta_2',0.2,0,10,0 )
        Aff_tau_1 = -Aff_delta_1 - Aff_delta_2
        Aff_tau_2 = -Aff_delta_1
        Aff_tau_3 = Aff_delta_1
        Aff_tau_4 = Aff_delta_1 + Aff_delta_2

        Aff3_tau_1 = (Aff_tau_1-MODEL_Aff3) / SIGMA_STAR_Aff3
        Aff3_tau_2 = (Aff_tau_2-MODEL_Aff3) / SIGMA_STAR_Aff3
        Aff3_tau_3 = (Aff_tau_3-MODEL_Aff3) / SIGMA_STAR_Aff3
        Aff3_tau_4 = (Aff_tau_4-MODEL_Aff3) / SIGMA_STAR_Aff3
        IndAff3 = {
            1 : bioNormalCdf(Aff3_tau_1),
            2 : bioNormalCdf(Aff3_tau_2)-bioNormalCdf(Aff3_tau_1),
            3 : bioNormalCdf(Aff3_tau_3)-bioNormalCdf(Aff3_tau_2),
            4 : bioNormalCdf(Aff3_tau_4)-bioNormalCdf(Aff3_tau_3),
            5 : 1-bioNormalCdf(Aff3_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_Aff3 = Elem(IndAff3,Aff3)

        Aff4_tau_1 = (Aff_tau_1-MODEL_Aff4) / SIGMA_STAR_Aff4
        Aff4_tau_2 = (Aff_tau_2-MODEL_Aff4) / SIGMA_STAR_Aff4
        Aff4_tau_3 = (Aff_tau_3-MODEL_Aff4) / SIGMA_STAR_Aff4
        Aff4_tau_4 = (Aff_tau_4-MODEL_Aff4) / SIGMA_STAR_Aff4
        IndAff4 = {
            1 : bioNormalCdf(Aff4_tau_1) ,
            2 : bioNormalCdf(Aff4_tau_2)-bioNormalCdf(Aff4_tau_1),
            3 : bioNormalCdf(Aff4_tau_3)-bioNormalCdf(Aff4_tau_2),
            4 : bioNormalCdf(Aff4_tau_4)-bioNormalCdf(Aff4_tau_3),
            5 : 1-bioNormalCdf(Aff4_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_Aff4 = Elem(IndAff4,Aff4)

        """Latent variable 3: Norm"""
        ### Coefficients
        coef_ASC_PNorm = Beta('coef_ASC_PNorm',0.0,None,None,1 )
        coef_Educ_PNorm = Beta('coef_Educ_PNorm',0.0,None,None,0 )
        coef_Age_PNorm = Beta('coef_Age_PNorm',0.0,None,None,0 )
        coef_CarOwnership_PNorm = Beta('coef_CarOwnership_PNorm',0.0,None,None,0␣
↪)
        coef_Income_PNorm = Beta('coef_Income_PNorm',0.0,None,None,0 )

        # Latent variable:Structural equation
        """
           1. Likey to have First or masters degree (35% and 36%)
           2. most likely does not own a car (57%) or own one car (34%)
           3. likey to be employed (67%) or retired (17%)
           4. most likey to be women
           5. Travel by PT or NMT, none in this class travel by Car
           6. Age between 25 and 64 years
```

```
    """
PerNorm = \
coef_ASC_PNorm +\
coef_Educ_PNorm * HighEduc  +\
coef_Age_PNorm * Age +\
coef_CarOwnership_PNorm * Car +\
coef_Income_PNorm * HighIncome +\
sigma_PNorm * omega_PNorm

"""Measurement Equations"""
#B^m_0i
INTER_Nrm8 = Beta ('INTER_Nrm8',0,None,None,0)
INTER_Nrm9 = Beta ('INTER_Nrm9',0.0,None,None,0 )
INTER_Nrm10 = Beta ('INTER_Nrm10',0.0,None,None,1 )
INTER_Aff5 = Beta ('INTER_Aff5',0.0,None,None,0 )

#B^m_i
B_Nrm8_F3 = Beta ('B_Nrm8_F3',0,None,None,0)
B_Nrm9_F3 = Beta ('B_Nrm9_F3',0.0,None,None,0 )
B_Nrm10_F3 = Beta ('B_Nrm10_F3',1,None,None,1 ) # Note
B_Aff5_F3 = Beta ('B_Aff5_F3',0.0,None,None,0 )

# B^m_0i + B^m_i.x
MODEL_Nrm8 = INTER_Nrm8 + B_Nrm8_F3*PerNorm
MODEL_Nrm9 = INTER_Nrm9 + B_Nrm9_F3*PerNorm
MODEL_Nrm10 = INTER_Nrm10 + B_Nrm10_F3*PerNorm
MODEL_Aff5 = INTER_Aff5 + B_Aff5_F3*PerNorm

# SIGMA_STAR = z^*_i
SIGMA_STAR_Nrm8 = Beta ('SIGMA_STAR_Nrm8',1,None,None,0)
SIGMA_STAR_Nrm9 = Beta ('SIGMA_STAR_Nrm9',1.0,None,None,0 )
SIGMA_STAR_Nrm10 = Beta ('SIGMA_STAR_Nrm10',1.0,None,None,1 )
SIGMA_STAR_Aff5 = Beta ('SIGMA_STAR_Aff5',1.0,None,None,0)

Norm_delta_1 = Beta('Norm_delta_1',0.1,0,10,0 )
Norm_delta_2 = Beta('Norm_delta_2',0.2,0,10,0 )
Norm_tau_1 = -Norm_delta_1-Norm_delta_2
Norm_tau_2 = -Norm_delta_1
Norm_tau_3 = Norm_delta_1
Norm_tau_4 = Norm_delta_1 + Norm_delta_2

Nrm8_tau_1 = (Norm_tau_1-MODEL_Nrm8) / SIGMA_STAR_Nrm8
Nrm8_tau_2 = (Norm_tau_2-MODEL_Nrm8) / SIGMA_STAR_Nrm8
Nrm8_tau_3 = (Norm_tau_3-MODEL_Nrm8) / SIGMA_STAR_Nrm8
Nrm8_tau_4 = (Norm_tau_4-MODEL_Nrm8) / SIGMA_STAR_Nrm8
IndNrm8 = {
    1 : bioNormalCdf(Nrm8_tau_1) ,
    2 : bioNormalCdf(Nrm8_tau_2)-bioNormalCdf(Nrm8_tau_1),
    3 : bioNormalCdf(Nrm8_tau_3)-bioNormalCdf(Nrm8_tau_2),
    4 : bioNormalCdf(Nrm8_tau_4)-bioNormalCdf(Nrm8_tau_3),
    5 : 1-bioNormalCdf(Nrm8_tau_4),
   -1: 1.0,
   -2: 1.0
    }
P_Nrm8 = Elem(IndNrm8,Nrm8)

Nrm9_tau_1 = (Norm_tau_1-MODEL_Nrm9) / SIGMA_STAR_Nrm9
Nrm9_tau_2 = (Norm_tau_2-MODEL_Nrm9) / SIGMA_STAR_Nrm9
Nrm9_tau_3 = (Norm_tau_3-MODEL_Nrm9) / SIGMA_STAR_Nrm9
Nrm9_tau_4 = (Norm_tau_4-MODEL_Nrm9) / SIGMA_STAR_Nrm9
IndNrm9 = {
    1 : bioNormalCdf(Nrm9_tau_1) ,
    2 : bioNormalCdf(Nrm9_tau_2)-bioNormalCdf(Nrm9_tau_1),
    3 : bioNormalCdf(Nrm9_tau_3)-bioNormalCdf(Nrm9_tau_2),
    4 : bioNormalCdf(Nrm9_tau_4)-bioNormalCdf(Nrm9_tau_3),
    5 : 1-bioNormalCdf(Nrm9_tau_4),
   -1: 1.0,
   -2: 1.0
    }
P_Nrm9 = Elem(IndNrm9,Nrm9)

