Acceptability and impacts of positive incentives for sustainable mobility behaviour

A segmentation approach in Curitiba, Brazil.

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The candidate confirms that the work submitted is his/her/their own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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Sections 1 and 2 of the paper are used in Chapter 1 of this thesis. Section 3 is used in the literature review (Chapter 2). Section 4.1 is used in Section 3.2 of the thesis, while Section 4.2 is used in sections 3.3 and 3.5. Section 4.3 is used in Section 3.5.3.

The co-authors of this paper are my PhD supervisors. Their contributions were in the form of advice and feedback on initial versions of the paper.

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Abstract

The development and delivery of positive incentives for the adoption of more environmentally friendly modes of transport is an emerging strategy to help tackle the problems associated with cars and other private conventionally-fuelled vehicles (CFVs) such as motorbikes. Policy-makers developing sustainable transport interventions that use positive incentives can benefit from the knowledge generated from research. Which groups respond best? And what environmental impacts can positive incentives have? Answers to these questions can support more effective transport policies and targeted interventions. The aim of this thesis is to examine the level of acceptability and the potential environmental impact of positive incentive schemes delivered using smartphone applications. A cross-sectional survey was completed by 920 university students in Curitiba, a Brazilian city with a population of 2 million people. The questionnaire was developed considering two groups of indicators: individual determinants of travel behaviour, which were extracted from theories of social psychology, and stated intentions and attitudes towards a range of eleven incentive strategies. Strategies included money, vouchers, points, rankings, and social media. Comparison across different behavioural profiles was performed using clustering and discriminant analyses. Stated intentions and mobility-related data were used to estimate environmental scenarios of incentives implementation. Results showed a higher individual preference for financial rewards and a relatively lower acceptability of social media tools. The acceptance level among groups with greater control over the use of non-motorised forms of transport was found to be higher than that among groups that are psychologically predisposed to private CFVs. The most conservative scenarios of modal shift in response to incentives indicate a potential reduction of 3.6-3.8% in carbon dioxide emissions, suggesting that positive incentives can play a small but important role in the global decarbonisation of the transport system demanded by the climate crisis.

Table of Contents

List of Tables

List of Figures

Chapter 1
Introduction

This chapter will outline the context of research, covering the main motivations behind the investigation and giving a critical view of the issues that still need to be addressed. Section 1.1 provides a discussion around the topic of research and briefly outlines its knowledge gaps. Next, transport issues in the area of study are presented in Section 1.2. To understand the link between these problems and the design of the thesis, the chapter proceeds to show a synthesis of the main issues to be addressed by the study (Section 1.3), its research questions (Section 1.4) and envisaged contributions (Section 1.5). The last section of the chapter is dedicated to present the thesis layout (Section 1.6).

1.1 Research context

Sustainable mobility is defined by the United Nations Human Settlements Program (UN-HABITAT) as the degree to which a city as a whole is accessible to all its inhabitants, with priority for public and non-motorised transport (UN-Habitat, 2009). A common feature of measures to improve sustainability across many cities is reductions in the use of single-occupancy private cars and other private conventionally-fuelled vehicles (CFVs), and their negative effects on society and the environment (van Acker et al., 2016). The use of private CFVs such as cars or motorbikes dominate personal travel in many cities and represent a growing mode worldwide, especially in low and middle-income nations. Addressing the causes of this unsustainable situation and the possible strategies to cope with it often involve understanding firstly the individual factors that underlie the use of private CFVs and secondly, how to incentivise change to more environmental-friendly modes.

There is much research assessing individual determinants for the use of different travel modes. Comprehensive meta-analyses and review studies have focused on the role that attitudes (Parkany et al., 2004), socio-demographic factors (Dargay, 2007) and other psychological or behavioural attributes (Gardner and Abraham, 2008; Lanzini and Khan, 2017) play in the use of different modes of transportation. Apart from the socio-demographic attributes that were found to affect these choices such as age, gender and income, psychological and behavioural determinants also demonstrate strong associations, particularly concepts related to the Theory of Planned Behaviour (TPB) (Ajzen, 1991). Situational factors such as the distance of the journey or the built environment also play an important role and their influence on transport-mode choice may, in fact, interact with psychological factors, as demonstrated by Collins and Chambers (2005) and Steg et al. (2001).

The utilisation of concepts from theories of social psychology such as the TPB or the Norm-activation model (NAM) (Schwartz, 1977) is extensive not only to explain general pro-environmental behaviours (e.g. Bamberg and Möser, 2007; Onwezen et al., 2013; Steg and Vlek, 2009), but also to explain the use of different travel modes (e.g. Anable, 2005; Bamberg et al., 2011; Bamberg and Möser, 2007; Donald et al., 2014; Nordlund and Garvill, 2003). In light of these models, researchers have stated that the psychological determinants of mode choice, such as those coming from theories of behaviour, need to be considered when designing transport policies aimed at behaviour change (Dargay, 2007; Richter et al., 2011). It is notable that different people are influenced by different factors and therefore respond differently to policy interventions (Richter et al., 2011). Based on this premise, recent research has suggested the formation of behavioural-based target groups to increase the effectiveness of transport policies (Salomon and Mokhtarian, 1998; Anable, 2005; Hunecke et al., 2010; Prillwitz and Barr, 2011; Mikiki and Papaioannou, 2012; Molin et al., 2016), especially those that focus on stimulating voluntary travel behaviour change (VTBC) (Richter et al., 2011). However, a lack of connection can be seen when analysing both the importance of psychosocial factors in explaining individual travel choices and the methodology used by other authors when trying to identify the target groups. The few authors who used theory-driven approaches (e.g. Outwater *et al.*, 2003; Anable, 2005; Hunecke *et al.*, 2010a; Prillwitz and Barr, 2011a; Mikiki and Papaioannou, 2012; Molin, Mokhtarian and Kroesen, 2016) have either: (1) not selected theories following a systematic manner that supports the decision between one theory over the others; (2) not considered the constructs postulated by the theories on their original form, but constructed new indicators that notably have weaker validity and reliability; or (3) not measured the theories' constructs for a variety of transport-modes, but were usually heavily inclined to assess only car use.

While some of these studies do provide policy suggestions for each identified target group, there is still an inadequate understanding of the differences in the responses that these groups would have to different types of policies, since there is a lack of empirical analysis on this issue. Richter, Friman and Gärling (2011) state that psychological determinants of mode choice, for example, influence the acceptance of behaviour change interventions and therefore should be considered when policies are designed. In addition, past research on the acceptance of persuasive measures for behaviour change is still heavily oriented to cities that are located in countries with predominantly advanced multi-modal transport systems such as western European nations or the United States (Anagnostopoulou et al., 2018). The SUPERHUB project, for example, was applied in the cities of Milan, Barcelona and Helsinki (Gabrielli et al., 2013), while the EMPOWER project had its 'living labs' located in Milton Keynes (UK), Enschede (Netherlands), Gothenburg and Helsinki (EMPOWER Project, 2019). The only option of mass transit in Curitiba is the bus and the cycling infrastructure is limited when compared to the cities above (more details about the transport infrastructure are provided in Section 3.2). Although Curitiba displays some mobility characteristics that are not usual in the majority of the Brazilian cities (e.g. the *Bus-Rapid-Transit* system), the city can still be considered representative of a middle-income country in economic terms[1]. Thus, travellers in Curitiba are assumed to have a particular behavioural and socioeconomic profile that has not been the subject of previous research on the acceptability of persuasive technologies. In addition, Curitiba notably has worse mobility infrastructure when compared to the cities where incentives projects were applied in the past.

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[1] The city's Gross National Income (GNI) per capita is below $12,235 (twelve thousand two hundred and thirty-five American dollars), which is the threshold defined by the World Bank (IBGE - Instituto Brasileiro de Geografia e Estatística, 2018a; World Bank, 2019).

To the best of this author's knowledge, studies dealing with behavioural determinants of travel mode choice and how to properly target different mobility profiles in Brazil with these technologies are non-existent to date.

This research focuses on a particular innovative form of stimulating VTBC, which has drawn attention in the past years: positive incentives based on Information and Communication Technologies (ICT). This scheme consists of using persuasive technologies in the form of rewards, information, gamification techniques or social media tools to stimulate the use of more sustainable travel modes, delivered either through the web or smartphone applications. This 'reward rather than punishment' approach is an alternative to the traditional punitive measures, like fuel tax, parking pricing or congestion charging (Grant-Muller, 2015). The development, application and evaluation of ICT-based positive incentives have been studied in several European projects, as the SUNSET and the EU-funded EMPOWER project (an extended and more detailed review can be found in Section 2.3). The SUNSET Project (2014) aimed to create and evaluate positive incentives schemes delivered through a smartphone application. Incentives developed in the project were in the form of travel information; feedback and self-monitoring tools; points and rewards and social network tools. Three European cities (Leeds, Gothenburg and Enschede) were subject to empirical research on attitudes towards the use of each incentive strategy. Positive perceptions of the surveyed participants were identified in regards to all schemes, especially 'Feedback and Self-monitoring' and the 'Points and Rewards' features, which showed a higher level of agreement about their effectiveness on behaviour (Kusumastuti et al., 2011). The EMPOWER Project aims at reducing individuals' dependence on CFV's using positive incentives delivered through smartphone technologies and the internet, collecting evidence from multiple cities in Europe. EMPOWER extends the knowledge created by SUNSET mainly through a systematically larger review of existing incentives programs, considering other stakeholders instead of system users alone and also using an experimentation phase prior to large scale implementation in several cities across Europe (EMPOWER project, 2018).

These previous programs provided promising findings but, notwithstanding, had some limitations that encourage further research. They were developed only in European countries or the United States and the majority of the experiments have either used small samples or did not provide an analysis of the impact on different traveller profiles (Anagnostopoulou et al., 2018). Those projects that used personalised incentives either did not employ a psychographic segmentation approach or identified the target groups based on information *a priori*, which may oversimplify the structure of the population (Anable, 2005). Thus, the distinction between this work and that of EMPOWER, for example, is in measuring the different acceptance levels of positive incentives by population segments using a theory-driven approach and especially on understanding the individual factors that are associated with the attitudes and intention to use this type of measure outside Europe. Using these findings to estimate the environmental impacts of the implementation of incentives in the city of Curitiba also represents a novelty of this work. To the best of this author's knowledge, there are only a few studies published to date that tested the responses of different groups of people to any particular type of persuasive tool. Semanjski et al. (2016) used attitudinal-based segments developed as part of the EU-funded SEGMENT project (SEGMENT, 2013) to examine their differences in response to information. Some discrepancies were reported between how the provision of information has translated into a modal switch for different groups, but the authors did not provide any empirical test to assess the significance of these differences and the results were limited to graphical representations of descriptive findings (Semanjski et al., 2016). Another relevant study that measured the impact of different motivational messages to behaviourally-constructed segments was made by Pangbourne and Masthoff (2016). The authors defined the segments using the specific set of questions from the SEGMENT project. Although some of the groups were represented by only four participants, the study serves as preliminary evidence that different messages implicate different effects in distinct clusters (Pangbourne and Masthoff, 2016).

Despite the existence of these materials, conclusions concerning the association of public segmentation and persuasive interventions are still preliminary, as the studies usually focus on a specific type of incentive and use small samples that do not permit more substantial findings. The extent to which individual attitudes and intentions toward positive incentives could translate to environmental benefits (i.e. in terms of carbon emissions) is also poorly understood at the moment, as none of the projects and studies reviewed in this research has made these estimations.

1.2 Area of study

This section gives an introductory overview of the area of study. A more detailed review is given in Chapter 3.

According to the Brazilian Department for Transport, the number of cars in the country has increased since 2000 (Departamento Nacional de Transito - DENATRAN, 2019). There has been an average yearly increase of 3.76% between 2015 and 2019, a period in which the car fleet increased from roughly 57 to 67 million cars and 22 to 27 million motorcycles (Departamento Nacional de Transito - DENATRAN, 2019).

This research will be conducted in the city of Curitiba, a well-known city in regards to urban planning and public transport system innovations (Newman, 1996; Cervero, 1998). The city has the highest motorisation rate among Brazilian Capitals, with 75 cars per 100 inhabitants, while the Brazilian average is 45 (IBGE - Instituto Brasileiro de Geografia e Estatística, 2018b; Departamento Nacional de Transito - DENATRAN, 2019). The city is known to be the first one to have implemented a Bus-rapid-transit system (BRT), which is still in full operation. Nevertheless, the average use of the bus system in Curitiba has fallen 13.9% between 2015 and 2017 (URBS, 2019), despite the city’s population growth. Research has shown that there is a short network of cycle lanes, lack of different transport mode integration and almost no measure aimed at restricting private car use (Miranda and Rodrigues da Silva, 2012). In addition, the population of Curitiba has trouble accepting restrictions to private car use, turning these measures in a political burden no one wants to take (Miranda and Rodrigues da Silva, 2012). This public rejection may be explained by a high individual annexation to the car and its use in Curitiba. The use of non-motorised modes, such as bikes, is not present in people's everyday life, as the use is more frequent in sporadic leisure activities than in regular, day-to-day transportation (Kienteka et al., 2014). The population perceptions of the cycling infrastructure are negative. A study with 412 university students in Curitiba showed that the factors which would most likely make the students consider taking the bicycle to campus would be "if there were more cycle lanes" and "if there were less traffic danger" (Franco, 2011). The study by Camargo (2012) found similar results. The most cited barriers to the use of bicycles in Curitiba were "lack of safety", "lack of cycling lanes" and "lack of structure".

Perhaps as a mean of responding to these criticisms about Curitiba's infrastructure, the transport interventions to reduce the use of private CFVs in the city have been limited to the traditional 'hard' measures and infrastructural changes in the past. The knowledge about the travel behaviour profile of the population was never explicitly considered in the formation of policies in Curitiba. The employment of 'soft' measures in Brazil is also very scarce. These issues urgently call for the empirical exploration of the general perceptions of the population in regards to these types of interventions and for the examination of the psychological profiles that exist in this particular context.

1.3 Main issues addressed by the thesis

Having briefly outlined the general research context in the earlier section, it is possible to summarise the knowledge gaps that this thesis aims to address:

1. The use of social-psychology theories is still at an early stage when it comes to supporting either the development of a public segmentation strategy for the delivery of transport interventions or the design and implementation of a positive incentives scheme. When considering these theories to analyse responses to positive incentives, there is still a strong dependence on the factors of the TPB;
2. Past studies have suggested the formation of target groups among the population to support better-tailored transport policy interventions, but

an empirical view of the individual differences in the responses to different types of schemes still remains unclear;

3. The few experiments that have measured individual attitudes and intentions towards the use of positive incentives used low samples and were implemented to a general audience without considering the importance of personalisation. Those projects that used personalised incentives either did not employ a public segmentation approach or identified the target groups based on information *a priori*;
4. The majority of research on positive incentives has been undertaken in European countries or other countries with advanced multi-modal transport systems. The perceptions of the population of middle-income countries with respect to these schemes remain unexplored;
5. Experiments of positive incentives have examined the impact of these initiatives on small samples of individuals. Authors usually report these benefits in terms of the reduction of private CFV trips, but haven't yet explored what would be the environmental benefits (e.g. in terms of carbon emissions) of the implementation of these schemes in wider populations.

From a theoretical perspective, this thesis unites three main concepts that still have not been subject to empirical research in conjunction: psychographic segmentation, theories of social psychology and the use of positive incentives for sustainable mobility, as illustrated in Figure 1.1.

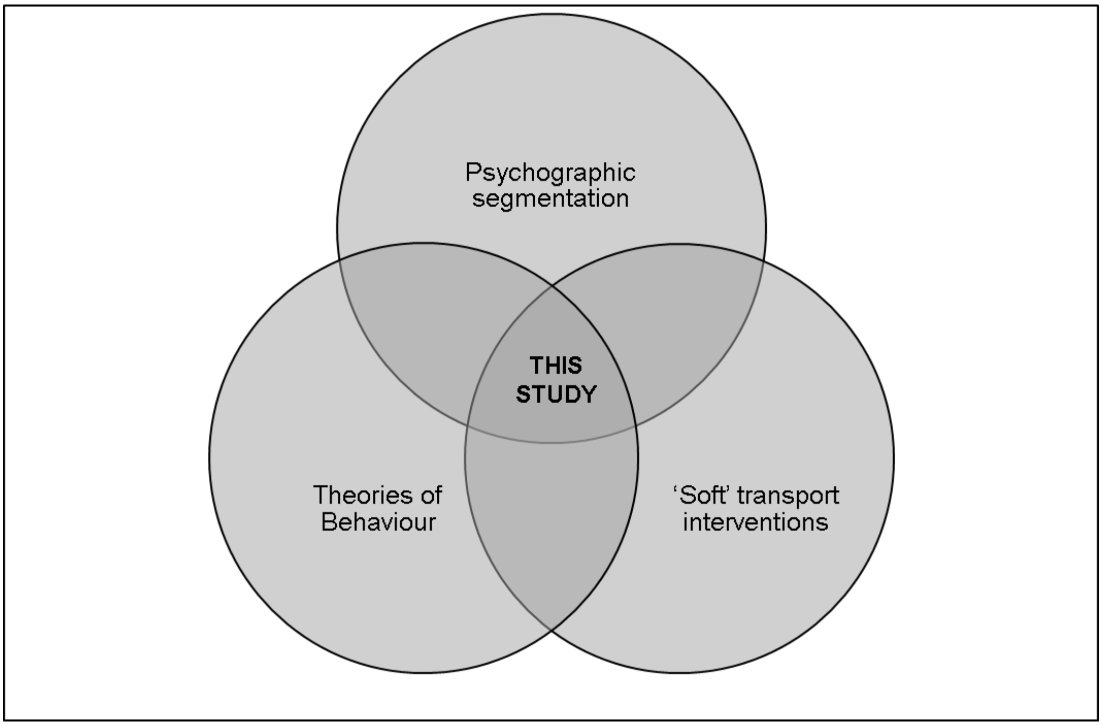

Figure 1.1 - Theoretical positioning of the thesis

1.4 Research aims and questions

To address the issues raised above, the aim of this research is to examine the degree of acceptability of different population segments to positive incentive schemes for sustainable mobility behaviour and the corresponding environmental impacts of these strategies. Therefore, it intends to answer the following main research question (RQ):

What levels of acceptability and environmental benefits are demonstrated from the use of different smartphone-based positive incentives, both in general and considering different population segments of Curitiba, Brazil?

