UNIVERSITY OF SOUTHAMPTON

FACULTY OF BUSINESS & LAW

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APPLICATION OF META-ANALYSIS, MULTIDIMENSIONAL SCALING, STRUCTURAL EQUATION MODELLING, AND MULTILEVEL MODELLING IN ANALYSING CARPOOLING BEHAVIOUR

Jun Guan Neoh

Thesis for the degree of Doctor of Philosophy

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Abstract

Carpooling, where two or more commuters travel together in the same private vehicle, brings public benefits. To encourage and incentivise it, transport practitioners and researchers must identify its private motivations and deterrents.

Existing studies often report conflicting results or non-generalisable findings. Thus, a quantitative systematic review of the literature body is needed. Using meta-analysis, this study synthesised 22 existing empirical studies (representing over 79,000 observations) to produce an integrated review of the carpooling literature. The meta-analysis determined 24 non-household carpooling factors, and their effect sizes. Factors such as number of employees ($\bar{r}$= 0.42), partner matching programs ($\bar{r}$= 0.42), female ($\bar{r}$= 0.22) and fixed work schedule ($\bar{r}$= 0.15) were found to have strong effects on carpooling while judgmental factors (such as the motivation to save costs) only exhibited small influence ($\bar{r}$ <0.1). Based on the significant effects, the paper discussed prospects for improving carpooling uptake by developing: *(i)* target demographics, *(ii)* selling points for marketing, *(iii)* carpooling partner programs and *(iv)* multiple employer 'super-pools'.

Merely identifying carpooling motivations and deterrents is insufficient, especially if there are no efforts to understand the causal process behind these factors. Thus, researchers should also investigate the motivations of commuter's current travel mode choice, particularly drivers of single-occupied vehicles, and how this relates to their acceptance of carpooling. This study applied the multidimensional scaling approach on a UK-based travel survey dataset (*N*= 423) and were able to extract four dimensions of driving determinants, namely: *(1) family responsibility; (2) public transport impractical changes; (3) rigid schedule;* and *(4) live in non-urban areas.* Next, a structural equation model was conducted (on a USA-based travel survey dataset with *N*= 1028) to explore the relationship of the four driving motivations with the acceptance to carpool. Finally, a multilevel model was used to examine the influence of the State where the driver is resident in on their carpooling decision. The findings show drivers who perceived public transport to be impractical, or have a rigid commute schedule, were unlikely to carpool; while drivers with family responsibilities, live in urban areas and have flexible commute schedules were more likely to carpool. It is recommended that partner matching services should account for drivers'

commute activities in their matching criteria. Instrumental driving reasons were found to have only a small influence on carpooling, prompting further research on the influence of affective and symbolic factors.

These findings are important to transportation researchers, who can use the outputs of this research in future modelling of car-use and carpooling; and practitioners, who can use the results to plan more targeted carpooling policies.

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Declaration of authorship

I, JUN GUAN NEOH declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

Application of meta-analysis, multidimensional scaling, structural equation modelling, and multilevel modelling in analysing carpooling behaviour.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date: **08.05.2016**

Research outputs

Part of this thesis has been produced as research outputs in the outlets exhibited in **Table 1.**

Table 1: Research output

Ref	Thesis chapter	Title	Type	Description
1	1, 2, 3 & 8	**Neoh J.G.**, Chipulu M, Marshall A (2015) What encourages people to carpool? An evaluation of factors with meta-analysis. *Transportation*:1-25. doi:10.1007/s11116-015-9661-7	Journal publication	Published. Recipient of the *Southampton Business School Postgraduate Researcher Publication* award.
2	1, 2, 4, 5, 6, 7 & 8	**Neoh, J.G.**, Chipulu, M. and Marshall, A. (2016), 'Modelling carpooling and driving motivations with multidimensional scaling, structural equation modelling and multilevel modelling'.	Journal publication	To be submitted to *Transportation Research Part A: Policy and Practice.*
3	1, 2, 4 & 7	**Neoh, J.G.**, and Chipulu, M. (2015) Why do people choose to drive over other travel modes? Interpreting multidimensional scaling dimensions with SAS®, *Proceedings of the SAS Global Forum 2015*, Dallas, Texas, USA.	Conference proceedings	Winner of the *SAS® Global Ambassador 2015* award.
4	1, 2, 3, 7 & 8	**Neoh, J.G.**, (2015), 'Carpooling and the environment', *Proceedings of the ISER 5th International Conference of Economics and Business Research 2015,* Singapore.	Conference proceedings	Winner of the *International Institute of Engineers and Researchers Best Paper* award.
5	1, 2, 3 & 8	**Neoh J.G.**, Chipulu M, Marshall A (2013) What encourages people to carpool? An evaluation of factors with meta-analysis. Poster presented at the *Research Development & Graduate Centre Showcase 2013*, Southampton, UK.	Poster presentation	Winner of the *Research Development & Graduate Centre Showcase 2013 "Highly Commended"* award.
6	1, 2, 3, 7 & 8	**Neoh J.G.,** Chipulu M, Marshall A (2016) Carpooling: Policy recommendations for the University of Southampton Transport Team. Southampton Business School, University of Southampton, Southampton, UK	Technical report	Technical report with policy recommendations to be submitted to the University of Southampton Transport Team to improve carpooling uptake on campus.
7	1, 2, 3 & 8	**Neoh J.G.**, Chipulu M, Marshall A (2013) What encourages people to carpool? An evaluation of factors with meta-analysis. Paper presented at the *3rd INTERREG Conference - Doctoral Colloquium 2013*, Deauville, France.	Conference presentation	

Ref	Thesis chapter	Title	Type	Description
8	1, 2, 3 & 8	**Neoh J.G.**, Chipulu M, Marshall A (2013) What encourages people to carpool? An evaluation of factors with meta-analysis. Paper presented at the *1st Young CORMSIS Conference 2013*, Southampton, UK.	Conference presentation	
9	1, 2, 4 & 7	**Neoh, J.G.**, and Chipulu, M. (2015) Why do people choose to drive over other travel modes?, Paper presented at the *Southampton Business School PhD/DBA Seminar Series 2015*, Southampton, UK.	Seminar presentation	

Author and supervisory team contributions

In compliance with paragraph **6** of the **Declaration of authorship** (page6 **ix**),

Table 2 lists the respective contributions of the author and the supervisory team in the production of this thesis. The supervisory team comprised of Dr Maxwell Chipulu as the primary supervisor and Dr Alasdair Marshall as the secondary supervisor.

Table 2: Author and supervisory team contributions

Thesis chapter	Author's contribution	Supervisory team's contribution
3	Collected and collated the data (studies). Computed the meta-analysis. Explained the results and discussed the findings, including policy recommendations, limitations and directions for future research. Completed the write-up of the chapter.	Provided guidance on the discussion section, particularly on policy recommendations. Reviewed the chapter and suggested improvements.
4	Cleaned and prepared (i.e. pre-processed) the secondary data. Conducted the coding of the keywords of the data. Computed the multidimensional scaling analyses, including the goodness-of-fit tests and the logistic regressions. Interpreted the dimensions. Explained the results. Completed the write-up of the chapter.	Connected the author with the University of Southampton Transport Team (the provider of the secondary data). Reviewed the keyword coding procedures. Provided guidance on the multidimensional scaling modelling techniques and dimension interpretation. Reviewed the chapter and suggested improvements.
5	Prepared and designed the USA travel survey. Cleaned and prepared the collected data. Computed the structural equation modelling analysis and the relevant goodness-of-fit tests. Explained the results. Completed the write-up of the chapter.	Provided guidance on the questionnaire. Advertised the travel survey on the *Amazon Mechanical Turk* platform, and handled the administration of the account. Provided guidance on the structural equation model. Reviewed the chapter and suggested improvements.
6	Cleaned and prepared the data for the multilevel model analysis. Computed the multilevel model analysis. Explained the results. Completed the write-up of the chapter.	Provided guidance on the multilevel model. Reviewed the chapter and suggested improvements.
7	Discussed the findings, including policy recommendations, limitations and directions for future research. Completed the write-up of the chapter.	Provided guidance on the discussion section, particularly on policy recommendations. Reviewed the chapter and suggested improvements.

Acknowledgements

On the shoulders of giants

My deepest gratitude goes out to my primary supervisor and modelling guru, Dr Maxwell Chipulu. Dr Max has trained me not only in the technical aspects, but also in developing my mind set to think 'statistically'. I fondly recall an occasion early in my research career where he was reluctant to eliminate cases from a dataset unless as a last resort. From him, I inherit this philosophy of not wanting to waste data, but instead believing that every row has a story to tell. Beyond the statistics lessons, he has helped me in numerous ways, including: involving me in other research projects, guiding me through the paper publication process, encouraging freedom and flexibility in my research, cultivating the joys of teaching in me, being my first port-of-call for questions of life in academia, and refereeing an A-to-Z list of personal and professional applications. His mentorship has provided me with valuable skillsets, both statistical and interpersonal, which I will forever be grateful for.

While Dr Max was the quantitative mind behind my PhD, my secondary supervisor, Dr Alasdair Marshall, was the qualitative eyes. With his expertise in psychology, Dr Alasdair was always able to see things from a different perspective and provide the right research angle to make this thesis more colourful and impactful. I thank him for energising this thesis.

I would like to thank Professor Cecilio Mar Molinero and Dr Ian Dawson for their participation in the thesis committee. In addition to providing feedback during the final viva, Dr Ian has also helped to shape the earlier versions of this thesis via his contributions at the 'upgrade' viva. Professor Cecilio's work in the field of multidimensional scaling was the basis of my Master's dissertation and this thesis. To have him and Dr Ian as my examiners is an incredible honour, and I thank them both for their valuable feedback and recognition.

I am also grateful for the help of Adam Tewkesbury of the University of Southampton Transport Team (UoSTT), for sharing his experience in travel demand management and providing the travel survey data. More excitingly, Adam's team offers me the powerful chance to transform my research findings into real-world impact, a rare opportunity not commonly afforded to any PhD student.

My work is also inspired by the faculty and friends of the Centre for Risk Research: Professor Udechukwu Ojiako, who I have the opportunity to co-author papers with and learn from his research skills; Professor Ming-Chien (Vanessa) Sung, who sincerely motivated me, especially during the early stages of my career; and Professor Johnnie Johnson, who galvanised my interest in academia via our discussions of enticing research work in betting markets.

A PhD can be a lonely passage, and so I must thank my fellow colleagues for their companionship. Firstly to my PhD siblings (via Dr Max) who best understand my research: Dr Layla Khoja, for being able to talk to her about DeSarbo indices! Walaa Ismael, for always pointing me towards the right resources. And Professor Hsin-Yun Lee, for imparting wise advice on academia and life. Next, to my dear office mates: Sarah Liedner, Phuoc (Philip) Le, Dr Çağrı Koç, Qazi Waheed Uz Zaman, Murat Oğuz and the straight-talking Xiaozhou (Joe) Zhao. I will miss our office pastime of swearing at our monitor screens, wishing that our research work would stop frustrating us!

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I was able to meet and learn from all the interesting people above thanks to the funding of my doctoral studies by the University of Southampton and the Southampton Business School. The Vice-Chancellor and the Business School Faculty Scholarships have conferred me with exceptional experiences and opened countless doors. Long may these generous funds continue to benefit future researchers.

On a personal note, I would like to thank my family and friends for their support. Yvonne Yap and the analogy-artist Tian Han Ng, thanks for providing the weekend entertainment during my studies. My mother and father, for all the extraordinary sacrifices they have made which enabled me to pursue this path. My brother, for being there for my parents while I was away. My sister, for her *cherkish* support. And finally, to my partner Charmian for literally enduring every second of my PhD. She has always supported my decision to take the road less travelled, even at the expense of surrendering her own luxuries.

Definitions and Abbreviations

Table 3 lists the abbreviations used in this thesis along with their respective definitions.

Table 3: Definitions and abbreviations

Terms	Definitions
Affective factors	Refers to the emotive reasons for using a car, for e.g., the thrill of speeding. See **Section 2.5**.
AMT	*Amazon Mechanical Turk*. Refers to the online platform used in **Chapter 5** to advertise and recruit respondents for the US Travel Survey.
Carpooling	In this thesis, carpooling refers to an arrangement where two or more persons, not living in the same household, travel together in the same private vehicle; this reduces the number of SOV needed per journey. It is also the dependent variable of the SEM and MLM analyses. See **Section 2.2**.
CFA	Confirmatory factor analysis. A goodness-of-fit test used in the SEM procedure in **Chapter 5**.
Classes	See “State”.
Dimensions	Refers to the output of the MDS in **Chapter 4**, i.e., the four driving motivations which have been extracted from the drivers of the UoSTT Travel Survey. Subsequently, these were used as the independent variables for the SEM in **Chapter 5** and the MLM in **Chapter 6**.
Driving motivation	Refers to a commuter’s reason to choose driving to work over other travel modes (for e.g., cycle, walk or using public transport). See **Section 2.5**.
***Family* (Dimension 1)**	The Dimension where the commuter chose to drive over other travel modes because of their responsibility to transport their family member(s). Also known as Dimension 1. See “Dimensions”.
HOV	High-occupancy vehicles. Refers to vehicles which have two or more passengers (including the driver).
Incentive keywords	Refers to the keywords which have been coded from the qualitative responses of the UoSTT Travel Survey, which represents the incentive which could persuade the respondents to switch to a non-driving travel mode. The keywords were later used as inputs for the MDS. See **Chapter 4**.
Instrumental factors	Refers to the functional/utilitarian reasons for using a car, for e.g., to travel faster and to carry other passengers. See **Section 2.5**.

Terms	Definitions
Keywords	Used to refer to the Incentive and Motivation keywords collectively. See **Chapter 4**.
Level 1 variables	Refer to the individual-level variables in the MLM, namely *Family* and *Rigid schedule.* See **Chapter 6**.
Level 2 variables	Refer to the variables which were treated as varying at each State in the MLM, namely the *Public transport impractical changes* and *Non-urban* variables. See **Chapter 6.**
MDS	Multidimensional scaling. Statistical method used to extract the dimensions of driving motivations, and is the focus of **Chapter 4**.
Meta-analysis	Statistical method to quantitatively synthesise the findings of the carpooling literature body. It is the focus of **Chapter 3**.
MLM	Multilevel modelling. Statistical method to examine the influence of factors caused by the hierarchical nature of the data; in this thesis it is used to investigate the role of the State on carpooling. It is the focus of **Chapter 6**.
Model 1	Refers to the "empty" (base) model in the MLM in **Chapter 6**.
Model 2	Refers to the MLM model which consists of the Level 2 variables. See **Chapter 6**.
Model 3	Refers to the MLM model which consists of the Level 1 variables. See **Chapter 6**.
Model 4	Refers to the random slope model in the MLM which consists of both the Level 1 and Level 2 variables. See **Chapter 6**.
Motivation keywords	Refers to the keywords which have been coded from qualitative responses of the UosTT Travel Survey, which represents the driving motivation of the respondent. The keywords were later used as inputs for the MDS. See **Chapter 4**.
NTML	Normal-theory maximum likelihood. Estimation method used in the SEM analysis in **Chapter 5.**
***Non-urban* (Dimension 4)**	The Dimension where the commuter chose to drive over other travel modes because they live in non-urban areas, such as suburban residential zones or rural areas. Also known as Dimension 4. See "Dimensions".

Terms	Definitions
Public transport impractical changes **(Dimension 2)**	The Dimension where the commuter chose to drive over other travel modes because they found difficulties with using public transportation. Also known as Dimension 2. See "Dimensions".
Rigid schedule **(Dimension 3)**	The Dimension where the commuter chose to drive over other travel modes because of the rigidness of their daily schedules (as opposed to a flexible schedule). Also known as Dimension 3. See "Dimensions".
RQ1/ RQ2/ RQ3	Research question 1/ 2/ 3. These are explained in **Section 1.1**.
SEM	Structural equation modelling. Statistical method used to examine the relationship between the driving motivations dimensions and the propensity to carpool. It is the focus of **Chapter 5**.
SOV	Single-occupied vehicles. Refers to private vehicles which are occupied by only one person (i.e. the driver), thus not fully utilising the empty seats in the vehicle. One of the main goals of this thesis is to reduce the number of SOVs by encouraging drivers to carpool.
State	Refers to the US State (for e.g., California) where the driver of the US Travel Survey is resident in. It features in the MLM, where the data is grouped into classes by State for analysis. See **Chapter 6**.
Symbolic factors	Refers to the reasons for using a car which relates to an individual's need to portray a certain status/identity, for e.g., as a demonstration of wealth. See **Section 2.5**.
UoSTT	University of Southampton Transport Team. Refers to the group which designed and collected the UoSTT Travel Survey.
UoSTT Travel Survey	Refers to the travel survey which collected qualitative responses from staff and postgraduate research students on their motivations and incentive to drive to work at a university. Secondary data source (administered by the UoSTT), and was used as an input for the MDS. See **Chapter 4**.
US Travel Survey	Refers to the online travel survey targeting drivers who are resident in the USA, and is analysed by the SEM and MLM. Primary data source. See **Chapter 5**.

Chapter 1: Introduction

1.1 Introduction

With projections that the global car population will grow to 2.8 billion and global road emissions will double by 2050 (Meyer, Kaniovski and Scheffran, 2012), sustainable travel remains an urgent agenda for transportation planners and researchers. Among the various travel demand management measures promoted, carpooling is touted as a possible solution. In carpooling, two or more participants travel together in the same private car, reducing the number of single-occupied vehicles (SOV) needed per journey. Carpooling offers environmental, economic and social benefits as reduced car use is associated with reduction in carbon emission, travelling costs, congestion, and efficient land use (Gärling and Steg, 2007; Greene and Wegener, 1997). The appeal of carpooling programmes lies in their leveraging of existing infrastructure, requiring relatively little investment for implementation (Garrison, 2007). In recent years, the micro-level social co-ordination of carpooling has been enabled by advancement in social network and smartphone applications which can easily match carpooling partners. Technology has also fuelled the rapid rise of the “sharing economy” phenomenon, where consumers are more open towards the idea of using goods or services shared among the local community, as observed in the global successes of websites such as car-sharer “Uber” and accommodation-sharer “Airbnb” (Hamari, Sjöklint and Ukkonen, 2015; Heinrichs, 2013). These developments have led to calls for further research into how such technologies and attitudinal changes can be harnessed at the macro level by transport planners (Chan and Shaheen, 2012).

Yet encouraging commuters to carpool remains a challenge. Solo-commutes continue to account for the majority of car travel. Taylor *et al.* (2013) reported that in 2012, 86% of UK work trips by car were single-occupied. Similarly in the US, solo-drivers accounted for 76% of all work commutes (Mckenzie and Rapino, 2011). This is unsurprising, since solo commuters can travel with privacy and flexibility over destinations and schedules. Carpooling, by contrast, entails sacrifices in these areas (Baldassare, Ryan and Katz, 1998).

One prolific line of research explores factors encouraging carpooling (e.g., Buliung *et al.*, 2010; Canning *et al.*, 2010; Correia and Viegas, 2011; Vanoutrive *et al.*, 2012). In particular, non-household carpools are of interest in the literature as well as in this present study. Non-household carpools refer to carpooling amongst members living in different residences, such as a work carpool where the driver picks up a co-worker at a pre-arranged location before heading off to the workplace together. Household carpools refer to carpools formed with participants of the same household, usually family members (for example, during a school run where the parent drops the child off at school on their way to work). The latter is easier to assemble because members share points of origin in household carpools and have higher levels of trust due to living together or family ties, as compared with the former, where participants who live in different households may have to make social, travel and waiting time adjustments to accommodate each other (Ferguson, 1997; Teal, 1987). Indeed, studies have reported that household carpools are more popular, making up of more than two thirds of all carpooling journeys (Li *et al.*, 2007; Morency, 2007). The extra difficulty justifies the concentration of the author's research efforts in establishing the factors which can improve the uptake of non-household carpools. This is a worthy research endeavour, considering the reward of potential reduction in SOV usage, especially for work carpools with almost daily commutes.

Judging from the review of the literature, it seems unlikely that transportation planners will be able to make policy decisions on promoting carpooling by relying on single studies. Single experiments may draw from samples which are not representative of the general population (Hedges and Olkin, 1985), as seen in some carpooling studies (Abrahamse and Keall, 2012; Bhat and Koppelman, 1999; Buliung *et al.*, 2010; Canning *et al.*, 2010; Daniels, 1981). This is also true where two or more studies report conflicting results on the effectiveness of certain carpooling measures. Hence, this study aimed to synthesise the empirical evidence of non-household carpools using meta-analysis. To the best of the author's knowledge, this study is the first meta-analysis on carpooling factors. Unlike previous literature reviews, which are qualitative (for e.g., Hwang and Giuliano, 1990) the meta-analysis paints a quantitative review of current carpooling research. It is expected that the meta-analytic results would be useful, firstly, to transportation practitioners, who can use the aggregation of the effect sizes of each carpooling factor to plan more effective carpooling policies; and secondly, to transportation researchers, who can use the list of factors and effect sizes to model carpooling behaviour and plan the allocation of future research efforts. The meta-analysis is the focus of **Chapter 3**.