Nrm10_tau_1 = (Norm_tau_1-MODEL_Nrm10) / SIGMA_STAR_Nrm10
Nrm10_tau_2 = (Norm_tau_2-MODEL_Nrm10) / SIGMA_STAR_Nrm10
Nrm10_tau_3 = (Norm_tau_3-MODEL_Nrm10) / SIGMA_STAR_Nrm10
Nrm10_tau_4 = (Norm_tau_4-MODEL_Nrm10) / SIGMA_STAR_Nrm10
IndNrm10 = {
    1 : bioNormalCdf(Nrm10_tau_1),
    2 : bioNormalCdf(Nrm10_tau_2)-bioNormalCdf(Nrm10_tau_1),
    3 : bioNormalCdf(Nrm10_tau_3)-bioNormalCdf(Nrm10_tau_2),
    4 : bioNormalCdf(Nrm10_tau_4)-bioNormalCdf(Nrm10_tau_3),
    5 : 1-bioNormalCdf(Nrm10_tau_4),
   -1: 1.0,
   -2: 1.0
```

```
    }
P_Nrm10 = Elem(IndNrm10,Nrm10)

Aff5_tau_1 = (Norm_tau_1-MODEL_Aff5) / SIGMA_STAR_Aff5
Aff5_tau_2 = (Norm_tau_2-MODEL_Aff5) / SIGMA_STAR_Aff5
Aff5_tau_3 = (Norm_tau_3-MODEL_Aff5) / SIGMA_STAR_Aff5
Aff5_tau_4 = (Norm_tau_4-MODEL_Aff5) / SIGMA_STAR_Aff5
IndAff5 = {
    1 : bioNormalCdf(Aff5_tau_1),
    2 : bioNormalCdf(Aff5_tau_2)-bioNormalCdf(Aff5_tau_1),
    3 : bioNormalCdf(Aff5_tau_3)-bioNormalCdf(Aff5_tau_2),
    4 : bioNormalCdf(Aff5_tau_4)-bioNormalCdf(Aff5_tau_3),
    5 : 1-bioNormalCdf(Aff5_tau_4),
   -1: 1.0,
   -2: 1.0
    }
P_Aff5 = Elem(IndAff5,Aff5)

"""Latent variable 4: Narcissism (Exhibitionism)"""
## Coefficients
coef_ASC_Exh = Beta('coef_ASC_Exh',0,None,None,0 )
coef_Gender_Exh = Beta('coef_Gender_Exh',0.0,None,None,0 )
coef_Income_Exh = Beta('coef_Income_Exh',0.0,None,None,0 )

Exh = \
coef_ASC_Exh +\
coef_Gender_Exh * Gender +\
coef_Income_Exh * HighIncome +\
omega_exh * sigma_exh

"""Measurement Equations"""
#B^m_0i
INTER_Nar2 = Beta ('INTER_Nar2',0.0,None,None,0)
INTER_Nar7 = Beta ('INTER_Nar7',0,None,None,1 )
INTER_Nar11 = Beta ('INTER_Nar11',0.0,None,None,0 )

#B^m_i
B_Nar2_F4 = Beta ('B_Nar2_F4',0.0,None,None,0)
B_Nar7_F4 = Beta ('B_Nar7_F4',1,None,None,1 )
B_Nar11_F4 = Beta ('B_Nar11_F4',0.0,None,None,0 ) # Note

# B^m_0i + B^m_i.x
MODEL_Nar2 = INTER_Nar2 + B_Nar2_F4*Exh
MODEL_Nar7 = INTER_Nar7 + B_Nar7_F4*Exh
MODEL_Nar11 = INTER_Nar11 + B_Nar11_F4*Exh

# SIGMA_STAR = z^*_i
SIGMA_STAR_Nar2 = Beta ('SIGMA_STAR_Nar2',1.0,None,None,0)
SIGMA_STAR_Nar7 = Beta ('SIGMA_STAR_Nar7',1,None,None,1 )
SIGMA_STAR_Nar11 = Beta ('SIGMA_STAR_Nar11',1.0,None,None,0 )

Nar_delta_1 = Beta('Nar_delta_1',0.1,0,10,0 )
Nar_delta_2 = Beta('Nar_delta_2',0.2,0,10,0 )
Nar_tau_1 = -Nar_delta_1 - Nar_delta_2
Nar_tau_2 = -Nar_delta_1
Nar_tau_3 = Nar_delta_1
Nar_tau_4 = Nar_delta_1 + Nar_delta_2

Nar2_tau_1 = (Nar_tau_1-MODEL_Nar2) / SIGMA_STAR_Nar2
Nar2_tau_2 = (Nar_tau_2-MODEL_Nar2) / SIGMA_STAR_Nar2
Nar2_tau_3 = (Nar_tau_3-MODEL_Nar2) / SIGMA_STAR_Nar2
Nar2_tau_4 = (Nar_tau_4-MODEL_Nar2) / SIGMA_STAR_Nar2
IndNar2 = {
    1 : bioNormalCdf(Nar2_tau_1) ,
    2 : bioNormalCdf(Nar2_tau_2)-bioNormalCdf(Nar2_tau_1),
    3 : bioNormalCdf(Nar2_tau_3)-bioNormalCdf(Nar2_tau_2),
    4 : bioNormalCdf(Nar2_tau_4)-bioNormalCdf(Nar2_tau_3),
    5 : 1-bioNormalCdf(Nar2_tau_4),
    -1: 1.0,
    -2: 1.0
    }
P_Nar2 = Elem(IndNar2,Nar2)

Nar7_tau_1 = (Nar_tau_1-MODEL_Nar7) / SIGMA_STAR_Nar7
Nar7_tau_2 = (Nar_tau_2-MODEL_Nar7) / SIGMA_STAR_Nar7
Nar7_tau_3 = (Nar_tau_3-MODEL_Nar7) / SIGMA_STAR_Nar7
Nar7_tau_4 = (Nar_tau_4-MODEL_Nar7) / SIGMA_STAR_Nar7
IndNar7 = {
    1 : bioNormalCdf(Nar7_tau_1),
    2 : bioNormalCdf(Nar7_tau_2)-bioNormalCdf(Nar7_tau_1),
    3 : bioNormalCdf(Nar7_tau_3)-bioNormalCdf(Nar7_tau_2),
    4 : bioNormalCdf(Nar7_tau_4)-bioNormalCdf(Nar7_tau_3),
    5 : 1-bioNormalCdf(Nar7_tau_4),
    -1: 1.0,
```

```
    -2: 1.0
    }
P_Nar7 = Elem(IndNar7,Nar7)

Nar11_tau_1 = (Nar_tau_1-MODEL_Nar11) / SIGMA_STAR_Nar11
Nar11_tau_2 = (Nar_tau_2-MODEL_Nar11) / SIGMA_STAR_Nar11
Nar11_tau_3 = (Nar_tau_3-MODEL_Nar11) / SIGMA_STAR_Nar11
Nar11_tau_4 = (Nar_tau_4-MODEL_Nar11) / SIGMA_STAR_Nar11
IndNar11 = {
    1 : bioNormalCdf(Nar11_tau_1),
    2 : bioNormalCdf(Nar11_tau_2)-bioNormalCdf(Nar11_tau_1),
    3 : bioNormalCdf(Nar11_tau_3)-bioNormalCdf(Nar11_tau_2),
    4 : bioNormalCdf(Nar11_tau_4)-bioNormalCdf(Nar11_tau_3),
    5 : 1-bioNormalCdf(Nar11_tau_4),
    -1: 1.0,
    -2: 1.0
    }
P_Nar11 = Elem(IndNar11,Nar11)