The following secondary research questions were designed:

- RQ1: What determinants of travel behaviour can be used to underpin a segmentation approach?
- RQ2: What behavioural factors are associated with individual acceptance of positive incentives to reduce the use of private conventionally-fuelled vehicles (CFVs)?
- RQ3: Which psychographic segments show higher acceptability of positive incentive schemes?

- RQ4: What are the behavioural differences between distinct segments of the population that are created based on the acceptance of incentives?
- RQ5: What environmental benefits can be estimated (in general and considering population segments) from a hypothetical implementation of positive incentives in Curitiba?

The main hypothesis of the study is that examining: (1) the general level of acceptance of positive incentives, (2) the relative level of acceptance demonstrated by homogeneous transport-related psychographic groups and (3) the corresponding environmental estimates, will offer new insights into travel psychology and persuasive technologies applied to transport.

1.5 Contributions of the thesis

The contributions of this work can be represented as methodological, technical and theoretical and are summarised in Figure 1.2.

The methodological and theoretical contributions are mainly related to offering evidence about the applicability of widely-established theories of social psychology on the field of travel behaviour. There is still an ongoing debate about the validity of these theories to certain research fields (Sniehotta et al., 2014) and this research provides an empirical evaluation of the constructs of these theories and to what extent they can underpin the formation of transport policies. This is done by examining a socio-economic context in which such theories have not yet been subject to substantial use by past research. The development of a scenario estimation using stated intention data also contributes to understanding how these type of data may be used by future authors.

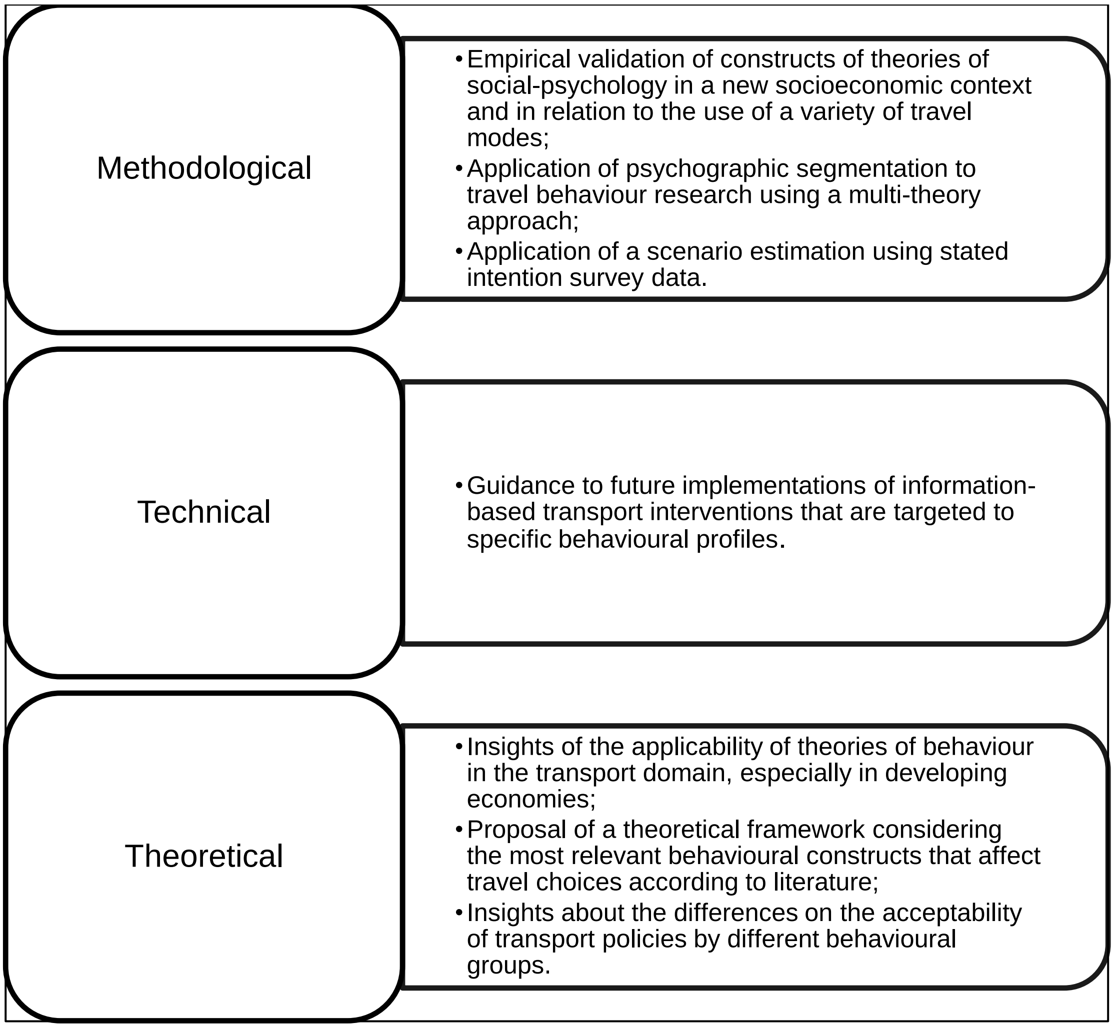

Figure 1.2 - Main contributions of the research

The information provided in this thesis contributes to some extent to future implementations of not only positive incentives but other information-based initiatives. The identification of travel-related psychographic groups offers insights about how they can be targeted differently by a policy. In the case of positive incentives, the most impactful schemes are enumerated and the relative acceptability among the groups are analysed. The scenario estimation offers not only a general estimate about the possible benefits that might come with an implementation of positive incentives but also the relative impact coming from different psychologic profiles. A cost-saving analysis also provides preliminary information to underpin future cost-benefit studies of future implementations. A preliminary approach of such a possibility is given in Chapter 6.

1.6 Thesis layout

This thesis contains six chapters that are briefly described in Table 1.1.

Table 1.1 - Structure of the thesis

Chapter number	Chapter Name	Description
1	Introduction	Provides the general research context, the arguments and ideas that will be assessed and the envisaged contributions of the thesis.
2	Literature review	Provides a critical discussion of the literature on the main topics of interest, culminating in the systematic formation of a theoretical framework.
3	Methodology	Informs about the methodological approaches. From survey design and implementation to the description of the area of study and the data analysis strategy.
4	Data preparation	Reports all the approaches that were taken since the data was collected to prepare it for analysis.
5	Results	Reports the findings of the research in a descriptive manner.
6	Discussion	Discusses the interpretation of the results in the light of the literature, identifying contrasts and similarities and evidencing the relevance of the results.

After setting out the background and focus of this research, the thesis now proceeds to the examination of the relevant literature in Chapter 2.

Chapter 2
Literature Review

This chapter aims to present and analyse the investigated theory that grounds this research and is divided into three main parts: the first part of the chapter (Section 2.1) discusses the literature on the individual determinants of transport mobility. The second part (Section 2.2) focuses on the existing research about the strategy of market segmentation and its use in the transport behaviour field. Current models are reviewed and analysed in this part. Past and current initiatives involving the use of positive incentives to change one's transport behaviour are reviewed in the third part (Section 2.3). The goal of this phase was to collect the types of incentives that have been implemented in different urban environments. Evidence of this type of intervention at reducing the use of Private conventionally-fuelled vehicles is also discussed.

The review focuses on published academic literature. Sections 2.1 and 2.2 are based mainly on articles from peer-reviewed journals. Some of the reviewed theories of behaviour were also published as books and these were also covered. Some of the information regarding the incentive projects, presented in Section 2.3, were collected from the respective project websites, although academic publications were always prioritised. Most of the reviewed work is quite recent (from the 2000s), but some fundamental studies in the field of social psychology from as old as 1931 were also accessed.

2.1 Determinant Factors for the use of different transport modes

The concept of travel behaviour is multidimensional and includes aspects such as preferences for particular routes, trip-chaining, destination choice, time of travelling, car purchasing etc. (van Acker et al., 2016). These travel choices are affected by multiple factors, which can be related to the individual or not. Non-individual factors may include the built environment, existence of cycle lanes or bus stops, while individual aspects may include sociodemographic characteristics such as age, income and gender or psychological aspects like attitudes or habit (Mikiki and Papaioannou, 2012). Due to scope-defining reasons, the literature review of this study covered only aspects that are inherent to the individual when making the *choice* of which transport mode to use. As will be seen later in the chapter, one of positive incentives' main concern is in reducing the use of private conventionally-fuelled vehicles by means of *switching* travel modes to encourage healthier and more environmentally sustainable choices (although other applications such as avoiding peak hour driving also exist).

Firstly, a comprehensive review was performed to collect the sociodemographic factors that influence transport mode choice. Secondly, theories of behaviour were reviewed to clarify the psychological factors that could play a role in travel behaviour. As it would be impractical to cover all the existing theories that explain behaviour adoption and change, even if only theories that have an application to transport behaviour were searched, the selection of theories to be reviewed here followed, briefly, two inclusion criteria:

1. Theories that were substantially used in past studies that focus on explaining travel choices. For this, an examination was done considering meta-analyses studies (Gardner and Abraham, 2008; Lanzini and Khan, 2017; Hoffmann et al., 2017), literature review studies focusing on either transport mode choices (Chng et al., 2018) or pro-environmental behaviours in general (Bamberg and Möser, 2007; Steg and Vlek, 2009; Gärling et al., 2014). The discussions presented by empirical studies that evaluate travel behaviour using multi-theory frameworks were also considered (Anable and Gatersleben, 2005; Bamberg et al., 2003b; Bamberg and Schmidt, 2001) or;
2. Theories that were used as the basis for the development of past positive incentives projects, such as the SUNSET Project (2014).

The remainder of this section will be devoted to presenting a fundamental and synthesised description of the theories that were selected for this research and a critical view about them. A more extensive descriptive material on the sociodemographic and psychological determinants of travel behaviour including theories that ended up not being part of the theoretical framework can be found in Appendix A.

2.1.1 The Theory of Planned Behaviour (TPB)

When trying to explain transport-related behaviours, various researchers (e.g. Heath and Gifford, 2002; Bamberg, Ajzen and Schmidt, 2003; Khoo and Ong, 2015) have used the Theory of Planned Behaviour (TPB), originally presented by Ajzen (1991). It is the most widely researched model of behaviour (Armitage and Conner, 2001).

The TPB is essentially an extension of the previously published Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1977). According to the TRA, the most important antecedent of behaviour is the intention to act. Intention is conceptualised as “a person’s readiness to perform a behaviour” (Fishbein and Ajzen, 2011, p.39) and is determined by two factors: attitude towards the behaviour in question and subjective norm concerning that behaviour. Attitude is defined as “a latent disposition or tendency to respond with some degree of favourableness or unfavourableness to a psychological object” (Fishbein and Ajzen, 2011, p.76), while norms are conceptualized as “a perceived social pressure to perform (or not to perform) a given behaviour” (Fishbein and Ajzen, 2011, p.130). Later, (Ajzen, 1991) extended the TRA by including a measure of perceived behavioural control (PBC) as a predictor of intentions and behaviour. The main reason behind this inclusion was that the original model (TRA) failed to explain behaviours that were not under an individual’s volitional control. Thus, if external factors prevent a person to engage in a certain behaviour, he will not perform it, even if he has strong attitudes, norms and intentions to do so (Sheppard et al., 1988). Having that explained, PBC is defined as an individual’s impression about how easy or difficult it would be to perform the behaviour of interest. In general, the higher the individual’s confidence on the ability to execute a given behaviour, the higher the likelihood to adopt it. Finally, the theory adds that attitudes, norms and perceived control are each determined by a set of beliefs. Respectively, beliefs about the consequences of the behaviour (behavioural beliefs), about the views of other people in respect to the behaviour (normative beliefs) and about the factors that may facilitate or impede the adoption of a behaviour (control beliefs) (Figure 2.1).

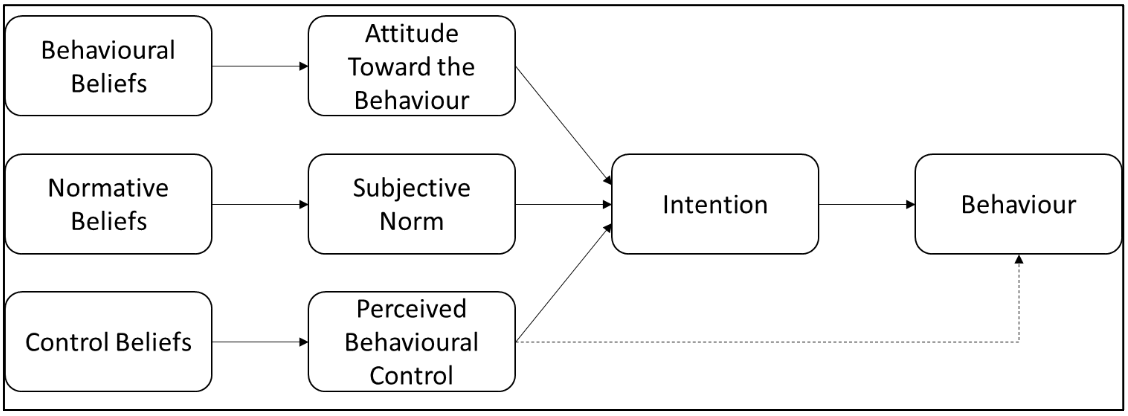

Figure 2.1 - The theory of planned behaviour

Next sections present a brief overview of the evidence of the influence of the main TBP's concepts on travel behaviour.

2.1.1.1 Intentions

Intentions are the most important antecedent of behaviour, although the direct influence of perceived behavioural control also has to be taken into account. It is defined as a person's readiness to perform a given behaviour and can be expressed in statements such as: "I will engage in the behaviour"; "I plan to engage in the behaviour", etc. (Fishbein and Ajzen, 2010). Some conceptual differences were subject to discussions in the past. For instance, 'willingness' and 'behavioural expectation' have been subject to empirical evaluation as to whether they are conceptually different from 'intentions' and better predictors of behaviour. However, such differences still lack further investigations as no conclusion has been found.

The meta-analysis by Lanzini and Khan (2017) and Gardner and Abraham (2008) have both found that intention to use the car, for example, is a substantial predictor of actual driving ($r = 0.82$ and $r = 0.53$, respectively). Lanzini also found a significant effect of intention when looking at using alternatives to the car ($r = 0.62$).

2.1.1.2 Perceived Behavioural Control (PBC)

The relative importance of PBC can vary between different behaviours. As stated by Ajzen (1991), the little the information a person has about the behaviour, the less the accuracy of the perception of control over that same behaviour. For example, assuming that most people have sufficient information about how to ride a bike, cycling would be explained far less by PBC and more by other TPB factors.

The concept of PBC has been found to translate into two different factors: autonomy and capacity. Capacity is related to the ability to perform a given factor, or the extent to which one feels that performing the behaviour is easy or difficult. Autonomy is more related to whether a person feels that performing a behaviour is entire “up to his will” (Fishbein and Ajzen, 2010). For example, riding a bicycle might be seen as an easy task to perform. However, one might choose not to use it because there is a lack of cycle lanes or because he can’t afford to have one.

In the meta-analysis of Lanzini and Khan (2017), Perceived behavioural control demonstrated to have a significant effect on the use of both the car and its alternatives (cycling, walking). Additionally, the literature review by Heinen et al., (2010) shows that people who cycle often perceive fewer barriers to commute by bike than non-cyclists do. PBC has also been found to be an important predictor of public transport use and has indeed demonstrated to be the strongest predictor of transport mode choice overall (Donald et al., 2014). The meta-analysis by Hoffmann et al. (2017) corroborates this finding, as PBC was identified to be the most relevant predictor for car and non-car use, higher than attitudes and subjective norms, respectively.

According to the theory, PBC is determined by beliefs about the existence of the so-called ‘control factors’, which refer to obstacles or facilitators of the behaviour in question (Fishbein and Ajzen, 2010). So, the greater the beliefs about the existence of certain facilitators to cycle, for example (cycle lanes), the higher the PBC in regards to cycling.