Further, rather than merely identifying and acting upon these carpooling factors, it is just as important to understand the reasons behind the motivations of the commuters; only then we could design carpooling initiatives which are truly effective (Gardner and Abraham, 2007). Interventions planned without any considerations to the commuters' motivations, especially drivers of SOV, will fail to address their specific travel needs and wants, and would most likely fail. In travel demand management studies, where the aim is to persuade car drivers to switch to sustainable alternatives, the drivers' motivations are explored in relation to public transportation, cycling or walking (Beirão and Sarsfield Cabral, 2007; Gatersleben and Uzzell, 2007; Redman *et al.*, 2013; Spinney, 2009).

Thus, this thesis also intends to firstly, identify the key underlying themes of a commuter's reason to choose driving over other travel modes. This study aims to do this via Multidimensional Scaling (MDS) analysis, a statistical method which has been scarcely applied in the car-use literature. A key output of the MDS model is the interpretations of the models' dimensions, which paints a picture of the data from multiple 'point-of-views' (Kruskal and Wish, 1978). The dimension interpretations will give us a better understanding of the key underlying reasons for driving. Secondly, this study aims to examine the relationships of these driving reasons with the drivers' acceptability to carpooling. Here, this study used Structural Equation Modelling (SEM), a method widely used in transportation behavioural research (Golob, 2003). SEM can be used to confirm the validity of the driving reasons of the MDS model, and capture the causal effects of the driving reasons on the commuter's likelihood to carpool (Bollen, 1989). Thirdly, this study intends to examine whether the influence of the carpooling dimensions on an individual's likelihood to carpool would differ by their home location. If such difference(s) exists, this study could identify whether there is scope for the local authority/government to introduce or amend policies to encourage carpooling. To accomplish this, this study conducted a Multilevel Model (MLM), where each individual in the data was nested within classes of the US state they are resident in (Maas and Hox, 2004). The MDS, SEM and MLM are the focus of **Chapter 4, Chapter 5, Chapter 6** and **Chapter 7**.

To the best of the author's knowledge, this is the first study in the carpooling literature to explore the relationship between driving motivation and carpooling by combining the use of multidimensional scaling with structural equation modelling. The results are useful to transportation researchers, who can use the dimensions from the MDS model and coefficients from the SEM in future modelling of car-use and carpooling; and practitioners, who can use the findings to plan car-use reduction and carpooling interventions.

Ergo, this thesis research questions are outlined as:

RQ1: What are the key factors influencing the commuter's decision to participate in a non-household carpool, and what are their effect sizes?

RQ2: How does the commuters' motivation to drive (as a travel mode) affects their willingness to carpool?

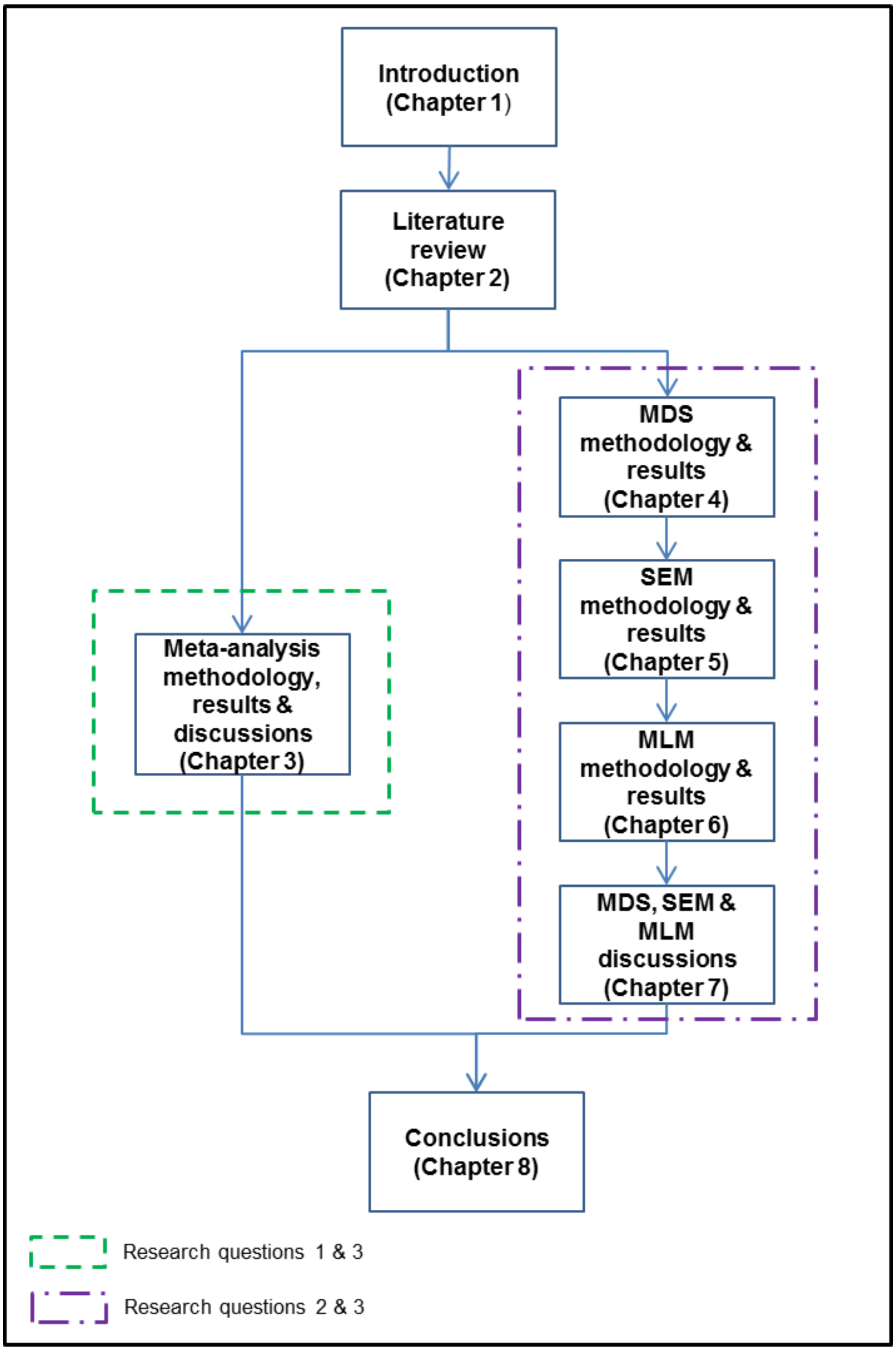
RQ3: What policy recommendations can be made for improving carpool participation?

1.2 Thesis format and layout

This thesis follows the style of the "traditional thesis" and is arranged as according to **Figure 1**. Following the introductory chapter**, Chapter 2** analyses the carpooling literature, paying particular attention to gaps in the literature relating to the factors which encourage/discourage carpooling, and the influence of driving motivations on carpooling. **Chapter 3** address the first research question, by employing meta-analysis; **sections 3.1** to **3.3** introduce the methodology, while **sections 3.4** to **3.7** discuss the results and implications of the meta-analysis (thus also answering the third research question).

The second research question is the focus of **Chapter 4, Chapter 5, Chapter 6** and **Chapter 7**. Utilising data from a university travel survey, **Chapter 4** introduces the methodology of the MDS procedure, along with the driving motivation dimension interpretations. **Chapter 5** uses a travel survey dataset of US workers for a structural equation model to draw out the relationship between the driving motivation dimensions and a commuter's likelihood to carpool. **Chapter 6** reuses the same US travel survey data with MLM to investigate the influence of the state on carpooling. **Chapter 7** unifies the results from the three preceding chapters to discuss the implications of the SEM, MLM and MDS models on transportation policy (hence answering the third research question). Finally, **Chapter 8** provides a summary of the lessons learnt from all the previous chapters, and concludes with directions for future research.

Figure 1: Thesis layout



Chapter 2: Literature Review

2.1 Overview

This chapter reviews the carpooling literature. Particularly, **section 2.4** forms the basis of the meta-analysis study (**Chapter 3**); while **section 2.5** provides the foundation for the multidimensional scaling, structural equation modelling and multilevel modelling studies (**Chapter 4, Chapter 5** and **Chapter 6**).

2.2 Carpooling definition

The selection of literature on ‘carpooling’ is complicated by the absence of agreed definitions (Buliung *et al.*, 2010; Vanoutrive *et al.*, 2012). Moreover, some authors use terms such as ‘lift-sharing’, and ‘ridesharing’ - often interchangeably. The literature further defines carpooling into sub-categories. In its simplest form, the driver and passenger(s) share the same journey origin and destination (Huang, Yang and Bell, 2000). Morency (2007) considered a more complex agreement where the carpoolers make two or more trips; the driver drops the passenger(s) at a different location, before arriving at the driver’s destination. Others explored agreements where passengers are picked up at pre-arranged locations (Rietveld *et al.*, 1999). Such carpools are less convenient as detours are required, increasing travel time and distance. Within these agreements (and as mentioned earlier), studies also differentiated between household and non-household carpools (Buliung *et al.*, 2010; Ferguson, 1997; Teal, 1987; Vovsha, Petersen and Donnelly, 2003). More recently, authors have begun to explore the potential for dynamic ridesharing, where carpools are formed on short-notice using internet-based applications, without long-term agreements (Agatz *et al.*, 2012). For the purpose of the current study, carpooling is defined as an agreement where two or more persons, not living in the same household, travel together in the same private vehicle to reduce the number of SOV needed per journey. Ideally, this agreement would lead to repeated journeys, thus reducing the number of SOVs on the road in the long run.

2.3 Background and context

Chan and Shaheen (2012) provided a comprehensive narrative on the history of carpooling in North America, describing it as an evolution of five phases, namely: *(Phase 1)* World War II car-sharing clubs (1942 - 1945); *(Phase 2)* major responses to energy crises (late 1960s - 1980); *(Phase 3)* early organised ridesharing schemes (1980 - 1997); *(Phase 4)* reliable ridesharing systems (1999 - 2004); and (*Phase 5*) technology-enabled ridematching (2004 - present). At *Phase 1*, the US government heavily encouraged her people to carpool with co-workers to work, as a means of saving rubber and gasoline for the war effort. In *Phase 2*, carpooling was adopted as a response to the decreased oil supply during that period, mainly due to the 1973 oil embargo by the Organisation of Arab Petroleum Exporting Countries (OAPEC) against the US (and the UK, among others), and the 1979 Iranian revolution (Weiner, 1999). As oil prices started a 6-year decline post-1980 in *Phase 3*, the agenda of carpooling efforts shifted from conserving resources to reducing traffic congestion and improving air quality. During this time, early carpooling schemes were operated by employers who were required by the state to limit the number of SOV commuters[1]. Meanwhile, telephone-based ridematching schemes where commuters could look for potential carpool partners were experimented on in a number of cities in the US and Canada; however these programs were generally unsuccessful due to their high operating costs and low uptake (Golob and Giuliano, 1996). Thus in *Phase 4*, the focus of carpool matching programs is to gather large numbers of registered users to increase the likelihood of successful partner matches; the advent of the internet at this time helped to facilitate this via online carpool notice boards and databases. Finally in *Phase 5*, the carpooling movement of the present day is more technologically-driven; dynamic and real-time partner matching is now a possibility with the aid of maturing

[1] Further discussion on employer-based carpooling schemes can be found in section **2.4.4**.

social networking platforms and mobile applications, along with growing public acceptance to the sharing economy culture (Hamari, Sjöklint and Ukkonen, 2015; Heinrichs, 2013).

Meanwhile in the UK, carpooling was not widely accepted before the 1980s due to the nature of its legal status (Tomlinson and Kellett, 1978). Bonsall (1981) explained that UK legislation from the 1930s which sought to regulate the licensing of taxis and public transportation has made it illegal for private car drivers to receive any form of reward for transporting passengers; carpooling was thought to fall within this scope as a carpool passenger who "returns the favour" by offering a future lift to the driver could have been interpreted as "rewarding" the driver. However, the 1978 Transport Act loosens this restriction, allowing carpools as long as the driver did not make a financial profit from the arrangement. This principle is upheld till today, where most UK motor insurance cover[2] for drivers will not be negatively affected if they were to give lifts to others, providing that any payments received are for the purposes of covering costs and not for profit (Association of British Insurers, 2014b). The legalisation of carpooling alongside the events of the 70s and 80s (the 1973 and 1979 oil crises, and the government-led carpool initiatives in the US) opened the doors for carpooling feasibility studies in the UK (Bonsall, 1981; Bonsall, Spencer and Tang, 1984; Bonsall, Spencer and Tang, 1980; Daniels, 1981). These in turn inspired and stimulated the current carpooling literature landscape of today.

2.4 Carpooling factors

There is extensive research studying factors which influence individual decisions to carpool, ranging from analyses of travel surveys (for e.g., Arbour-Nicitopoulos *et al.*, 2012; Deloach and Tiemann, 2011; Teal, 1987) to case studies of carpooling schemes (Cairns, Newson and Davis,

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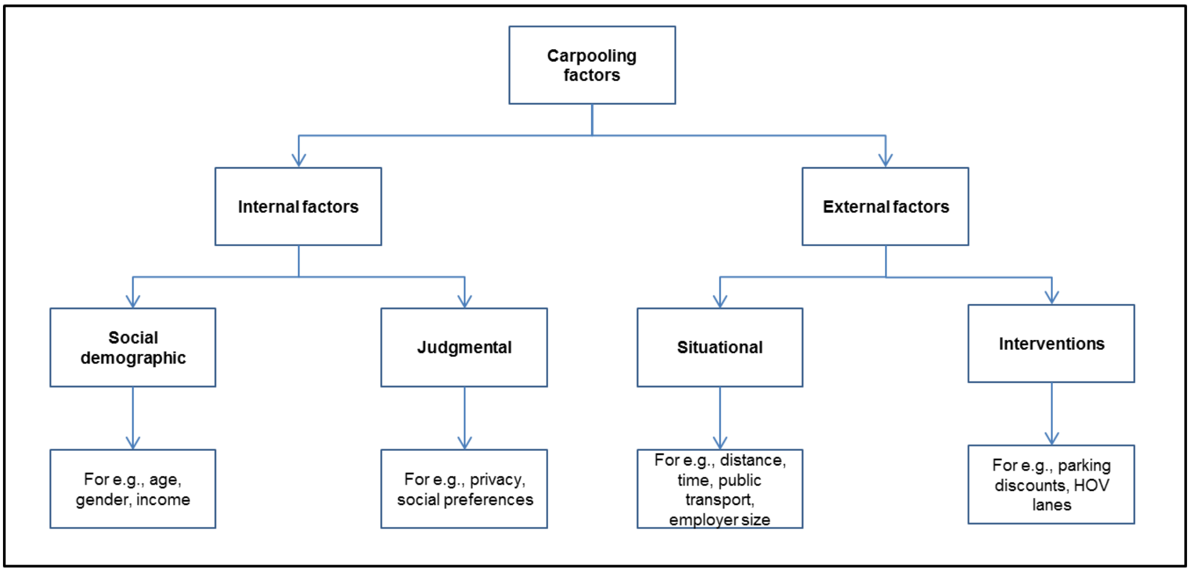
[2] This applies to motor insurance which has been approved by the Association of British Insurers. As stated on its website, the Association of British Insurer is an organisation which represents member companies which account for over 90% of the UK insurance market – see Association of British Insurers (2014a), *Association of British Insurers - About us* [Online]. Available: https://www.abi.org.uk/About [Accessed 14/02/2016 2016].

2010; Canning *et al.*, 2010; Shoup, 1997). Results tend to report common factors, which can be categorised in various ways; for example, Buliung *et al.* (2010) classified carpooling factors as socio-demographic, spatial, temporal, automobile availability, and attitudinal. Adapting this approach with some minor adjustments, this study grouped carpooling factors based on whether they are internal or external to the commuter. Internal factors occur at the individual level for each commuter, including demographic (i.e., individual characteristics) and judgmental factors (i.e., commuter's reason to carpool). External factors take place at the environment level of the commuter, including third-party interventions (i.e., policy measures to facilitate carpooling) and situational factors (i.e., location-based factors). This categorisation provides a basic framework for policy makers and helps identify areas for further action (see **Figure 2**).

Figure 2: Categorisation of carpooling factors



2.4.1 Demographics

It is widely agreed that socio-demographics do not strongly influence non-household carpooling behaviour (for e.g., Canning *et al.*, 2010; Ferguson, 1997; Teal, 1987). Even in cases where demographic factors do exhibit strong associations with carpooling, these relationships were usually credited to other underlying factors. For example, while carpooling is positively related to income and education status, these associations are attributed to individual car ownership – a better predictor of carpooling participation (Ferguson, 1995). Similarly, younger people were found to be more likely to adopt carpooling as passengers, due to their low vehicle ownership rates (Baldassare, Ryan and Katz, 1998; Correia and Viegas, 2011; Ferguson, 1997). Cline, Sparks and Eschbach (2009) and Blumenberg and Smart (2010) found that immigrants in the US are particularly likely to participate, even after accounting for socio-economic factors. Ferguson (1995) and Rosenbloom and Burns (1993) suggested that women are less likely to carpool than men due to household commitments causing inflexibility in their schedules, although this view is challenged in more recent studies (Deloach and Tiemann, 2011).

2.4.2 Situational factors

Carpooling is attractive when public transportation is unavailable, especially for long distances (Eriksson, Friman and Gärling, 2008). There is disagreement on whether longer travel distances encourage (Jacobson and King, 2009; Steg and Vlek, 1996) or discourage (Cervero and Griesenbeck, 1988; Kocur and Hendrickson, 1983) carpooling. Teal (1987) and Ferguson (1997) found that carpooling journeys tend to have longer distances than SOV journeys. Shoup (1997) noted that longer distances sometimes result from detours where drivers pick up or drop off passengers at meeting points. Likewise, Tsao and Lin (1999) found that the inconvenience of waiting for other carpool members can deter carpooling. Giuliano, Levine and Teal (1990) found travel time-saving to be an important determinant. Yet, Rietveld *et al.* (1999) found carpooling could take up to 17% more travelling time because of detours.

2.4.3 Judgmental factors

The literature has generally found psychological factors as salient in carpooling decision-making processes, rating such factors more important than socio-demographic ones (Gardner and Abraham, 2007). For example, Horowitz and Sheth (1978) found commuters more likely to carpool if they perceive it to be convenient; Ozanne and Mollenkopf (1999) found a statistical relationship between the commuter attitudes, namely “Personal Relative Advantage” and “Compatibility”, and intention to carpool.

Similarly, Dueker, Levin and Bair (1977) emphasised that commuter privacy and comfort are determinants of transport choices. People are often put off from carpooling because they value their privacy and personal space when driving (Correia and Viegas, 2011). Drivers are also sometimes unhappy about delegating the driving task to others, as they feel they are ceding control – which raises the question of the extent to which psychological need to feel in control (usually studied as 'locus of control') matters too (Huang, Yang and Bell, 2000; Stradling, Meadows and Beatty, 2001). Conversely, people are more willing to carpool if they perceive to be in control of the carpool setting (Ozanne and Mollenkopf, 1999). Research from Bonsall, Spencer and Tang (1984) linked carpooling to desirability to socialise, although not with strangers (Gardner and Abraham, 2007). Social differences and differences in values in potential members are barriers (Morency, 2007), hence carpoolers will consider the races and ethnicities (which are usually linked to cultural background) of other prospective partners (Charles and Kline, 2006).

The incentive to save travelling costs has been touted as a prominent carpooling motivator (Canning *et al.*, 2010; Deloach and Tiemann, 2011; Horowitz and Sheth, 1978), driven by the growing costs of travelling in SOVs (Washbrook, Haider and Jaccard, 2006). The desire to ease road congestion has also been studied as a motivator (Collura, 1994; Tischer and Dobson, 1979), suggesting that people may use local or even global environmental-ethical frames to socially construct their rationales. Likewise, intentions to reduce carbon footprints are important carpooling drivers (Canning *et al.*, 2010), with the British Social Attitude Survey (2012) reporting that 55% of respondents admit they should reduce car travel for environmental reasons. These are relevant as environmental attitudes are found to be positively linked with the willingness to change (Kilbourne, Beckmann and Thelen, 2002).