"""Choice model"""
# Coefficients
ASC_Car = Beta('ASC_Car',0,-10000,10000,0)
ASC_PT = Beta('ASC_PT',0,-10000,10000,1)
ASC_NMT = Beta('ASC_NMT',0,-10000,10000,0)
B_Dist_NMT = Beta('B_Dist_NMT',0.0,-10000,10000,0)
B_TT_Car = Beta('B_TT_Car',0,-10000,10000,0)
B_TT_PT = Beta('B_TT_PT',0,-10000,10000,0)
B_Work = Beta('B_Work',0,-10000,10000,0)
B_Age_Car = Beta('B_Age_Car',0,-10000,10000,0)
B_Age_NMT = Beta('B_Age_NMT',0,-10000,10000,0)
B_WalkingTime = Beta('B_WalkingTime',0,-10000,10000,0)
B_NCar_Car = Beta('B_NCar_Car',0,-10000,10000,0)
B_Edu_NMT = Beta('B_Edu_NMT',0,-10000,10000,0)
B_Cost_PT= Beta('B_Cost_PT',0,None,None,0)
B_Cost_Car= Beta('B_Cost_Car',0,-10000,10000,0)
B_Age_PT = Beta('B_Age_PT',0,None,None,0)
B_TrFreq = Beta('B_TrFreq',0,None,None,0)
B_INC_PT = Beta('B_INC_PT',0,None,None,0)
B_Gender_Car = Beta('B_Gender_Car',0,-10000,10000,0)
B_Exh_PT = Beta('B_Exh_PT',0,None,None,0)
B_Exh_Car = Beta('B_Exh_Car',0,None,None,0)
B_PerNorm_PT = Beta('B_PerNorm_PT',0,None,None,1)
B_PerNorm_Car = Beta('B_PerNorm_Car',0,None,None,0)
B_Affect_PT = Beta('B_Affect_PT',0,None,None,0)
B_Salience_PT = Beta('B_Salience_PT',0,None,None,0)


###Define Variables
NoOfCars = NoOfCars
WkTrip =  WkTrip
Distance_km = Distance_km
TimePT_1=TimePT_1
CostPT_1=CostPT_1
TimeCar_1=TimeCar_1
Gender = Gender
Age_band = Age_band
Age_group1 = Age_group1
Age_group3 = Age_group3
Age_group2 = Age_group2
Income7 = Income7
Income6 = Income6
CostCar2_1=CostCar2_1
Affect = Affect1
PerNorm = PerNorm1
Salience = Salience1
#Exh = Exh

"""Utility Equations"""
V_PT = ASC_PT +\
       B_TT_PT * TimePT_1 + \
       B_Cost_PT * CostPT_1 +\
       B_INC_PT * Income_band  +\
       B_Age_PT * Age_group1 +\
       B_Affect_PT * Affect +\
       B_Salience_PT * Salience  +\
       B_PerNorm_PT * PerNorm

V_Car = ASC_Car  +\
        B_TT_Car * TimeCar_1  + \
        B_NCar_Car * NoOfCars +\
        B_WalkingTime * (DistToBS_Des + DistToBS_Orig) +\
        B_Work * WkTrip +\
        B_Gender_Car * Gender +\
```

```
                B_TrFreq * TripFreq +\
                B_PerNorm_Car * PerNorm

        V_NMT = ASC_NMT +\
                B_Dist_NMT * Distance_km +\
                B_Age_NMT * Age_band +\
                B_Edu_NMT * Education

        """Associate utility functions with the numbering of alternatives"""
        V = {0: V_PT,
             1: V_Car,
             2: V_NMT}

        """Associate the availability conditions with the alternatives."""
        av = {0: 1,
              1: 1,
              2: 1}

        "Associate utility functions with the numbering of alternatives"
        V = {0: V_PT,
             1: V_Car,
             2: V_NMT}

        "Associate the availability conditions with the alternatives."
        av = {0: 1,
              1: 1,
              2: 1}

        """The choice model is a logit, conditional to the value of the latent␣
↪variable"""
        condprob = models.logit(V,av,MChoice_3)
        condlike = P_PTExp1b * \
                   P_PTExp2b *\
                   P_PTExp3b * \
                   P_PTExp4b * \
                   P_PTExp5b * \
                   P_Aff3 * \
                   P_Aff4 * \
                   P_Nrm8 * \
                   P_Nrm9 * \
                   P_Nrm10 *\
                   P_Aff5 * \
                   condprob

        loglike= log(MonteCarlo(condlike))
        biogeme = bio.BIOGEME(database,loglike,numberOfDraws= 10000)
        biogeme.DRAWS = {'omega_aff': ('NORMAL_MLHS'), 'omega_sal':␣
↪('NORMAL_MLHS'),\
                        'omega_exh': ('NORMAL_MLHS'), 'omega_PNorm':␣
↪('NORMAL_MLHS')}

        biogeme.modelName = "SEM_ICLV_Revised_Thesis_Final"
        results = biogeme.estimate()

        print(f"Estimated betas: {len(results.data.betaValues)}")
        print(f"Final log likelihood: {results.data.logLike:.3f}")
        print(f"Output file: {results.data.htmlFileName}")
        print("Results=",results)
```

ICLV Model Simulation

```
[ ]: In [6]: import pandas as pd
            import numpy as np
            import biogeme.database as db
            import biogeme.biogeme as bio
            import biogeme.loglikelihood as ll
            import biogeme.models as models
            import biogeme.distributions as dist
            import biogeme.results as res

            pandas = pd.read_csv("Data-20.csv")
            database=db.Database("Data-20",pandas)
            from headers import *

            exclude = ( MChoice_3== -1 )
            database.remove(exclude)

            "Normalise weight to one"
            sumWeight = database.data['Weight'].sum()
            normalizedWeight = Weight /sumWeight

            omega_PNorm = bioDraws('omega_PNorm','NORMAL_MLHS')
            omega_aff = bioDraws('omega_aff','NORMAL_MLHS')
            omega_sal = bioDraws('omega_sal','NORMAL_MLHS')
            omega_exh = bioDraws('omega_exh','NORMAL_MLHS')
            sigma_PNorm = Beta('sigma_PNorm',0,None,None,0)
            sigma_aff = Beta('sigma_aff',0,None,None,0)
            sigma_sal = Beta('sigma_sal',0,None,None,0)
            sigma_exh = Beta('sigma_exh',0,None,None,0)

            """Latent variable 1: Salience"""
            ### Coefficients
            coef_ASC_sal = Beta('coef_ASC_sal',0,None,None,1 )
            coef_Age_sal = Beta('coef_Age_sal',0.0,None,None,0 )

            ## Define Variables
            NCar =  DefineVariable('NCar',CarAvail * ( CarAvail >= 1),database)
            """
            1. Members of this class are mostly car users (46%), 25% PT users and␣
   ↪28% NMT Users
            2. They are either in full time employment or retired
            3. 51% own a ridacard indicating frequent users
            4. 62% of members of this class own at least
            5. Likely to be women
            """
            Salience = \
            coef_ASC_sal + \
            coef_Age_sal * Age +\
            sigma_sal * omega_sal

            ### Measurement Equations
            #B^m_0i
            INTER_PTExp1b = Beta ('INTER_PTExp1b',0.0,None,None,0)
            INTER_PTExp2b = Beta ('INTER_PTExp2b',0.0,None,None,0 )
            INTER_PTExp3b = Beta ('INTER_PTExp3b',0.0,None,None,0 )
            INTER_PTExp4b = Beta ('INTER_PTExp4b',0,None,None,0)
            INTER_PTExp5b = Beta ('INTER_PTExp5b',0,None,None,1 )

            #B^m_i
            B_PTExp1b_F1 = Beta ('B_PTExp1b_F1',0.0,None,None,0)
            B_PTExp2b_F1 = Beta ('B_PTExp2b_F1',0.0,None,None,0 )
            B_PTExp3b_F1 = Beta ('B_PTExp3b_F1',0.0,None,None,0 )
            B_PTExp4b_F1 = Beta ('B_PTExp4b_F1',0.0,None,None,0)
            B_PTExp5b_F1 = Beta ('B_PTExp5b_F1',1,None,None,1 )

            # B^m_0i + B^m_i.x
            MODEL_PTExp1b = INTER_PTExp1b + B_PTExp1b_F1*Salience
            MODEL_PTExp2b = INTER_PTExp2b + B_PTExp2b_F1*Salience
            MODEL_PTExp3b = INTER_PTExp3b + B_PTExp3b_F1*Salience
            MODEL_PTExp4b = INTER_PTExp4b + B_PTExp4b_F1*Salience
            MODEL_PTExp5b = INTER_PTExp5b + B_PTExp5b_F1*Salience