2.1.1.3 Subjective Norm (SN)

’Subjective norm’ refers to “the perceived social pressure to perform or not to perform the behaviour” (Ajzen, 1991). The author also argues that not only the so-called ‘social norms’ could explain intentions but also ‘personal norms’ or 'moral norms', which refers to a people's judgements as to whether they themselves think they should perform or not perform a behaviour (Fishbein and Ajzen, 2010). This idea is corroborated by (Armitage and Conner, 2001) who state that this construct should be expanded as it has weakly explanatory power for intentions. Indeed, other theories of behaviour already use 'personal norms' as a direct predictor of intention to behave, especially when dealing with pro-environmental behaviours (like the Norm-activation Model, to be detailed later in the chapter).

According to the TPB, a person might feel pressure to engage in a certain behaviour if they think that an important person to them might reward or punish them, might request it, because he is an expert, or because they want to be like this person (Fishbein and Ajzen, 2010). In regards to mobility choices, a person might start cycling if she or he starts noticing that people around are judging her or him for using the car too much, for example.

Originally, the TPB considered subjective norms as only to what may be called 'injunctive norms'. But later on, the authors have recognised the existence of 'descriptive norms', another component of social pressure that refers to the perception that other people are or are not performing the behaviour in question (Fishbein and Ajzen, 2010).

Similarly to the PBC, subjective norms are determined by 'Normative beliefs' according to the TPB, which refer to beliefs that a particular group or person would exert this 'social pressure' towards the performance of a behaviour. For example, one might think that a particular family member thinks he should not cycle.

2.1.1.4 Attitudes (ATT)

The study of attitudes is one of the main areas of social psychology. In particular, most part of the scientific discussions deals with the interactions between attitudes and people's behaviour (Christian et al., 2003). After the development of some controversy about the existence of a direct influence of attitudes in human's behaviour, the researchers who would later develop the

TPB identified that intention act as a mediator variable in this relationship (Fishbein and Ajzen, 1977).

Attitudes are defined by the TPB authors as “a latent disposition or tendency to respond with some degree of favourableness or unfavourableness to a psychological object” (Fishbein and Ajzen, 2010, p.76). This concept was created based on the work of Thurstone (1931), who was the first author to create a scale to measure attitudes. His work served as the basis for the further development of attitude scales such as the Likert-type scale. Within the scope of the TPB, attitude is an evaluation of an object or behaviour along a dimension of favour or disfavour. For example, the extent to which a person likes riding a bicycle or not might be considered as a measure of attitude on this perspective.

Just like PBC are formed by control beliefs and SN are formed by normative beliefs, attitudes are determined by behavioural beliefs. These opinions are formed in an individual by the association of a given behaviour with certain characteristics, qualities or attributes (Fishbein and Ajzen, 2010). The extent to which a person has positive attitudes to driving a car, for example, can be determined by the extent to which he believes the journey will be comfortable, fast, or safe.

Despite being widely used and cited, the effectiveness of TPB on its original form has been questioned when explaining more complex behaviours, such as the ones related to mobility (Anable, 2005). Other theories of behaviour have the potential to help constructing a more reliable theoretical framework for behaviour change to reduce private CFVs dependence.

2.1.2 The Norm Activation Theory (NAM)

The Norm Activation Model (NAM) was originally proposed by Schwartz (1977) and has ‘personal norms’ as the main predictor of individual behaviour (Figure 2.2). The theory was originally created to explain pro-environmental behaviours and states that personal norms are regulated by two factors: the notion that performing or not performing a given behaviour can lead to consequences (Awareness of Consequences - AC) and the ascription of one’s own responsibility in these adverse effects (Ascription of Responsibility – AR) (Schwartz, 1977; Onwezen et al., 2013).

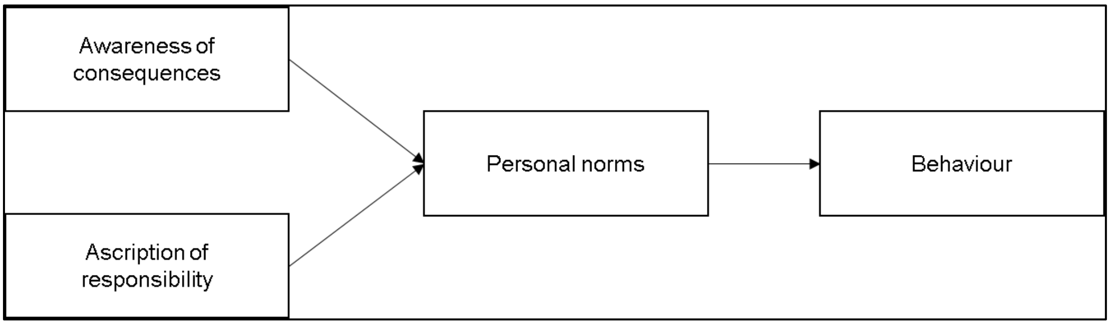

Figure 2.2 - The Norm Activation Model

The model has been vastly used to understand pro-environmental behaviour (Steg and Vlek, 2009; Onwezen et al., 2013) and more specifically car use reduction (Anable, 2005; Bamberg et al., 2011). The concept of personal norms was already recognised by the TPB authors to be important in explaining general behaviour adoption, besides ‘subjective norms’. In fact, recent studies have successfully used a combination of the TPB and the NAM to understand mobility-related behaviours (Bamberg and Möser, 2007; da Silva et al., 2011). One of the main findings of these studies, for example, is that social norm does not influence intentions directly. Instead, this relation can be mediated by personal norms.

In respect to the influence of ‘awareness of consequences’ in travel behaviour, the study of Nordlund and Garvill (2003) examined the causal relationship between personal awareness of environmental problems and willingness to reduce car use. They also tested how personal norms and personal values influence disposition to leave the car. The model showed that problem awareness conserving the biosphere and humankind are positively related to problem awareness in relation to car use, which in turn, affects willingness to reduce its usage. Another study showed that the use of public transport is affected by the ticket price and an individual's "personal norms" in relation to travel and the environment, with a similar effect. (Hunecke et al., 2001)

Bamberg et al. (2011) postulate that reductions to car use may be better explained by the NAM theory than the TPB, as car use reduction depends strongly on pro-environmental motives. The authors, therefore, propose the integration of constructs from the TPB and the NAM for the study of transport mode choice. This integration is, in fact, used in many studies of transport mode choice (Bamberg and Schmidt, 2003; Anable, 2005; Haustein et al., 2009; Setiawan et al., 2014) or general pro-environmental behaviours (Onwezen et al., 2013).

2.1.3 The Value-Belief-Norm (VBN)

The norm-activation theory (Schwartz, 1977) explains that prosocial behaviour is influenced by feelings of moral obligation originated from an individual's personal norms. The Value-Belief-Norm (VBN) theory, developed by Stern et al. (1999), advances this theoretical relation to explain specifically pro-environmental behaviours. The most substantial difference to the NAM is that, in the VBN theory, 'personal norms' are activated by a hierarchical sequence of variables, instead of 'Awareness of consequences' and 'ascription of responsibility', together (Figure 2.3). Specifically, awareness of consequences is still a predictor of personal norms but mediated by a perception that one's future *actions* have the potential to contribute or alleviate the consequences, referred by the authors as "Perceived ability to reduce threat" (Stern et al., 1999). On Stern and colleagues' point of view, this is a generalisation of the original concept of Schwartz's "Ascription of responsibility", who had argued that just the perception that one's have a responsibility on the existence of the problem would influence personal norms. Despite this conceptual difference, some authors have used both terms interchangeably (Han et al., 2017).

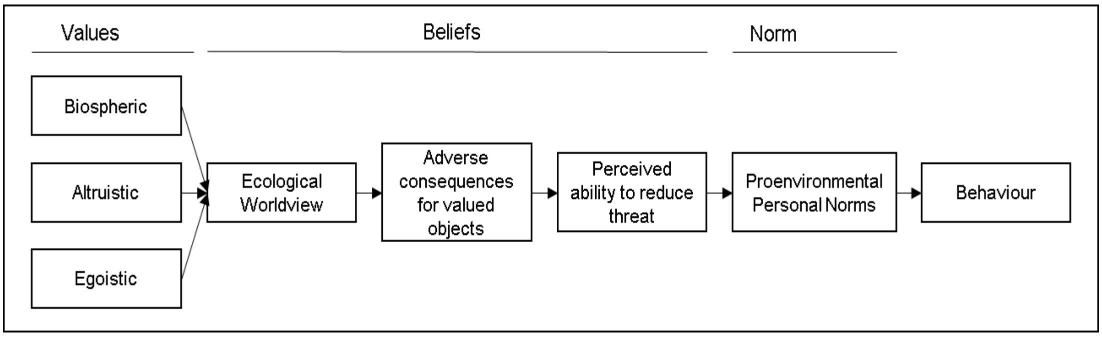

Figure 2.3 - The Value-Belief-Norm theory

Stern and colleagues also claim that awareness of consequences (AC) occurs in response to a more general sense of environmental awareness, which they called ‘Ecological Worldview’. This in turn, would be influenced by personal biospheric, altruistic or egoistic values. These assumptions could be translated into the transport domain as if one's awareness of the bad consequences of excessive use of private CFVs were determined by this individual's environmental awareness, which in turn was influenced by his or her personal values.

When it comes to providing empirical support to the VBN in transport behaviour, the conclusive meta-analysis of Gardner and Abraham (2008) showed a weak effect of general pro-environmental attitudes of use and intention to use the car, whereas aspects of other theories such as intentions, habit and perceived behavioural control demonstrated much larger effects (Gardner and Abraham, 2008). Hunecke et al. (2011) tested a model on which perception of ecological problems would have an effect on personal norms associated with travel mode choice on a specific route. The results showed that this construct could not be treated independently of other factors such as AC, AR or the TPB’s factor: ‘Subjective Norms’. The more recent meta-analysis of Lanzini and Khan (2017) showed that general ‘environmental values’ are not significantly related to the use of alternatives to the car, but concepts like AC, AR, general problem awareness and personal norms, have a small to medium effect on non-car use.

The TPB, the NAM and related theories (like the VBN) are the most used theories to explain travel behaviour (Chng et al., 2018). Nevertheless, the next sections present other theories from social psychology that have met the inclusion criteria established earlier in the chapter.

2.1.4 The Theory of Interpersonal Behaviour (TIB)

TIB is a general theory of social behaviour and was proposed by Triandis (1977). This theory has similarities with the Theory of Planned Behaviour as both theories consider intentions as the main predictor of actual behaviour. One of the main distinctions, however, is that the TIB includes the formation of habit as an explanatory factor of behaviour, arguing that the individual does not always have conscious control of behaviour and that the level of consciousness decreases as the level of habit increases (Bamberg and Schmidt, 2003). Triandis defined a habit as situation-behaviour sequences that are or have become automatic so that they occur without self-instruction. The individual is usually not ‘conscious’ of these sequences (Triandis, 1977). This concept confronts the original form of the TPB, which viewed behaviour as something totally controlled, reasoned and planned (Bamberg, Rölle, et al., 2003). It can be assumed that the habitual use of the car, for example, can make the individual not conscious about other available options of transport. Actually, considering habit as a predictor of the use of cars or other transport modes is relatively usual. Several studies have indicated that habit plays a significant role on an individuals’ transport choices (Bamberg, Ajzen, et al., 2003; Bamberg and Schmidt, 2003; Fujii and Gärling, 2007; Eriksson et al., 2008b; Gardner and Abraham, 2008). Habit has demonstrated to be one of the most influential aspects of both car and non-car use by different meta-analyses (Gardner and Abraham, 2008; Hoffmann et al., 2017; Lanzini and Khan, 2017).

Habit is formed by the frequency of a certain past behaviour. In fact, Lally *et al.* (2010) provide robust empirical evidence that the automaticity of behaviour increases continuously only when a person repeats this behaviour consistently, thus forming a new habit. Triandis (1977) also recognises the frequency of past behaviour as predictor of habit.

Some researchers argue that past behaviour is the best predictor of future behaviour (Bamberg, Rölle, et al., 2003). Past behaviour and habit are often used as synonyms in literature, but they are not the same. Past behaviour only may turn into automatic responses that become habits when repeated sufficiently and satisfactorily (Verplanken and Aarts, 1999).

In the transport research context, frequency of past car use and non-car use have shown to strongly predict the future use of travel modes. In the case of alternatives to the car, even stronger than the TPB’s ‘intention’ (Lanzini and Khan, 2017). The structural model developed by Bamberg et al. (2003b), to explain public transport (PT) use, has revealed that past car use significantly influences the three main predictors of intentions of the TPB (in this case related to the use of PT): attitudes, subjective norms and perceived behavioural control. It also acted as a strong predictor of PT habit.

‘Social factors’ are also predictors of behaviour, according to the TIB. This concept is formed by the following factors: the normative belief construct of the TPB; personal norms; role beliefs about the appropriateness of the behaviour for one’s perceived social role; self-definitions; and interpersonal agreements (Bamberg and Schmidt, 2003).

In respect to attitudes, Triandis divided the concept in two manners: affective and cognitive. According to the author, affective attitudes represent the evaluation an individual makes about the consequences associated directly with the performance of the behaviour, whereas cognitive attitudes refer to the evaluation of long-term behavioural consequences. This multi-dimensional nature of attitudes was object of later discussions by transport researchers (who argued that travel mode choice can be influenced by instrumental, affective and symbolic motives) (Steg, 2005) and by theoretical researches like the authors of the TPB (Fishbein and Ajzen, 2010), who recognised that attitudes can be both instrumental (or cognitive) and experiential (affective).

The relationship of Habit with Behaviour, theorised by Triandis (1977), has successfully demonstrated to influence transport choices, especially when used as a complement to other theories like the TPB or the NAM (Bamberg and Schmidt, 2003).

Having described the theories to be used in this study, the chapter now moves to the examination of the empirical evidence of their use in transport-related research.

2.1.5 The influence of theories of behaviour in car and non-car use

This section aims to give a more solid empirical justification for the use of such theories within this thesis.

The three meta-analyses that were indicated at point 1 on the previous section(page 14) were evaluated. They focused on examining the influence of theoretical constructs on car use and non-car use, which on the majority of reviewed studies refer to public transport, cycling or walking (Gardner and Abraham, 2008; Hoffmann et al., 2017; Lanzini and Khan, 2017). To the best of this author's knowledge, these are the only systematic reviews available in the literature to date. Table 2.1 and Table 2.2 were constructed based on the information provided in each one of the studies (for car and non-car use, respectively). The total effect sizes of certain variables on car use (or other modes) were extracted directly from the studies and categorised here. Values representing the same variable were organised on the same line. In case a given variable has not been subjected to analysis in any of the studies, a dash (-) is shown.

Apart from the factors presented above, a few other behavioural factors were assessed by a relatively small number of the studies reviewed by the meta-analyses. Namely, attitudes that are not specifically related to travel modes but to travelling in general or to the environment, which showed non-significant and small negative associations with car use, respectively; 'Identity pro-car' and 'identity anti-car', which showed very small effects on car use; and general altruistic value orientation, which showed a medium negative correlation with car use (Hoffmann et al., 2017). The other two studies did not report results on any other behavioural factor other than what is displayed in the tables.

Overall, the studies attest the relevance of the theories described in the earlier sections of this chapter (TPB, NAM, VBN and the TIB), since few factors that were present in the studies were not extracted from these theories.

Perhaps the constructs showing the weakest relationships with car use are descriptive norms and ascription of responsibility (which were non-significant in two meta-analyses). Particular emphasis should be given to the roles of habit, intention, PBC, past experience and attitudes, as these constructs have shown strong associations with both car and non-car use.

Table 2.1 - Total effect sizes (r) of psychological determinants to car use, according to meta-analyses.

	Hoffman et al. (2017)		Gardner and Abraham (2008)		Lanzini and Khan (2017)	
Variables of the NAM[1]/VBN[2] theories	**N**	**r**	**N**	**r**	**N**	**r**
Ascription of Responsibilities	642	−0.14	403	-0.18***	644	-0.14
Awareness of Consequences	2139	−0.22***	-	-	671	-0.13
Environmental concern	-	-	1462	-0.13***	2621	-0.19***
Perceived personal threat	-	-	1151	-0.20***	-	-
Personal Norms - Non-car	793	−0.35***	563	-0.41***	4222	-0.26***
Problem awareness	-	-	799	-0.24***	5545	-0.17***
Variables of the TPB[3]/TIB[4] theories	**N**	**r**	**N**	**r**	**N**	**r**
Attitudes - Car	4647	0.22***	569	0.27***	4290	0.41***
Attitudes - Non-car	812	−0.23**	1270	-0.41***	3283	-0.36***
Descriptive norms - Car	532	−0.07	993	0.36***	2199	0.25
Habit - Car	2058	0.47***	934	0.50***	8098	0.42***
Intention - Car	2375	0.50***	2517	0.53***	3441	0.82***
Intention - Non-car	943	−0.38*	-	-	3300	-0.51**
Perceived Behavioural Control - Car	1605	0.39***	324	0.31***	2399	0.27***
Perceived Behavioural Control - Non-car	1200	−0.42***	2334	-0.51***	1092	-0.43**
Subjective norms - Car	1455	0.20**	555	-0.07	2866	0.23***
Subjective Norms - Non-car	944	−0.15***	1069	-0.36***	3681	-0.15***
Other variables	**N**	**r**	**N**	**r**	**N**	**r**
Past car use	1248	0.58***	-	-	1699	0.69***

* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$ (for the meta-analysis by Lanzini and colleagues, $p < 0.01$)
N: Total sample size.
r: Total effect size.
[1]: Norm-activation theory.
[2]: Value-belief-norm theory.
[3]: Theory of Planned Behaviour.
[4]: Theory of Interpersonal Behaviour.