Ozanne and Mollenkopf (1999) have tried to explain carpooling decisions with psychological theories of behavioural change, such as Ajzen and Fishbein's (1975) Theory of Reasoned Action and Azjen's (1985) Theory of Planned Behaviour. In general terms, the Theory of Reasoned Action explains that a person's behaviour can be predicted by the degree of his/her beliefs that the behaviour: *(i)* would lead to a positive outcome; and *(ii)* would be approved by persons who are significant to him/her. The Theory of Planned Behaviour extends this concept to include perceived behavioural control as a predictor; i.e., an individual's willingness to perform a behaviour is also determined by the degree of their beliefs that they have control to perform the behaviour at will. Apart from this work, however, there is a lack of literature linking underlying psychological theories to carpooling. A possible reason for this absence of psychological theory in the carpooling literature could be that the majority of research in this area is empirically rather than theoretically driven. Hence, it would be useful to borrow models from related domains to explain carpooling; for example, in the literature on the decision to drive (rather than on carpooling behaviour), several psychological models were adapted, including Schwartz's (1977) Norm Activation model (Klöckner and Matthies, 2004) and Triandis's (1977) Theory of Interpersonal Behaviour (Lanken et al 1994; see Gardner and Abraham, 2007). Car-use motivation researchers have utilised Dittmar's (1992) model of material possession to discover that affective (emotive) and symbolic (status) motivations play a larger role than instrumental (functional) reasons in the commuter's decision to drive (Lois and López-Sáez, 2009; Steg, 2005); this implies that psychological reasons could impair on the commuter's judgment to be economically rational when choosing their travel mode. If this irrationally extends to carpooling, then it could be described by the classic 'Prisoner's Dilemma' problem from game theory: individuals would prefer to drive alone and bear the full travel costs and commute stress, rather than to secure a better payoff (shared travel costs and driving duties) by cooperating with other commuters to form a carpool. In other words, utilitarian incentives do not guarantee a mode switch in commuters; if interventions are to be effective, they must originate from a solid understanding of the underpinning psychological theories behind the decision to carpool (Gardner and Abraham, 2007).

2.4.4 Intervention

Drawing from the previous section, carpooling interventions could be planned according to the commuters' motivations. In co-operative behaviour research, punishments are thought to be more effective than rewards in deterring selfish behaviour (Andreoni, Harbaugh and Vesterlund, 2003). Carpooling studies tend to agree that 'sticks' such as extra parking charges for SOVs, are more effective motivators than 'carrots' such as reserved parking and partner matching services (Hwang and Giuliano, 1990; Jakobsson, Fujii and Gärling, 2002). However, commentators (Baldassare, Ryan and Katz, 1998; Giuliano, Hwang and Wachs, 1993; Möser and Bamberg, 2008) warned that sticks are resented by those affected and are therefore politically risky for policy makers; thus carrots are preferred.

One instance where carpooling was mandated was during the implementation of California's Regulation XV in the late 1980s and early 1990s. Employers were required to reduce the number of vehicles traveling to the work place; depending on geographic area, employers must achieve average vehicle ridership (AVR) targets between 1.3 – 1.75, by conducting various trip reduction schemes, including carpooling (Dill, 1998; Giuliano, Hwang and Wachs, 1993). Although Giuliano, Hwang and Wachs (1993) reported early success of increased AVR, Regulation XV was opposed by businesses and employees, and was ultimately dismissed by Senate Bill 437 in 1995 (Dill, 1998). Dill (1998) identified the reasons behind the failure of this mandatory employer-based trip reduction scheme as, among others, issues with problem definition, assessment of targets and results, and the implementation process.

Nevertheless, Collura (1994) described the workplace as an opportune setting for encouraging carpooling because (i) both employers and employees are motivated due to parking pressures; (ii) employers can act as facilitators; and (iii) there is access to potential participants. On the latter, (Ferguson, 1995) noted that larger firms tend to have higher carpooling propensity due to the large amount of employees; having a large pool of potential carpoolers to choose from is a major factor in carpooling success (Kaufman, 2002; Teal, 1987). Furthermore, it is more convenient to form carpools with co-workers who share the same regular work schedule (Buliung *et al.*, 2010) since the inflexibilities of carpooling member's schedules are found to be a deterrent (Morency, 2007). Ergo, 'flexitime' working schedules are seen to deter carpooling, although Habib, Tian and Zaman (2011) noted that flexitime can motivate carpooling if the commuter has already included carpooling as a choice in their travelling decision.

To overcome concerns regarding the inconvenience of carpooling especially during emergencies (Morency, 2007), some workplace schemes offer a 'guaranteed ride home' by reimbursing the carpooler's travel expenses (for e.g., taxi fare) if the carpooler has to leave for home outside the pre-determined time. Studies (Giuliano, Hwang and Wachs, 1993; Kingham, Dickinson and Copsey, 2001; Menczer, 2007; Rye, 1999) found that this guarantee leads to more carpooling, although Hwang and Giuliano (1990) doubted its effectiveness, describing such schemes as not significantly correlated to increased carpooling (Mcclelland *et al.*, 1981). In terms of marketing, Meyer (1999) suggested that transport policies which emphasises the cost of a SOV are effective in getting commuters to change travelling behaviours. Shoup (1997) found that cash incentives are more attractive and effective to carpoolers as compared to parking discounts. Canning *et al.* (2010) found that carpoolers are motivated by preferential parking only where a shortage of parking exists. High Occupancy Vehicle (HOV) lanes, priority lanes reserved for carpoolers, were found to offer only small travel time savings - which are not enticing to carpoolers (Kwon and Varaiya, 2008; Washbrook, Haider and Jaccard, 2006). Furthermore, HOV lanes require significant effort to implement and maintain; for the lanes to be successful, investment is required for regional coordination, enforcement, monitoring, and marketing (Chan and Shaheen, 2012).

Another useful intervention is a carpooler matching service. Levin (1982) noted that the practicality of finding carpool partners is an important factor in carpool formation. In this aspect, new developments in internet-based applications offer the opportunity for dynamic carpooling arrangements (Agatz *et al.*, 2012). The maturing of internet adoption allows internet-based carpooling platforms to grow; for example Blablacar.com claimed to have around 10 million verified members as of March 2015. By not limiting oneself to the same partner(s), online matching services can overcome problems with schedule inflexibility.

2.5 Driving motivations

Policy makers should incorporate the factors above in the planning of effective carpooling interventions, with the caveat that some of the factors could be proxies to other underlying determinants. Crucially, any intervention introduced should correspond to the causal reasons behind these factors to ensure that the intervention directly address the travel demands and concerns of the commuter (Gardner and Abraham, 2007; Steg, 2005). One possible avenue to understand this causal process is to investigate the root cause, by exploring the travel choice motivations of current drivers (i.e. why do individuals chose driving as a travel mode in the first place?). Indeed, as a starting point, several travel demand management researchers incorporated the drivers' motivations in their studies of sustainable alternatives, for example with public transportation, cycling and walking (Beirão and Sarsfield Cabral, 2007; Gatersleben and Uzzell, 2007; Redman *et al.*, 2013; Spinney, 2009). It is somewhat surprising that there is a lack of carpooling studies which focus on drivers instead of passengers (Ciari and Axhausen, 2011; Correia and Viegas, 2011; Deloach and Tiemann, 2011). Focussing on drivers is sensible; since the objective is to reduce the number of SOV on the road, drivers are the ideal target to be converted to carpoolers. Persuading other travel groups to switch to carpooling will not reduce SOV use, and in some cases, may unwittingly cause them to travel more unsustainably than before; for example, asking a group of walkers or cyclist to form a carpool will necessitate an additional automobile vehicle.

So what causes commuters to drive over other travel modes? Some car-use motivation studies examined the macro environment of the driver (such as the land use mix, accessibility to railway stations and urban characteristics) but these were found to have weak influence over their decision to drive (Choi and Ahn, 2015; Crane and Crepeau, 1998; Suzuki and Muromachi, 2009). In studies which examined drivers at the individual level, instrumental reasons were proclaimed as a main motivator to drive (see Jakobsson, 2007). Instrumental reasons refer to the practicality functions of the car to the driver; for instance, reasonable cost, high flexibility, faster travel, commute with comfort, and for carrying goods (Axhausen and Garling, 1992; Bamberg and Schmidt, 2001; Bhat and Koppelman, 1999; Jakobsson, Fujii and Gärling, 2002; Kingham, Dickinson and Copsey, 2001). Here, commuters were assumed to be rational; they will aim to maximise their utility by making travel mode choices solely based on instrumental considerations (Golob and Beckmann, 1971). This assumption was disputed by subsequent studies (Mokhtarian and Salomon, 2001; Steg, 2005; Steg, Vlek and Slotegraaf, 2001). By applying Dittmar's (1992) model for material possession, Steg, Vlek and Slotegraaf (2001) hypothesised that on top of instrumental reasons, symbolic and affective values are car-use determinants too. Symbolic values refer to the identity or social status which the car-user wishes to exhibit through association with his/her car (Allen, 2002); for example, driving an expensive sports car can be the drivers' way of expressing his/her wealthy image (Mann and Abraham, 2006). Affective factors relate to the emotions induced by driving or car-ownership (Russell and Lanius, 1984); for example, exhilaration caused by speeding (Steg, 2005), the pleasures of enjoying the scenery (Mokhtarian and Salomon, 2001), and the power of being in control (Stradling, Meadows and Beatty, 2001). In later studies, affective and symbolic factors were noted to be stronger than the instrumental reasons for car-use. (Lois and López-Sáez, 2009; Redman *et al.*, 2013; Steg, 2005). Anable and Gatersleben (2005) found that the journey purpose will influence the relative importance of the instrumental and affective factors; work commutes were more likely to be motivated by instrumental reasons, while affective factors were given higher attachments to leisure trips. In exploring the relationship between the affective, symbolic and instrumental factors, Steg and Tertoolen (1999) proposed a theoretical framework, where car-use motivations were the result of the three factors, with affective values also being the consequences of instrumental and symbolic factors. Lois and López-Sáez (2009) partially verified this model empirically, with the exception that the symbolic and instrumental factors were only indirectly related to car-use through their relationship via the affective factor.

2.6 Statistical methods in carpooling

Nijkamp and Blaas (2012) categorised approaches to analyse transport policies by whether they are based on quantified data (also labelled as the 'structured approach'), or expert judgments and direct interviews. The former is the focus of this thesis due to its reliance on statistical tests and empirical data. Within the structured approach, the prevailing methods applied by the carpooling literature are the revealed preference and stated preference models. The revealed preference model is based on direct observations of the commuter's travel behaviour, i.e., the commuter's preference to carpool is determined by their actual participation in a carpool (Buliung *et al.*, 2009; Cline, Sparks and Eschbach, 2009; Ferguson, 1997). Typically, logistic regression models would be used to investigate the influence of factors in encouraging carpooling. Meanwhile, the stated preference method is based on hypothetical travel mode choice scenarios put forward to the commuter; the commuter's preference to carpool is determined by their ranking of scenarios involving carpooling over other non-carpooling scenarios (Ciari and Axhausen, 2011; Correia and Viegas, 2011; Washbrook, Haider and Jaccard, 2006). Generally, these are analysed via non-metric regression techniques which are suitable for rank order data (Kroes and Sheldon, 1988). Both methods have their respective merits and limitations. Mainly, stated preference is more flexible as it can account for scenarios which the respondents were unaware of, including conditions which are yet to exist (Hensher, 1994). For example, a person may choose to carpool if parking discounts were offered, but if there were no discounts in reality, no consideration would be given to this factor by the respondent and hence this could not be tested by the revealed preference method. However, unlike stated preference, revealed preference directly addresses the "walk-the-talk" question (Nijkamp and Blaas, 2012; Wardman, 1988): would respondents who *said* they would carpool, actually go on to carpool?

The statistical methods applied in this thesis, namely meta-analysis, multidimensional scaling, structural equation modelling and multilevel modelling, were not employed in the spirit of competitiveness to 'outperform' the methods above or those already employed in the carpooling literature. Rather, the objective is to complement them; meta-analysis recognises the ability of the abovementioned methods to measure carpooling factors, by synthesising and reporting their results. Multidimensional scaling, structural equation modelling and multilevel modelling are means to explore the relationships of these carpooling factors with other variables. Further discussions on the justification and limitation of the methods applied in this thesis can be found in their respective chapters.

2.7 Chapter summary

In summarising the literature, the carpooling field is rich in studies but doubts remain about the generalisability of the results, making it difficult for policy makers to translate the findings into practice. Researchers now need to reallocate future effort more efficiently by focussing less on factors with effect sizes which have been largely agreed, to concentrate more on factors with effect sizes which requires further confirmation and more detailed interrogation. **Chapter 3** presents meta-analysis as a method to quantitatively synthesis the findings from the carpooling literature, thus addressing these issues.

It was also found that there is a lack of studies which empirically addressed the relationship between driving motivation and carpool participation. Given the calls within the travel demand management literature body for further investigation in the antecedent factors of carpooling, it is interesting that the relationship between driving motivation and carpooling is understudied. This link will be examined later in **Chapter 4, Chapter 5, Chapter 6** and **Chapter 7** by multidimensional scaling, structural equation modelling and multilevel modelling.

Chapter 3: Meta-analysis – Methodology, Results and Discussions

3.1 Overview

This chapter will explain the meta-analysis methodology to answer the first research question:

"What are the key factors influencing the commuter's decision to participate in a non-household carpool, and their effect sizes?"

The chapter will report on the results, discussions and conclusions of this study.

3.2 Meta-analysis in carpooling research

Meta-analysis is used to assimilate independent studies which address the same research questions; this is achieved by collecting summary statistics from each study, such as correlation coefficients, and combining the results to produce an effect size (Hunter and Schmidt, 2004). The goal is to provide a quantitative review of existing empirical evidence. To some extent this reduces the reviewer-bias associated with traditional narrative reviews, such as discriminative weightings of studies and misinterpretation of findings (Wolf, 1986). A meta-analysis allows comparison of the similarities and differences of findings of individual studies; and the identification of conflicting findings. Leck (2006, p.44) described the advantage of meta-analysis in painting a general picture of the literature:

'... by accumulating results across studies, one can enlarge the sample size of the research, gain a more accurate representation of the population relationship and a higher statistical significance than one achieved in a single underlying study.'

Furthermore, as the research objective is to advise policymakers on how to encourage carpooling, a quantitative systematic review of the literature is suitable for this purpose, keeping in mind that it is insufficient for policy decisions to be inferred from any single experiments (Hedges and Olkin, 1985). In addition, two studies with lower statistical significance may be in combination, more powerful than a single study with higher statistical significance (Rosenthal and Di Matteo, 2001).

Meta-analysis has been widely used in the areas of psychological studies, clinical trials and medicine science. To the best of the author's knowledge, there is no published meta-analysis on carpooling factors to date. The most relevant meta-analyses the author could find in this area are from Möser and Bamberg (2008) and Graham-Rowe *et al.* (2011), which examine 'soft' transport policy measures and concentrate on car use reduction rather than carpooling. In both studies, the authors experienced difficulties with their data. Möser and Bamberg (2008) used government reports and largely ignored commercial data in their study, claiming that these were published by transportation consultants with a financial interest in reporting positive results. Nevertheless Wall *et al.* (2011) criticised the inaccuracy of Möser and Bamberg (2008) government data, highlighting problems such as inappropriate sample sizes. Meanwhile, Graham-Rowe *et al.* (2011) complained that their study were not able to carry out a meta-analysis due to lack of methodological sound data (only 12 out of 77 evaluations in the study were considered 'methodologically strong').

However, meta-analysis is not without its pitfalls. A main criticism of meta-analysis is whether it is appropriate to combine results from studies of different characteristics ('apples and orange'). As mentioned earlier, varying contextual effects of individual studies may influence the results of some of the carpooling factors. This study tried to control for this bias by (i) excluding studies where these confounders are present (such as in Giuliano, Hwang and Wachs (1993) which is influenced by California's Regulation XV); (ii) providing background information on the studies in this meta-analysis; and (iii) account for these contextual factors through moderator analysis (see next sections). Answering this criticism, Borenstein *et al.* (2009) stated that meta-analysis is meant to answer the broader research questions than individual studies. Rosenthal and Di

Matteo (2001) argued that in fact studies of the same characteristics will have restricted generalisability; if the goal is to generalise about fruit, then mixing ‘apples’ and ‘oranges’ is necessary.

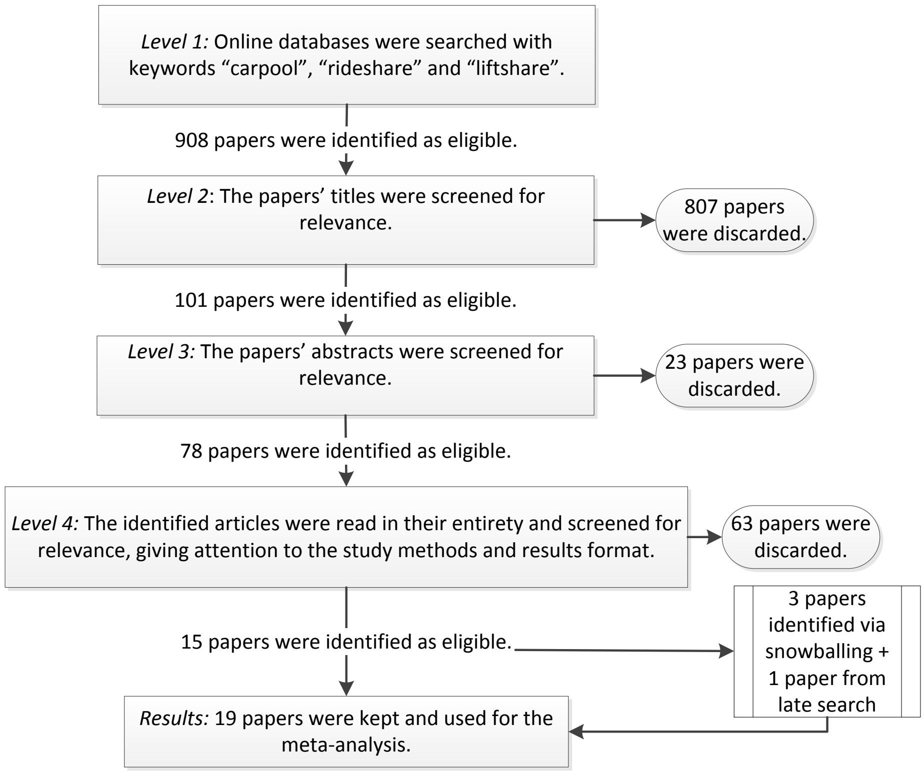
3.3 The meta-analysis process

3.3.1 Literature search strategy

To be included in the meta-analysis, studies must be on non-household carpools (household carpools and fampools are excluded) and have to satisfy one of the following criteria: (i) report carpooling interventions; (ii) include behavioural-change measures; or (iii) examine carpooling preferences. This excluded studies which used follow-up datasets as these are considered to be duplicates.

The search strategy is explained in **Figure 3.** Studies were searched using carpooling related search keywords on three online databases which were believe to cover the literature on transportation research (Web of Knowledge, Science Direct and Transportation Research Information Services).

Figure 3: Literature search strategy flow chart



Starting with 908 papers, the elimination process narrowed the search to 15 relevant papers with published results which could be inputted into the meta-analysis. Additionally, a snowballing literature search method was employed on these papers to further identify another three relevant studies. Systematic reviews and meta-analyses on transportation demand management, particularly the Graham-Rowe *et al.* (2011) and Möser and Bamberg (2008) studies, were also consulted to check for missing relevant studies. Also, unpublished masters and doctoral thesis were considered for inclusion; these were searched via the Open Thesis database and also through dissertations which were known to the authors. A late search was carried out during the revision stages of this study to ensure that newer studies are included in the analysis.

The required summary statistics from eligible studies were collected, namely: the carpooling factors from each study (factors which influence the probability of a commuter to choose carpooling as a travel mode), the correlation coefficient of each factor with carpooling, and the sample size of the study, *N* (number of travel mode choices made by all individual respondents in each study: *N* equals to the total number of respondents in most studies where only one travel mode choice was recorded per individual; but in stated preference survey studies with repeated observations where each respondent is asked about their travel mode choice in more than one scenario, N equals to the total number of scenarios answered by all respondents). Other information such as Z-scores, odds-ratio, standard deviations, means, t-values and p-values were also noted, and where appropriate, transformed into *Pearson's r* for consistency. The information were collated and arranged according to the carpooling factors.

19 papers (with 22 datasets) were selected (see **Table 4);** this is a relatively small pool of evidence for a meta-analysis, but is not unusual (see Gardner and Abraham, 2008; Gooding and Tarrier, 2009). To provide some context of the popularity of carpooling in these studies, the proportion of carpoolers within their respective sample or population was reported; driving alone was the main travel mode of the population in all studies. Most studies recruited samples that consisted of drivers and non-drivers (passengers and commuters), except for studies 5, 7, 14 and 20 which examined drivers only. In terms of the carpooling role, all studies (except for Ciari and Axhausen (2011)) do not discriminate nor specify whether the carpooler should be the driver, passenger or have shared duties. This could be problematic, as the influence of certain factors on carpooling uptake may depend on whether the participant is a driver or passenger. Thus, this meta-analysis can only claim that the factors affect participation in a carpool, but the study is unable to make conclusions on the factors' effects on a specific carpooling role. In the case of Ciari and Axhausen (2011), only "travel time" was modelled separately for carpool passengers and drivers; in the synthesis the researcher tried both passenger and driver effect sizes, and found that the difference to the travel time effect size is minimal and negligible ($r = 0.001$).