            # SIGMA_STAR = z^*_i
            SIGMA_STAR_PTExp1b = Beta ('SIGMA_STAR_PTExp1b',1.0,None,None,0)
            SIGMA_STAR_PTExp2b = Beta ('SIGMA_STAR_PTExp2b',1.0,None,None,0 )
            SIGMA_STAR_PTExp3b = Beta ('SIGMA_STAR_PTExp3b',1.0,None,None,0 )
            SIGMA_STAR_PTExp4b = Beta ('SIGMA_STAR_PTExp4b',1.0,None,None,0)
            SIGMA_STAR_PTExp5b = Beta ('SIGMA_STAR_PTExp5b',1,None,None,1 )

            sal_delta_1 = Beta('sal_delta_1',0.1,0,10,0 )
            sal_delta_2 = Beta('sal_delta_2',0.2,0,10,0 )
            sal_tau_1 = -sal_delta_1 - sal_delta_2
            sal_tau_2 = -sal_delta_1
```

```
        sal_tau_3 = sal_delta_1
        sal_tau_4 = sal_delta_1 + sal_delta_2

        PTExp1b_tau_1 = (sal_tau_1-MODEL_PTExp1b) / SIGMA_STAR_PTExp1b
        PTExp1b_tau_2 = (sal_tau_2-MODEL_PTExp1b) / SIGMA_STAR_PTExp1b
        PTExp1b_tau_3 = (sal_tau_3-MODEL_PTExp1b) / SIGMA_STAR_PTExp1b
        PTExp1b_tau_4 = (sal_tau_4-MODEL_PTExp1b) / SIGMA_STAR_PTExp1b
        IndPTExp1b = {
            1 : bioNormalCdf(PTExp1b_tau_1),
            2 : bioNormalCdf(PTExp1b_tau_2)-bioNormalCdf(PTExp1b_tau_1),
            3 : bioNormalCdf(PTExp1b_tau_3)-bioNormalCdf(PTExp1b_tau_2),
            4 : bioNormalCdf(PTExp1b_tau_4)-bioNormalCdf(PTExp1b_tau_3),
            5 : 1-bioNormalCdf(PTExp1b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp1b = Elem(IndPTExp1b,PTExp1b)

        PTExp2b_tau_1 = (sal_tau_1-MODEL_PTExp2b) / SIGMA_STAR_PTExp2b
        PTExp2b_tau_2 = (sal_tau_2-MODEL_PTExp2b) / SIGMA_STAR_PTExp2b
        PTExp2b_tau_3 = (sal_tau_3-MODEL_PTExp2b) / SIGMA_STAR_PTExp2b
        PTExp2b_tau_4 = (sal_tau_4-MODEL_PTExp2b) / SIGMA_STAR_PTExp2b
        IndPTExp2b = {
            1 : bioNormalCdf(PTExp2b_tau_1),
            2 : bioNormalCdf(PTExp2b_tau_2)-bioNormalCdf(PTExp2b_tau_1),
            3 : bioNormalCdf(PTExp2b_tau_3)-bioNormalCdf(PTExp2b_tau_2),
            4 : bioNormalCdf(PTExp2b_tau_4)-bioNormalCdf(PTExp2b_tau_3),
            5 : 1-bioNormalCdf(PTExp2b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp2b = Elem(IndPTExp2b,PTExp2b)

        PTExp3b_tau_1 = (sal_tau_1-MODEL_PTExp3b) / SIGMA_STAR_PTExp3b
        PTExp3b_tau_2 = (sal_tau_2-MODEL_PTExp3b) / SIGMA_STAR_PTExp3b
        PTExp3b_tau_3 = (sal_tau_3-MODEL_PTExp3b) / SIGMA_STAR_PTExp3b
        PTExp3b_tau_4 = (sal_tau_4-MODEL_PTExp3b) / SIGMA_STAR_PTExp3b
        IndPTExp3b = {
            1 : bioNormalCdf(PTExp3b_tau_1),
            2 : bioNormalCdf(PTExp3b_tau_2)-bioNormalCdf(PTExp3b_tau_1),
            3 : bioNormalCdf(PTExp3b_tau_3)-bioNormalCdf(PTExp3b_tau_2),
            4 : bioNormalCdf(PTExp3b_tau_4)-bioNormalCdf(PTExp3b_tau_3),
            5 : 1-bioNormalCdf(PTExp3b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp3b = Elem(IndPTExp3b,PTExp3b)

        PTExp4b_tau_1 = (sal_tau_1-MODEL_PTExp4b) / SIGMA_STAR_PTExp4b
        PTExp4b_tau_2 = (sal_tau_2-MODEL_PTExp4b) / SIGMA_STAR_PTExp4b
        PTExp4b_tau_3 = (sal_tau_3-MODEL_PTExp4b) / SIGMA_STAR_PTExp4b
        PTExp4b_tau_4 = (sal_tau_4-MODEL_PTExp4b) / SIGMA_STAR_PTExp4b
        IndPTExp4b = {
            1 : bioNormalCdf(PTExp4b_tau_1),
            2 : bioNormalCdf(PTExp4b_tau_2)-bioNormalCdf(PTExp4b_tau_1),
            3 : bioNormalCdf(PTExp4b_tau_3)-bioNormalCdf(PTExp4b_tau_2),
            4 : bioNormalCdf(PTExp4b_tau_4)-bioNormalCdf(PTExp4b_tau_3),
            5 : 1-bioNormalCdf(PTExp4b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp4b = Elem(IndPTExp4b,PTExp4b)

        PTExp5b_tau_1 = (sal_tau_1-MODEL_PTExp5b) / SIGMA_STAR_PTExp5b
        PTExp5b_tau_2 = (sal_tau_2-MODEL_PTExp5b) / SIGMA_STAR_PTExp5b
        PTExp5b_tau_3 = (sal_tau_3-MODEL_PTExp5b) / SIGMA_STAR_PTExp5b
        PTExp5b_tau_4 = (sal_tau_4-MODEL_PTExp5b) / SIGMA_STAR_PTExp5b
        IndPTExp5b = {
            1 : bioNormalCdf(PTExp5b_tau_1),
            2 : bioNormalCdf(PTExp5b_tau_2)-bioNormalCdf(PTExp5b_tau_1),
            3 : bioNormalCdf(PTExp5b_tau_3)-bioNormalCdf(PTExp5b_tau_2),
            4 : bioNormalCdf(PTExp5b_tau_4)-bioNormalCdf(PTExp5b_tau_3),
            5 : 1-bioNormalCdf(PTExp5b_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_PTExp5b = Elem(IndPTExp5b,PTExp5b)


        """Latent variable 2: Affect"""
        ### Coefficients
        coef_ASC_aff = Beta('coef_ASC_aff',0.0,None,None,0 )
        coef_Ridacard_aff = Beta('coef_Ridacard_aff',0.0,None,None,0 )
```

```
        coef_CarAvail_aff = Beta('coef_CarAvail_aff',0.0,None,None,0 )

        ###Define Variables
        #HighEducation =  DefineVariable('HighEducation', Education *␣
↪((Education  == 5) +\
        #                                         (Education  == 6) + (Education ␣
↪== 7)) ,database)
        """
        1. Likely to be people aged 54 years and below
        2. without a car or own one car
        3. Single
        4. in full time employment or student
             (possibly people who make frequent and routine trips)
        """

        Affect = \
        coef_ASC_aff +\
        coef_CarAvail_aff * Car +\
        coef_Ridacard_aff * Tr_Pass +\
        sigma_aff * omega_aff

        ### Measurement Equations
        #B^m_0i
        INTER_Aff3 = Beta ('INTER_Aff3',0,None,None,1)
        INTER_Aff4 = Beta ('INTER_Aff4',0.0,None,None,0 )

        #B^m_i
        B_Aff3_F2 = Beta ('B_Aff3_F2',1,None,None,1)
        B_Aff4_F2 = Beta ('B_Aff4_F2',0.0,None,None,0 )

        # B^m_0i + B^m_i.x
        MODEL_Aff3 = INTER_Aff3 + B_Aff3_F2*Affect
        MODEL_Aff4 = INTER_Aff4 + B_Aff4_F2*Affect

        # SIGMA_STAR = z^*_i#
        SIGMA_STAR_Aff4 = Beta ('SIGMA_STAR_Aff4',1.0,None,None,0 )
        SIGMA_STAR_Aff3 = Beta ('SIGMA_STAR_Aff3',1,None,None,1 )