Table 2.2 - Total effect sizes (r) of psychological determinants to non-car use, according to meta-analyses.

	Hoffmann et al. (2017)		Lanzini and Khan (2017)	
Variables of the NAM[1]/VBN[2]	**N**	**r**	**N**	**r**
Ascription of Responsibilities	-	-	1746	0.22***
Awareness of Consequences	-	-	1571	0.12
Environmental concern	-	-	936	0.14***
Environmental Values	-	-	4417	0.14
Personal Norms - Non-car	-	-	6219	0.34***
Problem awareness	-	-	2698	0.20***
Variables of the TPB[3]/TIB[4]	**N**	**r**	**N**	**r**
Attitudes - Non-car	2597	0.36***	13282	0.31***
Descriptive norms - Non-car	-	-	2231	0.21*
Habit - Non-car	-	-	929	0.68*
Intentions - Non-car	3493	0.48***	11411	0.62***
Perceived Behavioural Control - Non-car	3500	0.49***	12649	0.38***
Subjective Norms - Non-car	2745	0.28***	12737	0.23***
Other variables	**N**	**r**	**N**	**r**
Past non-car use	-	-	2205	0.85***

** $p < 0.01$
*** $p < 0.001$ (for Lanzini and colleagues meta-analysis, $p < 0.01$)
N: Total sample size.
[1]: Norm-activation theory.
[2]: Value-belief-norm theory.
[3]: Theory of Planned Behaviour.
[4]: Theory of Interpersonal Behaviour.

So far in the section, the studies that applied theories of behaviour (like the TPB) in the transport field were examined by looking at their effectiveness to predict the use of (or intention to use) different modes. Nevertheless, there is also evidence that such theories might be useful in predicting changes to more sustainable modes of transport that occur in response to an intervention, especially using cross-sectional studies. This section now proceeds to the examination of this tranche of research.

2.1.6 The role of theories of behaviour in travel behaviour change

The increasing number of policy interventions aimed at behaviour change worldwide, especially for the formation of pro-environmental behaviours, has raised curiosity about how well-received these initiatives can be by the target population and what are the determinants for such effectiveness. Jackson (2005) emphasizes that policy development for behaviour change is difficult, especially because human motivations and behaviours are complex, which makes it hard to predict how policy interventions will affect the people. In view of this, authors have started to examine how determinants of behaviour from theories of social-psychology might help to understand the individual acceptance of policies.

Although it is notable that behavioural interventions have their effectiveness increased when they are aimed at relevant antecedents of behaviour (Steg and Vlek, 2009), studies that test the influence of these theories in transport-related interventions are still rare (Bird et al., 2018). Systematic reviews have provided strong evidence about the utility of theoretical antecedents of behaviour on the design of interventions (Hardeman et al., 2002; Webb et al., 2010). But the majority of studies are focused on health-related behaviours (stop smoking, exercising, etc.) and use the TPB or extended versions of the TPB (e.g. including habit). Steinmetz et al. (2016) performed a meta-analysis including studies that report using the TPB to support behaviour interventions. The vast majority of the studies that were found dealt with health-related behaviours such as engaging in physical activities (33% of studies), improving nutrition (19%) or quitting alcohol and drug use (11%). 7% of the interventions were related to transport, but mainly to safety aspects like the use of seat belts or helmets and compliance with speed limits (Steinmetz et al., 2016).

In terms of discontinuing car use or shifting to more sustainable travel modes, a few studies were published. Bamberg and Schmidt (2001) examined the extent to which TPB's constructs explain a shift from car use to public transport following the implementation of a combination of information and monetary incentive (free PT ticket). The authors found significant differences in attitudes to PT, subjective norms and PBC after the implementation of the interventions. Other study found that attitudes, PBC and Habit related to cycling or walking significantly increased at either 1 year or 2 years after the implementation of a program to improve infrastructure for non-motorised modes in the United Kingdom (Bird et al., 2018). Eriksson et al. (2010) demonstrated that NAM and

VBN's 'personal norm' construct does affect the intention to reduce car use subject to an improvement in public transport and taxes on fossil fuels. However, the authors did not test other antecedents of behaviour like PBC, for example. Perhaps the most comprehensive study about how theories of behaviour could help to understand the willingness to reduce car use is the one by Bamberg (2013). The author proposes and tests a framework to explain intentions to adopt environmental-friendly transport behaviours like increasing PT use. A resulting structural model using constructs derived from theories such as the VBN, NAM and TPB explained intention to implement a behaviour change to a relatively high degree (Bamberg, 2013b). A subsequent study has demonstrated that an intervention (marketing campaign) constructed based on this model was significantly more efficient than a general one in terms of shifting from the car to PT (Bamberg, 2013a). However, Bamberg's model still lacks replication in other transport contexts.

After the examination of the utility of social psychology theories in regards to behaviour adoption and behaviour change, next sections aim to bring a broader perspective about the use of such theories, in a critical manner, and insightful conclusions.

2.1.7 Concluding remarks of Section 2.1

Despite the substantial quantity of studies utilising the theory, the TPB may not be sufficient to explain transport mode use according to some research that is critical to the approach (Sniehotta et al., 2014). With respect to the explanation of transport mode use, a behavioural model can substantially benefit from the inclusion of other acknowledged influential aspects of this type of behaviour (apart from the TPB). In fact, the theory fails to consider some other concepts that were demonstrated to have significant relationships with the adoption of behaviour, especially within the domain of the so-called pro-environmental behaviours (including transport mode use). Personal norm (or moral norm) for example, do not play a role in the original model but was further recognised by the TPB authors as a construct that improves the explained variance of the model (Fishbein and Ajzen, 2014). That may be the reason why a substantial tranche of transport research that tried to explain mode choice has used not only personal norms but also predictive concepts belonging to theories that advocate this type of norm as a direct predictor of behaviour (NAM and VBN). The TIB also accounts the relevance of ‘personal normative beliefs’ apart from ‘social normative beliefs’. The first referring to a perception of social pressure and the second to feelings of moral obligation to perform the behaviour.

Another limitation of the TPB is that it focuses exclusively on rational reasoning to explain behaviour. Other unconscious influences on behaviour should be considered, such as habit. TIB is one of the first theories to propose habit as a predictor of behaviour. Triandis (1969) suggests that when the attitude-behaviour relationship is weak, habit is strong, whereas when the habit is weak, the attitude-behaviour link is strong. This trade-off between these two different predictors of behaviour (attitudes and habit) was confirmed on travel-related behaviours such as mode choice (Lanken et al., 1994). Past studies have shown that the addition of car use habit has increased the predictive power of behaviour within the TPB (Lanken et al., 1994; Bamberg, 1996; Verplanken et al., 1998; Bamberg and Schmidt, 2003) and the Norm-Activation (NAM) theories (Klöckner, Matthies and Hunecke, 2003; Klöckner and Matthies, 2004). This indicates that the inclusion of Habit in any travel behaviour framework is beneficial.

The role of emotions on behaviour was also pointed out by critics of the TPB, who advocate that the theory is too rational (Sniehotta et al., 2014). However, the TPB authors reasonably state that individual emotional states act as background factors on the formation of beliefs and therefore are implicitly present in the theory (Fishbein and Ajzen, 2010).

The following conclusions can be synthesised from the discussions of the earlier sections:

- The vast majority of studies that aim to explain car or non-car use did use the TPB, NAM and VBN, either solely or as combined frameworks;
- Habit (from the TIB theory) increases the predictive power of the above-cited theories when researchers have integrated this concept to explain car or non-car use;

– Other individual-related concepts that were found to affect the use of different transport modes were socio-demographic (i.e. income, gender, educational level and household size) and frequency of past use of the travel modes.

The evidence provided so far in this chapter highlights the particular utility of some theories over others on the transport research field and how each theory has been used to understand the choice among different travel modes. This section will limit itself to providing this theoretical evidence of the theories and their use. Later in the chapter, a formalised procedure to decide which concepts from the theories to select for this research's framework will be presented (Section 2.4). Before that exercise takes place, a particular strategy that has drawn attention from the transport research field over the past years will be presented: the use of market segmentation techniques to the delivery of transport interventions. Many authors who advocate for this technique to be used to underpin transport policies make their arguments based on concepts of the theories reviewed in the previous sections, as will be seen next.

2.2 Public segmentation strategies in transport research

In an attempt to explain how the population is organised in terms of travel behaviour characteristics and also to inform policy about the effective ways of targeting this population, some researches have used the technique of market segmentation.

The identification of particular population segments in terms of mobility behaviour allows the consideration of relevant personal divergences in a cost-beneficial and practical way for policymakers and transport planners. These models consist of identifying homogeneous groups that have particular needs and preferences and can be targeted in the same manner (Wedel and Kamakura, cited in Anable, 2005). Also, there is a general consensus that targeted strategies of travel behaviour change are more effective than the "one size fits all" approach (Anable et al., 2006).

Most of the segmentation models adopted to date have used *a priori* approaches, on which the segments are estimated based on past knowledge or common sense, using already available variables like age or car ownership and creating groups like the ‘young’ versus the ‘old’, or ‘users’ versus ‘non-users’, etc. (Anable et al., 2006). But in order to create segments that translate the complexities of human behaviour more accurately, analytical approaches using multivariate techniques, conducted based on data that was collected for the specific goal of segmentation (*post-hoc* approaches), are needed (Anable et al., 2006).

In view of this call for more analytical approaches, some studies were conducted to investigate the existence of ‘travel groups’ in terms of the characteristics of individuals, either using behavioural or sociodemographic variables (Hunecke et al., 2010). Some studies also use measures of actual behaviour, such as the frequency of public transport use (Kieu et al., 2015).

Table 2.3 briefly presents six studies that used this approach in travel behaviour research.

Table 2.3 - Studies using attitude-based segmentation approaches

Authors	Research Goals	Variables used for segmentation	Country
Outwater et al. (2003)	Develop a structural equation model for an attitudinal market segmentation approach to mode choice forecasting.	Desire to help the environment; Need for time savings; Need for flexibility; Sensitivity to travel stress; Insensitivity to transport cost; Sensitivity to the personal travel experience.	United States
Anable (2005)	Propose an attitude-based segmentation approach and analyse how different groups relate in terms of travel behaviour.	Aspects of car use (e.g. attachment, car dependence, sense of freedom, enjoyment, perception of negative effects, willingness to reduce, etc.); Perceived behavioural control and social norms; Attitudes to the environment.	United Kingdom
Ohnmacht et al. (2008)	Test the assumption that transport behaviour can be better explained by analysing different groups of mobility styles.	Values, orientations and opinions in regards to different transport modes.	Switzerland
Hunecke et al. (2010)	Analyse the ability of different segmentation approaches (geographical, sociodemographic and psychological) to predict the ecological impact of mobility behaviour.	Perceived behavioural control; Social norms; Personal norms; Perceived mobility necessities; Perceived autonomy, privacy, excitement and status related to Public Transport, Car and Bicycle; Weather Resistance.	Germany

Prillwitz and Barr (2011)	Investigate the varying importance of attitudes for travel behaviour decisions and identify aspects of individual travel as a potential basis for changes towards more sustainable mobility.	Attitudes towards different modes of transport.	United Kingdom
Mikiki and Papaioannou (2012)	Propose an attitude-based segmentation for the promotion of sustainable travel	Greener route intention; intention to use Public Transport; intention to use a bicycle; Car dependence; Physical activity/active travel; Pro-environmental behaviour.	Greece
Molin et al. (2016)	Identify multimodal travel groups and analyse the effects of sociodemographic, work-related and attitudinal variables on the probability of belonging to each cluster.	Frequency of use of four different travel modes; sociodemographic factors; behavioural beliefs related to the four different modes; work-related factors like the number of working days per week.	Netherlands
Magdolen et al. (2019)	Identify mobility types that are prevalent in urban structures in three different cities and explore their main differences.	Attitudes towards modes of transportations and travel behaviour variables like trips per day, mode choice and trip distance.	China, Germany and the United States.

The study conducted by Hunecke et al. (2010) evaluated three different target-group approaches for transport marketing based on geographic, sociodemographic and psychological variables. According to the authors, a geographic approach (regarding the available infrastructure and accessibility) is better for long-term traffic infrastructure interventions. A sociodemographic approach is better applied to promote mobility services aimed at different life cycles. Finally, a psychological method should be used for the development of soft policy measures to promote travel modes. In regards to the effect of transport policies in transport mode choice, Hunecke et al. (2010) concluded that the attitude-based approach, using psychological variables, is more effective. Although this study offers insightful conclusions about the segmentation structure of a population in a multi-modal perspective, the question about how these groups would respond to different persuasion strategies (and if there would be any differences in the responses) still remains unclear.

Anable (2005) divided the respondents into six clusters with respect to psychological attachment to the car and proposed policy options for each of the groups. The segment with the highest affection to car use (‘Die Hard Drivers’) should be targeted with hard measures, according to the author, while the so-called ‘Aspiring Environmentalists’, who have the lowest attachment to the car, should be targeted with environmental messages and positive aspects of available alternatives, as this segment has a high potential for switching to other modes.

Using a similar approach, Mikiki and Papaioannou (2012) were able to identify different segments from an attitude-based survey conducted in Greece. Three groups were found with respect to car dependence on everyday mobility (‘Active travellers’, ‘Non-active travellers’ and ‘Active and pro-environmental travellers’). Outwater et al. (2003) used a simpler approach and grouped people based only on their sensitivity to stress, need for time savings and environmental awareness and developed a model to forecast transport mode share scenarios. The limitation of both studies above is the number of variables that were used for the segmentation model. Using only attitudes towards travel modes or the environment, although useful, ignores the complexity of factors that underlie human decisions.

Ohnmacht et al. (2008) were able to find systematically different groups when specifically looking at leisure activities and mobility orientation factors. The authors demonstrated that significant differences in travel behaviour exist between groups with different leisure orientations (sports, cultural activities, etc.)

Molin et al. (2016) constructed clusters based not only on attitudinal or sociodemographic variables but also on the frequency of use of different transport modes in the Netherlands. The authors discovered that different psychological profiles exist among the users of the same transport mode and proposed policy designs accordingly. The study by Molin and colleagues has a strong methodological background with a quite large sample of travellers (n = 2548). Different from the majority of the other studies reviewed in this section, which use traditional forms of cluster analysis (*k-means* algorithm or hierarchical techniques), they used the more recent technique of latent class cluster analysis. Nevertheless, this study also considered only attitudes as part of an individual’s perception of transport modes, omitting other important theoretical factors. Moreover, while they offer a discussion of the possible interventions that should be directed at different groups, this is done only theoretically, but not empirically.

More recently, Magdolen et al. (2019) performed cluster analysis in a pooled dataset of three different cities. A particularity of this study was the identification of a relatively high number of distinct groups (eleven), possibly as a result of using an intercultural setting.

The EU-funded SEGMENT project used market segmentation techniques to deliver specific transport marketing campaigns to different groups (SEGMENT project, 2013). The population was clustered in terms of multiple psychological factors, such as attachment to the car, self-identification with alternative travel modes and motivations for environmental protection. Results showed different variance levels on car use as a result of marketing campaigns in different population attitudinal segments. A limitation of this project is that just one marketing campaign was delivered to each one of the groups. Therefore, it is impossible to know whether the groups would respond in the same manner to other types of interventions. A later study, however, used the methodology developed in the SEGMENT to analyse differences in the responses to a particular type of positive incentive (Semanjski et al., 2016). The authors examined how the provision of new route suggestions impacted commuters' behaviour. The findings suggest that two groups who are generally more environmentally-aware were more likely to change to more sustainable modes in response to this information. But the interpretation of the study results is very limited because it was based only on descriptive statistics (Semanjski et al., 2016). Also, the main focus of the information provided was not particularly modal shifts, but the adoption of new routes instead.

2.2.1 Concluding remarks of Section 2.2

The plurality of applications making use of an attitude-based transport market segmentation is evident in the literature. It is evident that the development of more tailored interventions aimed at voluntary travel behaviour change would benefit greatly from a psychographic type of segmentation.

Despite their conclusive results, the research reviewed in this section did not test the responses of each target group to transport interventions, using real data on the same sample that was subject to the segmentation analyses. Despite some references to the TPB, the studies also did not consider other theories of behaviour that were demonstrated to influence travel behaviour earlier in this thesis, such as the NAM or the TIB. Neither had they explicitly used measures of multiple theories as segmentation variables. When they referred to the theories, they have either used TPB's constructs (mostly attitudes) (Anable, 2005; Hunecke et al., 2010; Prillwitz and Barr, 2011; Mikiki and Papaioannou, 2012) or isolated measures of the NAM, but not all of the theory's relevant constructs for travel behaviour (Anable, 2005; Hunecke et al., 2010). The study that used a more multi theory-driven approach was the one by Anable (2005), but the author also did not consider important concepts like 'ascription of responsibility' and 'awareness of consequences'. Additionally, all the above studies have made adaptations from the original form of measuring each concept (suggested by the original author of each theory). In many cases, the authors constructed their own measures, based on the theories, and performed factor analysis, which in some cases led to the integration of conceptually distinct variables like personal norms and social norms, for example (Hunecke et al., 2010).