Table 4: Selected studies for meta-analysis

Ref	**Study**	***N***	**Study outcomes and details**	**Carpoolers in the study**[3]	**Location**
1	*Abrahamse and Keall (2012)*	634	Retrospective self-reported commute mode choice and beliefs about carpooling for work carpools.	12.20% of sample	New Zealand
2	*Brownstone and Golob (1992)*	1,904	Ordered probit discrete choice modelling of commuters' mode choice to work estimated from travel survey data; followed by simulation of carpooling policies.	17.14% of sample	US
3	*Buliung et al. (2010)*	613	Logistic regression analysis of carpooler's data from online carpooling matching program for work carpools.	15.40% of population	Canada
4	*Canning et al. (2010)*	895	Case studies of formal work place carpool schemes.	7.60% of population	UK
5	*Ciari and Axhausen (2011)*	5,885	Stated preferences of commuters' acceptance of carpooling.	27% of sample	Switzerland
6	*Cools et al. (2013)*	662	Logistic regression analysis of Flemish household travel survey.	11.27% of sample	Belgium
7	*Correia and Viegas (2011)*	996	Stated preference experiments of commuter's acceptance of carpooling.	47% of sample	Portugal
8	*Daniels (1981: study A)*	214	Case study of carpooling behaviour to work.	36% of sample	UK
9	*Daniels (1981: study B)*	174	*Ibid.*	36% of sample	UK
10	*Daniels (1981: study C)*	159	*Ibid.*	36% of sample	UK
11	*Daniels (1981: study D)*	1,051	*Ibid.*	36% of sample	UK
12	*Deloach and Tiemann (2011)*	13,615	Self-reported commuters' mode choice from the American Time Use Survey.	7.46% of sample	US
13	*Ferguson (1997)*	19,558	Retrospective self-reported commute mode choice with US census data.	5.87% of sample	US
14	*Giuliano, Levine and Teal (1990)*	1,041	Comparison of carpooling rate of HOV lane with control group for work commutes.	23.72% of sample	US
15	*Habib, Tian and Zaman (2011)*	13,522	Hybrid modelling of carpooling as a mode choice in the overall commuter mode choice to work.	9.30% of sample	Canada
16	*Koppelman, Bhat and Schofer (1993)*	951	Retrospective self-reported work trip mode choice; followed up with prospective stated-preference experiments.	18% of sample	US
17	*Su and Zhou (2012)*	6,234	Nested logit modelling of the impact of parking, financial subsidies and HOV intervention on commuters' mode choice to work.	13.57% of sample	US
18	*Techanakamron (2011)*	2,284	Survey of carpooling beliefs of university students and employees.	5% of sample	UK
19	*Vanoutrive et al. (2012)*	7,460	Multilevel regression model to predict carpooling at large workplaces based on location, organisation type, and promotion measures.	3.31% of sample and 12.3% of population	Belgium
20	*Washbrook, Haider and Jaccard (2006)*	529	Discrete choice experiments of prospective commuters' mode choice to work; followed by predictive modelling of commuters' response to interventions.	15% of sample	Canada
21	*Willson (1992)*	713	Multinomial logit model examining the effect of employer-paid parking on parking demand and commute mode choice to work.	15% of sample	US

[3] The "Carpoolers in the study" column provides the reader an indicative overview of the "popularity" of carpooling in the context of where the study took place; this is reported in the same format as it was conveyed in each study. For e.g., study 1 reported that the proportion of carpoolers in their study sample is 12.20%, while study 3 (which did not state how many people in their study are carpoolers) reported that 15.40% of the population of Canadian commuters are carpoolers.

Ref	**Study**	***N***	**Study outcomes and details**	**Carpoolers in the study**[3]	**Location**
22	*Zhou (2012)*	508	Self-reported travel survey of university students.	8.50% of sample	US
	Total *N*	**79,602**			

3.3.2 Effect size calculations

There are two widely-used meta-analysis models in the literature: the fixed-effects method, which assumes a fixed population (Hedges and Olkin, 1985); or the random-effects method, which assumes a variable population (Hunter and Schmidt, 2004). The fixed-effect model assumes that the effect sizes across the studies are homogenous, and variability in the effect sizes is caused solely by within-study variability (i.e. sampling error, which will exist in all studies due to the use of different samples). Meanwhile, the random-effect model assumes that the average effect sizes are heterogeneous, and variability in effect sizes are caused by within-study and between-study variability (such as difference in research design, sample profile, and methodology quality).

To choose the appropriate model, we must consider the sources of variability and whether the meta-analysis aims to generalise the findings beyond the population of the collected studies; if so, a random-effects model should be used, and vice versa (Field, 2001). Scholars have argued that (ideally) a random-effects model should be preferred over the fixed-effects model because it is highly unlikely that between-studies variability do not exist (NRC 1992; Hunter and Schmidt 2000; see Field, 2001). Theoretically, the meta-analysis which covered studies from 7 different countries over a span of 31 years is vulnerable to between-studies variability due to differing cultures (national and gender), economic environments, transportation standards, and legislations.

A Q-test (see Cochran, 1954) can be conducted to confirm or reject the homogeneity of the studies (Hedges and Olkin, 1985). The Q-statistic can be defined as follows:

Equation 1: Q-statistic

$$Q = \sum w_i \, (z_i - \bar{z})^2$$

Where w_i is the weighting factor for study *i;*

z_i is the Fisher (1948) *r*-to-*z* transformed effect size reported in study *i;* and

$\bar{z}$ is the effect size for the fixed-effects model (this is defined in **Equation 3**).

If the Q-statistic was found to be not significant, we cannot reject the homogeneity assumption and should apply the fixed-effects model. Likewise, if the Q-statistic was found to be significant, we can reject the homogeneity assumption and apply the random-effects model. In this case, most of the effect sizes are heterogeneous as the Q-tests showed that the effect sizes for 20 out of 24 factors are statistically significant ($p < 0.001$). The fixed-effects model's assumption of the studies representing a fixed-population is not satisfied for most of the factors, thus a random effects model is a more appropriate method to estimate effect sizes. In the present study, a varied effect size was assumed for the collected studies, and a random-effects model was used (Hunter and Schmidt, 2004).

Next, the effect sizes of each carpooling factor are to be estimated. The effect size tells us the strength of a factor in influencing carpooling uptake. A positive effect size indicates that the factor increases the likelihood of carpooling, while a negative value suggests the opposite. Following the random-effects model, the sample-sized weighted mean effect size, $\bar{r}$, for each carpooling factor can be estimated by (Hunter and Schmidt, 2004):

Equation 2: Sample-sized weighted mean effect size (random-effects model)

$$\bar{r} = \frac{\sum_{i=1}^{k} n_i r_i}{\sum_{i=1}^{k} n_i}$$

Where k is the number of studies synthesised per carpooling factor;

n_i is the sample size of study *i;* and

r_i is the effect size reported in study *i.*

However, it has to be acknowledged that five factors (one-fifth of the total factors) were found by the Q-test to be homogeneous ($p>0.001$); hence following other meta-analysts (Möser and Bamberg, 2008), this study also report the effect sizes of the fixed-effects model, $\bar{z}$ (Hedges and Olkin, 1985), which is derived by:

Equation 3: Effect size (fixed-effects model)

$$\bar{z} = \frac{\sum_{i=1}^{k}(n_i - 3)z_i}{\sum_{i=1}^{k}(n_i - 3)}$$

Where k is the number of studies synthesised per carpooling factor;

n_i is the sample size of study *i;* and

z_i is the Fisher (1948) *r*-to-*z* transformed effect size reported in study *i.*

In line with common practice in meta-analyses, this study also reported the generalisability of individual effect sizes across studies with credibility variance (CrV) and the variability of the mean effect size with confidence intervals (CoI) (Dieckmann, Malle and Bodner, 2009). This study reported the confidence intervals at the 95% level and the credibility variance at the 80% level. If the upper and lower bounds of the confidence interval do not overlap with zero, we can be 95% confident of the direction of the mean effect size. If the 80% credibility variance is nonzero, this means that 90% (80% + 10% at the top/bottom end of the interval) of the individual studies' effect sizes fall within the same direction. In other words, an 80% credibility variance (which excludes zero) provides a reasonable level of assurance that 90% of the individual effect sizes will be in agreeance on whether a factor encourages or discourages carpooling uptake. The CrV interval at the 80% level is also consistent with the standards used by other meta-analysts (see Judge and Bono, 2001).

3.4 Results

The meta-analysis identified 24 factors examined by the carpooling literature (**Table 5**). The effect size and direction of each factor, which tells us the strength of that factor in influencing carpooling uptake among commuters, is listed under column r .

Table 5: Meta-analysis of carpooling factors

No	Factors	*k*	*N*	$\bar{z}$	$\bar{r}$	80% CrV_l	80% CrV_u	95% CoI_l	95% CoI_u	*Q-statistic*	Studies
Demographic factors											
1	Age (continuous)	6	35,952	-0.01	**-0.01**	-0.02	0.00	-0.01	0.00	4.14	*3, 6, 7, 12, 13, 22*
2	Female (dummy)	7	44,717	-0.04	-0.03	-0.35	0.30	-0.25	0.26	3,789.4*4	*2, 3, 5, 13, 15, 16, 18*
3	Income (continuous)	6	31,601	0.04	**0.03**	-0.15	0.21	-0.01	0.37	1,250.24*	*2, 3, 7, 12, 13, 16*
4	Number of people in household (discrete)	3	27,347	0.22	**0.22**	0.11	0.32	-0.01	0.29	214.24*	*2, 5, 13*
5	Marital status (dummy)	3	15,180	-0.04	**-0.04**	-0.34	0.26	-0.08	0.11	19.06*	*6, 7, 12*
6	University students (dummy)	2	1,504	0.03	**0.03**	-0.34	0.41	-0.22	0.21	16.32*	*7, 22*
7	Number of cars in household (discrete)	6	3,162	0.09	**0.09**	-0.08	0.27	0.02	0.23	38.17*	*3, 8, 9, 10, 11, 16*
Judgmental factors											
8	Saving money (ordinal)	4	3,093	0.07	**0.07**	-0.06	0.20	-0.07	0.18	36.50*	*1, 3, 4, 16*
9	Reduce congestion (ordinal)	2	8,094	0.08	**0.08**	0.07	0.09	0.00	0.12	2.40	*1, 19*
10	Reliability (ordinal)	2	6,836	-0.03	**-0.03**	-0.13	0.08	-0.13	0.19	22.11*	*5, 16*
Interventions											
11	Parking availability (ordinal)	4	9,979	-0.03	**-0.01**	-0.28	0.25	-0.44	0.25	583.63*	*1, 4, 7, 19*
12	Parking cost (continuous)	3	7,127	-0.06	**-0.06**	-0.13	0.02	0.00	-0.02	2.50	*5, 20, 21*
13	Finding potential partner (dummy)	4	23,900	-0.08	**-0.08**	-3.02	2.86	-0.41	0.50	3,460.66*	*1, 15, 18, 19*
14	Reserved parking (dummy)	3	77,772	-0.02	**0.03**	-0.45	0.52	-0.84	0.63	18,737.41*	*2, 15, 17*
15	Cost subsidy (continuous)	2	64,250	0.00	**0.00**	-0.01	0.02	-0.04	0.11	11.65	*2, 17*

No	Factors	k	N	$\bar{z}$	$\bar{r}$	80% CrV_l	80% CrV_u	95% CoI_l	95% CoI_u	*Q-statistic*	Studies
16	Guaranteed ride home (dummy)	6	88,512	0.05	**0.20**	-0.26	0.67	-0.09	0.11	632.87*	*2, 7, 15, 17, 18, 19*
17	HOV lane available (dummy)	3	3,558	0.21	**0.21**	-0.87	1.29	0.17	0.26	3.80*	*2, 3, 14*
Situational factors											
18	Fixed (regular) work schedule (dummy)	3	3,179	0.16	**0.15**	-0.07	0.38	-0.07	0.48	121.12*	*2, 3, 6*
19	Commute distance (continuous)	10	32,399	0.01	**0.01**	-0.59	0.61	-0.03	0.19	568.26*	*2, 5, 6, 8, 9, 10, 11, 13, 18, 22*
20	Time commuting (continuous)	11	39,247	0.01	**0.01**	-0.13	0.15	-0.04	0.13	543.07*	*1, 5, 7, 8, 9, 10, 11, 12, 15, 18, 21*
21	Travel cost[4] (continuous)	3	20,496	0.36	**0.32**	-0.23	0.87	-0.69	0.52	3,815.56*	*5, 7, 12*
22	Number of employees (continuous)	2	69,806	0.46	**0.42**	-0.12	0.95	0.14	0.83	1,915.55*	*17, 19*
23	Population density at home postcode (continuous)	4	41,733	0.02	**0.02**	-0.01	0.05	-0.02	0.05	29.62*	*12, 13, 17, 18*
24	Live in urban area (dummy)	4	34,448	-0.07	**-0.07**	-0.28	0.14	-0.22	0.21	862.16*	*3, 6, 12, 13*

Where k = number of studies; N= total sample size;
***$\bar{z}$=** mean effect size of a fixed-effects model; **$\bar{r}$**= mean corrected effect size of a random-effects model; CrV_l and CrV_u= lower and upper bounds of credibility variance; CoI_l and CoI_u= lower and upper bounds of confidence interval; Q= homogeneity measure; *p<0.001. Underlined values indicate nonzero variables which have been identified as relevant.*

Generalisability-wise, there were two factors which were nonzero at 80% credibility variance ("number of people in household" and "reduce congestion"). In terms of confidence intervals, three factors were found to be nonzero at the 95% level ("number of cars in household", "HOV lane available", and "number of employees").

3.4.1 Homogeneity test and moderator analysis

As mentioned earlier, the Q-test suggested that most of the factors consist of heterogeneous studies. This implies that within those factors, there exist studies which are atypical from the rest of the studies and therefore could be unsuitable for meta-analysis synthesis (Hunter and

[4] *Travel cost* is a variable which encompass the cost required by the individual to complete the commute, including: price of gasoline, parking, tolls, and public transport fares.

Schmidt, 2004). This irregularity may be due to a third factor, most likely associated to the characteristics of the study, for example, the year the study was conducted, the country of the target sample, or the quality of the methodology used.

To identify the presence and influence of this third factor, meta-analytic scholars tend to conduct moderator analyses, such as meta-regression (Dieckmann, Malle and Bodner, 2009). However, moderator analysis is only suitable for meta-analysis where there is a large sample size of studies, *k* (Gardner and Abraham, 2008). Thus, the present study, which reported a relatively small sample size (k = 22), requires a different approach. In car-use reduction meta-analyses, researchers eliminate the studies which exhibit outlier effect sizes within heterogeneous factors (Gardner and Abraham, 2008; Möser and Bamberg, 2008). This approach was adopted: studies which reported effect sizes beyond the 95% confidence intervals were considered as outliers and removed from analysis.

Table 6 reports the revised results. Removing outliers has caused the heterogeneity of 15 factors to be reduced considerably, with most factors achieving homogeneity at the level of $p > 0.001$[5]. Five factors remained heterogeneous ($p < 0.001$): “university students”, “reliability”, “fixed (regular) work schedule”, “travel cost”, and “number of employees”; their heterogeneity could be explained by differences in study characteristics: “university student” and “number of employees” could perhaps be explained by the cultural difference of the study locations, namely Portugal (Correia and Viegas, 2011) and Belgium (Vanoutrive *et al.*, 2012) with the USA (Su and Zhou, 2012; Zhou, 2012). For “reliability”, Ciari and Axhausen (2011) examined the no-show risk of the carpool member, while Koppelman, Bhat and Schofer (1993) looked at their punctuality. Heterogeneity in “travel cost” could be explained, again, by the country

[5] The less conventional critical value of 0.001 was used for p instead of the more conventional 0.05 because there were six factors which remained heterogeneous at the $p < 0.05$ level, but these factors achieved homogeneity at the $p<0.001$ level: “Number of people in household”, “”Saving money”, “Parking availability”, “Finding potential partner”, “Reserved parking” and “Time commuting”.

difference of Portugal (Correia and Viegas, 2011), USA (Deloach and Tiemann, 2011) and Switzerland (Ciari and Axhausen, 2011); but also, DeLoach and Tiemann's (2011) measure of travel cost is solely on gas prices, while Correia and Viegas (2011) included gas, tolls and parking. "Fixed (regular) work schedule" perhaps differ because of location or the time period gaps between the three studies (Brownstone and Golob, 1992; Buliung *et al.*, 2010; Cools *et al.*, 2013).

Table 6: Effect sizes after removal of outlier studies.

No	Factors	k	N	$\bar{z}$	$\bar{r}$	80% CrV_l	80% CrV_u	95% CoI_l	95% CoI_u	Q-statistic	Removed studies
	Demographic factors										
1	Age (continuous)	6	35,952	-0.01	-0.01	-0.02	0.00	-0.01	0.00	4.14	*None*
2	Female (dummy)	5	25,310	0.23	**0.22**	0.20	0.24	0.18	0.24	10.13	*5, 15*
3	Income (continuous)	5	30,605	0.00	**0.00**	-0.01	0.02	-0.02	0.02	0.30	*7*
4	Number of people in household (discrete)	2	7,789	0.08	**0.08**	0.07	0.09	0.05	0.11	1.49	*13*
5	Marital status (dummy)	2	1,658	0.06	0.06	-0.11	0.23	0.00	0.12	1.44	*12*
6	University students (dummy)	2	1,504	**0.03**	**0.03**	-0.34	0.41	-0.22	0.21	**16.32***	*None*
7	Number of cars in household (discrete)	5	2,211	0.16	**0.16**	0.11	0.21	0.00	0.09	2.28	*16*
	Judgmental factors										
8	Saving money (ordinal)	3	2,198	0.01	**0.01**	-0.05	0.06	-0.08	0.08	7.24	*4*
9	Reduce congestion (ordinal)	2	8,094	0.08	**0.08**	0.07	0.09	0.00	0.12	2.40	*None*
10	Reliability (ordinal)	2	6,836	**-0.03**	**-0.03**	-0.13	0.08	-0.13	0.19	**22.11***	*None*
	Interventions										
11	Parking availability (ordinal)	2	8,094	0.03	**0.03**	0.01	0.05	-0.03	0.13	3.75	*4, 7*
12	Parking cost (continuous)	3	7,127	-0.06	**-0.06**	-0.13	0.02	0.00	-0.02	2.50	*None*
13	Finding potential partner (dummy)	2	8,094	0.45	**0.42**	-1.84	2.68	0.35	0.59	0.05	15, 18
14	Reserved parking (dummy)	2	64,250	0.21	**0.20**	-0.01	0.42	0.15	0.23	3.98	*15*
15	Cost subsidy (continuous)	2	64,250	**0.00**	**0.00**	-0.01	0.02	-0.04	0.11	11.65	*None*
16	Guaranteed ride home (dummy)	2	63,342	0.08	**0.08**	0.04	0.11	0.05	0.13	2.06	*2, 15, 18, 19*
17	HOV lane available (dummy)	3	3,558	0.21	**0.21**	-0.87	1.29	0.17	0.26	3.80	*None*
	Situational factors										

No	Factors	k	N	$\bar{z}$	$\bar{r}$	80% CrV_l	80% CrV_u	95% CoI_l	95% CoI_u	Q-statistic	Removed studies
18	Fixed (regular) work schedule (dummy)	3	3,179	0.16	**0.15**	-0.07	0.38	-0.07	0.48	**121.12***	*None*
19	Commute distance (continuous)	5	21,061	0.03	**0.03**	-0.64	0.71	0.01	0.12	9.34	*2, 5, 8, 11, 18*
20	Time commuting (continuous)	5	28,183	0.01	**0.01**	-0.01	0.04	-0.01	0.06	15.55	*1, 5, 7, 8, 11, 18*
21	Travel cost (continuous)	3	20,496	**0.36**	**0.32**	-0.23	0.87	-0.69	0.52	**3,815.56***	*None*
22	Number of employees (continuous)	2	69,806	**0.46**	**0.42**	-0.12	0.95	0.14	0.83	**1,915.55***	*None*
23	Population density at home postcode (continuous)	3	28,118	0.00	**0.00**	-0.02	0.02	0.00	0.00	0.01	*12*
24	Live in urban area (dummy)	3	14,890	0.11	**0.11**	-0.07	0.28	0.01	0.14	7.63	*13*

Where k = number of studies; N= total sample size; $\bar{z}$*= mean effect size of a fixed-effects model;* $\bar{r}$*= mean corrected effect size; CrV_l and CrV_u= lower and upper bounds of credibility variance; CoI_l and CoI_u= lower and upper bounds of confidence interval; Q= homogeneity measure; *p<0.001. Underlined values indicate nonzero variables which have been identified as relevant.*

The revised effect sizes are as follow[6]:

Demographic factors

"Female" ($\bar{r}$= 0.22 [95% CoI: 0.18, 0.24]) reported a medium and positive effect size, implying that women are more likely to carpool than men. *"Age"* ($\bar{r}$ = -0.01 [95% CoI: -0.02, 0.00]) as a factor indicated almost zero influence on carpooling; however readers are cautioned on the interpretation of this result; age is a complex factor to explain, due to the variation of behaviour within different age groups in the sample. Such is the case in the study: from the 5 studies which explored age, the age of the sample ranged from 20 years old to 64 years old, with 2 studies failing to clarify their age profiles. Therefore, it is difficult to draw conclusions from the effects of any segmented age group on carpooling. It is possible that the younger age group exhibits an opposing effect to the older age group, thus cancelling out each other's effects (hence $\bar{r}$ is close to zero).