        Aff_delta_1 = Beta('Aff_delta_1',0.1,0,10,0 )
        Aff_delta_2 = Beta('Aff_delta_2',0.2,0,10,0 )
        Aff_tau_1 = -Aff_delta_1 - Aff_delta_2
        Aff_tau_2 = -Aff_delta_1
        Aff_tau_3 = Aff_delta_1
        Aff_tau_4 = Aff_delta_1 + Aff_delta_2

        Aff3_tau_1 = (Aff_tau_1-MODEL_Aff3) / SIGMA_STAR_Aff3
        Aff3_tau_2 = (Aff_tau_2-MODEL_Aff3) / SIGMA_STAR_Aff3
        Aff3_tau_3 = (Aff_tau_3-MODEL_Aff3) / SIGMA_STAR_Aff3
        Aff3_tau_4 = (Aff_tau_4-MODEL_Aff3) / SIGMA_STAR_Aff3
        IndAff3 = {
            1 : bioNormalCdf(Aff3_tau_1),
            2 : bioNormalCdf(Aff3_tau_2)-bioNormalCdf(Aff3_tau_1),
            3 : bioNormalCdf(Aff3_tau_3)-bioNormalCdf(Aff3_tau_2),
            4 : bioNormalCdf(Aff3_tau_4)-bioNormalCdf(Aff3_tau_3),
            5 : 1-bioNormalCdf(Aff3_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_Aff3 = Elem(IndAff3,Aff3)

        Aff4_tau_1 = (Aff_tau_1-MODEL_Aff4) / SIGMA_STAR_Aff4
        Aff4_tau_2 = (Aff_tau_2-MODEL_Aff4) / SIGMA_STAR_Aff4
        Aff4_tau_3 = (Aff_tau_3-MODEL_Aff4) / SIGMA_STAR_Aff4
        Aff4_tau_4 = (Aff_tau_4-MODEL_Aff4) / SIGMA_STAR_Aff4
        IndAff4 = {
            1 : bioNormalCdf(Aff4_tau_1) ,
            2 : bioNormalCdf(Aff4_tau_2)-bioNormalCdf(Aff4_tau_1),
            3 : bioNormalCdf(Aff4_tau_3)-bioNormalCdf(Aff4_tau_2),
            4 : bioNormalCdf(Aff4_tau_4)-bioNormalCdf(Aff4_tau_3),
            5 : 1-bioNormalCdf(Aff4_tau_4),
           -1: 1.0,
           -2: 1.0
            }
        P_Aff4 = Elem(IndAff4,Aff4)

        """Latent variable 3: Norm"""
        ### Coefficients
        coef_ASC_PNorm = Beta('coef_ASC_PNorm',0.0,None,None,1 )
        coef_Educ_PNorm = Beta('coef_Educ_PNorm',0.0,None,None,0 )
        coef_Age_PNorm = Beta('coef_Age_PNorm',0.0,None,None,0 )
        coef_CarOwnership_PNorm = Beta('coef_CarOwnership_PNorm',0.0,None,None,0␣
↪)
        coef_Income_PNorm = Beta('coef_Income_PNorm',0.0,None,None,0 )
```

```
# Latent variable:Structural equation
"""
   1. Likey to have First or masters degree (35% and 36%)
   2. most likely does not own a car (57%) or own one car (34%)
   3. likey to be employed (67%) or retired (17%)
   4. most likey to be women
   5. Travel by PT or NMT, none in this class travel by Car
   6. Age between 25 and 64 years
   """
PerNorm = \
coef_ASC_PNorm +\
coef_Educ_PNorm * HighEduc  +\
coef_Age_PNorm * Age +\
coef_CarOwnership_PNorm * Car +\
coef_Income_PNorm * HighIncome +\
sigma_PNorm * omega_PNorm

"""Measurement Equations"""
#B^m_0i
INTER_Nrm8 = Beta ('INTER_Nrm8',0,None,None,0)
INTER_Nrm9 = Beta ('INTER_Nrm9',0.0,None,None,0 )
INTER_Nrm10 = Beta ('INTER_Nrm10',0.0,None,None,1 )
INTER_Aff5 = Beta ('INTER_Aff5',0.0,None,None,0 )

#B^m_i
B_Nrm8_F3 = Beta ('B_Nrm8_F3',0,None,None,0)
B_Nrm9_F3 = Beta ('B_Nrm9_F3',0.0,None,None,0 )
B_Nrm10_F3 = Beta ('B_Nrm10_F3',1,None,None,1 ) # Note
B_Aff5_F3 = Beta ('B_Aff5_F3',0.0,None,None,0 )

# B^m_0i + B^m_i.x
MODEL_Nrm8 = INTER_Nrm8 + B_Nrm8_F3*PerNorm
MODEL_Nrm9 = INTER_Nrm9 + B_Nrm9_F3*PerNorm
MODEL_Nrm10 = INTER_Nrm10 + B_Nrm10_F3*PerNorm
MODEL_Aff5 = INTER_Aff5 + B_Aff5_F3*PerNorm

# SIGMA_STAR = z^*_i
SIGMA_STAR_Nrm8 = Beta ('SIGMA_STAR_Nrm8',1,None,None,0)
SIGMA_STAR_Nrm9 = Beta ('SIGMA_STAR_Nrm9',1.0,None,None,0 )
SIGMA_STAR_Nrm10 = Beta ('SIGMA_STAR_Nrm10',1.0,None,None,1 )
SIGMA_STAR_Aff5 = Beta ('SIGMA_STAR_Aff5',1.0,None,None,0)

Norm_delta_1 = Beta('Norm_delta_1',0.1,0,10,0 )
Norm_delta_2 = Beta('Norm_delta_2',0.2,0,10,0 )
Norm_tau_1 = -Norm_delta_1-Norm_delta_2
Norm_tau_2 = -Norm_delta_1
Norm_tau_3 = Norm_delta_1
Norm_tau_4 = Norm_delta_1 + Norm_delta_2

Nrm8_tau_1 = (Norm_tau_1-MODEL_Nrm8) / SIGMA_STAR_Nrm8
Nrm8_tau_2 = (Norm_tau_2-MODEL_Nrm8) / SIGMA_STAR_Nrm8
Nrm8_tau_3 = (Norm_tau_3-MODEL_Nrm8) / SIGMA_STAR_Nrm8
Nrm8_tau_4 = (Norm_tau_4-MODEL_Nrm8) / SIGMA_STAR_Nrm8
IndNrm8 = {
    1 : bioNormalCdf(Nrm8_tau_1) ,
    2 : bioNormalCdf(Nrm8_tau_2)-bioNormalCdf(Nrm8_tau_1),
    3 : bioNormalCdf(Nrm8_tau_3)-bioNormalCdf(Nrm8_tau_2),
    4 : bioNormalCdf(Nrm8_tau_4)-bioNormalCdf(Nrm8_tau_3),
    5 : 1-bioNormalCdf(Nrm8_tau_4),
   -1: 1.0,
   -2: 1.0
    }
P_Nrm8 = Elem(IndNrm8,Nrm8)

Nrm9_tau_1 = (Norm_tau_1-MODEL_Nrm9) / SIGMA_STAR_Nrm9
Nrm9_tau_2 = (Norm_tau_2-MODEL_Nrm9) / SIGMA_STAR_Nrm9
Nrm9_tau_3 = (Norm_tau_3-MODEL_Nrm9) / SIGMA_STAR_Nrm9
Nrm9_tau_4 = (Norm_tau_4-MODEL_Nrm9) / SIGMA_STAR_Nrm9
IndNrm9 = {
    1 : bioNormalCdf(Nrm9_tau_1) ,
    2 : bioNormalCdf(Nrm9_tau_2)-bioNormalCdf(Nrm9_tau_1),
    3 : bioNormalCdf(Nrm9_tau_3)-bioNormalCdf(Nrm9_tau_2),
    4 : bioNormalCdf(Nrm9_tau_4)-bioNormalCdf(Nrm9_tau_3),
    5 : 1-bioNormalCdf(Nrm9_tau_4),
   -1: 1.0,
   -2: 1.0
    }
P_Nrm9 = Elem(IndNrm9,Nrm9)