This research, besides developing a segmentation model that is uniquely driven by theoretical factors that influence travel behaviour,will test if the resulting target groups display different acceptability levels towards the strategy of using positive incentives to stimulate sustainable travel, the extent of these differences and the groups that are more susceptible to certain incentives (if any). The chapter now proceeds to examine the projects that have made use of positive incentives and the empirical evidence around their effectiveness on individual persuasion.

2.3 Positive Incentives for sustainable travel

With regards to interventions to tackle the increasing use of private CFVs, regulation, pricing and physical modification of transport infrastructure are alternatives (Stead, 2016). However, these 'hard' (or structural) measures alone often fail to promote the reduction of car use (e.g. Stopher, 2004) and their implementation can involve high political costs which, in turn, can make them less desirable for policymakers (Möser and Bamberg, 2008). 'Soft' measures, on the other hand, focus on stimulating a voluntary travel behaviour change (VTBC), traditionally with the use of information-based techniques such as public awareness campaigns, travel feedback programs or personalised travel planning. A problem with these techniques is that they often require face-to-face contacts with the targeted individuals (e.g. Meloni et al., 2013), along with travel diary filling or other costly and time-consuming activities that act as barriers for a large scale implementation. The study conducted by Friman et al. (2013) shows a good example of an extensive application of these initiatives in Sweden, but there is no evidence of a large application of such measures in middle-income countries to date. While these traditional schemes have shown to be effective in stimulating reductions in private CFVs' use (for reviews, see Brög et al., 2009; Cairns et al., 2008; Möser and Bamberg, 2008), positive incentives have the potential to stimulate behaviour change with a much wider range, taking advantage of the continuously rising use of ICT. The increasing proportion of individuals using smartphone applications, for example, allows new and exciting opportunities for the transport sector (Brazil and Caulfield, 2013). For instance, using a single device that is equipped with a GPS and internet access, the user can have access to a variety of persuasive information such as real-time traffic conditions, the environmental and health impacts of their daily travel, public transit arrival and departure times and much more. Therefore, the potential of a positive incentives program in the context of widespread ICT dissemination is much greater than the opposite.

An incentive can be defined as an event or object external to the individual that can incite action (Locke and Latham, 1991). A positive incentive approach is about giving rewards for the adoption of sustainable alternatives to the car or improving travel choices in general (Kusumastuti et al. 2012). This 'reward rather than punishment' approach is an efficient alternative to the traditional punitive measures, like fuel tax, parking pricing or congestion charging (Grant-Muller, 2015). However, rewards are not the only form of incentivising people.

Personalised information, gamification techniques or social media tools can also be used to stimulate the use of more sustainable travel modes through ICT. Other authors refer to these schemes as ‘persuasive technologies’ or ‘persuasive interventions’ (Anagnostopoulou et al., 2018).

With the advent and popularization of smartphones from the 2000s, several projects based on positive incentives were implemented worldwide aiming to stimulate individuals’ shift to more sustainable forms of travel. The recent EU ‘*Horizon 2020*’ funded project EMPOWER (EMPOWER project, 2018), for example, not only have offered synthesised evidence of the impact of these projects in travel behaviour but also implemented these schemes in several cities across Europe (EMPOWER Project, 2018a). Project EMPOWER also provides support material to organizations that are willing to execute an incentive scheme, independently (business models, evaluation strategies, etc.).

Section 2.3.1, below, describes some positive incentives programs and their impacts (when published). Section 2.3.2 details the types of incentives found to be impactful on behaviour change and deepens the theoretical evidence about their effectiveness.

2.3.1 Projects using positive incentives to change travel behaviour

Since covering all the smartphone applications, systems and platforms that offer positive incentives to stimulate sustainable mobility would be impractical, the selection of projects or programs focused on initiatives that were subject to empirical evaluation with at least 200 participants. In addition, programs with relatively larger scopes than just launching an incentive scheme were prioritised. That is, projects that have had systematic life cycles with phases of development, implementation and evaluation. Some of the selected projects have developed knowledge databases related to incentives and business models. Four of the eight programs reviewed have been financed by the European Commission with total amounts starting from around € 3,000,000 (Three million Euros) (European Commission, 2019).

Six of the projects included in this section were developed in the European context (in cities such as Gothenburg, Enschede, Helsinki, etc.), one in Adelaide, Australia and one in Singapore. The remaining if this section summarizes their implementation methods and impacts. More critical reviews are provided in the following sections (2.3.2 and 2.3.3).

2.3.1.1 The TravelSmart project

TravelSmart was a project developed in Adelaide, Australia, aimed to reduce the citizen's private car use through the provision of information through guided personal conversations, either by phone or face-to-face (Zhang et al., 2013). Informative tools were also provided to help to empower people to seek for alternatives to car use. Tools included guides for more local activities reducing travel demand, cycle and walking maps, letters stating the benefits of not using the car, individually tailored journey plans using alternative modes, etc.

18% car use reduction, 6% fewer car trips and an estimated carbon emission savings of 28,000 tons during the project's life cycle (Hallion, 2009). Substantial changes were also observed in attitudes towards sustainable forms of travelling. A particular practical limitation of this project resides in its form of operationalization. More than 22,000 households were contacted in a face-to-face approach, which often requires relatively high financial, human and time resources. The positive outcomes of TravelSmart are encouraging but the use of ICTs on the delivery of positive incentives might provide similar results without such high investments.

2.3.1.2 The *Spitsmijden* experiments

The *Spitsmijden* experiments consist of a group of different initiatives aiming to reduce peak hour's congestion or to increase cycling in the Netherlands in 2006. The incentives ranged from cash rewards to the accumulation of points that could be further exchanged for cash, gift vouchers and personalized route information (Knockaerta et al., 2012). 340 participants took part in the project and the data collection was done using a transponder that was installed in the participants’ vehicles, along with license plate recognition systems installed on the desired routes.

The provision of financial rewards has demonstrated to be an effective tool in relation to switches in travel mode and driving outside peak hours. Public transport users increased from 3.9% before the incentives program to 9.5% with a 3 Euro reward and 11.4% with a 7 Euro reward, while the number of off-peak car trips increased by approximately 15% (Ben-Elia and Ettema, 2011).

2.3.1.3 The INSINC project

The INSINC Project (Incentives for Singapore Commuters) was designed to stimulate the use of the Singaporean public transport system and the avoidance of peak times through monetary and social incentives schemes delivered through the Web (Pluntke and Prabhakar, 2013). Points were given for every kilometre travelled using public transport and were multiplied every time the user commuted during any of the pre-set off-peak times. The participant could then exchange these points for instant cash or try to win bigger random cash prizes through a self-administered raffle. Users could also win points by inviting friends using multiple social network tools. A ranking list of the user and her/his friends were also part of the application, with the most off-peak travellers on top (Lin, 2015).

The project showed a significant percentage decrease on the number of peak-hour trips overall (7.49%), this was calculated among the high number of signed up participants (22,867 in six months) (Pluntke and Prabhakar, 2013).

A larger decrease rate in peak trips was shown by users who had friends using the system (9.7%), long-distance commuters (9.1%) and who used a gaming environment. Better results on peak-hour avoidance were also obtained when a weekly challenge was presented to the users, based on the user’s past travel behaviour: 9.34% shifts to off-peak hours while the shift rate without challenge was 7.49% (Pluntke and Prabhakar, 2013).

A particularity of the INSINC program is the use of a multi-incentive approach instead of focusing on one or two forms of incentives.

2.3.1.4 The STREETLIFE project

The main incentive tools provided on the EU-funded StreetLife project are multi-mode journey planners and gamification techniques such as earning points, badges and competing in leader boards (StreetLife Project, 2016).

A smartphone application was developed and tested in the city of Rovereto, Italy. On the first phase of the test, when no incentives were provided, the number of car trips represented 34.8% of total trips registered by 40 participants. At the end of the second phase, when sustainable journey planners were administered, the percentage decreased to 27.2%. Gamification techniques were introduced in phase 3, and the car trips dropped to only 16,9% of total trips among the application users, with a correspondent increase in the number of bike trips (1% to 6%) and walking (5% to 12%) (Kazhamiakin et al., 2015). This program is quite particular as it did not use any form of financial rewards and still demonstrated positive findings on their experiment.

A more recent publication has reported the findings of the StreetLife project using data from 300 citizens that had downloaded the application (Kazhamiakin et al., 2016). The findings indicate that the provision of specific challenges related to particular travel modes acquired a substantial increase in the distance travelled with these modes. For example, the implementation of a ‘public-transport week’ made the participation of PT on the total weekly kilometres travelled to reach 44%, the highest percentage across all weeks of the experiment (Kazhamiakin et al., 2016).

2.3.1.5 The SUPERHUB project

SUPERHUB started in 2011 as part of the 7th Framework Programme of the European Commission and involves multiple European cities (Superhub Project, 2016). One of the main incentive techniques is a multi-mode journey planner using real-time data, which includes information about the impacts of each journey option such as the carbon footprint associated with a certain choice (Forbes et al., 2012). The design of the project`s techniques to achieve behaviour change was tied to behaviour change theories, unlike other related projects. SUPERHUB persuasion strategies were selected based on the work of Michie *et al.* (2008), who identified the types of behaviour change techniques that are tied to predictors of behavioural theories and are thus more effective (Michie et al., 2008). Forbes et al. (2012) concluded that the most potent tools for travel behaviour change within the context of SUPERHUB were: goal-setting and goal review, feedback and rewards, social comparison and personalised information.

A small scale experiment was conducted as part of the SUPERHUB project, with 8 participants. In this 4-week experiment, the percentage of journeys that were made by car dropped from 68% to 54% (Gabrielli and Maimone, 2013). Later on, another study with 418 participants was performed and showed a high overall evaluation of the system by its users, although no conclusions could be drawn with respect to differences in travel behaviour before and after the experiment (Gabrielli et al., 2014). The authors argue that the lack of commitment shown by participants when completing travel diaries impeded such conclusions.

2.3.1.6 The SUNSET project

SUNSET was a project developed from 2011 to 2014 and designed to test the behavioural responses of different types of smartphone-based positive incentives to change an individual's mobility habits. The project was developed considering four different incentives groups (Kusumastuti et al., 2011):

- Real-time travel information: refers to the delivery of precise and timely travel information to the user, ranging from the weather forecast to departure time of next bus, availability of alternative modes and road conditions
- Feedback and self-monitoring: presenting feedback with the financial and environmental impacts of the individual's mobility behaviour, creating awareness of the negative effects of car use.
- Rewards and points: refers to rewarding people for adopting certain behaviour. The type of rewards can vary from a simple compliment to cash prizes.
- Social networks: refers to the use of this type of web tool to incentivize behaviour change. People tend to consider their friends and relatives

opinions and achievements when forming a behaviour, among other reasons.

The most evident impacts of the project were on congestion, with a decrease on peak hour departures (3%) and car use (63% to 57-47%), along with an increase in public transport use (9% to 10-16%) (SUNSET Project, 2014).

Additionally, there were wider socio-economic impacts for the cities involved in the project, such as an improvement on safety indicators when being able to inform people about road conditions in route. An overall improvement to the mobility of people and goods was also observed in the urban environment as a result of the incentives program, together with an improvement on population's quality of life (SUNSET Project, 2014).

A spin-off company from the SUNSET project called Mobidot® has developed the open ICT platform MoveSmarter, which is a smartphone application that automatically detects trip characteristics such as time of departure and arrival, origins and destinations and travel mode. The app also delivers positive incentives for sustainable behaviour in the following categories (Geurs et al., 2015):

- Intrinsic motivation, giving feedback about the user's travel behaviour;
- Information and advice: about possible routes and alternative modes;
- Gamification (challenges) and social comparison with relatives;
- Financial and voucher rewarding;
- Loyalty, rewarding repetitive travel habits.

A recent experiment conducted in Holland showed that the automated tracking of MoveSmarter to be relatively reliable in detecting the mode of transport, trip duration and destinations: more than 70% of trip distances and 69% of trip duration were correctly classified by the app (Geurs et al., 2015). In regards to travel mode, walking and cycling were properly classified in 83% and 85% of the cases. Car and train were properly categorised on 76% and 61% of trips, respectively (Geurs et al., 2015). This program has the advantage of not having to ask the users to log their trips, potentially decreasing the likelihood of the user losing motivation using the app. However, the not very precise automated tracking system may lead to wrong feedbacks, information and the delivery of not so personalized incentives. To the best of this author's knowledge, there are still no published results of this program in regards to changing behaviour.

2.3.1.7 The EMPOWER project

The EU-funded EMPOWER project started in 2015 and its main goal is to understand how positive incentive schemes can stimulate citizens to reconsider their travel habits and consequently reduce their dependence on private conventionally-fuelled vehicles (CFVs) (EMPOWER project, 2018). Besides a positive incentives database, the project main outputs included tested business models for the implementation of a positive incentives strategy in an urban environment. One of the project tasks is reviewing the state of the art on successful interventions to reduce car use. (EMPOWER Project, 2018a) describes the groups of positive incentives to be evaluated by the project:

- Rewards (e.g. point credits, discounts, lottery draws);
- Adding objects to the environment (e.g. maps, timetables, leaflets);
- Shaping knowledge (e.g. training, classes);
- Goals and planning (e.g. set goals and making plans to achieve goals);
- Feedback and monitoring (e.g. tracking behaviour and giving feedback);
- Natural consequences (e.g. giving awareness of behaviour impacts to the environment);
- Comparison of behaviour (e.g. websites permitting the comparison of own behaviour to others').

To this date, several European cities have taken part in the project, where incentives were implemented in the form of living-lab experiments that displayed encouraging results. In Odense (Denmark), the use of challenges and campaigns have led to an 11% reduction in the use of private CFVs, while the number of kilometres travelled by bike and walking increased by 22% and 33%, respectively (EMPOWER Project, 2019). In Reading (United Kingdom), a survey across 600 participants of the programme identified a 24% reduction in car use (EMPOWER Project, 2019).

2.3.1.8 The CAPRI program

This app was created to nudge a university community away from travelling in peak-hours, to use underutilised parking lots and adopt non-motorised transport modes. More than 4,000 university affiliates used the app during the two and a half years duration of the programme (Zhu et al., 2014).

As incentives, the app provided a social environment, where users could invite friends and see friends' 'status' on the app in terms of travel behaviour and prizes won as incentives. Additionally, financial incentives in the form of points that could later be exchanged for cash and non-monetary rewards (such as free tickets to university events) were used (Zhu et al., 2014).

60.2% of users reported having changed the time of travelling to the university (Zhu et al., 2014). The study did not report reliable evidence about travel mode shifts as a result of the incentives.

2.3.1.9 Other initiatives

The literature review by Anagnostopoulou et al. (2018) uses a broader approach focusing on available incentives systems and suits as complementary material to this thesis' review. The authors provide a comprehensive analysis of the state-of-the-art concerning the use of incentives for sustainable mobility over the past years. 23 different systems were reviewed (some previously included here) and their impacts were evaluated, either in terms of behaviour change, attitude change or the software/application usability. For instance, 65% of the applications were evaluated as completely successful on either one of these indicators (Anagnostopoulou et al., 2018).

2.3.2 Positive incentives strategies

Based on the review of the existing initiatives, positive incentives can be divided into three main categories: rewards, information and social elements (Table 2.4).

Table 2.4 – Positive incentives categories

Rewards	Information	Social tools
- Financial (Cash, Discount vouchers, Free event tickets, Free PT tickets); - Non-financial (points, badges, rankings, challenges and other gamification techniques).	- Maps; - Journey planner; - Information about alternatives; - Real-time road conditions; - Feedback on travel behaviour; - Advises for sustainable travel behaviour; - Increasing knowledge about consequences.	- Results sharing on social media; - Performance comparison; - Buddying with someone to engage in the same travel behaviour (e.g. riding a bike together).

The following section presents a more detailed explanation of each category.

2.3.2.1 Rewards

Rewarding people for adopting a certain behaviour is an effective alternative to traditional punitive measures and its use in the transport context has achieved significant positive results (Ben-Elia and Ettema, 2009). Congestion pricing strategies, for instance, will depend on the availability of alternatives to be effective and the individual response depends on the person’s income (Ettema and Verhoef, 2006). High-income commuters are less sensitive to pricing measures than the poor ones, which makes this kind of schemes socially unfair. Previous studies have demonstrated that road pricing leads to negative reactions by the public, such as perceptions of infringement of freedom and unfairness (Jakobsson et al., 2000) and that these measures may not impact at the individual’s motivations to reduce car use (Jakobsson et al., 2002). Past research also shows that an average of just 35 per cent of users are in favour of these strategies (Schade and Schlag, 2003; Jaensirisak et al., 2005).

Reward schemes, on the other hand, are more influential to travel behaviour than charging (Tillema et al., 2013). Rewards can be divided into financial or non-financial. Direct cash payments or discount vouchers for retail stores, public transport tickets or public attractions (financial incentives) were used in multiple projects (*Spitsmijden*, INSINC and MoveSmarter) and the results were positive for peak hour avoidance. The reviewed projects did not use financial rewards for choosing alternative transport modes. This was probably due to the difficulty in tracking the use of different travel modes using smartphone technologies. The *Spitsmijden* rewarded people for replacing the car but depended on previous in-vehicle detection equipment to be installed (Ben-Elia and Ettema, 2009).