Judgmental factors

[6] In interpreting the effect size, the following definitions were adapted, as proposed in Cohen, J. (1992), 'Statistical Power Analysis', *Current Directions in Psychological Science,* Vol. 1, No. 3, pp. 98-101. Small effects are defined as -0.20< ρ < 0.20; medium as 0.20« ρ < 0.40 (or -0.40< ρ «-0.20); and large as ρ » 0.40 (or ρ «-0.40).

All motivation to carpool factors indicated small effect sizes, with the largest influencer being "reduce congestion" ($\bar{r}$= 0.08 [95% CoI: 0.00, 0.12]).

Intervention factors

Reserved parking ($\bar{r}$= 0.20, [95% CoI: 0.15, 0.23]) and HOV lanes ($\bar{r}$= 0.21 [95% CoI: 0.17, 0.26]) were found to increase the likelihood of carpooling. Interestingly, when surveyed about the attractiveness of partner matching programs in encouraging carpooling, respondents were sceptical of their effectiveness ($\bar{r}$= -0.34, [95% CoI: -0.37, -0.28]); yet in studies where such partner matching programs were already implemented, they were found to increase the number of carpoolers ($\bar{r}$= 0.42 [95% CoI: 0.35, 0.59]). All other intervention factors were found to have small effect sizes ($-0.1<\bar{r}<0.1$).

Situational factors

Employer size was the largest positive factor ($\bar{r}$= 0.42, [95% CoI: 0.14, 0.83]), while travelling costs ($\bar{r}$= 0.32, [95% CoI: -0.69, 0.52]), an employee's fixed (regular) work schedule ($\bar{r}$= 0.15, [95% CoI: -0.07, 0.48]) and live in urban area ($\bar{r}$= 0.11, [95% CoI: 0.01, 0.14]) were found to have moderate effects in encouraging carpooling. All other situational factors were found to have small effect sizes ($\bar{r}<0.1$).

3.5 Discussions

This study presents the following recommendations based on the results:

(i) *Targeting the right people*

Campaigns are best advised to strategically target groups which are more likely to carpool. The findings reveal the profile of this individual: female, in full-time employment with a fixed (regular) work schedule, and has vehicle ownership. Where in the past it was suggested that women are less likely to carpool than men due to their schedules being tied by household commitments (Ferguson, 1995; Rosenbloom and Burns, 1993), the results question this notion. A possible explanation comes from the economic psychology literature, which suggests women take stronger standpoints on ethical, environmental and pro-social behaviour as compared to men (Glover *et al.*, 1997). Linking this evidence with carpooling would require further research. The fixed schedule factor explains that full-time employees make reliable carpooling partners (Huang, Yang and Bell, 2000), as their matching and regular work hours lessen the inconvenience of one partner having to adjust his/her schedule for the other (Morency, 2007). Buliung *et al.* (2010) posits that people in households with additional number of cars are more determined to form a carpool to distribute the burden of the costs associated to car use and ownership.

(ii) *Marketing the benefits of carpooling*

The results showed that most of the motivation factors produced positive but small effect sizes. This suggests that the motivations explored in previous studies are not strong influencers in encouraging carpooling; yet, these factors are often touted in carpooling marketing materials. For example, in current campaigns, carpool organisers Blablacar.com focuses on promoting the cost-saving benefits, which recorded positive but small effect sizes in the results. The results imply that while these factors should not be abandoned, they should be used alongside other selling points with larger effects on carpooling decision.

The meta-analysis also points to a lack of psychological factors to synthesise empirically. One such factor which was found in the literature but had to be abandoned is "convenience", because it was unclear how the factor was defined in the studies (Gensch, 1981). Further research is needed to look at how commuters perceive convenience within the carpooling context, as "convenience" is simply a state of being able to do something without difficulty and so it can be perceived and understood differently depending on what action the respondent has in mind. Perhaps carpooling researchers could learn from the car-use literature: over the past decade, growing research found that psychological motivations (affective and symbolic factors) are stronger influencers of car-use than instrumental reasons (Lois and López-Sáez, 2009; Mokhtarian and

Salomon, 2001; Steg, 2005). This was not previously discovered because it is easier for drivers to justify environmentally-unfriendly travel choices with instrumental reasons, rather than symbolic and affective motivations (Steg, Vlek and Slotegraaf, 2001). This may also apply to carpooling. Future carpool psychology research needs to adapt the car-use research techniques to elicit honest responses from commuters (Mann and Abraham, 2006).

(iii) Partner matching programs

The implementation of a partner matching program, such as a searchable database of potential carpoolers, was found to be effective in promoting carpooling; this is promising news for research within the dynamic ridesharing domain. Yet, interestingly, non-carpoolers said they were less likely to carpool when asked if the introduction of a partner matching program would encourage them to do so. This discrepancy suggests perceptual differences among commuters in the effectiveness of certain factors, depending on whether they are currently carpooling or not. It may be useful for future research to explore the effectiveness of factors at different stages of the carpooling cycle: entrance level factors which convert non-carpoolers into carpoolers, maintenance level factors which encourage carpoolers to continue carpooling, and exit level factors which cause carpoolers to stop carpooling.

(iv) Creating larger pools of potential carpoolers (situational)

Carpooling uptake was seen to be more likely to occur at organisations with greater employee numbers (in relative terms, i.e., the ratio of carpoolers to total number of employees is higher for larger organisations); this in line with previous studies emphasising that a large pool of potential carpoolers is a major factor in carpooling success (Teal, 1987). Thus, organisations should look at ways to enlarge their pool of potential carpoolers. A possible solution is to combine their current pool with the databases of neighbouring organisations, forming an inter-organisational 'super-pool'. This could be most effective at industrial parks or business centres: since firms within the same industry are expected to cluster near each other (Howells and Bessant, 2012), it is likely that the 'super-pool' will contain individuals with similar occupations and cultures, providing the employees more matches with like-minded carpooling partners. A mediator, such as local government, may be useful in coordinating and encouraging such co-operative efforts among competing firms.

3.5.1 Limitations

Regrettably, the number of studies per factor in this meta-analysis is relatively small: the largest number of studies per factor is 11, while the smallest is two. This echoes the problems of finding 'methodologically strong' studies in transport demand management research reported in previous meta-analyses (Graham-Rowe *et al.*, 2011; Möser and Bamberg, 2008). During the literature search, 63 studies were eliminated because of failure to report compatible summary statistics in their results. In particular, most of these studies did not report the correlation coefficients of the carpooling factors. However, to alleviate any concerns about insufficient studies in this meta-analysis, the reader is reminded that two studies with lower statistical significance, in combination, may be more powerful than a single study with higher statistical significance; hence the meta-analysis of even just two studies can provide meaningful insights (Rosenthal and Di Matteo, 2001).

The small number of available studies meant that the meta-analysis had to inevitably rely on studies from different decades and countries; it is possible that for some factors, the meta-analysis had synthesised results from heterogeneous populations. For instance, government policies, transportation costs, gender roles and technology access differ between regions and time periods; yet these factors could influence commuter behaviour (Deloach and Tiemann, 2011). Hence caution is advised when generalising the results, particularly for the factors which remained heterogeneous.

3.6 Conclusions

The meta-analysis of 22 studies identified 24 carpooling factors, categorised into four dimensions: demographic, judgmental, intervention and situational factors. The results have three key implications. Firstly, they resolve earlier conflicting findings and provide a comprehensive list of factors for transport researchers interested in modelling carpooling activity. Secondly, they can help transportation practitioners plan policies which improve carpooling participation, specifically in the areas of determining the target demographics, developing selling points for marketing, identification of partner matching facilities as an efficient intervention, and the merging of employee database among neighbouring organisations to create a super-pool of potential carpoolers. Thirdly, this research provides evidence of the application of meta-analysis in informing policy-making in the transportation demand management field, an area which have relatively few meta-analyses.

The study unearthed a number of avenues for further research. The meta-analysis highlights a lack of studies within the carpooling literature which are methodologically appropriate for quantitative synthesis; future empirical studies should look at presenting their data in more standardised and compatible formats, especially in the reporting of summary statistics. Nevertheless, the table of effect sizes could be used to plan more efficient allocation of future research efforts: future experiments should move away from examining factors which were found by the majority of literature to have insignificant influence over carpooling decisions (for e.g., income, commuting time and population density); more importantly, future studies should focus on examining factors which have been found significant by a minority of studies (for e.g., number of employees and reserved parking for carpoolers). Also, future studies could use the results as inputs to inform policy evaluation research. For example, the effect sizes could be used to populate rate values in a system dynamics model to investigate carpooling uptake at a work site over time (for instance, the researcher can dictate the rate of increment in carpooling participation based on the rate of growth of the number of employees in the model; see Di Febbraro, Gattorna and Sacco (2013)). Likewise, researchers will be better informed when designing experiments intended to examine the multiple effects of various factors on carpooling.

3.7 Chapter summary

This chapter explained the meta-analysis methodology, including the literature search strategy and the effect size calculation methods for both the fixed-effects and random-effects models. 22 studies were selected for the meta-analysis. The results were presented and discussed, with recommendations provided for transportation policy planners and researchers. Thus, research questions 1 (carpooling factors' effect sizes) and 3 (policy recommendations) were answered in this chapter.

The meta-analysis study is concluded here. The next chapters will take on the carpooling challenge from a different angle, by addressing the second research question (on examining the link between driving motivations and carpooling).

Chapter 4: Multidimensional Scaling – Methodology and Results

4.1 Overview

Following the literature review section on carpooling and driving motivations **(Section 2.5),** this chapter (along with **Chapter 5, Chapter 6** and **Chapter 7**) will attempt to answer the second research question:

"How does the commuters' motivation to drive (as a travel mode) affects their acceptability to carpooling?"

Particularly, the multidimensional scaling procedure and results are presented in this chapter.

4.2 Introduction to multidimensional scaling

Multidimensional scaling (MDS) is a statistical method for identifying underlying themes in a dataset and has been widely applied in research domains such as psychology, finance, education, brand analytics, economics, biotechnology and project management, but has been rarely used in car-use research (Alvarez and Fournier, 2016; Chipulu *et al.*, 2013; Ding, 2016; Khoja, Chipulu and Jayasekera, 2014; Mar Molinero and Xie, 2007; Nakamura and Tomii, 2016; Yenilmez and Girginer, 2016). MDS accomplishes this by measuring the similarity (or dissimilarity) in the cases of a dataset, and grouping the cases which are similar to each other; this allows the researcher to form conclusions on the themes or characteristics which binds the similar cases together (and dissimilar cases apart). In the words of Kruskal and Wish (1978, p.5), MDS *"enables the researcher to uncover the "hidden structure" of data bases"* by providing an overview of the data from different angles. Mar Molinero and Xie (2007) explained how MDS works with an excellent analogy: it would be hard to identify a town merely by knowing its position on a north-south dimension; but a clearer picture could be painted by providing further characterisations (dimensions) such as the town's location on an east-west dimension, the town's altitude from sea level and even the town's annual rainfall levels. Putting this concept into practice, Chipulu *et al.* (2013) (for example) used MDS on a sample of job advertisements to identify the competencies demanded from employers of project managers, which could be described as industry-specific skills, project management knowledge, senior managerial skills, positive personal traits, project management methodology experience and risk management expertise.

There are two other advantages of MDS: firstly, MDS can incorporate qualitative data into quantitative analysis. Secondly, MDS can portray its results on visual maps, thus making the findings more accessible to non-specialists (Neophytou and Molinero, 2004). The former advantage is particularly relevant, as the data used in this study is of a qualitative format (as discussed in the next section).

4.3 Data and coding

To understand the factors which make people chose to drive to work; this study examined secondary data provided by the University of Southampton's Transport Team (UoSTT), a department which oversees operational transportation matters for the university's campuses in Hampshire, UK. The University of Southampton is one of Hampshire's largest employers, with *circa* 5000 staff and 23,500 students (of which *circa* 7,600 are postgraduates). The UoSTT has conducted an online travel survey in 2013 and have gathered 1170 responses from staff (89.15%) and postgraduate students (10.85%). As the dataset was secondary in nature, it was difficult to draw conclusions on the representativeness of the sample: firstly, demographic information, such as age or gender, were not collected. Secondly, there were no information provided on the response rate of the survey; hence it is hard to infer the characteristics of the individuals who did not respond. However, the dataset reported the respondents' occupational status (full-time staff/ part-time staff/ postgraduate student). From this, it was possible to estimate that the staff respondents represented *circa* 20.87% of the total number of staff, while the postgraduate student respondents represented *circa* 1.67% of the total number of postgraduate students.

Among the 1170 respondents, 423 individuals (full-time staff = 79.90%; part-time staff = 16.55%; postgraduate students = 3.55%) have identified "driving to university" as their main mode of travel (either in Single-Occupied Vehicles (SOV) (N = 356); or in carpools by driving with other passenger(s) (N = 67)). They have all also answered the following open-ended questions in the survey:

i. *If you drive, why is having access to a car important to you?*

ii. *What incentives would encourage you to try a different mode of travel?*

The qualitative nature of the responses is suitable for a MDS analysis. To ensure the data is transformed into an appropriate input format, the responses were coded into keywords using *QSR NVivo 10*. A pilot sample of 45 responses (roughly 10% of the total sample) underwent an initial stage of coding to identify common keywords; the keywords identified at this stage were used as a guide to code the rest of the sample. To capture the true intention of the respondents, keywords are named as closely as possible to the wordings submitted in the responses. Keywords were then labelled as "Motivation" (reason for car-use) or "Incentive" (incentives which would encourage a travel mode switch) variables. These would be then populated into a case (respondent) by variable (keyword) matrix, where each variable is binary-marked as "1" if the keyword is present in a case and "0" if it is absent.

4.4 MDS procedure

Next, the researcher builds a MDS model with *SPSS 21*, using the matrix from the previous section as the input. A key consideration for constructing the model is the number of dimensions to produce, to ensure goodness-of-fit. Here, the study adopts an 'elbow test' of normalised raw stress values (Cattell, 1966), followed by a model degeneracy test (see Chipulu *et al.*, 2013).

Once optimal dimensionality has been determined, the model is operated using the Russell and Rao similarity measure (Rao, 1948); while there is a number of similarity coefficient methods to select from, the Russell and Rao algorithm was chosen because firstly, it is appropriate for binary data (as is the case of our matrix) (Yin and Yasuda, 2005). Secondly, it measures similarity (and dissimilarity) by assigning equal weightings to keywords which are jointly present and jointly absent in each case. The measure can be defined as:

Equation 4: Russell and Rao similarity measure

$$RR\ (i,j) = \frac{a}{a+b+c+d}$$

Where for variable (keyword), *K, i* and *j* refer to two different cases (respondents) as demonstrated by the matrix in **Figure 4:**

Figure 4: Russell and Rao matrix

$$\begin{array}{cc|cc} & & \multicolumn{2}{c}{j} \\ & & 1 & 0 \\ \hline & 1 & a & b \\ i & & & \\ & 0 & c & d \end{array}$$

Where *a* is the number of *K* variables which are jointly present in both *i* and *j* case (1,1);

b is the number of *K* variables which are present in case *i* but absent in case *j* (1,0);

c is the number of *K* variables which are absent in case *i* but present in case *j* (0,1); and

d is the number of *K* variables which are jointly absent in both *i* and j cases (0,0).

The output is a list of final coordinates for the cases for each dimension, indicating the proximity of each case from one to another on each dimension. This will tell us how similar (or dissimilar) the drivers in the dataset are from each other, in each dimension. Finally, the study attempts to interpret the meaning of each dimension. Previous studies interpreted MDS dimensions by looking for common themes between variables located on the extreme sides of the dimension map axes (Mar Molinero and Xie, 2007), or examining the variables with coordinates having large absolute values (Chipulu *et al.*, 2013); the idea being that these variables are strongly associated thus representative of the dimension. However this can be a difficult process: it is hard to draw similarities between variables, especially in dimensions with many extreme variables. Even more challenging, the interpretation needs to portray the themes of the positive variables and negative variables on a dimension as 'opposites' (Kruskal and Wish, 1978).

This study adopts a different approach to make interpretation easier: we aim to keep the number of variables to interpret per dimension small, by only considering variables which are statistically significant (hence strongly associated) to that dimension. We ran multiple logistic regression models in *SAS 9.4*, treating the final coordinates of the dimensions, arranged in cases, as independent variables; and each "1" or "0" values for each "Motivation" and "Incentive" keyword as outputs. An estimated coefficient with large and positive values will mean that the drivers with large and positive values on that dimension are likely to mention that keyword. Likewise, a large and negative coefficient indicates that drivers with large and negative values on that dimension are likely to declare that keyword. The results are reported in section 4.5.

4.5 Results

From the UoSTT travel survey, we identified 43 keywords of the respondents' reason for car-use ("Motivation") and incentives that could persuade them to switch to other travel modes ("Incentive"). 11 outlier keywords (appeared in less than 1% of the data) were either removed or combined with other variables, leaving 32 keywords (see **Table 7**).

Table 7: Coded "Motivation" for car-use and "Incentive" to switch keywords

Keyword	Count	Count (%)	Description/examples
Nothing_inc	119	28	No incentive can persuade me to give up driving
Time	103	24	Saving travel time is important
PublicTransportImpracticalChanges	87	21	Public transport requires too many changes
SchoolRun	78	18	Dropping children off at school before work
CheaperPublicTransport_inc	61	14	I would use public transport if it was cheaper
LinkedTripsWork	52	12	I need my car to travel between work sites
PublicTransportUnavailable	48	11	No public transport goes to my workplace
Independence	46	11	I can drive anywhere and/or at any time I like
PublicTransportExpensive	44	10	Travelling by car because public transport is too expensive
Distance	42	10	Long travelling distance between home and work
IrregularWorkSchedule	38	9	Work start/end times vary
CycleScheme_inc	35	8	Incentivised by cycling schemes, for e.g., improved cycle routes
CostSubsidy_inc	34	8	I would give up car-use if my travel-expenses are subsidised
LinkedTripNonWork	32	8	Use the car after work for personal reasons, e.g., shopping, visiting friends etc.
PublicTransportDirect_inc	31	7	Would use public transport if no changes are required
PublicTransportRegular_inc	30	7	Would use public transport if frequency is more regular
Time_inc	25	6	Would give up driving if other travel modes can save time
Convenience	24	6	Travelling by car is convenient
PublicTransportInconvenientTimes	17	4	No public transport on my required times, or too irregular
Reliability_inc	17	4	Would give up driving if other travel modes are more reliable
CarpoolWithFamily	16	4	Carpooling with adult family member
ChildrenEmergency	16	4	Attend to children in times of emergency
CaringElderlyFamilyMember	15	4	Attend to elderly family member
FlexiTime_inc	14	3	Would give up driving if allowed to work flexible hours
Reliability	14	3	Car travel is reliable
Security_inc	10	2	Would give up driving if other travel modes are safer (traffic and personal)
MedicalReasons	9	2	Travel by car because of medical condition
CarpoolWithColleagues	8	2	Carpooling with co-workers
CarryEquipment	8	2	Need car to carry work equipment (e.g., laptop)
ParkAndRide_inc	7	2	Would consider other travel options if Park and Ride facility is provided.
Security	7	2	Security of travelling (e.g., traffic, alone at night, with children)
Weather	5	1	Bad weather forces me to travel by car

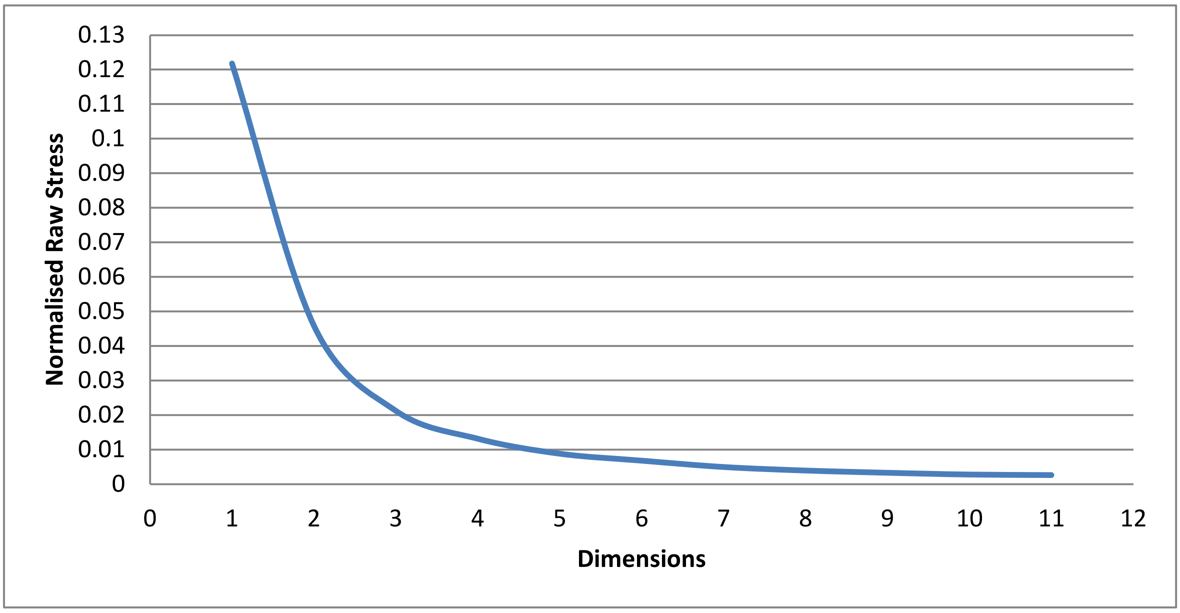
_inc denotes a "incentive to switch to other travel mode" keyword

The test to specify the optimum number of dimensions failed to produce an evident "elbow" in the scree plot of normalised raw stress values (

Figure 5), although this is not atypical of multidimensional studies (see Chipulu *et al.* (2013) and Khoja, Chipulu and Jayasekera (2014)). A large improvement of stress can be observed between dimensions 1 and 2. Stress improvement is smaller but still clear between dimensions 2 and 4. The gains are marginal between dimensions 4 and 6, and beyond 6 dimensions, improvements are very small (less than 0.002). MDS models are recognised to be a “good” fit when stress levels are at 0.05 and a “very good” fit at 0.01 (Kruskal and Wish, 1978). While stress levels for 6 or more dimensions indicated a fit above “very good”, higher dimensions are increasingly difficult to interpret as they may include residual variation (Neophytou and Molinero, 2004). Thus, the researcher decided to trade off higher dimensionality (with marginally better fit) with lower dimensionality (with higher interpretability); six dimensions were extracted to obtain a “very good” fit, but only the first four dimensions were interpreted as these are sufficient to explain the structure of the data.