Nrm10_tau_1 = (Norm_tau_1-MODEL_Nrm10) / SIGMA_STAR_Nrm10
Nrm10_tau_2 = (Norm_tau_2-MODEL_Nrm10) / SIGMA_STAR_Nrm10
Nrm10_tau_3 = (Norm_tau_3-MODEL_Nrm10) / SIGMA_STAR_Nrm10
Nrm10_tau_4 = (Norm_tau_4-MODEL_Nrm10) / SIGMA_STAR_Nrm10
IndNrm10 = {
```

```
        1 : bioNormalCdf(Nrm10_tau_1),
        2 : bioNormalCdf(Nrm10_tau_2)-bioNormalCdf(Nrm10_tau_1),
        3 : bioNormalCdf(Nrm10_tau_3)-bioNormalCdf(Nrm10_tau_2),
        4 : bioNormalCdf(Nrm10_tau_4)-bioNormalCdf(Nrm10_tau_3),
        5 : 1-bioNormalCdf(Nrm10_tau_4),
       -1: 1.0,
       -2: 1.0
        }
    P_Nrm10 = Elem(IndNrm10,Nrm10)

    Aff5_tau_1 = (Norm_tau_1-MODEL_Aff5) / SIGMA_STAR_Aff5
    Aff5_tau_2 = (Norm_tau_2-MODEL_Aff5) / SIGMA_STAR_Aff5
    Aff5_tau_3 = (Norm_tau_3-MODEL_Aff5) / SIGMA_STAR_Aff5
    Aff5_tau_4 = (Norm_tau_4-MODEL_Aff5) / SIGMA_STAR_Aff5
    IndAff5 = {
        1 : bioNormalCdf(Aff5_tau_1),
        2 : bioNormalCdf(Aff5_tau_2)-bioNormalCdf(Aff5_tau_1),
        3 : bioNormalCdf(Aff5_tau_3)-bioNormalCdf(Aff5_tau_2),
        4 : bioNormalCdf(Aff5_tau_4)-bioNormalCdf(Aff5_tau_3),
        5 : 1-bioNormalCdf(Aff5_tau_4),
       -1: 1.0,
       -2: 1.0
        }
    P_Aff5 = Elem(IndAff5,Aff5)

    """Latent variable 4: Narcissism (Exhibitionism)"""
    ## Coefficients
    coef_ASC_Exh = Beta('coef_ASC_Exh',0,None,None,0 )
    coef_Gender_Exh = Beta('coef_Gender_Exh',0.0,None,None,0 )
    coef_Income_Exh = Beta('coef_Income_Exh',0.0,None,None,0 )

    Exh = \
    coef_ASC_Exh +\
    coef_Gender_Exh * Gender +\
    coef_Income_Exh * HighIncome +\
    omega_exh * sigma_exh

    """Measurement Equations"""
    #B^m_0i
    INTER_Nar2 = Beta ('INTER_Nar2',0.0,None,None,0)
    INTER_Nar7 = Beta ('INTER_Nar7',0,None,None,1 )
    INTER_Nar11 = Beta ('INTER_Nar11',0.0,None,None,0 )

    #B^m_i
    B_Nar2_F4 = Beta ('B_Nar2_F4',0.0,None,None,0)
    B_Nar7_F4 = Beta ('B_Nar7_F4',1,None,None,1 )
    B_Nar11_F4 = Beta ('B_Nar11_F4',0.0,None,None,0 ) # Note

    # B^m_0i + B^m_i.x
    MODEL_Nar2 = INTER_Nar2 + B_Nar2_F4*Exh
    MODEL_Nar7 = INTER_Nar7 + B_Nar7_F4*Exh
    MODEL_Nar11 = INTER_Nar11 + B_Nar11_F4*Exh

    # SIGMA_STAR = z^*_i
    SIGMA_STAR_Nar2 = Beta ('SIGMA_STAR_Nar2',1.0,None,None,0)
    SIGMA_STAR_Nar7 = Beta ('SIGMA_STAR_Nar7',1,None,None,1 )
    SIGMA_STAR_Nar11 = Beta ('SIGMA_STAR_Nar11',1.0,None,None,0 )

    Nar_delta_1 = Beta('Nar_delta_1',0.1,0,10,0 )
    Nar_delta_2 = Beta('Nar_delta_2',0.2,0,10,0 )
    Nar_tau_1 = -Nar_delta_1 - Nar_delta_2
    Nar_tau_2 = -Nar_delta_1
    Nar_tau_3 = Nar_delta_1
    Nar_tau_4 = Nar_delta_1 + Nar_delta_2

    Nar2_tau_1 = (Nar_tau_1-MODEL_Nar2) / SIGMA_STAR_Nar2
    Nar2_tau_2 = (Nar_tau_2-MODEL_Nar2) / SIGMA_STAR_Nar2
    Nar2_tau_3 = (Nar_tau_3-MODEL_Nar2) / SIGMA_STAR_Nar2
    Nar2_tau_4 = (Nar_tau_4-MODEL_Nar2) / SIGMA_STAR_Nar2
    IndNar2 = {
        1 : bioNormalCdf(Nar2_tau_1) ,
        2 : bioNormalCdf(Nar2_tau_2)-bioNormalCdf(Nar2_tau_1),
        3 : bioNormalCdf(Nar2_tau_3)-bioNormalCdf(Nar2_tau_2),
        4 : bioNormalCdf(Nar2_tau_4)-bioNormalCdf(Nar2_tau_3),
        5 : 1-bioNormalCdf(Nar2_tau_4),
        -1: 1.0,
        -2: 1.0
        }
    P_Nar2 = Elem(IndNar2,Nar2)

    Nar7_tau_1 = (Nar_tau_1-MODEL_Nar7) / SIGMA_STAR_Nar7
    Nar7_tau_2 = (Nar_tau_2-MODEL_Nar7) / SIGMA_STAR_Nar7
    Nar7_tau_3 = (Nar_tau_3-MODEL_Nar7) / SIGMA_STAR_Nar7
    Nar7_tau_4 = (Nar_tau_4-MODEL_Nar7) / SIGMA_STAR_Nar7
```

```
        IndNar7 = {
            1 : bioNormalCdf(Nar7_tau_1),
            2 : bioNormalCdf(Nar7_tau_2)-bioNormalCdf(Nar7_tau_1),
            3 : bioNormalCdf(Nar7_tau_3)-bioNormalCdf(Nar7_tau_2),
            4 : bioNormalCdf(Nar7_tau_4)-bioNormalCdf(Nar7_tau_3),
            5 : 1-bioNormalCdf(Nar7_tau_4),
            -1: 1.0,
            -2: 1.0
            }
        P_Nar7 = Elem(IndNar7,Nar7)

        Nar11_tau_1 = (Nar_tau_1-MODEL_Nar11) / SIGMA_STAR_Nar11
        Nar11_tau_2 = (Nar_tau_2-MODEL_Nar11) / SIGMA_STAR_Nar11
        Nar11_tau_3 = (Nar_tau_3-MODEL_Nar11) / SIGMA_STAR_Nar11
        Nar11_tau_4 = (Nar_tau_4-MODEL_Nar11) / SIGMA_STAR_Nar11
        IndNar11 = {
            1 : bioNormalCdf(Nar11_tau_1),
            2 : bioNormalCdf(Nar11_tau_2)-bioNormalCdf(Nar11_tau_1),
            3 : bioNormalCdf(Nar11_tau_3)-bioNormalCdf(Nar11_tau_2),
            4 : bioNormalCdf(Nar11_tau_4)-bioNormalCdf(Nar11_tau_3),
            5 : 1-bioNormalCdf(Nar11_tau_4),
            -1: 1.0,
            -2: 1.0
            }
        P_Nar11 = Elem(IndNar11,Nar11)