Rewards in the *Spitsmijden* and INSINC projects were in the form of direct payment, while projects CommuteGreener and MoveSmarter used discounts which were acquired with the accumulation of credits or points. Although the results of both approaches were positive in regards to decreasing car use, the comparison between their effectiveness is difficult, as the impacts are often measured using different metrics and methods.

Ben-Elia and Ettema (2011), in a qualitative analysis of the *Spitsmijden* experiment, state that participants consider rewards as an important tool for initial motivation to engage in the program, but do not depend on them to continue participation. This hypothesis can be aligned with the difference on the perceptions of alternative modes by those who have already used such modes and those who have not (Fujii et al., 2001; Beirão and Sarsfield Cabral, 2007). Car users tend to evaluate public transport worse than actual users (Javid et al., 2016), so an initial motivation might be sufficient for drivers to shift behaviour and start using alternative modes, as their perception and attitudes towards these modes may instantly change at the moment they start using them, motivated by a reward. Past research also shows that increasing the size of monetary rewards only has marginal effects on behaviour change (Ben-Elia and Ettema, 2011; Tillema et al., 2013). Thus, from a cost-benefit perspective, the implementation of a small cash reward can achieve a significant change in commuter's mobility choices. The use of different types of rewards such as fast food discount vouchers, free drinks in restaurants and free WIFI also had a positive effect on peak hour avoidance (Zhang et al., 2014).

Rewarding does not always mean monetary prizes. The use of points and other gamification techniques has been popular on recent projects such as CommuteGreener, MoveSmarter and SUNSET. Gamification is a recently created concept and is defined as ”the use of game design elements in non-game contexts” (Deterding et al., 2011). The application of this technique has considerably increased since 2010 and it has shown satisfactory results in motivation and personal engagement across multiple contexts. Examples of an application include motivating students (Denny, 2013), incentivising people to engage in physical exercises (Hamari and Koivisto, 2013) and stimulating people to reduce energy consumption (Gustafsson et al., 2009).

The use of gamification in urban mobility is still modest. However, the few applications of this strategy in transport have shown optimistic results, especially in terms of switches to sustainable travel modes. An experiment during the STREETLIFE project shows that the proportion of sustainable trips among all recorded journeys went from 42.7% to 60.6% after introducing gamification techniques (i.e. points, badges and leader boards) (Kazhamiakin et al., 2015). As in the case of the STREETLIFE project, these elements can be combined with financial rewards. Players with the highest amount of points at the end of one month can be rewarded with discount vouchers, for example. This combination is advocated by the SUNSET project (Kusumastuti et al., 2011).

The following elements can be part of a gamification strategy to stimulate voluntary travel behaviour change:

- Points: travellers accumulate points when choosing to commute out of peak hours or by more sustainable modes;
- Badges: different badges (bronze, silver, gold) are given to commuters as a reward for continuing using the system and not using the car. The more the person cycles, for example, the higher the badge. This has the potential to motivate continuous participation in the incentive program;

- Leader boards: rankings are built with the more green travellers on top;
- Challenges: setting up goals for the traveller to earn extra rewards in case of completion.

Financial and non-financial rewards have empirical evidence of effectiveness on travel behaviour. The literature on paying travellers for adopting sustainable behaviour (using cash or vouchers) is more robust, but the studies are focused on the examination of peak-hour avoidance instead of replacing or avoiding private CFV trips. The evidence about the impact of gamification strategies (with or without associated prizes) for this purpose is stronger.

A relevant point of consideration is that non-financial incentives are better at provoking *intrinsic* motivation on the individual, which have been linked to being more constant and sustainable in the long run (Gneezy et al., 2011). These types of motivations are the ones that do not rely on apparent rewards, while extrinsic motivations are dependents of some external controlling variable apart from the individual's own discretion (Cameron and David Pierce, 1994). The use of reward tools to stimulate behaviour change has been subject to discussions in the past about whether it has negative effects on individuals' *intrinsic* motivations. In fact, the provision of rewards may lead to positive outcomes in the short term, but may actually weaken intrinsic motivations to a point even lower than it was before the intervention (Gneezy et al., 2011). Thus, a balance should be reached between not offering incentives at all and offering incentives for such a long period that would rather develop a reduction on intrinsic motivations. Also, assessing these particular impacts of rewards on intrinsic motivations in the transport behaviour field is encouraged, as the literature is still scarce. Next sections provide a discussion about alternative forms of incentives which might not have this possible 'negative' outcome.

2.3.2.2 Information

Information as an incentive for adopting sustainable mobility behaviour can take the following forms: act as a support for the trip decision-making process, influencing time of departure, route or mode of transport; provide feedback about the consequences of daily travel habits; or inform people about the benefits of active travel and the disadvantages of driving. In addition to the ability to persuade people out of private CFVs, information also decreases stress by reducing the unknown element associated with a particular route or mode of travel. Increasing knowledge about the long-term impacts of unsustainable travel behaviour on society and the environment is a crucial aspect of behaviour change (Gärling et al., 2015). Current research also suggests that the provision of real-time information does affect mobility behaviour. Tseng et al. (2013) compared individuals' travel choices in three different conditions: without incentives, with the provision of real-time information and with the provision of rewards (credits to buy a smartphone) combined with real-time information. Car trips, which represented 80.9% of the sample at the beginning of the experiment, dropped to 75.6% with information and to 71.2% with the provision of rewards as well. More sustainable modes increased their use, such as public transport (5.8% to 9% and 13.2%, respectively). The delivery of real-time information has traditionally been grounded in data generated by transport agencies, public authorities or other organisations. But more recent initiatives have demonstrated how crowdsourcing can also be a useful tool for generating real-time public transit information, such as the *GetThereBus* application (Corsar et al., 2018).

A longitudinal survey conducted by Taniguchi and Fujii (2007) showed a significant increase in the use of public transport after the provision of advertising leaflets about the bus service and two free bus tickets. A particular strength of this study was the use of a control group. The target group used PT more than two times more than the control group after the incentives intervention (Taniguchi and Fujii, 2007). The authors also provided evidence that financial rewards are not necessary for people to maintain a more sustainable travel behaviour in the longer term. The authors tested the frequency of bus use when just information was provided (without free tickets) at a later point in time and the level of PT use remained the same as when both incentives were used (Taniguchi and Fujii, 2007). The use of social marketing campaigns to stimulate non-motorised modes such as cycling also has great potential. A study by Rissel et al. (2010) showed that a locally applied social marketing campaign increased the proportion of people who cycled (from 16.2% of participants to 28.3%).

The notion that lack of information (especially bus routes and timetables) is one of the main issues involving low levels of public transport usage is also supported by Beirão and Sarsfield Cabral (2007). The authors report that non-users tend to have a perception of difficulty to use the bus service and evaluate its performance worse than actual users. The provision of quality information may, therefore, be sufficient to eliminate these gap of perception between users and non-users and convince people to change their travel habits. Another study evaluated the effect of descriptive social norm information on the decrease of car use. The authors found that the increase on the use of sustainable modes behaves as a function of the provision of information about how other people are doing in terms of decreasing car use (Kormos et al., 2015).

Generally, a combination of marketing strategies with information provision is considered essential to stimulate the use of public transport (Ibraeva and Sousa, 2014).

Another form of using the information to persuade people towards sustainable forms of transport is the provision of travel feedback. The study of Jariyasunant et al. (2015) evaluated a Web system that calculated a person's travel footprint in terms of emissions, calories, time and cost. The use of the system significantly increased people's awareness of the consequences of travelling using private CFVs, attitudes to sustainable forms of transport and intention to cycle and walk (Jariyasunant et al., 2015).

2.3.2.3 Social tools

Six out of the eight reviewed incentive-based projects use performance comparison and sharing tools to stimulate people to make more sustainable travel choices, usually using web-based social networks (Commute-Greener, MoveSmarter, INSINC, SUPERHUB, SUNSET and EMPOWER). The notion that sharing and comparing performance may produce an effect on behaviour is supported by the Theory of Planned Behaviour, which indicates that the likelihood of adopting a behaviour is influenced by the perceived social pressure in direction to that behaviour (more details are presented in section 2.3). Research in the field of travel behaviour reveals that an individual's willingness to use a more sustainable mode is influenced by the perception of other people using it (Anable, 2005). Particularly, specific social groups such as upper socio-economic people might have a higher power to influence others by reducing the stigma associated with certain travel modes. Da Silva et al. (2011) expands this concept by arguing that social norms impact on an individual's personal norm (feelings of personal obligation to perform a certain behaviour), attitudes and perceived behavioural.

ICT-based social incentives can take the form of comparing an individual's performance to that of his/her acquaintances. In addition, the system may provide functionalities to allow users to share their accomplishments on social media (Anagnostopoulou et al., 2018). With this, a positive incentive program can also increase its use potential, as social influence is notably a crucial aspect of technology acceptance (Venkatesh and Morris, 2000).

The specific impact of social comparison tools as part of an incentives program in behaviour change remains unexplored in empirical terms, but some initiatives that used this strategy as part of a broader incentives system has shown promising results (e.g. Castell *et al.*, 2016). Ettema (2018) states that incorporating social comparison in a travel feedback program, for example, would increase its impact on travel behaviour.

2.3.3 Concluding remarks of Section 2.3

The literature on projects using the strategy of positive incentives for travel behaviour change is recent, especially the ones that use ICTs as the form to deliver incentives. These initiatives represent an advance to the traditional travel feedback programs or personalized travel plans, which often require multiple personal contacts to be effective in changing behaviour. Recently popularised technologies such as smartphones and its derived applications permitted incentives (in all its forms) to reach wider populations and be more personalised, using digital traces of smartphone users, for example. The utility of smartphone-based incentives may grow even further with the advance in technologies such as automatically GPS tracking systems (Weber et al., 2018). The delivery of incentives supported by ICTs not only presents benefits in terms of behaviour change but also can generate data that can be used to support other types of transport policies like infrastructure improvement, for example.

The combination of different incentives strategies may be efficient at increasing both intrinsic and extrinsic individual motivations to reduce private car use. Rewards have shown to increase extrinsic motivation whereas informational measures such as positive feedback and verbal reinforcement impact positively on intrinsic motivation (Deci, 1971). Most of the projects reviewed here do use a combination of incentives instead of just one or two strategies. That is one of the reasons why empirical evidence about the effectiveness of the use of particular incentives in isolation is quite rare.

The table below (Table 2.5) presents a summary of the impacts reported by the reviewed programs of positive incentives.

Table 2.5 – Impacts of projects or apps using the strategy of positive incentives for travel behaviour change

Project/app (Reference)	Location (Year of release)	Objectives	Incentives	Impacts
TravelSmart (Hallion, 2009)	Adelaide, Australia (2005)	Reduce private car use.	- Personalised information	- Average 18% reduction in car use per day (10.4km) on participants; - Average 5% reduction in car trips among participants; - Annual public transport patronage increased by 6.16%.
SPITSMIJDEN (Ettema et al., 2010)	Haia, Netherlands (2006)	Peak hours avoidance; Reduce private car use.	- Financial; - Points (smartphone cycling app); - Information (multilayer web-based map).	- 2,500 fewer drivers in the peak hours in road A12 in six weeks - 46-50% of participants travelling during rush hour dropped to 26%; - Public transport use increased from 4%to 9.5-12% of participants.

SUPERHUB Project (Gabrielli et al., 2013)	Milan, Barcelona and Helsinki (2011)	Reduce private car use.	- Goal-setting and goal review; - Feedback and rewards; - Social comparison; - Personalized information.	14% increase in sustainable transport choices (apart from the car).
SUNSET (SUNSET Project, 2014)	Enschede (Netherlands), Gothenburg and Leeds (UK) (2011)	Reduce CFVs' use; Avoid peak hours.	-Real-time travel information; -Feedback and self-monitoring; -Rewards and points; -Social networks.	- Departure in peak hours dropped by 3%; - Car use dropped from 63% to 57-47%; - Use of public transport increased from 9% to 10-16%.
INSINC Project (Pluntke and Prabhakar, 2013)	Singapore (2012)	Diminish the use of public transportation on peak hours.	- Financial; - Points; - Social incentives.	7.49% decrease in peak hour trips.
STREETLIFE Project (Kazhamiakin et al., 2015)	Berlin, Tampere (Finland) and Rovereto (Italy) (2013)	Reduce private car use.	- Multi-mode journey planner; - Advises for sustainable journeys; - Gamification techniques.	- Reduction on private car use (24.8% to 16.9% of trips); - Increase in cycling (1% to 6% of trips); - Increase in walking (5% to 12% of trips).
EMPOWER (EMPOWER Project, 2018b)	Milton Keynes (UK), Enschede (Netherlands), Gothenburg and Helsinki (2015)	Reduce private CFVs' dependence.	-Rewards; -Adding objects to the environment; -Shaping knowledge; -Goals and planning; -Feedback and monitoring; -Natural consequences; -Comparison of behaviour.	- The Commute-Greener app has about 50,000 participants; - Developers of the Commute-Greener app estimate that 37 million kilometres were travelled by public transport using the tool; - The SMART app registered 102,609 trips made by 1,146 active users in August 2017; - Project outputs are currently being gathered within seven European take-up cities and results are still to be published.
CAPRI App (Zhu et al., 2014)	Stanford, United States (unknown)	Reduce peak hour traffic	- Gamification - Rewards - Competition	Participants avoided peak hours by up to 30.1%.

While most studies have been successful in demonstrating either behaviour or attitude changes, many applications are delivered to general audiences using a single persuasive technique and thus more exploration of the effectiveness of personalised strategies are required (Anagnostopoulou et al., 2018). This assertion sounds reasonable once it corroborates with other authors who indicate the need of transport interventions that are more tailored to the need of certain individual profiles (Richter et al., 2011), or who recommend that smartphone applications to promote sustainable travel behaviour should consider different segments of the population (Andersson et al., 2018). The lack of studies that investigate the potential of positive incentives in cities with 'less advanced' transport systems is also a relevant limitation thus far. Some initial research efforts were done but their results were inconclusive due to the employment of small sample sizes (e.g. Castellanos, 2016).

With the examination of the incentives strategies that were reviewed in this section (summarised in the table above) and the theories of behaviour reviewed in Section 2.1, a theoretical connection can be made in regards to the mechanisms by which positive incentives would influence the adoption of more sustainable travel behaviours. Table 2.6 presents some assumptions about how some forms of incentives might be able to cause changes in these behavioural predictors.

Table 2.6 - Influence of positive incentives in theoretical dimensions of behaviour.

Theory/reference	Determinants of behaviour	Potential impacts of positive incentives	Examples of incentives
The Theory of Planned Behaviour (Ajzen, 1991)	Intentions; Atti-tudes; Subjective norm; Perceived Behavioural Control.	- Changing an individual's attitudes through informational incentives; - Increasing feelings of moral obligations to reduce the use of private CFVs; - Increase the perceived social pressure to engage in more sustainable mobility behaviours through the use of comparison mechanisms in social media, for example; - Increase the perceived control of behaviour through informational incentives and training incentives.	- Giving information about the environmental impacts of car use (leaflets, videos, classes); - Sharing accomplishes in social media (points accumulated for using the bike); - Giving maps of cycle lanes, bus timetables, cycling training, etc.
The Theory of Interpersonal Behaviour (Triandis, 1977)	Intentions; Habit; Facilitating conditions; Social norms; Personal norms; Attitudes.	- Increasing personal norms with reinforcing information; -Increase affective and cognitive evaluations of alternative modes; - Decrease the habit of car use by stimulating small changes.	-Inform about the good feelings of riding a bike or walking; -Reward small changes (going out for leisure once a week by bike).

The Social Learning Theory (Bandura, 1977)	Direct experience; Observation of other's behaviours; Positive rein-forcements; Self-efficacy.	-Providing tools for self-monitoring and self-evaluation; - Providing real experiences in alternative modes; - Making the observation of others' accomplishes possible.	-Sharing tools in social media; -Give free public transport tickets or bike hiring; - Provide travel diaries to stimulate self-monitoring.
The Norm Activation Model (Schwartz, 1977)	Personal norms; Awareness of consequences; Ascription of re-sponsibility.	- Informing about conse-quences of behaviour and emphasizing the individual's responsibility with society and the environment.	- Educational texts and videos.
The Value-Belief-Norm Theory (Stern, 2000)	Personal norms; Ecological worldview, adverse consequences for valued objects and perceived ability to reduce threat; Biospheric, al-truistic and egoistic values.	- Increasing the perception of the consequences of car use to valued objects; - Increasing the perceived ability to reduce threats to the environment.	- Informing total of CO2 emitted in atmosphere due to car use; - Informing how much greenhouse gases were avoided due to walking/cycling/PT use.
The Goal-Setting Theory (Locke and Latham, 1991)	Setting goals.	- Help to establish goals to reduce car use; - Giving personalized feedback on goal; - Increase feelings of commitment to the goal; - Reducing the perceived complexity of the tasks; - Reducing perceived situational constraints.	- Make challenges to reduce car use (e.g. 'make X fewer trips by car in X days'); - Giving feedback through self-monitoring tools; - Informing about cycle routes near the person's house/job; - Rewarding when the goal is achieved (points, discounts).