A further degeneracy test justifies this decision: the sum-of-squares of DeSarbo’s Intermixedness Indices were 0.001 and Shepard’s Rough Nondegenaracy Index was 0.71, indicating that the model is unlikely to suffer degeneracy problems (Busing, Groenen and Heiser, 2005). Also, the model accounted for 80% of the variance at a normalised stress value of 0.03, signalling a good fit for the data.

Figure 5: Dimensionality of MDS Model's Goodness-of-fit



The MDS model produced a list of coordinates for the 32 variables on six dimensions; the coordinates of Dimensions 1, 2, 3 and 4 were plotted on two maps (see **Figure 6**) while the final two dimensions were dropped in the interest of interpretability. Running a logistic regression on these final coordinates case-wise produced the Maximum Likelihood Estimates displayed in **Table 8**, with the highly statistically significant variables highlighted.

Figure 6: **MDS configuration for Dimension 1 v. 2 and Dimension 3 v. 4**

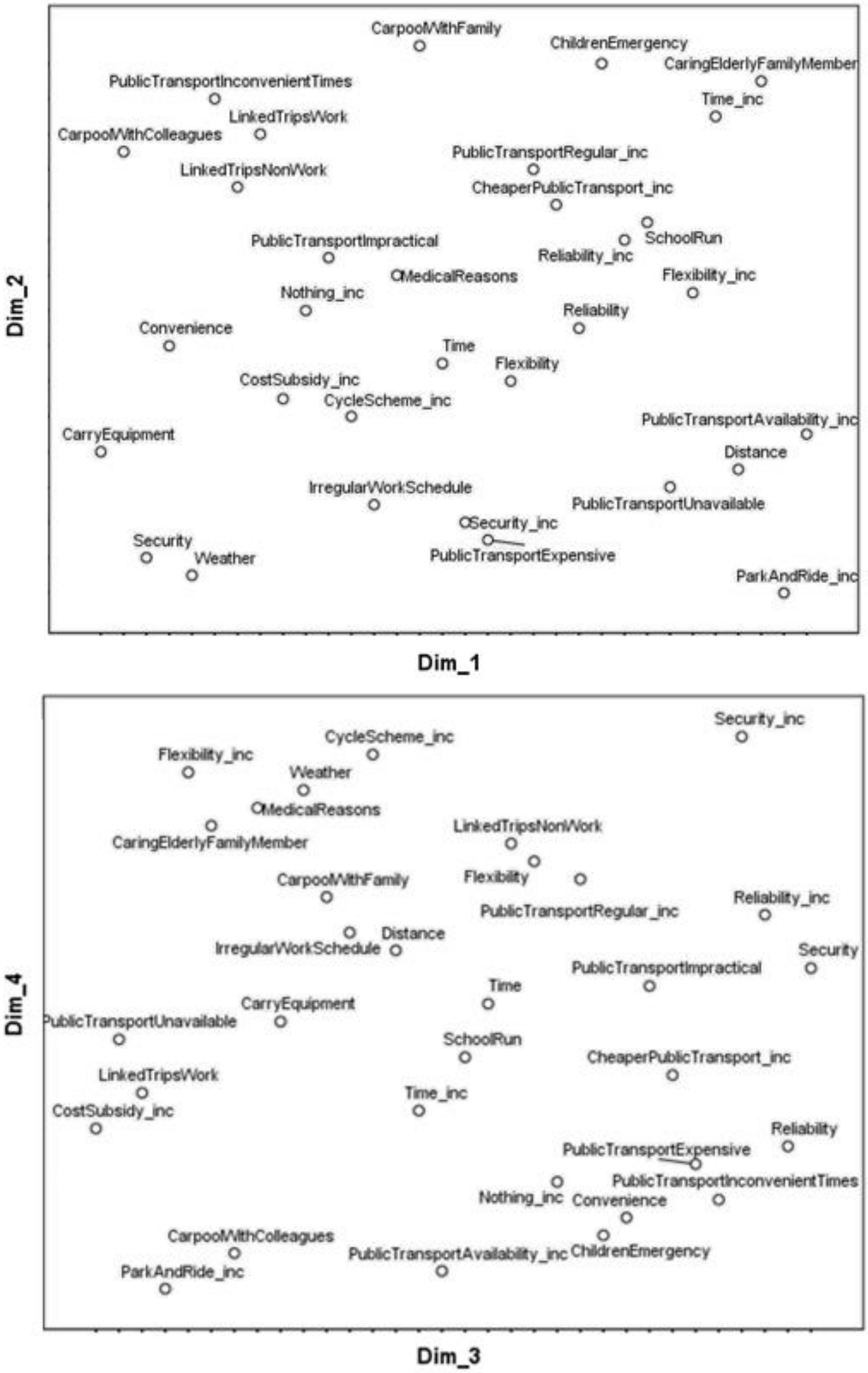


Table 8: Maximum likelihood estimates of the dimensions with "Motivation" and "Incentive" keywords.

Keywords	*R^2*	*Max-rescaled R^2*	*Intercept*	*Dim_1*	*Dim_2*	*Dim_3*	*Dim_4*	*Dim_5*	*Dim_6*
CaringElderly FamilyMember	0.03	0.03	-4.08***	**10.32***	1.57	-1.97	2.3	0.24	**-5.03***
CarpoolWith Colleagues	0.04	0.25	-5.5***	-0.02	0.91	6.55	**8.14***	-0.14	**-11.76****
CarpoolWith Family	0.03	0.10	-3.66***	2.54	2.48	-0.97	**-3.01***	2.72	-1.31
Carry Equipment	0.02	0.13	-4.47***	-0.09	-1.01	-1.06	-2.49	-2.22	**-6.44***
CheaperPublic Transport_inc	0.56	1.00	-71.94	54.09	53.07	-282.4	437.7	-0.14	88
Children Emergency	0.06	0.23	-4.22***	4.25	0.41	3.37	-3.62	**6.43***	-1.91
Convenience	0.01	0.04	-2.93***	0	1.45	-1.09	-1.11	1.04	-2.08
CostSubsidy_inc	0.09	0.21	-3.03***	-0.19	**3.2****	-1.36	**-4.33*****	0.78	**-5.59*****
CycleScheme_inc	0.41	0.94	-15.76***	-1.41	**-29.09****	**-67.52****	**-10.24***	-0.89	**22.92***
Distance	0.13	0.26	-2.89***	-0.16	-0.45	0.47	**3.06****	**-5.29*****	**7.48*****
FlexiTime_inc	0.04	0.14	-4.03***	4.41	1.6	1	-2.71	0.93	**5.34****
Independence	0.05	0.09	-2.29***	1.37	0.45	**-3.09*****	-0.64	**-1.98***	0.68
Irregular WorkSchedule	0.45	1.00	-96.36	35.32	-148.4	-176.4	171.4	-636.4	-110.1
LinkedTrips NonWork	0.03	0.07	-2.66***	0.22	0.22	**-3.08****	-0.16	-1.23	-0.98
LinkedTrips Work	0.51	0.97	-11.82**	27.31	**-54.94***	**-15.56***	**22.92***	15.16	**-45.83***
MedicalReasons	0.04	0.23	-5***	-0.08	-2.12	2.57	**-9.26*****	2.09	2.28
Nothing_inc	0.45	0.64	-2.17***	0.04	**-6.13*****	**12.6*****	1.09	**-8.42*****	**-4.71*****
ParkAnd Ride_inc	0.02	0.13	-4.73***	0.77	0.66	2.17	-3.14	-2.42	**6.02****
PublicTransport Direct_inc	0.23	0.57	-5.2***	0.87	**5.66*****	0.95	2.44	5.47	**17.89*****
PublicTransport Expensive	0.09	0.18	-2.58***	-0.12	**2.46****	-1.17	**4.9*****	-1.72	-2.59
PublicTransport Impractical Changes	0.37	0.58	-2.61***	0.57	**10.38*****	**3.52****	**6.58*****	**-5.47*****	**-3.92***
PublicTransport Inconvenient Times	0.08	0.27	-4.62***	-0.02	**4.37****	**9.16*****	**8.29****	-2.04	-5.08
PublicTransport Unavailable	0.44	0.87	-7.9***	-0.2	**-22.1*****	**4.58***	**12.12*****	**-7.76*****	**32.05*****
PublicTransport Regular_inc	0.12	0.29	-3.74***	0.32	-0.12	-2.15	**2.38***	**13.4*****	0.36
Reliability	0.03	0.13	-3.95***	0.02	**3.49***	-1.4	2.03	**5.82***	1.77
Reliability_inc	0.06	0.23	-4.26***	1.23	**5.9****	-0.83	2.97	**7.09****	1.25
SchoolRun	0.39	0.63	-4.36***	**47.91*** **	**-1.95***	2.43	-0.3	0.42	-0.07
Security	0.01	0.08	-4.58***	5.26	0.75	0.11	-2.69	-2.52	-3.59
Security_inc	0.03	0.15	-4.43***	-0.02	**4.23***	-3.94	-0.04	**-3.97***	2.77

Keywords	R^2	Max-rescaled R^2	Intercept	Dim_1	Dim_2	Dim_3	Dim_4	Dim_5	Dim_6
;f	0.31	0.46	-2.05***	-0.11	**3.37*** **	**-9.08*** **	-0.03	1.51	**-10.2*** **
Time_inc	0.09	0.26	-3.9***	2.32	**3.3** **	**-4.16** **	**2.85***	**8.63*** **	-2.93
Weather	0.12	1.00	-17.56	-81.47	-13.86	-2.14	2.27	-4.53	-7.39

*p < 0.05; **p < 0.01; ***p < 0.001

By identifying the variables which are strongly associated and representative of the dimensions, the author was able to interpret the first four dimensions. In dimensions with many statistically significant variables, the scope is narrowed to focus on the variables with higher statistical significance such as the case in Dimension 2.

It is noted that some of the keywords have intercepts and independent variables with relatively large (absolute) coefficients (for e.g., "*CheaperPublicTransport_inc*" and *"IrregularWorkSchedule"*). These large values could be explained by the logistic regression equation, which formulates the probability of a keyword occurring as:

Equation 5: Logistic regression equation

$$P(Keyword_i) = \frac{1}{\left(1 + e^{-(k_i + \beta_1 Dim_{1i} + \beta_2 Dim_{2i} + \beta_3 Dim_{3i} + \beta_4 Dim_{4i} + \beta_5 Dim_{5i} + \beta_6 Dim_{6i} + \epsilon_i)}\right)}$$

Where for *Keyword i*,

k is the intercept;

Dim is the final coordinate value for each of the six dimensions;

β is the corresponding coefficient for each dimension; and

ϵ is the error term.

As the coefficients are the negative powers of the exponent, an increase (decrease) of the coefficient will increase (decrease) the odds of the keyword occurring; in other words, a large coefficient in absolute terms means that the dimension is strongly predictive of a keyword. Considering that the final coordinates for the dimensions are relatively small (mean = 0.00, 95% upper confidence interval = 0.01, 95% lower confidence interval = -0.01), it is thus not abnormal for coefficient values to be relatively large when a dimension is strongly associated to the keyword.

The author's interpretation of the dimensions are as follows:

1) **Dimension 1 (*Family*):** The very strong and positive associations with *"SchoolRun"* and *"CaringElderlyFamilyMember"* suggests that Dimension 1 represent drivers with caring responsibilities to their family, either to drop children of at school on the way to work, or to attend to an elderly family member at times of emergency.

2) **Dimension 2 (*Public transport impractical changes*):** The five highly significant ($p < .001$) keywords here suggest that Dimension 2 reflects a spectrum of the difficulties with public transport commute. The positive end describes a group of drivers who declared the *"PublicTransportImpracticalChanges", "PublicTransportDirect_inc"* and *"Time"* keywords, suggesting that although public transport is an option, travelling by car is preferable to avoid having to make multiple bus/train changes and the accompanying longer commuting times. The negative extreme describes a group of drivers who faced larger difficulties with public transport, as public transport is completely unavailable (*"PublicTransportUnavailable"*), and no incentive (*"Nothing_inc"*) can make them switch from driving.

3) **Dimension 3 (*Rigid schedule*):** The highly significant positive values ($p < 0.001$) of Dimension 3 paint a picture of drivers who follow a rigid and routine schedule when leaving home and the workplace. *"PublicTransportInconvenientTimes"* suggest that the drivers avoid public transport because it requires them to inconveniently leave their homes earlier or workplace later in order to arrive on time; and no incentive (*"Nothing_inc")* can persuade these drivers to change their travel mode. On the other hand, Dimension 3 is negatively associated to keywords which represent the flexibility of driving (*"Independence", "LinkedTripsNonWork", "LinkedTripsWork", "Time"* and *"Time_inc"*), implying that these set of drivers use their commute for other tasks, aside from travelling to/from

work. Hence, Dimension 3 could represent the flexibility of the drivers' schedule (rigid versus flexible schedules).

4) **Dimension 4 (*Non-urban area*):** The positive extreme describes the drivers who live in an area far from the workplace (*"distance", "time_inc"*); hence public transport to work would costs more (*"PublicTransportExpensive"*) or may be unsuitable (*"PublicTransportImpracticalChanges", "PublicTransportUnavailable"* and "*PublicTransportInconvenientTimes*"). Incentive-wise, an increase of public transport regularity (*"PublicTransportRegular_inc"*) may encourage them to stop driving. Following this line of logic, the negative end should explain a scenario where public transportation links are better. But why would the respondents on this side still choose to drive? They probably have strong reasons to do so, such as "*MedicalReasons*"; or it is more economical to drive and only a subsidy of their travelling costs ("*CostSubsidy_inc*") could cause them to reconsider. Ergo, one could label the positive end of Dimension 4 as a description of non-urban areas (suburb residential zones or rural towns), while the negative end describes urban areas.

4.6 Chapter summary

In this chapter, multidimensional scaling was introduced as a means to identify themes of "reasons for car-use". Employing secondary data from a university travel survey, qualitative responses from 423 drivers were coded into keywords (of "motivations for car-use" and "incentives to switch travel mode"), transformed into a binary matrix and inputted into the MDS model. Goodness-of-fit tests were conducted and these determined that four dimensions were to be used to explain the data. The four dimensions were interpreted with the aid of logistic regression, resulting in the following explanation for an individual's reason for choosing to drive as a travel mode to work: (i) the driver has a duty to transport family members and would need their own vehicle; (ii) driving is more practical than public transport due to the numerous changes involved; (iii) the inflexibility of the drivers' schedule requires a private vehicle as to not rely on others; and (iv) living in non-urban areas (such as a residential suburb) which is of a distance to work and with limited public transport options.

These four dimensions will be carried forward to the next chapter, where structural equation modelling will be applied to explore the relationship between an individual's "reasons for driving to work" and their acceptance to participate in a carpool.

Chapter 5: Structural Equation Model – Methodology and Results

5.1 Overview

This chapter is a continuation from **Chapter 4** and will report on the methodology and results of the structural equation model.

In the previous chapter, the MDS model has identified four themes of “reasons for driving to work”, namely: family responsibilities, public transport is impractical, rigid schedule and living in non-urban areas. This chapter will employ a structural equation model to investigate the relationship between these four themes with the driver’s acceptance to carpooling. Data for the model were collected from an online travel survey designed by the researcher, which targeted a large sample of drivers in the USA.

5.2 Structural equation modelling procedure

While the MDS dimensions (from the previous chapter) could provide us with some exploratory insights to driving motivations and switching incentives, it is important to test the validity of the MDS interpretations. This will help us to explore and explain the causal relationships (if any) between these dimensions with carpooling. Hence this study applied a Structural Equation Model (SEM). SEM has been widely applied in a variety of academic disciplines, including the transportation behavioural research literature (Golob, 2003; Lo *et al.*, 2016). Among some of the benefits of SEM include its strengths in modelling unobserved (latent) variables, its ability to integrate multiple regression equations concurrently (yet reporting a better performance as compared to multiple regression models in establishing the “best-fitting” model), and its easy-to-read graphical interface (Joseph F. Hair *et al.*, 1995; Nusair and Hua, 2010). In the present study, SEM can be used to validate the driving reasons of the MDS model via various goodness-of-fit tests. Once this has been confirmed, the SEM can examine the causal effects of the latent variables (i.e. the driving reasons) on the dependent variable (i.e. propensity to carpool) (Bollen, 1989).

The SEM procedure is as follows: firstly, the author designed a survey to test the relationship of the four MDS dimensions with an individual's tendency to carpool. Survey respondents were recruited online from October to November 2014 via *Amazon's Mechanical Turk* [7] (AMT), a platform which was found to be an inexpensive and quick method to gather large and diverse samples, yet of comparable reliability to traditional survey collection methods [8] (Buhrmester, Kwang and Gosling, 2011; Mason and Suri, 2012). The survey targeted respondents who drive to work and resides in the US, for two reasons. Firstly, this allowed us to extend the generalisability of the MDS (which was conducted in the UK) to the US. Secondly, the terms and conditions of AMT only permitted recruitment of respondents with a legitimate US social security number. It was not possible to ascertain the non-response rate of the survey as the listing for the survey was placed on AMT's online notice board which was accessible to any visitor[9]; there were no mechanism in place to track the number of viewers versus the number of respondents.

Using a 7-point Likert scale, the researcher designed an average of six sub-items ("indicators") to measure each of the four dimensions and the dependent variable ("Carpool"). To ensure that these indicators are measuring the same construct, the Cronbach's alpha reliability test was conducted on the indicators (Cronbach, 1951). An alpha coefficient of $\geq$ 0.7 suggests high correlation (hence high reliability) among the indicators (Nunnally, Bernstein and Berge, 1967). Indicators which were found to cause the alpha to decrease (i.e. suggesting disagreement with the other sub-items) would be deleted to improve reliability.

[7] The supervisory team assisted the author with the account administration and the advertising of the survey on the *Amazon Mechanical Turk* platform.
[8] The limitations of this survey is further discussed in **section 8.3**.
[9] Any visitor can view the invitation to participate in the survey, but only AMT account holders can access the survey and submit their responses.

Next, a Confirmatory Factor Analysis (CFA) was conducted to test whether the dimensions and indicators are a good fit to the data (Child, 1990), using *SAS 9.4*'s *PROC CALIS* procedure. The normal-theory maximum likelihood estimation method (NTML) was used, with the Browne and Cudeck (1993) Expected Cross-Validation Index (ECVI) implemented at a confidence interval of 90%. NTML was used ahead of other estimation methods such as Partial Least Squares, because it has been reported that NTML can produce comparable or sometimes even better estimates than Partial Least Squares when there is a large sample size, as is the case of our dataset (Ringle, Sarstedt and Straub, 2012; Sas Institute, 2013).

If the model was found to be a good fit, we can proceed with running the SEM by adding the dependent variable ("Carpool") to the CFA model. The goodness-of-fit of the new model is tested once again to confirm the suitability of adding the dependent variable to the model. Finally, the outputs of the SEM are reported in section 5.3, including: the parameter estimates of each dimension to the *Carpool* variable, estimates of each indicator to the dimension, covariance between the dimensions, and error estimates.