        """Choice model"""
        # Coefficients
        ASC_Car = Beta('ASC_Car',0,-10000,10000,0)
        ASC_PT = Beta('ASC_PT',0,-10000,10000,1)
        ASC_NMT = Beta('ASC_NMT',0,-10000,10000,0)
        B_Dist_NMT = Beta('B_Dist_NMT',0.0,-10000,10000,0)
        B_TT_Car = Beta('B_TT_Car',0,-10000,10000,0)
        B_TT_PT = Beta('B_TT_PT',0,-10000,10000,0)
        B_Work = Beta('B_Work',0,-10000,10000,0)
        B_Age_Car = Beta('B_Age_Car',0,-10000,10000,0)
        B_Age_NMT = Beta('B_Age_NMT',0,-10000,10000,0)
        B_WalkingTime = Beta('B_WalkingTime',0,-10000,10000,0)
        B_NCar_Car = Beta('B_NCar_Car',0,-10000,10000,0)
        B_Edu_NMT = Beta('B_Edu_NMT',0,-10000,10000,0)
        B_Cost_PT= Beta('B_Cost_PT',0,None,None,0)
        B_Cost_Car= Beta('B_Cost_Car',0,-10000,10000,0)
        B_Age_PT = Beta('B_Age_PT',0,None,None,0)
        B_TrFreq = Beta('B_TrFreq',0,None,None,0)
        B_INC_PT = Beta('B_INC_PT',0,None,None,0)
        B_Gender_Car = Beta('B_Gender_Car',0,-10000,10000,0)
        B_Exh_PT = Beta('B_Exh_PT',0,None,None,0)
        B_Exh_Car = Beta('B_Exh_Car',0,None,None,0)
        B_PerNorm_PT = Beta('B_PerNorm_PT',0,None,None,1)
        B_PerNorm_Car = Beta('B_PerNorm_Car',0,None,None,0)
        B_Affect_PT = Beta('B_Affect_PT',0,None,None,0)
        B_Salience_PT = Beta('B_Salience_PT',0,None,None,0)


        ###Define Variables
        NoOfCars = NoOfCars
        WkTrip =  WkTrip
        Distance_km = Distance_km
        TimePT_1=TimePT_1
        CostPT_1=CostPT_1
        TimeCar_1=TimeCar_1
        Gender = Gender
        Age_band = Age_band
        Age_group1 = Age_group1
        Age_group3 = Age_group3
        Age_group2 = Age_group2
        Income7 = Income7
        Income6 = Income6
        CostCar2_1=CostCar2_1
        Affect = Affect1
        PerNorm = PerNorm1
        Salience = Salience1
        #Exh = Exh

        """Utility Equations"""
        V_PT = ASC_PT +\
               B_TT_PT * TimePT_1 + \
               B_Cost_PT * CostPT_1 +\
               B_INC_PT * Income_band  +\
               B_Age_PT * Age_group1 +\
               B_Affect_PT * Affect +\
               B_Salience_PT * Salience  +\
               B_PerNorm_PT * PerNorm
```

```
        V_Car = ASC_Car  +\
                B_TT_Car * TimeCar_1  + \
                B_NCar_Car * NoOfCars +\
                B_WalkingTime * (DistToBS_Des + DistToBS_Orig) +\
                B_Work * WkTrip +\
                B_Gender_Car * Gender +\
                B_TrFreq * TripFreq +\
                B_PerNorm_Car * PerNorm

        V_NMT = ASC_NMT +\
                B_Dist_NMT * Distance_km +\
                B_Age_NMT * Age_band +\
                B_Edu_NMT * Education

        """Associate utility functions with the numbering of alternatives"""
        V = {0: V_PT,
             1: V_Car,
             2: V_NMT}

        """Associate the availability conditions with the alternatives."""
        av = {0: 1,
              1: 1,
              2: 1}

        "Associate utility functions with the numbering of alternatives"
        V = {0: V_PT,
             1: V_Car,
             2: V_NMT}

        "Associate the availability conditions with the alternatives."
        av = {0: 1,
              1: 1,
              2: 1}

        "Define Probabilities"
        PT = models.logit(V, av, 0)
        probPT = log((PT))

        pCar = models.logit(V, av, 1)
        probCar = log((pCar))

        NMT = models.logit(V, av, 2)
        probNMT = log((NMT))

        condlike = models.logit(V,av,MChoice_3)
        prob = log((condlike))

        PNorm = ((PerNorm))
        Sal = ((Salience))
        Aff = ((Affect))

        "Define Elasticities"
        #"Time"
        cross_elas_car_time = Derive(exp(probCar),'TimePT_1') * TimePT_1/
↪exp(probCar)
        cross_elas_pt_time = Derive(exp(probPT),'TimeCar_1') * TimeCar_1/␣
↪exp(probPT)
        direct_elas_car_time = Derive(exp(probCar),'TimeCar_1') * TimeCar_1 /␣
↪exp(probCar)
        direct_elas_pt_time = Derive(exp(probPT),'TimePT_1') * TimePT_1/␣
↪exp(probPT)

        #"Cost"
        #cross_elas_car_cost = Derive(exp(probCar),'CostPT_1') * CostPT_1/␣
↪exp(probCar)
        #cross_elas_pt_cost = Derive(exp(probPT),'CostCar2_1') * CostCar2_1/
↪exp(probPT)
        #direct_elas_car_cost = Derive(exp(probCar),'CostCar2_1') * CostCar2_1/␣
↪exp(probCar)
        direct_elas_pt_cost = Derive(exp(probPT),'CostPT_1') * CostPT_1/␣
↪exp(probPT)

        #"Income"
        direct_elas_car_TripFreq = Derive(exp(probCar),'TripFreq') * TripFreq/␣
↪exp(probCar)

        direct_elas_pt_income = Derive(exp(probPT),'Income_band') * Income_band/␣
↪exp(probPT)
        direct_elas_pt_carownership = Derive(exp(probPT),'NoOfCars') * NoOfCars/␣
↪exp(probPT)
        #"Age"
```

```
        direct_elas_pt_age = Derive(exp(probPT),'Age_group1') * Age_group1/␣
↪exp(probPT)
        direct_elas_NMT_age = Derive(exp(probNMT),'Age_band') * Age_band/
↪exp(probNMT)


        #"Distance"
        direct_elas_NMT_dist = Derive(exp(probNMT),'Distance_km') * Distance_km/
↪exp(probNMT)

        #"Education"
        direct_elas_NMT_educ = Derive(exp(probNMT),'Education') * Education/
↪exp(probNMT)

        #"PerNorm"
        direct_elas_car_pernorm = Derive(exp(probCar),'PerNorm1') * PerNorm1/␣
↪exp(probCar)
        direct_elas_pt_pernorm = Derive(exp(probPT),'PerNorm1') * PerNorm1/␣
↪exp(probPT)

        #"Affect"
        direct_elas_car_affect = Derive(exp(probCar),'Affect') * Affect/␣
↪exp(probCar)
        direct_elas_pt_affect = Derive(exp(probPT),'Affect1') * Affect1/␣
↪exp(probPT)

        #"Salience"
        direct_elas_car_salience = Derive(exp(probCar),'Salience') * Salience/␣
↪exp(probCar)
        direct_elas_pt_salience = Derive(exp(probPT),'Salience1') * Salience1/␣
↪exp(probPT)


        simulate = {'weight': normalizedWeight,
                    'Prob. PT': probPT,
                    'Prob. car': probCar,
                    'Prob. NMT':probNMT,
                    'Prob':prob,
                    'XE of Car wrt PT time':cross_elas_car_time,
                    'DE of Car wrt time':direct_elas_car_time,
                    'XE of PT wrt car time':cross_elas_pt_time,
                    'DE of PT wrt time': direct_elas_pt_time,
                    'DE of PT wrt cost': direct_elas_pt_cost,
                    'DE of PT wrt Income': direct_elas_pt_income,
                    'DE of NMT wrt Educ':direct_elas_NMT_educ,
                    'DE of NMT wrt Age':direct_elas_NMT_age,
                    'DE of PT wrt Age': direct_elas_pt_age,
                    'DE of PT wrt CarOwnership': direct_elas_pt_carownership,
                    'DE of Car wrt TripFreq': direct_elas_car_TripFreq,
                    'DE of NMT wrt trip length':direct_elas_NMT_dist,
                    'DE of PT wrt PerNorm': direct_elas_pt_pernorm,
                    'DE of Car wrt PerNorm': direct_elas_car_pernorm,
                    'DE of PT wrt Affect': direct_elas_pt_affect,
                    'DE of PT wrt Salience': direct_elas_pt_salience,
                    'Salience':Sal,
                    'Norm':PNorm,
                    'Affec':Aff}

        biosim = bio.BIOGEME(database,simulate,numberOfDraws=100000)
        biosim.DRAWS = {'omega_aff': ('NORMAL_MLHS'), 'omega_sal':␣
↪('NORMAL_MLHS'),\
                        'omega_exh': ('NORMAL_MLHS'), 'omega_PNorm':␣
↪('NORMAL_MLHS')}
        biosim.modelName = "SEM Model_Simul"