The preliminary results of the projects described in section 2.3.1 demonstrate how positive incentives might strengthen these determinants and help in the process of behaviour change. Different individual profiles might have different levels of susceptibility to use and to change behaviour subject to a particular positive incentive. People with more positive attitudes towards the use of non-motorised forms of transports could have higher acceptability of the information incentives, while people that are more inclined to using the car would be more impacted by rewards, for example. This research will help to advance knowledge of these differences and how they can be addressed when designing positive mobility interventions.

Building on from the review of the literature in the above sections, a theoretical framework needs to be constructed. The theoretical framework acts as a link between the relevant concepts from the literature and the operationalisation of the research. Notably, the concepts or theories need to be selected in the light of the questions that the research aims to answer and the limitations of the envisaged methodology. Next section presents the rationale behind the development of this framework.

2.4 Theoretical framework

The literature reviewed in this chapter presented four theories that seek to explain individual behaviour and their past use in transport behaviour research (pages 15 to 24). Three additional theories that are relevant for the topic of research are outlined in Appendix A. Explaining the rationale behind the selection of the specific four theories described in the present chapter is the aim of this Section.

The Goal-Setting Theory and the Social Learning Theory present factors that stimulate people to pursue a desired behaviour, instead of explaining the factors underlying the adoption of an already established behaviour. Similarly, the trans-theoretical model of behaviour change aims at explaining the stages through which an individual passes until effectively maintaining a desired behaviour. Although being very useful theories, their use within the transport research field is limited to understanding how to stimulate behaviour change (e.g. reducing car use) using their concepts (Gärling et al., 2002) and the number of studies utilising them is very small (Chng et al., 2018). These theories also were not used in combination with the TPB, TIB, NAM or VBN, basically because they are different at their approaches. Thus, the above theories were discarded due to not being adequate for what this study proposes, basically because they are focused on *behaviour change* rather than being able to explain the *use* of different transport modes. The relative underutilization of these theories in the field of travel behaviour also explains their exclusions.

Having established that, the use of the totality of the constructs of the four remaining theories (TPB, TIB, NAM and VBN) is not feasible for a survey research design. The measurement of all indicator variables would impose a very large number of questions. Thus, the decision of which theoretical constructs will compose the framework of this research has to be made cautiously and following specific criteria.

From this point on, a competency-question (CQ) approach was used to select which constructs of these theories would compose the methodology. CQs are defined as a set of questions that place demands on an underlying ontology (Uschold and Gruninger, 1996) and have the potential to help to determine a theoretical framework when there are a number of alternative theories to be selected. The goal is to form an underlying ontology that is capable to answer and represent the CQs using its concepts. The questions should be structured in a hierarchical form, with more ‘general’ ones, which give rise to more specific ones. The construction of the CQs followed the guidelines of Uschold & Gruninger (1996). Firstly, a motivating scenario is set, which is described by the authors as “story problems or examples which are not adequately addressed by existing ontologies” (Uschold & Gruninger, 1996, p.113). In the context of research, this can be interpreted as the identified research questions. Given the motivating scenarios configurated here as RQs, a set of ‘informal’ competency questions is produced, which, after the establishment of a formal set of standardised terminologies, give birth to ‘formal’ competency questions (Uschold and Gruninger, 1996).

This approach has been widely used in computer sciences, especially in the Semantic Web (Pinto and Martins, 2004) and software development (Ren et al., 2014). The CQs, under which the theoretical constructs belonging to the theoretical framework of this research need to be expressed, are shown below:

- CQ1: Is the theoretical construct a direct predictor of individual behaviour or with a maximum of two mediating constructs?
- CQ2: Has the behavioural construct been subject to previous empirical evaluation in relation to being a determinant of the use of travel modes (either CFVs or non-CFVs)?

- CQ3 Can the construct be translated into measurable indicators and, specifically, be operationalised using a questionnaire?
- CQ4 Has the construct demonstrated validity and reliability in regards to the use of travel modes (either CFVs or non-CFVs) in previous empirical research?

Eleven constructs attended the inclusion criteria and formed the exogenous (or independent) constructs of the theoretical framework. The main constraints imposed by the competency questions were in regards to the previous empirical establishment of each theoretical construct on transport research and the existence of more than two mediating constructs in their influence on travel behaviour (e.g. personal values (VBN), affective factors (TIB) or ecological worldview (VBN)).

With the exogenous (or independent) constructs established, the concept of acceptability of positive incentives (dependent) has to be operationalised with measurable indicators. Acceptability, also called adoptability (Hu et al., 1999; Ma et al., 2005), can be defined as how well an intervention will be received by the target population and the extent to which the intervention and its elements meet people's demands (Ayala and Elder, 2011). Witt and Martens (1983) related the concept of acceptance to how an intervention is evaluated by its users. In more recent studies of the acceptance of sustainable transport technologies and policies, the concept of acceptance has been assigned to public intentions to perform a behaviour (Khoo and Ong, 2015). Concerning the adoption of ICTs, the Technology Acceptance Model (TAM), proposed by Davis (1989) also has intention as the main explanatory factor for acceptability, alongside perceived usefulness and perceived ease of use. Examples of this relation have also been found in studies involving the adoption of smartphone applications (Holloway et al., 2014). For the cases where the intervention has already been implemented, acceptability may correspond to the actual proportion of use of a new product or service (Ben-Zeev et al., 2014). Eriksson, Garvill and Nordlund (2008a) considered acceptability as how favourable people were to these policies. In this study, acceptability to each form of positive incentive was measured using three indicators: intention to use; attitudes (a direct predictor of intention according to the TPB) and perceived probability of switching to alternatives to private CFVs in response to the incentive (perceived personal impact).

Additional factors that were assumed to influence the acceptability of positive incentives to some extent were included: vehicle ownership, commuting distance, familiarity with transport-related apps and general socio-demographic factors. The theoretical framework is illustrated in Figure 2.4.

Before moving on to the operationalisation of the concepts outlined on the theoretical framework (next chapter), the literature review chapter has its conclusion below, with the summary of the contributions of this research to the current state-of-the-art.

2.5 The contributions to the state-of-the-art

Recalling what was postulated in Section 1.3 (the five knowledge gaps) and based on the literature review presented in this chapter, this section aims to briefly highlight the advances to the current published literature that this research aims to accomplish.

Table 2.7 synthesises the gaps in knowledge (for a more detailed description, see Section 1.3) and shows the correspondent expected contributions of the thesis.

This thesis aims to provide evidence that an individual's daily travel choices are based not only on the utilitarian attributes of each mode of travel, but rather on a much more complex psychological process that varies significantly between individuals, even considering those that are part of a same physical environment (in this case university students). In addition, it intends to reinforce the idea that separating the population into "psychographic groups" can have a substantial impact on the personal acceptance and the impact of a new technology that focuses on encouraging the use of healthy and environmentally friendly modes of transport.

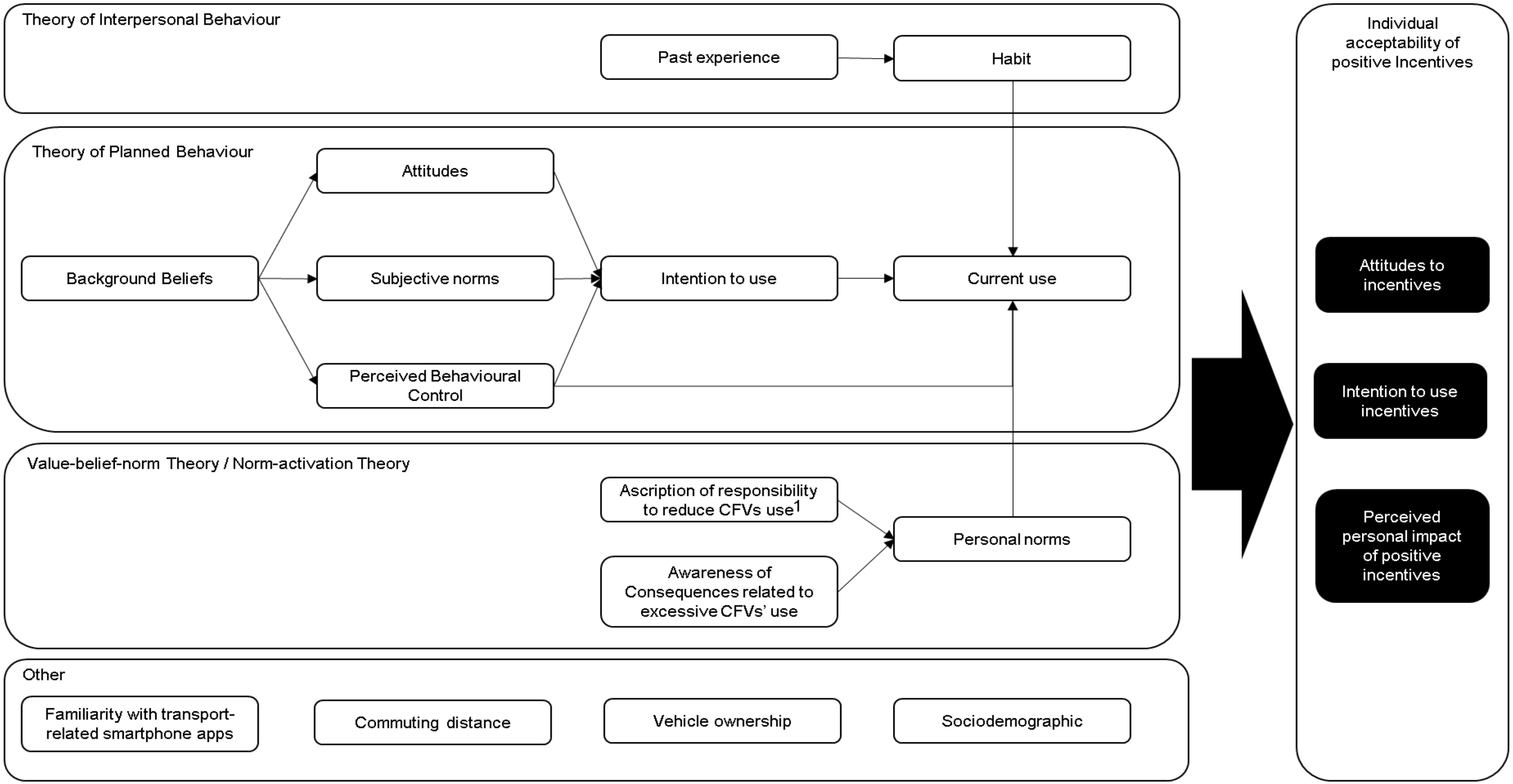

Figure 2.4 - Theoretical framework of the research

[1]CFVs: Conventionally-fuelled vehicles (in this research, car and motorcycle are considered). Note: Arrows indicate the theoretical causal relationships that exist between the variables, according to their underlying theories, but it is beyond the scope of this research to test these relationships

Table 2.7 - Identified Knowledge gaps and advances of this study

Gaps in knowledge	Advances to the state-of-the-art
1. Lack of studies that use a variety of systematically selected theories to either develop segmentation models or implement positive incentives schemes.	The psychographic segmentation model presented in this thesis will be developed using a comprehensive set of theory-driven factors that notably influence travel mode choices.
2. Lack of studies that measure the responses that different public segments would have to particular transport interventions.	This study will not only profile and interpret a set of psychographic mobility segments that exist within a sample but will also test the significance of differences with regards to the acceptability of a set of persuasive technologies aimed to reduce the dependence in private conventionally-fuelled vehicles.
3. A very limited number of studies that use segmentation approaches to deliver positive incentives. The few ones have used segments that were either defined *a priori* or constructed based on a limited number of theoretical determinants of behaviour.	This study will offer technical guidelines to enhance the potential of a positive incentives scheme through the use of a *post-hoc* statistical segmentation procedure, based on a complex set of psychological variables.
4. Lack of studies that are conducted in countries without advanced transport systems such as those found in Western Europe.	This study will evaluate the acceptability of persuasive technologies in the context of a middle-income country.
5. Lack of studies that estimate the environmental and financial benefits of the implementation of a variety of incentives schemes.	This study will provide a mathematical method to estimate the potential benefits associated with a hypothetical implementation of incentives in the area of study.

As has been shown in this chapter, there is a complexity of individual factors that determine travel choices, especially the choice between different modes of travel. Theories from social psychology have been a useful source of knowledge to help understand how an individual makes the decision between one particular transport mode over others. Market segmentation techniques have been useful not only to demonstrate the existence of different traveller profiles within a population but also to drive future policies for behaviour change. Finally, positive incentives have been shown to be a prominent technique to persuade people towards more sustainable modes of travel. The chapter culminated in the development of the theoretical framework and the selected concepts are now ready to be operationalised. This and other issues around the study's design are covered next, in the methodology chapter.

Chapter 3
Research Methodology

This chapter describes the methodology used to operationalise the collection and analysis of the data. Section 3.1 presents the research strategy. Details of the area of study and sample are presented in Section 3.2 and 3.3, respectively. The data collection protocol is discussed in Section 3.4, followed by the data analysis strategy in Section 3.5. Section 3.6 covers the process of coding and cleaning the data for the analysis, followed by a description of how missing data was handled, in Section 3.7. The variables' levels of measurement are discussed in Section 3.8. The chapter ends with a discussion about the ethical issues, in Section 3.9.

3.1 Research Strategy

This section gives an introductory explanation of the methodological phases of the study. Each of the steps outlined here will be explained in more details in later sections of the chapter.

Firstly, to allow comprehension of how each research question was addressed in the research, the methodological design and main hypothesis associated with each question are shown in Table 3.1.

Table 3.1 - Methodological design of the research questions

Research Questions		Main source of data	Methodological design	Hypothesis
RQ1	What determinants of travel behaviour can be used to underpin a segmentation approach?	Literature/Questionnaire	Review theories of behaviour and systematically select suitable theoretical constructs considering the purpose of this research. Analyse the discriminatory power of these variables to form the behavioural segments and the variability of the variables' scores among the discovered groups.	An empirical evaluation of the theoretical factors will offer insights about the appropriate ones to be included in future segmentation-based studies.
RQ2	What behavioural factors are associated with individual acceptance of positive incentives to reduce the use of Private conventionally-fuelled vehicles (CFVs)?	Questionnaires	Analyse significant correlations between behavioural mobility factors and three different indicators of positive incentives' acceptance: attitudes, intention to use and perceived likelihood of an individual reduction in private CFV use.	The behavioural factors are significantly correlated with the individuals' indicators of positive incentives acceptability.
RQ3	What psychographic segments show higher acceptability of positive incentive schemes?	Questionnaires	Create and interpret psychographic segments and analyse significant differences in the acceptability of positive incentives.	There are significant differences in the acceptance level of each positive incentive between different psychographic segments
RQ4	What are the behavioural differences between distinct segments of the population that are created based on the acceptance of incentives?	Questionnaires	Define segments according to incentives acceptability factors and analyse significant differences in their psychological profile.	There are significant differences among behavioural variables between different groups of acceptance of positive incentives.
RQ5	What environmental benefits can be estimated (in general and considering population segments) from a hypothetical implementation of positive incentives in Curitiba?	Questionnaires	Perform a scenario estimation considering the individual perceived impact of the students with respect to each type of incentive.	The hypothetical implementation of incentives in the study's context would lead to considerably positive outcomes for the environment.

As can be seen in Table 3.1, the main method of data collection of this study is questionnaires. A number of measures were taken to ensure the quality of the final survey. After the definition of the theoretical framework (done in the previous chapter), a first draft of the questions was done. To allow a first critical scrutiny of these measures, PhD researchers of the Institute for Transport Studies of the University of Leeds made a qualitative assessment of the questions. Another initial step was the execution of an elicitation study. Three of the variables of the Theory of Planned Behaviour (namely, the belief-based measures) are based on a set of attributes that have to be assessed within the study's sample *a priori,* according to Fishbein and Ajzen (2010) and this is done using an elicitation questionnaire (where the attributes are elicited by participants). With these results in hand, a first version of the main questionnaire was developed and a first pilot test was run. Due to a large number of practical issues revealed by the test, including problems with question comprehensions and the time taken to complete the survey, a second pilot test was performed. This test also uncovered a number of issues, which were assumed to be manageable. Finally, the main questionnaire was split into two versions due to its excessive length, and the belief measures of the Theory of Planned Behaviour (Behavioural, Control and Normative), which were identified in the elicitation study, were assessed in a complementary questionnaire. This second questionnaire was sent to the same participants that completed the main one. Figure 3.1 illustrates the sequence of the research phases described above.