5.3 Results of SEM

As expected, the online survey managed to collect a sizable sample; 1239 people responded to the survey, although for reliability, 211 cases were eliminated due to the respondents committing one or more of the following violations: (*i)* provided incomplete replies; (ii) declared that they are not a driver resident in the US; and/or *(iii)* took a much shorter time than the average respondent to complete the survey (< 3.5 minutes, which is less than half the mean time taken). This leaves a sample of N = 1028. Approximately 47% of the respondents are female while the mean age is 32.6 years (median = 30 years; minimum = 18 years; maximum = 70 years).

The removal of offending indicators ensured that the Cronbach's alpha coefficients for all latent variables (dimension) and the dependant variable were high (≥0.7), meaning that the indicators are highly consistent in measuring the same construct for each variable; thus it is appropriate to combine the indicators to form these variables. However, this process has caused some of the variables identified in the MDS to be dropped (for e.g., *CaringElderlyFamilyMember* was removed from the *Family* dimension). This is acceptable for the purpose of this study, as the MDS was intended to identify underlying themes for the SEM (i.e. the *Family* theme is still captured in the SEM). The results of the Cronbach's alpha tests are displayed in **Table 9**.

Table 9: Cronbach's Alpha coefficients and indicators

Latent Variable	Alpha	Indicator		Measure	Scale
Family	**0.87**	p1	Res_Child_Home	Picking up your children from school (after work)	1=Not at all responsible 4 = Neutral 7=Completely responsible
		p2	Res_Child_Work	Dropping off your children at school (on your way to work)	1=Not at all responsible 4 = Neutral 7=Completely responsible
		p3	ChildEmergency	While at work, how often do you need to attend to your children in an emergency in a month?	1=Never 4 = Neutral 7=Every time
Public transport impractical changes	**0.92**	q1	PT_Home_Work_Time_	The total commuting time with public transport between home and work (include waiting and changing times)	1=Perfectly acceptable 4 = Neutral 7=Totally unacceptable
		q2	PT_Home_Work_ChangingTimes_	The amount of time you need for making public transport changes (including waiting times)	1=Perfectly acceptable 4 = Neutral 7=Totally unacceptable
		q3	PT_Home_Work__Changes_	The number of transport changes you need to make to get to work (for example, changing buses)	1=Perfectly acceptable 4 = Neutral 7=Totally unacceptable
Rigid schedule	**0.79**	r1	Flex_JourneyHome_Work	Flexibility of your daily schedule for the journey to work	1= Extremely Flexible 4 = Neutral 7=Rigid
		r2	Flex_WorkHours	Flexibility of number of work hours in a day	1= Extremely Flexible 4 = Neutral 7=Rigid
		r3	Flex_JourneyWork_Home	Flexibility of your daily schedule for the journey home from work	1= Extremely Flexible 4 = Neutral 7=Rigid
Non-urban	**0.73**		NonUrban_1	Which best describes your	0 = Urban

Latent Variable	Alpha	Indicator		Measure	Scale
		s1		neighbourhood?	1 = non-Urban
		s2	PopDensityRating	Please rate the population density of your neighbourhood.	1 = Extremely dense 4 = Neutral 7 = Not at all dense
		s3	PT_Unavail_Home_Work	Public transport availability when you need to leave to work on time	1=Not at all unavailable 4 = Neutral 7= Always unavailable
		s4	PT_Unavail_Worke_Home	Public transport availability from the workplace to your home	1=Not at all unavailable 4 = Neutral 7= Always unavailable
Carpool (output variable)	**0.84**	z1	Accept_CarpoolDriver	Will you carpool as the driver of the carpool (i.e., you drive your colleague(s))	1=Totally unacceptable 4=Neutral 7=Perfectly acceptable
		z2	Carpool_1	Are you currently in a carpool to work with your colleagues (i.e. you share a car ride to work with your co-workers)?	1= Yes 0= No
		z3	CarpoolConsider	I would consider carpooling my first choice of transportation to work	1=Strongly disagree 4=Neutral 7=Strongly agree
		z4	CarpoolNextTimeWork	The next time I travel to work, I will carpool	1=Strongly disagree 4=Neutral 7=Strongly agree
		z5	CarpoolFuture	I look forward to carpooling to work in the future	1=Strongly disagree 4=Neutral 7=Strongly agree
		z6	CarpoolEmployerBenefits	I will carpool if my employer provides me with other benefits, for example, a reserved parking spot for carpoolers.	1=Strongly disagree 4=Neutral 7=Strongly agree
		z7	CarpoolNextFewMths	I will carpool to work in the next few months	1=Strongly disagree 4=Neutral 7=Strongly agree

The CFA (see **Table 10**) corroborates that the hypothesised model (of the latent variables and the indicators) is a 'good fit', as the RMSEA value was less than 0.06 (Browne and Cudeck, 1993), and the three fit indices recorded values above 0.90 (Mcdonald and Marsh, 1990). Adding the outcome variable improved the model fit slightly (see **Table 11**), with the upper RMSEA 90% confidence limit[10] at 0.0516 and all other fit indices above 0.90, proving that the model fits the data well (Hu and Bentler, 1999).

Table 10: Confirmatory factor analysis goodness-of-fit

Confirmatory Factor Analysis	
RMSEA Estimate	0.0468
Bentler Comparative Fit Index	0.9839
Bentler-Bonett NFI	0.9767
Bentler-Bonett Non-normed Index	0.9788

Table 11: Structural equation model goodness-of-fit

Structural Equation Model	
RMSEA Estimate	0.0443
Bentler Comparative Fit Index	0.9835
Bentler-Bonett NFI	0.9779
Bentler-Bonett Non-normed Index	0.9667

Figure 7 displays the completed model. *"Public transport impractical changes"* (Dimension 2) and "*Rigid schedule*" (Dimension 3) were found to be significant predictors of "*Carpool*" at the $p< 0.05$ level. Positive estimates were recorded for "*Family*" (Dimension 1), suggesting that this factor can encourage carpooling, while "*Public transport impractical changes*" (Dimension 2), "*Rigid schedule*" (Dimension 3) and "*Non-urban*" (Dimension 4) logged negative estimates, indicating these factors discourage carpooling. All indicators (**Table 12**) and error terms (**Table 14**) were statistically significant to their respective constructs. **Table 13** shows that for some latent variables, the covariance among them is significant and strong, especially between "*Public transport impractical changes - Non-urban"* (0.79), "*Public transport impractical changes - Rigid schedule*" (0.28), and "*Rigid schedule - Non-urban*" (0.27).

[10] The confidence intervals are estimated at the 90% level using the cumulative distribution function of the non-central chi-square distribution; see Steiger, J.H. (1998), 'A note on multiple sample extensions of the RMSEA fit index'.

Figure 7: Structural equation model of the driving motivation dimensions with carpooling

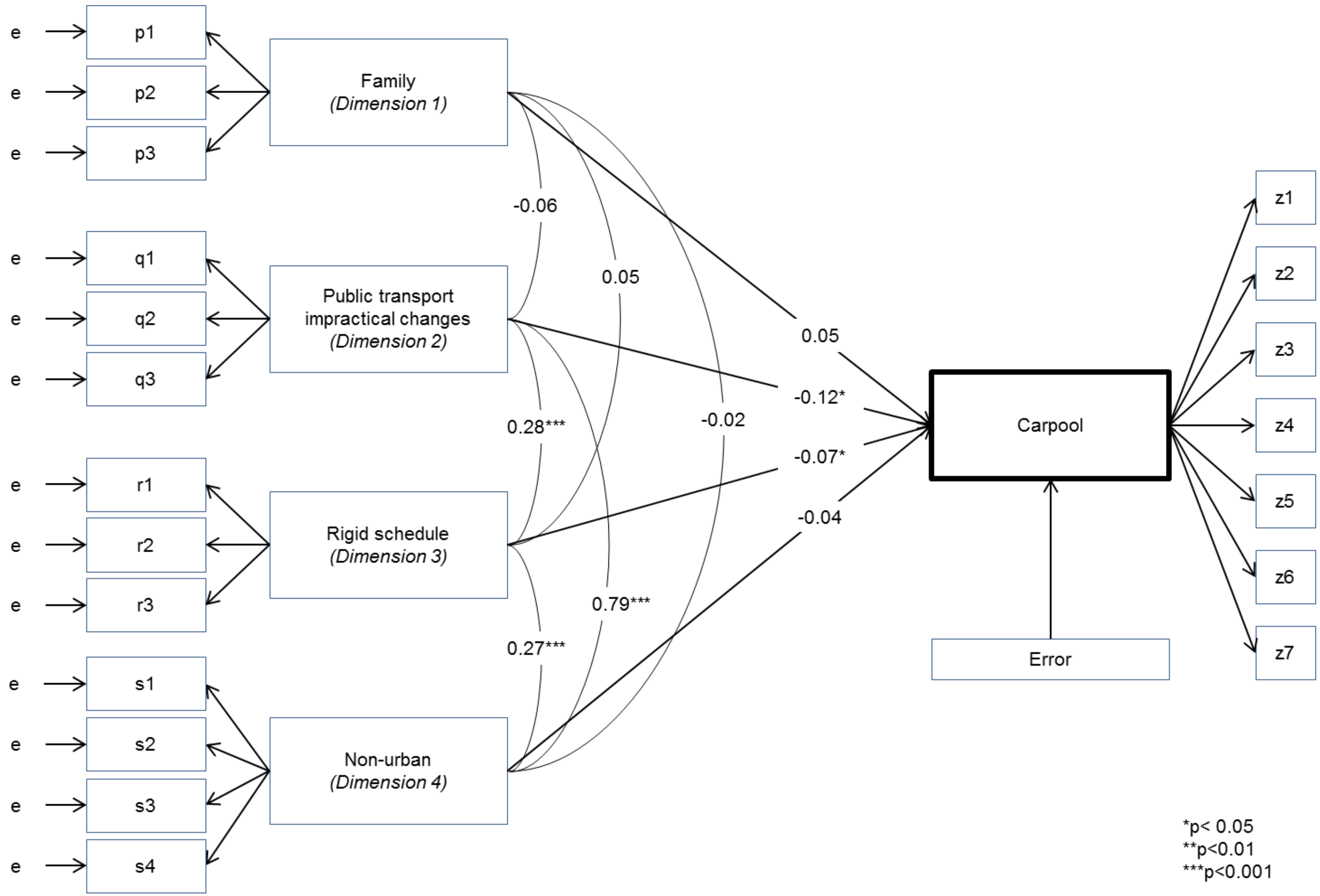


Table 12: Indicator estimates for latent variables

Latent Variable	Indicator		Estimate	t Value
Family	p1	Res_Child_Home	0.9347***	84.7576
	p2	Res_Child_Work	0.9231***	82.5312
	p3	ChildEmergency	0.6437***	32.0507
Public transport impractical changes	q1	PT_Home_Work_Time_	0.8392***	78.4397
	q2	PT_Home_Work_ChangingTimes_	0.9561***	168
	q3	PT_Home_Work__Changes_	0.8893***	107.3
Rigid schedule	r1	Flex_JourneyHome_Work	0.9062***	45.4799
	r2	Flex_WorkHours	0.6627***	28.8552
	r3	Flex_JourneyWork_Home	0.6791***	30.0357
Non-Urban	s1	PT_Unavailable_Work_Home	0.9410***	139.1
	s2	PT_Unavailable_Home_Work	0.9568***	150.1
	s3	NonUrban_1	0.3091***	10.3727
	s4	PopDensityRating	0.3631***	12.6782

*p< 0.05; **p< 0.01; ***p<0.001

Table 13: Covariance between variables

Variable 1	Variable 2	Estimate	Standard Error	t Value
Family	*PT impractical*	-0.06488	0.03409	-1.90318
Family	*Rigid schedule*	0.05313	0.03574	1.48681
Family	*Non-urban*	-0.02189	0.03411	-0.64174
PT impractical	*Rigid schedule*	0.2762***	0.03329	-8.29815
PT impractical	*Non-urban*	0.78833***	0.01417	55.63135
Rigid schedule	*Non-urban*	0.27215***	0.03324	-8.18682

*p< 0.05; **p< 0.01; ***p<0.001

Table 14: Error estimates

Variable	Estimate	Standard Error	t Value
e-p1	0.12629***	0.02062	6.1259
e-p2	0.14784***	0.02065	7.15896
e-p3	0.58564***	0.02586	22.64915
e-q1	0.29572***	0.01796	16.46775
e-q2	0.08584***	0.01088	7.88934
e-q3	0.20914***	0.01474	14.19063
e-r1	0.17888***	0.03611	4.95384
e-r2	0.56087***	0.03044	18.42715
e-r3	0.53888***	0.0307	17.55041
e-s1	0.11458***	0.01274	8.99706
e-s2	0.08453***	0.0122	6.92898
e-s3	0.90445***	0.01842	49.09397
e-s4	0.86816***	0.0208	41.74258
e-Carpool	0.96251***	0.01227	78.44883

*p< 0.05; **p< 0.01; ***p<0.001

5.4 Chapter summary

In this chapter, a structural equation model was employed to *(i)* validate the MDS interpretations from the previous chapter; and *(ii)* to explore the relationship between the four driving reasons and an individual's propensity to carpooling. Using an online survey (which was designed based on the MDS dimensions), responses from 1028 drivers in the US were collected. With the approvals of a number of goodness-of-fit tests, the survey results were inputted into the structural equation model. A key finding from the model was that the impracticality of public transport and the rigid schedules of the driver negatively influence their likelihood to carpool (at a statistically significant level). The results of the model will be further discussed later in **Chapter 7**. Prior to that discussion, the next chapter will examine the effects of hierarchical factors on carpooling via multilevel modelling.

Chapter 6: Multilevel Model – Methodology and Results

6.1 Overview

This chapter is a continuation of **Chapter 5** and will report on the methodology and results of the multilevel model. In the previous chapter, the structural equation model has successfully incorporated the four "reasons for driving" dimensions from the multidimensional scaling model of **Chapter 4**. This chapter will use a multilevel model to examine whether the state where the driver is resident in (indirectly referring to factors such as local regulation, policy and infrastructure) could influence their likelihood of carpooling.

6.2 Multilevel modelling procedure

In this chapter, a multilevel model (MLM) was applied to complement the structural equation model (SEM) analysis from the previous chapter. This study aims to examine if the influence of the carpooling dimensions (discussed in the previous chapter with the SEM) on an individual's likelihood to carpool differs by the state which they reside in (the "State"). If such difference(s) exists, we could identify whether if there is scope for the local authority to introduce or amend policies to encourage carpooling.

The MLM could also be used to support the findings of the SEM; essentially the advantage of the MLM is that unlike the SEM, it recognises that the data is hierarchical in nature, i.e., the observations are nested within groups. Ignoring the groups could lead to underestimating (i) the influence of the group on the outcome variable; and (ii) the standard errors of the regression coefficients (Maas and Hox, 2004). MLM has been used in the travel demand management literature for the purposes of (for example) estimating the influence of 'work industry'-level effects on carpooling, examining the importance of city-level factors on the decision to drive, and understanding the significance of neighbourhood environment characteristics on the commuter preferences for sustainable travel modes (Choi and Ahn, 2015; Saelens, Sallis and Frank, 2003; Vanoutrive *et al.*, 2012). In the present study, this model will be able to estimate the variance accounted for by the differences in States; therefore, allowing us to understand to what extent policies implemented by a State may influence individual choices in carpooling.

Reusing the dataset of 1028 respondents collected via Amazon Mechanical Turk (from **Chapter 5**), drivers were grouped into different classes by the US state which they are resident in. To ensure each class has sufficient cases, the US states which constitute less than 1% of the sample was removed from the dataset. This exercise eliminated 20 states, comprising of 87 cases. 940 cases from 30 states remained[11]. The surviving states are displayed in **Table 15,** accompanied with their respective population data (as adapted from the U.S. Census Bureau (2014)):

Table 15: US States as classes

US State	Total respondents, *N*	Carpoolers to work as a percentage of the total population in employment in 2014 (%)	Total population in employment in 2014
Alabama	18	8.6	2,999,928
Arizona	21	10.4	4,360,251
California	110	10.5	25,486,535
Colorado	25	9.6	3,904,224
Connecticut	10	8.1	2,573,850
Florida	79	9.1	13,097,864
Georgia	33	10.1	6,553,039
Illinois	34	8.0	8,927,357
Indiana	23	9.0	4,545,939
Kansas	16	9.5	2,095,610
Kentucky	17	10.0	2,819,662
Louisiana	14	9.8	2,952,109
Massachusetts	26	7.4	4,910,975
Maryland	16	9.3	4,296,274
Michigan	43	8.9	6,564,595
Minnesota	16	8.8	4,218,358
Missouri	16	8.9	4,159,785
North Carolina	33	9.7	6,610,357
New Jersey	29	7.9	6,301,885
New York	52	6.5	13,369,977

[11] A limitation relating to the sample size of individuals per US State is discussed in **section 8.3.**

US State	Total respondents, *N*	Carpoolers to work as a percentage of the total population in employment in 2014 (%)	Total population in employment in 2014
Ohio	32	7.8	8,013,526
Oklahoma	13	10.5	2,591,579
Oregon	20	10.8	2,668,648
Pennsylvania	47	8.5	8,814,905
South Carolina	18	9.3	3,158,271
Tennessee	30	9.2	4,275,700
Texas	67	10.6	18,345,773
Virginia	42	9.3	5,896,293
Washington	24	10.1	4,873,585
Wisconsin	16	8.2	4,290,777
Total	**940**		**193,677,631**

Running the model in *SAS 9.4* with *PROC MIXED*, four models with a 2-level structure were produced (Level 2 comprises the classes (i.e. State), while Level 1 comprises the respondents residing in each class) (Hox, 2010; Vanoutrive *et al.*, 2012). By comparing the four models, we will be able to estimate the effect of the State versus the effect of each individual level variable on carpooling. Model 1 is an "empty" model with no independent variables included; Model 2 comprises the level 2 variables as fixed effects; *Public transport impractical changes* and *Non-urban* are treated as the Level 2 variables, since these variables are location-based and were likely to be influenced by the State (i.e. they vary randomly at each State) (Marsden *et al.*, 2011; Pucher, 1995). Model 3 comprises the Level 1 variables (i.e. the remaining variables, *Family* and *Rigid schedule*); while Model 4 is the random slope model (with both Level 1 and 2 variables included). A random intercept is incorporated in all four models.

6.3 Results of MLM

The MLM results are displayed in **Table 16:**

Table 16: Multilevel model of carpooling dimensions by US State

	Model 1		Model 2		Model 3		Model 4	
	Type III estimate	Standard error	Type III estimate	Standard error	Type III estimate	Standard error	Type III estimate	Standard error
Random part								
Level 2 intercept/intercept	0.3551	0.4961	0.01883	0.4193	0.436	0.5371	2.8722	5.8533
Level 2 PT impractical changes/intercept							0.2234	0.3086
Level 2 PT impractical changes/PT impractical changes							0.02518	0.03396
Level 2 Non-urban/intercept							-0.4851	0.6186
Level 2 Non-urban/PT impractical changes							-0.04335	0.04611
Level 2 Non-urban/Non-urban							0.08444	0.08066
Level 1 intercept/intercept	60.4765**	2.8283	58.9644**	2.7772	59.7874**	2.8428	57.8857**	2.8502
Fixed part								
Intercept	19.772**	0.2845	23.8803**	0.8339	21.8554**	0.8523	24.7592**	1.1228
Family					0.1074*	0.04418	0.1015*	0.0438
PT impractical changes			-0.09519	0.0587			-0.05616	0.06905
Rigid Schedule					-0.1976**	0.05798	-0.1476*	0.05927
Non-urban			-0.1761*	0.07662			-0.1792	0.09853
-2 Loglikelihood	6480.0		6375.7		6269.3		6171.7	
AIC	6486		6385.7		6279.3		6195.7	
BIC	6490.2		6392.8		6286.3		6212.5	
Level 2 (State) *N*= 30								
Level 1 (Individual) *N*= 940								
**p< 0.01; *p< 0.05								

The random slope model (Model 4) was the best fitting model among the four models, as it had the lowest Akaike Information Criterion (AIC) and Bayesian information criterion (BIC) values. The fit of the MLM significantly improved between the empty and random slope model (i.e. after the independent variables at both the individual and State levels are included); this is concluded from examining the difference between the -2Loglikelihood (-2LL) between Model 1 and 4:

Equation 6: Difference between the -2LL of Model 1 and Model 4

$$-2LL_{Model\ 1} - -2LL_{Model\ 4} = 6480.0 - 6171.7 = 308.3$$

As the change in number of parameters between Model 1 and 4 was 3, then according to the critical values for the Chi-square statistic with 3 degrees of freedom for 308.3, the change between the models was statistically significant at the $p < 0.05$ level.

The Intraclass Correlation Coefficient (ICC) of the empty model (Model 1) indicates that relative to the total variance in carpooling, only *circa* 1% (0.36/(0.36+60.48)) of the variance could be explained by the differences in the States. Thus, the remaining 99% of variance were attributable to the differences between individuals. Only 1.14% of the Level 1 (individual) variance in carpooling were accounted for by the *Family* and *Rigid schedule* variables added at Level 1 (by comparing Model 1 and 3), while 94.7% of the Level 2 (State) variance in carpooling could be explained by the Level 2 variables (comparing Model 1 and 2). The addition of the Level 2 variables (*Public transport impractical changes* and *Non-urban*) increased the variance in the random intercept at the State level by 560% (comparing Model 3 and 4).