        """ Retrieve the names of the parameters """
        betas = biosim.freeBetaNames

        """ Read the estimation results from the file """
        results = res.bioResults(pickleFile='SEM_ICLV_Revised_thesis_final.
↪pickle')

        """ Extract the values that are necessary """
        betaValues = results.getBetaValues(betas)

        """
        simulatedValues is a Panda dataframe with the same number of rows as the
        database, and as many columns as formulas to simulate.
        weighted_simulatedValues has the same structure.
        """
        simulatedValues = biosim.simulate(betaValues)

        """ Calculate the elasticities """
```

```
        simulatedValues['Weighted prob. car'] = simulatedValues['weight'] *␣
↪simulatedValues['Prob. car']
        simulatedValues['Weighted prob. PT'] = simulatedValues['weight']  *␣
↪simulatedValues['Prob. PT']
        simulatedValues['Weighted prob. NMT'] = simulatedValues['weight'] *␣
↪simulatedValues['Prob. NMT']

        denominator_car = simulatedValues['Weighted prob. car'].sum()
        denominator_pt = simulatedValues['Weighted prob. PT'].sum()
        denominator_NMT = simulatedValues['Weighted prob. NMT'].sum()

        cross_elas_term_car_time = (simulatedValues['Weighted prob. car']
        * simulatedValues['XE of Car wrt PT time'] / denominator_car).sum()
        print(f"Aggregate cross elasticity of Car wrt PT time:␣
↪{cross_elas_term_car_time:.3g}")

        #cross_elas_term_car_cost = (simulatedValues['Weighted prob. car']
        #   * simulatedValues['XE of Car wrt PT cost'] / denominator_car).sum()
        #print(f"Aggregate cross elasticity of Car wrt PT cost:␣
↪{cross_elas_term_car_cost:.3g}")

        cross_elas_term_pt_time = (simulatedValues['Weighted prob. PT']
          * simulatedValues['XE of PT wrt car time'] / denominator_pt).sum()
        print(f"Aggregate cross elasticity of PT wrt car time:␣
↪{cross_elas_term_pt_time:.3g}")

        """cross_elas_term_pt_cost = (simulatedValues['Weighted prob. PT']
          * simulatedValues['XE of PT wrt car cost'] / denominator_pt).sum()
        print(f"Aggregate cross elasticity of PT wrt Car cost:␣
↪{cross_elas_term_pt_cost:.3g}")"""

        direct_elas_term_car_time = (simulatedValues['Weighted prob. car']
          * simulatedValues['DE of Car wrt time'] / denominator_car).sum()
        print(f"Aggregate direct elasticity of Car wrt time:␣
↪{direct_elas_term_car_time:.3g}")

        #direct_elas_term_car_cost = (simulatedValues['Weighted prob. car']
        #   * simulatedValues['DE of Car wrt cost'] / denominator_car).sum()
        #print(f"Aggregate direct elasticity of Car wrt cost:␣
↪{direct_elas_term_car_cost:.3g}")

        direct_elas_term_pt_time = (simulatedValues['Weighted prob. PT']
          * simulatedValues['DE of PT wrt time'] / denominator_pt).sum()
        print(f"Aggregate direct elasticity of PT wrt time:␣
↪{direct_elas_term_pt_time:.3g}")

        direct_elas_term_pt_cost = (simulatedValues['Weighted prob. PT']
          * simulatedValues['DE of PT wrt cost'] / denominator_pt).sum()
        print(f"Aggregate direct elasticity of PT wrt cost:␣
↪{direct_elas_term_pt_cost:.3g}")

        direct_elas_term_NMT_dist = (simulatedValues['Weighted prob. NMT']
          * simulatedValues['DE of NMT wrt trip length'] / denominator_NMT).sum()
        print(f"Aggregate direct elasticity of NMT wrt distance (km):␣
↪{direct_elas_term_NMT_dist:.3g}")

        direct_elas_term_pt_income = (simulatedValues['Weighted prob. PT']
          * simulatedValues['DE of PT wrt Income'] / denominator_pt).sum()
        print(f"Aggregate direct elasticity of PT wrt income:␣
↪{direct_elas_term_pt_income:.3g}")

        direct_elas_term_pt_age = (simulatedValues['Weighted prob. PT']
          * simulatedValues['DE of PT wrt Age'] / denominator_pt).sum()
        print(f"Aggregate direct elasticity of PT wrt age:␣
↪{direct_elas_term_pt_age:.3g}")

        direct_elas_term_car_TripFreq = (simulatedValues['Weighted prob. car']
          * simulatedValues['DE of Car wrt TripFreq'] / denominator_car).sum()
        print(f"Aggregate direct elasticity of Car wrt TripFreq:␣
↪{direct_elas_term_car_TripFreq:.3g}")

        direct_elas_term_pt_carownership = (simulatedValues['Weighted prob. PT']
          * simulatedValues['DE of PT wrt CarOwnership'] / denominator_pt).sum()
        print(f"Aggregate direct elasticity of PT wrt CarOwnership:␣
↪{direct_elas_term_pt_carownership:.3g}")

        "NMT"
        direct_elas_term_NMT_educ = (simulatedValues['Weighted prob. NMT']
          * simulatedValues['DE of NMT wrt Educ'] / denominator_NMT).sum()
        print(f"Aggregate direct elasticity of NMT wrt Education:␣
↪{direct_elas_term_NMT_educ:.3g}")

        direct_elas_term_NMT_age = (simulatedValues['Weighted prob. NMT']
```

```
          * simulatedValues['DE of NMT wrt Age'] / denominator_NMT).sum()
        print(f"Aggregate direct elasticity of NMT wrt age:␣
↪{direct_elas_term_NMT_age:.3g}")

        "MINDSPACE"
        direct_elas_term_pt_pernorm = (simulatedValues['Weighted prob. PT']
          * simulatedValues['DE of PT wrt PerNorm'] / denominator_pt).sum()
        print(f"Aggregate direct elasticity of PT wrt PerNorm:␣
↪{direct_elas_term_pt_pernorm:.3g}")

        direct_elas_term_pt_affect = (simulatedValues['Weighted prob. PT']
          * simulatedValues['DE of PT wrt Affect'] / denominator_pt).sum()
        print(f"Aggregate direct elasticity of PT wrt Affect:␣
↪{direct_elas_term_pt_affect:.3g}")

        direct_elas_term_pt_salience = (simulatedValues['Weighted prob. PT']
          * simulatedValues['DE of PT wrt Salience'] / denominator_pt).sum()
        print(f"Aggregate direct elasticity of PT wrt Salience:␣
↪{direct_elas_term_pt_salience:.3g}")

        direct_elas_term_car_pernorm = (simulatedValues['Weighted prob. car']
          * simulatedValues['DE of Car wrt PerNorm'] / denominator_car).sum()
        print(f"Aggregate direct elasticity of Car wrt PerNorm:␣
↪{direct_elas_term_car_pernorm:.3g}")


        "Append Probabilities to the pandas Dataframe"
        pandas['prob_PT'] = (simulatedValues['Prob. PT'])
        pandas['prob_Car'] = (simulatedValues['Prob. car'])
        pandas['prob_NMT'] = (simulatedValues['Prob. NMT'])
        pandas['prob'] = (simulatedValues['Prob'])

        """Export dataframe to csv and excel"""
        pandas.to_csv('Data-20-Simul.csv', index=False)
        "Print Results"
        print(sum((simulatedValues['Prob'])))
        print("Results=",results)
```