All effect sizes in Model 4 were in the same direction as in the SEM. Comparing the MLM results to the results in the SEM from the previous chapter, the effect sizes of all but one of the carpooling dimensions were slightly “stronger” (in absolute terms) in encouraging carpooling participation when the data was arranged in a multilevel structure as opposed to when the multilevel structure was ignored (MLM results v. SEM results): *Family* (*ß* = 0.10 v. 0.05); *Rigid schedule* (*ß* = –0.14 v. –0.07); and *Non-urban* (*ß* = –0.18 v. –0.04). Only *Public transport impractical changes* (*ß* = –0.06 v. –0.12) reported a weaker effect size in the MLM as compared to in the SEM. The *Family* and *Rigid schedule* dimensions significantly predicted participation in carpooling at the $p<0.05$ level; while *Public transport impractical changes* and *Non-urban* were found to be not statistically significant.

6.4 Chapter summary

In this chapter, a multilevel model was carried out to examine if the state where the driver is resident in has played a role in influencing his/her decision to carpool. Among the key findings are: *(i)* the low intraclass correlation coefficient rate, in addition to the statistically insignificant Level 2 variables, signified that the State had a weak influence on a driver's carpooling decision; and *(ii)* the effect sizes of the four dimensions explored in the MLM are similar to the results of the structural equation model, thus the MLM validates the SEM. The implications of the results of the MLM will be discussed concurrently with the results of the MDS (of **Chapter 4)** and the SEM (of **Chapter 5)** analyses in the next chapter.

Chapter 7: Discussions

7.1 Overview

This chapter is a continuation of the previous three chapters (**Chapter 4**, **Chapter 5**, and **Chapter 6**), and will discuss the implication of the results from the multidimensional scaling, structural equation modelling and multilevel modelling studies.

7.2 Discussions

In this study's efforts to reduce the use of SOV through targeted interventions, the antecedent factors of carpooling determinants were explored. This study hypothesised that driving motivations (as a work commute travel mode choice) have a causal relationship with the commuters' willingness to carpool, and applied *(i)* MDS to extract the themes of driver motivations, and *(ii)* SEM to explain its relationship to carpooling.

The MDS extracted four dimensions of drivers' motivations: *(1) family; (2) public transport impractical changes; (3) rigid schedule;* and *(4) living in non-urban areas*. These motivations can be classified as instrumental reasons, meaning that the respondents from the MDS data largely did not report symbolic and affective reasons to drive. Two possible reasons explain this: firstly, corroborating with previous research, instrumental reasons are given higher attachments in determining car-usage for work commutes than affective or symbolic factors (Anable and Gatersleben, 2005). Secondly, people may be unwilling to admit that they drive due to symbolic and affective reasons, since instrumental reasons are more justifiable for the pollution and congestion effects of driving (Steg, Vlek and Slotegraaf, 2001). The MDS result could not be guaranteed as free from this bias because the study relied on data from a secondary source and thus the researcher have no control over the survey design. However, it is expected that the bias in the data is limited, as the travel survey had some similarities with studies which were successful in eliciting affective and symbolic confessions, such as, not explicitly exposing the research aim, and collecting responses in a qualitative format (Mann and Abraham, 2006; Steg, 2005).

The SEM, with its low RMSEA value and high fit indices, is a good fit and is comparable to the fit of structural equation models in other travel behaviour studies (Golob, 2003; Lois and López-Sáez, 2009). Two relationships were verified with statistical significance at the $p < 0.05$ level. For the *Public transport impractical changes* dimension, the negative relationship between Public transport impractical changes and Carpool, along with the positive and significant covariance between Public transport impractical changes and rigid schedule, perhaps suggests that for these drivers, convenience and journey time are important factors. Recall from the MDS in **Chapter 4** that the drivers of this dimension do actually have the option to use public transport (but the trip requires making one or more changes). They chose to drive instead because it was more convenient and faster. For them, carpooling is not attractive because of the perceived hassle (waiting for, picking up and dropping off passengers), and the additional journey time it entails.

Similarly for the *Rigid schedule* dimension, its negative relationship with the *Carpooling* variable implies that for this group of drivers, carpooling is unattractive because it requires them to break away from their rigid travel schedules before and after work. These drivers have a strict need to leave to work and arrive home at fixed times. Their journey to and from work does not allow for additional linked trips for other activities; adding carpool partners into their journey will disrupt their routine (Tsao and Lin, 1999). Contrariwise, if the drivers are more flexible with the commute schedule, they will be more likely to carpool. This is confirmed by rerunning the SEM analysis, but this time with the scales in the *Rigid schedule* dimension reversed; the new results show a positive and statistically significant relationship ($\beta = +0.07$; $p < 0.05$) between drivers with a flexible commute schedule and *Carpooling*. Having no fixed schedule to adhere to, the drivers are free to detour to pick up and drop off passengers.

So what does this mean for travel demand policy? Future carpooling intervention efforts should place more weight on the individuals aligned with the *Rigid schedule* dimension, and less on the individuals described by the *Public transport impractical changes* dimension. The drivers who find public transport inconvenient are unlikely to be persuaded to carpool, as the inconvenience factor still persists. Likewise, drivers who have rigid commuting schedules are also unpersuadable due to not wanting to break away from their routine. Any effort spent on encouraging these two groups of drivers to carpool will be wasteful, as carpooling does not address their underlying travel mode choice reasons. Meanwhile, drivers who have flexible commute schedules are more likely to be persuaded to carpool. Identifying this group of flexible drivers is vital. A warning need to be heeded: according to the MDS analysis, these people chose to drive because driving gives them the freedom to carry out activities during their commute, such as linked trips for grocery shopping. While these drivers are not tied to a fixed schedule, the challenge here is to ensure compatibility by finding carpool passengers who can accept the flexible schedules. Carpool partner matching services should account for these activities, and include them in their matching criteria. When advertising for partners on carpool databases, drivers should be encouraged to declare their commute activities. This will avoid misunderstandings among potential passengers regarding travel time, and reassure the drivers that carpooling will not restrict their schedules.

Meanwhile, the MLM validates the SEM findings, with similar results reported in terms of effect size magnitude and direction, even when we control for the effect of the US State where the individual is resident. However, the low ICC and non-significant estimates of the variables at State level indicate that currently, the differences in States do not majorly influence an individual's decision to carpool. A possible explanation of the lack of variance across States is that none of the States have implemented carpool interventions differently as compared to the others. Thus generally, all the States carpool policies are equally ineffectual. This finding is corroborated by other MLM studies within the travel demand management area which found that in general, the individual-level factors are stronger in influencing the decision to drive as compared to region-level factors (Choi and Ahn, 2015; Crane and Crepeau, 1998).

The notable difference with the MLM as compared to the SEM was that the driver's family responsibility was found to be statistically significant in predicting carpooling participation at the individual level, (i.e. this factor is more salient when controlling for the State effects). This is an interesting result; even with the responsibility of transporting his/her family member(s), these individuals are found to be open to participate in a work carpool. There are two possible explanations for this: firstly, the individual being already experienced to carpooling as the driver in a family carpool, is comfortable with extending his/her carpooling routine to include work colleagues. Having family responsibilities could mean that these individuals are more willing to engage with prosocial and pro-environmental behaviour, a notion which is supported by the psychology literature (Delhomme and Gheorghiu, 2016; Kollmuss and Agyeman, 2002; Whitmarsh and O'neill, 2010). Secondly, as the driver of children, the individual is likely to be in possession of a sufficiently spacious vehicle fit for carpooling. Despite their willingness and means to carpool, these individuals are not necessarily easy carpool convert targets. Their family responsibility could prevent them from making the switch, as implied by the SEM results: the effect size of the *Family* factor is smaller and insignificant as compared to the negative and significant factors of *Rigid schedule* and *Public transport impractical changes*. Policy makers at the state level should identify and target family drivers in carpooling campaigns, but the challenge is to help these drivers overcome the practicality issues of transporting their children (perhaps, for example, by providing their children with a reliable bus route to school).

Although not a statistically significant predictor in both the MLM and SEM (and also the smallest effect size in the SEM), living in non-urban areas was found by the MLM to be a strong obstacle to carpooling. This is perhaps caused by the factors associated with living in rural/sub-urban areas as compared to urban areas, such as less availability of public transportation to work; and residing in a less populous neighbourhood (which has a lower likelihood of living close to a co-worker who potentially could be a carpool partner). Furthermore, in the SEM, this factor's covariance is strong, positive, and statistically significant ($p< 0.05$) with *Public transport impractical changes* (0.79) and *Rigid schedule* (0.27) respectively; this implies that individuals living in non-urban areas may share some characteristics with these two dimensions which discourage them from carpooling, namely a demand for convenience when commuting and an inflexible travel schedule. Indeed, the social geography literature concurs that this demand is justified by the additional amount of daily commute time spent by rural and suburban individuals as compared to their urban counterparts (Buehler and Pucher, 2012; Kamruzzaman and Hine, 2012; Nutley, 1996). Hence, policy makers at the State level could attempt to (i) focus efforts on urban drivers as potential carpoolers; and/or (ii) nullify the Non-urban effects by improving public transportation links in rural and suburban areas (for example, by increasing the frequency of busses and creating more direct bus routes). The latter move has the potential to encourage SOV drivers to switch to public transport, although it is costlier to implement and may not guarantee an increase uptake in carpooling.

The coefficients of all latent variables with the dependent variable in both the SEM and MLM (at the individual level) are relatively small, with the largest absolute value recorded at $\beta = -0.18$. This indicates that the four dimensions of instrumental reasons could only explain a small part of carpooling propensity. Further, the effect of the differences in States has a low variance in relative to the total variance of carpooling. In other words, there could be other factors which would be better predictors of a driver's acceptability to carpool. This could be either other instrumental reasons which were unreported in the MDS data, or more likely, affective and symbolic reasons, which were given heavy weightings in previous car-use research (Lois and López-Sáez, 2009). This is supported by the carpool literature, where judgmental factors such as privacy and locus of control (which are affective and symbolic factors) featured as obstacles to carpool (Correia and Viegas, 2011; Morency, 2007; Stradling, Meadows and Beatty, 2001). Future research should look into exploring the effects of the non-instrumentals factors on carpooling.

7.3 Conclusions

Chapter 4, Chapter 5, Chapter 6, and **Chapter 7** examined the relationship between the commuters' reasons for driving with their acceptability to carpooling. The results have three implications. Firstly, reaffirming previous research, this study found that the commuters' self-reported reasons for driving to work are largely instrumental, specifically: responsible for other family members as a driver; found public transport too impractical for commuting; driving is necessary to keep to their daily schedules; and the location of their residence, especially in non-urban areas with a lack of public transport links, requires driving. Secondly, for transportation practitioners, the study offers direction for the design of effective carpooling interventions, particularly: the need to target drivers with flexible commute schedules, rather than those with rigid schedules or who perceives public transport as inconvenient; and to incorporate the commute activities of drivers as a matching criterion on carpool partner platforms. Thirdly, this study provided evidence of the application of multidimensional scaling modelling as an exploratory factor analysis tool for a structural equation model, a relatively novel approach in the context of travel demand management research.

The study unearthed a number of themes for further research. The small (absolute) coefficients of the self-reported driving reasons, which were all instrumental, raised questions of the influence of affective and symbolic factors on carpooling; future studies should focus on these non-instrumental reasons and plan travel policies accordingly. For example, if symbolic factors such as portraying an eco-friendly identity were found to strongly affect carpooling uptake, then carpool promoters should look into initiatives which encourages commuters to express this status when carpooling (perhaps by allowing the carpooler to display on social media the amount of carbon emission reduced). Future studies should also try to extend the findings (which examined samples from the UK and the USA) to other countries, where the generalisability of the present study may not hold (particularly, for non-Western countries, which are neglected by the carpooling literature body); car dependency and carpooling views could vary in other regions due to, for instance, cultural differences, safety standards of the environment and the quality of public transport.

7.4 Chapter summary

In this chapter, the results of the multidimensional scaling, structural equation modelling and multilevel modelling studies were discussed. Recommendations were provided for transportation policy planners and researchers, thus answering research questions 2 (the relationship between driving motivations and carpooling) and 3 (policy recommendations). Hence, the MDS, SEM and MLM studies are concluded here. The next chapter will conclude the entire thesis by summarising the conclusions from these studies (including the meta-analysis research of **Chapter 3**).

Chapter 8: Conclusions

8.1 Overview

This chapter will unify the findings from all preceding chapters and present the main contributions of this thesis. The limitations of the studies will be addressed, and followed by recommendations for future research.

8.2 Main contributions

Carpooling can reduce the number of single occupied vehicles on the road, thus producing environmental, societal and cost savings benefits. The thesis aimed to improve carpooling participation by *(i)* identifying and understand the factors which can encourage/discourage carpooling; *(ii)* recommend travel policy for transportation practitioners to implement accordingly; and *(iii)* provide transportation researchers with directions for future research.

In **Chapter 2**, the thesis summarised the carpooling literature body. It was found that a quantitative synthesis (i.e. meta-analysis) of the literature was needed, as there were conflicting and non-generalizable results between studies regarding the effects of certain factors on carpooling. Furthermore, the literature review identified a need to explore the relationship between driving motivations and an individual's acceptability to carpooling. This will aid understanding of the causal process behind the carpooling factors, which is vital to the development of effective carpooling interventions.

In **Chapter 3**, the thesis attempted to settle the debate within the carpool literature body by conducting a meta-analysis of carpooling motivators and deterrents, by quantitatively synthesizing results from 22 empirical studies representing over 79,000 observations. The meta-analysis was able to determine the effect sizes of 24 carpooling factors; these are useful for transportation researchers, who can use the effect sizes as inputs in their models. For travel demand managers, this study was able to recommend prospects for improving carpooling by developing:

(i) target demographics, (ii) selling points for marketing, (iii) carpooling partner programs and *(iv) multiple employer 'super-pools'*.

In **Chapter 4, Chapter 5, Chapter 6** and **Chapter 7** the study aimed to improve our understanding of the underlying factors influencing carpool acceptance, by investigating the relationship between the motivations of a commuter's current travel mode choice (particularly, drivers of single-occupied vehicles), and their propensity towards carpooling. To determine the reasons for commuting by car to work as a travel mode choice, the study applied a multidimensional scaling analysis on a UK-based travel survey dataset (*N*= 423) and were able to extract four dimensions of driving determinants, namely: *(1) family responsibility; (2) public transport impractical changes; (3) rigid schedule;* and *(4) live in non-urban area.* To explore the relationships of these four driving motivations with carpooling, the study operated a structural equation model, using a USA-based travel survey dataset (*N*= 1028). The results identified likely carpoolers as drivers with flexible commute schedules, while drivers who perceived public transport to be impractical or have a rigid commute schedule are unlikely to carpool. In terms of policy recommendations, partner matching services should include the drivers' commute activities as a matching criterion. At the State-level, the multilevel model found that currently the States are equally uninfluential in encouraging carpooling. However, the MLM results suggested that the State could implement certain actions to improve carpool uptake, such as targeting urban drivers and drivers with the responsibilities of driving his/her family members (in carpool campaigns). The former are more likely to carpool than their rural/suburban counterparts; the latter have shown a desire to carpool, but the State should look at ways to relieve these drivers from their family-ferrying duties (for e.g., by providing a direct school bus route for the driver's children).

Methodologically-wise, the thesis contributed to the transportation research area in a number of ways. To the best of the author's knowledge, the meta-analysis of carpooling factors is the first quantitative literature review of the carpooling research body; this study provided evidence of its application within the travel demand management research domain, which itself is rich in empirical studies but has very few meta-analyses. The use of multidimensional scaling is also novel within this area; particularly the conducting of logistic regression on the variables to aid dimension interpretation. The application of multidimensional scaling for forming the foundations of a structural equation model demonstrated its usefulness as an exploratory factor analysis tool, which could also be applied in other research domains.

8.3 Limitations

The studies in this thesis are burdened with the following limitations:

- In **Chapter 3,** it must be acknowledged that a meta-analysis approach on carpooling behaviour has limitations in capturing the contextual effects of where the study took place on the studied factors, especially if the context is unreported or not controlled for. For example, the availability of High-Occupancy Vehicle lanes, the standard of public transportation links, cultural norms and local regulations could affect the commuters' acceptance to carpooling interventions, and ultimately, influence the likelihood of individual carpooling behaviour. This drawback is more pronounced when the pool of available evidence are small and the year and country examined are diverse; attempts to generalise results from such heterogeneous populations could lead to biased conclusions. In this scenario, the reader should interpret the results with caution, but also remember that one of the purposes of meta-analysis is to promote discussions and further investigations of the sources of heterogeneity in the effect sizes (Borenstein *et al.*, 2009).
- In **Chapter 4**, the multidimensional scaling analysis used secondary data from a university travel survey. (Steg, Vlek and Slotegraaf, 2001) recognised a bias in travel surveys where respondents downplay the roles of symbolic and affective factors in the decision to choose driving over other travel modes, while overstating the roles of instrumental factors. As the researcher was restricted from altering the survey design used in this chapter, there is no assurance

that this survey was sufficiently designed to extract accurate admissions from the respondents. It should be noted that the survey did share some similarities to other surveys which have successfully evoked symbolic and affective reasons for driving (such as allowing open-ended responses and being inexplicit about the survey's objectives (Mann and Abraham, 2006; Steg, 2005)). Further, previous research has showed that driving reasons for work-commute are more likely to be influenced by instrumental rather than symbolic or affective factors (Anable and Gatersleben, 2005).

- In **Chapter 5,** the online survey which targeted US drivers did not incorporate a 'manipulation check' to test whether the respondents were paying attention when answering the questions (for e.g., a question could have been set up to request the respondents to select a pre-determined answer to prove that they are reading the questions thoroughly). As there were no checks, it is possible that some of the respondents in the sample may have answered the survey randomly, which in turn would have led to bias in the results. However, it is hoped that this bias is limited by the other controls implemented, such as removals of cases where respondents have provided incomplete answers and/or completing the survey within an unrealistically short amount of time.
- In **Chapter 6**, some of the US States used in the MLM have small sample sizes (there were less than 20 respondents in 11 states); this could lead to bias in the results (Maas and Hox, 2005). It is hoped that this bias (if any) would be limited: firstly, the MLM results were validated by the SEM results. Secondly, the MLM found that the State has no effect on carpooling, which is in line with the results from the carpooling literature. Future research could prevent this bias by (i) gathering a larger sample of individuals per state, or/ and (ii) increasing the number of classes, by breaking down each state into further sub-classes such as districts, counties or cities.

8.4 Directions for future research

The thesis has uncovered a number of directions for future research. In **Chapter 3**, the meta-analysis highlighted a lack of methodologically-appropriate carpool studies for synthesis; thus future empirical studies should aim to report their statistical findings in more compatible formats. Future research efforts could be efficiently allocated by focusing on the factors which were reported as having a strong effect in the meta-analysis but only examined by a few studies, while factors which were largely agreed by the majority of studies but were found to have weak effects should be ignored. Future travel policy research could also directly use the effect sizes to model carpooling behaviour, for example in a system dynamics or simulation model.

The influence of affective and symbolic driving factors on carpooling should also be the focus of future studies. In **Chapter 7** it was explained that the multidimensional scaling analysis revealed driving reasons which were purely instrumental; these in turn were found by the structural equation model to have small influences on carpooling, implying that there is room for other factors (possibly affective and symbolic ones) to feature in the commuter's decision to carpool. The multilevel model ruled out the role of the State in affecting carpooling propensity, thus giving more credence to this theory. For generalisability purposes, future investigations should also try to replicate the study to regions outside of the UK and the US, especially to non-Western countries, which have been largely overlooked in the carpooling literature body.

Finally, as most carpooling studies often conclude with recommendations on possible intervention measures to improve carpooling uptake, this raises a question for policy makers: how do we verify whether a carpool has took place? This is important to *(i)* measure the success of interventions, and *(ii)* enforce reward (or penalty) schemes for carpoolers (or solo drivers). Without a mechanism to confirm a carpool, any intervention would be susceptible to abuse. Researchers and transportation practitioners should look to creative answers; for example, a system which confirms carpool participation by comparing the speed of travel of the driver and carpool passengers (Alberth Jr and Chau, 2015). However, future recommendations have to be mindful of costs, as one of the most appealing aspects of carpooling as a travel demand management solution is that it requires relatively low investment for the policy maker (Garrison, 2007).

8.5 Closing remarks

In the global battle to protect the environment and reduce our unsustainable reliance on limited resources, carpooling has been advocated as a possible answer. Given the high stakes involved (i.e. the future of our planet) and the current technological advances available on hand, there is no time like now for transportation researchers and planners to convince drivers to open up their car doors for their neighbours and co-workers. It is hoped that the current research developments in this area, including from this thesis, will be able to bring the vision of carpooling as a widely embraced mode of travel closer to reality.

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