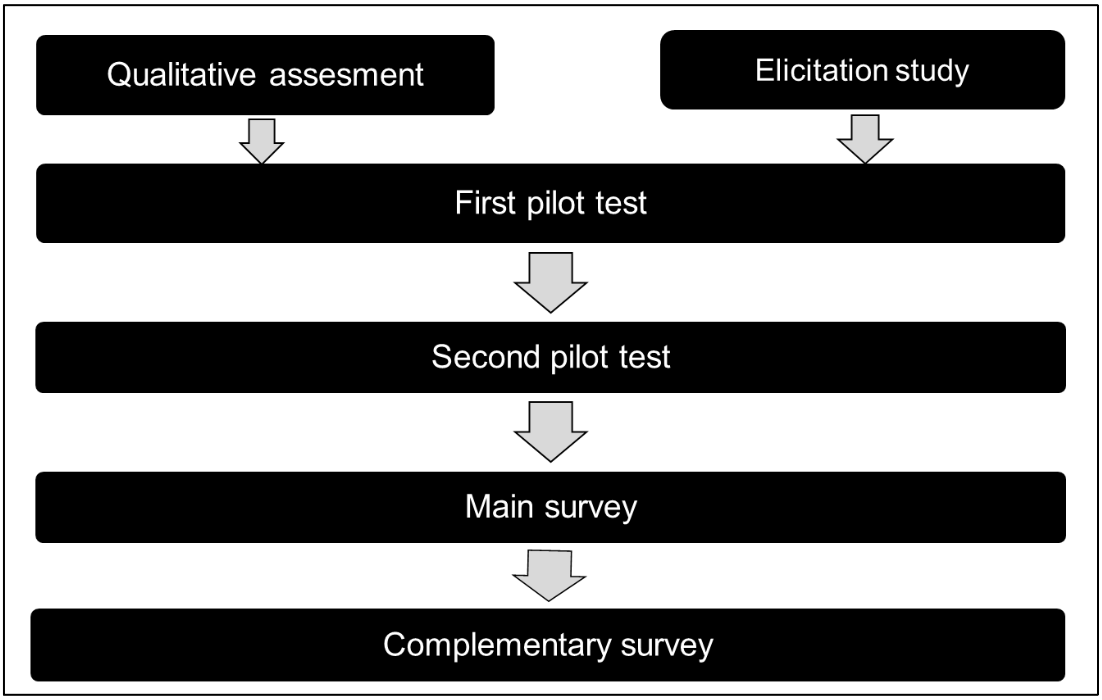

Figure 3.1 - Chronology of the application of the main research instruments

Section 3.4 of this chapter will elaborate in more detail the methodological steps outlined above. Before that, the characteristics of the city of Curitiba and the sample are explored next.

3.2 Mobility characteristics of Curitiba

Curitiba is a city known for its urban development plan implemented from 1965 when the population was around 500.000 (Smith and Raemaekers, 1998). The transport system of Curitiba became famous mainly because of the association between land use development, urban transportation and environmental preservation (Nikitas and Karlsson, 2015). One of the main proposals was the creation of a trinary road system, constituted by three parallel roads. Two external streets are used to provide fast and direct connections between the periphery areas and the city centre, while a central road is reserved for dedicated express bus lanes alongside two external slower single traffic lanes. Commerce and services are stimulated on these corridors, which now have a high transit demand (Miranda and Rodrigues da Silva, 2012).

Also in the mid-'60s, the first Bus Rapid Transit (BRT) system was implemented in Curitiba, although dedicated lanes began to be used only on 1974. The basic characteristics of this type of system, besides a dedicated lane, are busway alignment, off-board fare collection and platform-level boarding. Other concepts form a BRT standard according to ITDP (2016): good pavement quality, minimisation of bus emissions, safe and comfortable stations, integration with other public transport and cycle lanes, etc. The introduction of the urban development plan and the BRT system have made Curitiba one of the finest examples of land use development and integrated transport (Cervero 1998).

The use of more environmental-friendly modes in Curitiba such as bikes, for example, is not culturally present in people's everyday life, as their use is more frequent in sporadic leisure activities than in regular, day-to-day transportation (Kienteka et al., 2014). The cycling infrastructure is one of the highest among Brazilian capitals. With a total of 192km, the city is in fifth place, ahead of other capitals with approximately the same population, such as *Belo Horizonte* (87,4km) and *Recife* (41,6km) (Mobilize, 2015; IPPUC, 2016). Although having a relatively good cycling infrastructure when comparing to other Brazilian cities, it is still quite limited for a city of this size.

The macroeconomic Brazilian context also favours the use of cars, as public expenses towards individual transport are much higher than in public systems. The government has lowered fuels taxes and others related to the car industry. Parking prices and car ownership taxes are also considered low (Vasconcellos, 2012). Vasconcellos also presents the proportion of 8-1 between subsidies to motorized individual transport and public transport. That means that for every R$800 spent in subsidies for cars and motorcycles, just R$100 is spent in mass transit systems.

Past research has found that people in developing countries have a greater desire to own a car when compared to more developed nations (Belgiawan et al., 2014). The reasons behind this assumption are still poorly understood, but there is a chance that behavioural factors do play an important role in this issue.

3.2.1 Origin-destination survey data from Curitiba

An origin-destination survey was undertaken in Curitiba and 16 other municipalities that are part of its metropolitan area in 2017, resulting in 76,224 trips being recorded by 45,067 people (IPPUC, 2017). Table 3.2 presents the results, which provide an up-to-date indication of vehicle ownership and average trips per day.

Table 3.2 - Mobility indicators of Curitiba

% of households with at least one car	71%
% of households with at least one motorcycle	15%
% of households with at least one bicycle	41%
Avg. number of trips per day	2,76
Avg. trip time (bus)	47m50s
Avg. trip time (car)	22m18s
Avg. trip time (bike)	20m15s
Avg. trip time (walking)	15m45s

Data source: IPPUC (2017).

The percentage of households with a car is notably greater than the Brazilian rate for 2015 (45,8%) (IPEA, 2016). Whereas the percentage of motorcycle among citizens of Curitiba is less than the national average, which is 21.2% (IPEA, 2016). The average duration is considerably higher for bus trips, in comparison with other modes. Figure 3.2 shows the transport mode shares divided by gender (IPPUC, 2017).

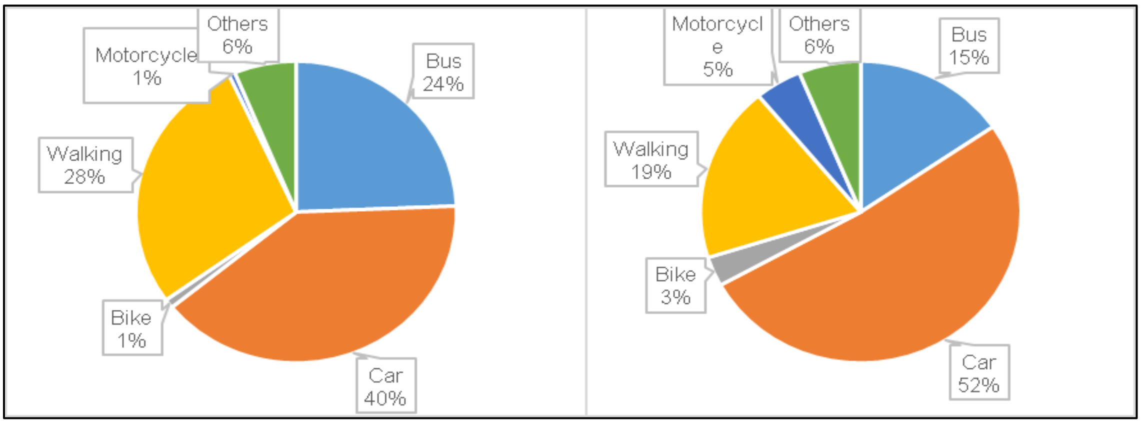

Figure 3.2 - Trip mode-share for women (left chart) and men (right chart).

While men are more oriented to travelling by car, bike and motorcycle, women have a tendency to walk and take the bus in Curitiba. Even when in the car, women are not driving it on 63% of the times (IPPUC, 2017).

Figure 3.3 and Figure 3.4 present mode shares by trip purposes and age groups, respectively (IPPUC, 2017).

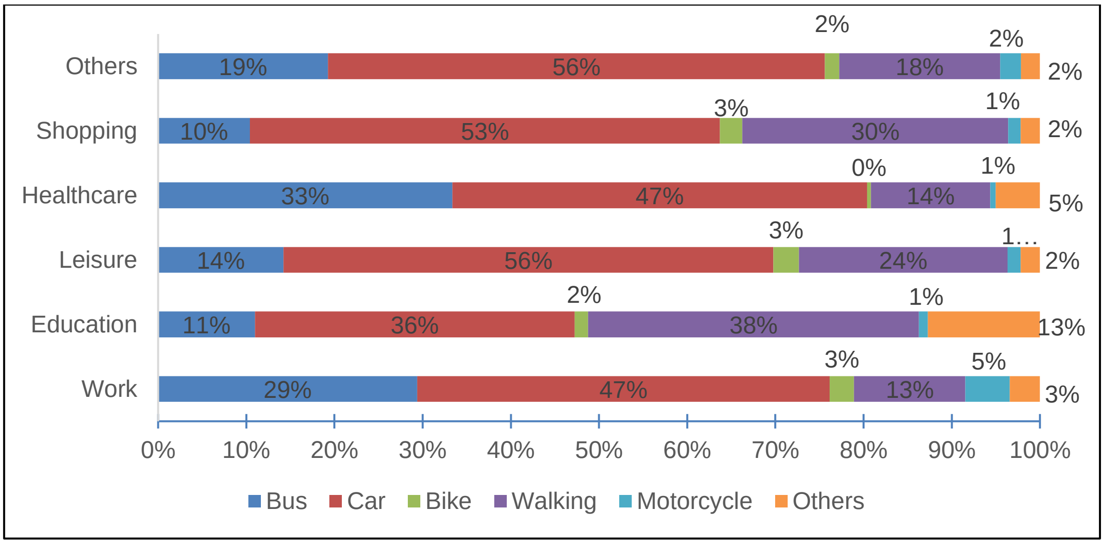

Figure 3.3 - Mode share (total trips) per different trip purposes.

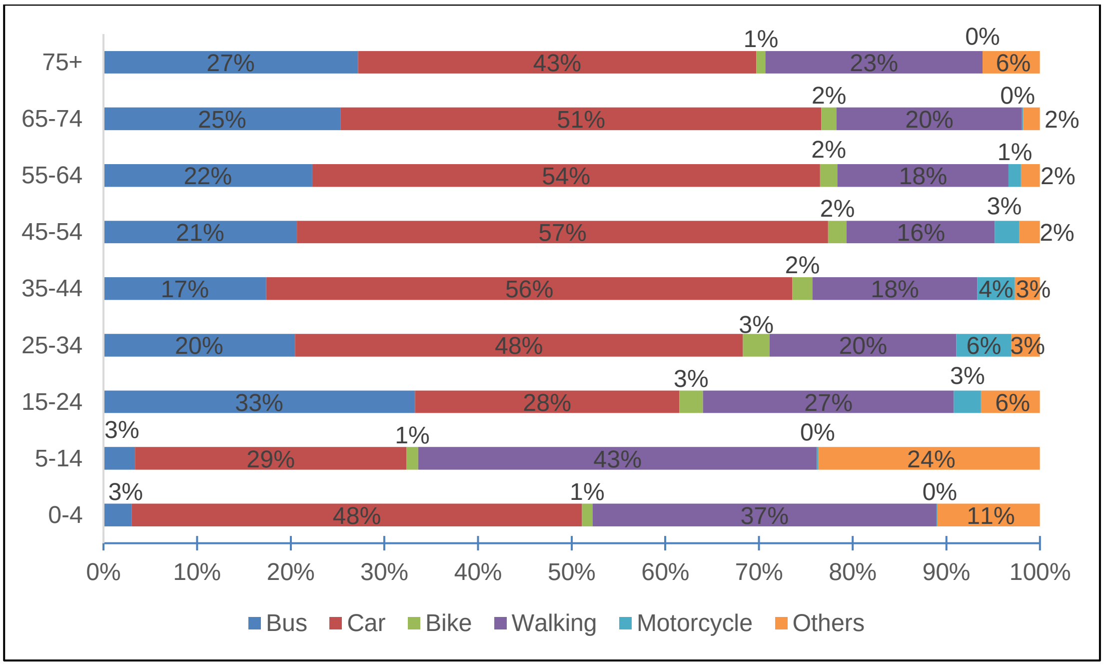

Figure 3.4 - Mode share (total trips) per age group.

Walking or cycling are forms of transport which are more used for those going for shopping, leisure or an educational service (e.g. college). Public transport, as well as cycling and walking, are more popular among the younger people of Curitiba.

3.3 Sample

This research followed a cross-sectional design. In this format, data is collected at one point in time and can have the purpose of observing relevant relationships between variables of interest (Fowler, 1986). Therefore, researchers are interested in variation (Bryman, 2012). Substantial variation in the behavioural profile with respect to personal travel and positive incentives is necessary to allow the identification of patterns of association between the two. Thus, the sample of this study has to contain different psychological and socioeconomic profiles, transport mode users and different attitudes and intentions to use positive incentives schemes, but it does not need to be statistically representative of the population. In fact, it is not the goal of this research to generalise its findings. Instead, it aims at exploring data in a way that uncovers relevant behavioural patterns among a group of university students, generating new information on a topic that has not been explored yet, which is the acceptability of positive incentives in Brazil.

Therefore, this research used a non-probability sample, which is defined as "any sampling method in which the researcher has discretion in selecting which people are included" (de Vaus, 2014, p.88). This sampling method can also be defined as a selection of individuals in a way that there is a maximum chance for any relationship to be observed (Punch, 2005). When defining the sample of this study, the likelihood that it would contain people that are more familiar with a smartphone or internet-based applications was considered. This criterion of selecting cases that are judged to belong to some category of interest to the researcher is known as *purposive sampling* (de Vaus, 2014). Undergraduate students of twelve campuses belonging to eight different universities located in Curitiba formed this study's sample. People from 18 to 24 years old are the group that mostly use the internet in Brazil: 85.3% against a 64.7% average of the entire population (IBGE, 2016). People that started college also have a very high rate of internet usage (97.1%) (IBGE, 2016). Data concerning smartphone ownership also show this discrepancy between educational levels: 97.1% of people who at least started college against 77.1% average (IBGE, 2016). It is assumed that applying the survey to this sample increases the probability that respondents are familiar with the presented smartphone-based incentives.

When it comes to mobility, a report describing the socioeconomic and cultural profile of the undergraduate students in Brazil showed that 2.94% of the 136,711 students that participated cycle to the university, while 20.14% use their own cars or motorcycles, 15.42% walk and 53.78% use public transport (FONAPRACE, 2014). It is also notable that 39.41% of students live more than 10 kilometres away from their respective universities. The use of the internet is widespread among undergraduates as 90.37% of them indicate the web as their main source of information (FONAPRACE, 2014). Computing skills are also notably high among students as more than 91% declare at least "having some notion" (FONAPRACE, 2014).

Using the information available at the universities websites, individual invitation e-mails were sent to 131 professors, separately. Invitations were sent during a period of 67 days, from the 2nd April 2018 to 7th June 2018, which was roughly the same period of the questionnaire applications that occurred following each professor's availability (more details of the questionnaire application are presented later in Section 3.4.7). 920 students from 38 classrooms of 19 different courses were surveyed, from 6 different areas of knowledge (Table 3.3).

Table 3.3 - Undergraduate courses covered on the survey

Faculty	Course
Engineering	Automation engineering; Civil engineering; Computer engineering; Forest engineering; Industrial engineering.

Social Sciences	Accounting; Administration; Architecture; Economy; Financial management; Information management; Public administration.
Biological Sciences	Zoology; Physical education.
Education	Pedagogy; Social services.
Environmental Sciences	Agronomy.
Informatics	Computer sciences; Information systems.

Table 3.4 shows the main characteristics of the assessed universities.

Table 3.4 - Characteristics of surveyed universities

University	N. of participants	Domain	Bus stop next to campus	On-campus car parking available	On-campus bike parking available	Cycle lane next to campus
PUC	120	Private	Yes	Yes (paid)	Yes	No
UTFPR ('Centro' Campus)	49	Public	Yes	No	Yes	Yes
UTFPR ('Ecoville' Campus)	26	Public	Yes	Yes (free)	Yes	No
UP	50	Private	Yes	Yes (free)	Yes	No
UP ('Osorio' Campus))	79	Private	Yes	No	No	Yes
CTUP	59	Private	Yes	No	No	No
UFPR ('Politecnico' campus)	262	Public	Yes	Yes (free)	Yes	No
UFPR ('Agrarias' campus))	37	Public	Yes	Yes (free)	Yes	No
UFPR ('Botanico' campus)	150	Public	Yes	Yes (free)	Yes	No
UFPR – ('SEPT' campus)	17	Public	Yes	Yes (free)	Yes	No
UNINTER	58	Private	Yes	No	Yes	No
UNOPAR	30	Private	Yes	No	No	No

The group of universities is heterogeneous when it comes to their administrative category (public or private) and the existence of car parking on-campus. All of the universities are have at least one bus stop on an adjacent street. Only two universities have adjacent cycle lanes. Surprisingly, one of them does not have bike parking available. However, most of the remaining institutions give this option to cyclists.

Figure 3.5 shows a map of Curitiba along with its main mobility infrastructure characteristics and the location of the surveyed universities. The bus terminals displayed are integration sites for multiple urban lines. The cycle lanes displayed are either completely segregated from traffic, buffered lanes with in-road painted demarcations or cycle paths that share space with pedestrians and other non-motorised traffic.

3.4 Data collection protocol

This section describes the methodological phases and is organised in chronological order. It expands the description already presented in the first section of this chapter. Figure 3.6 presents a summary of the activities related to data collection. Namely, the steps that were followed to develop and administer the survey questionnaire. It also presents the section where the research phase is explained.

Each subsequent section of this chapter is dedicated to providing more details about each phase of the data collection process.

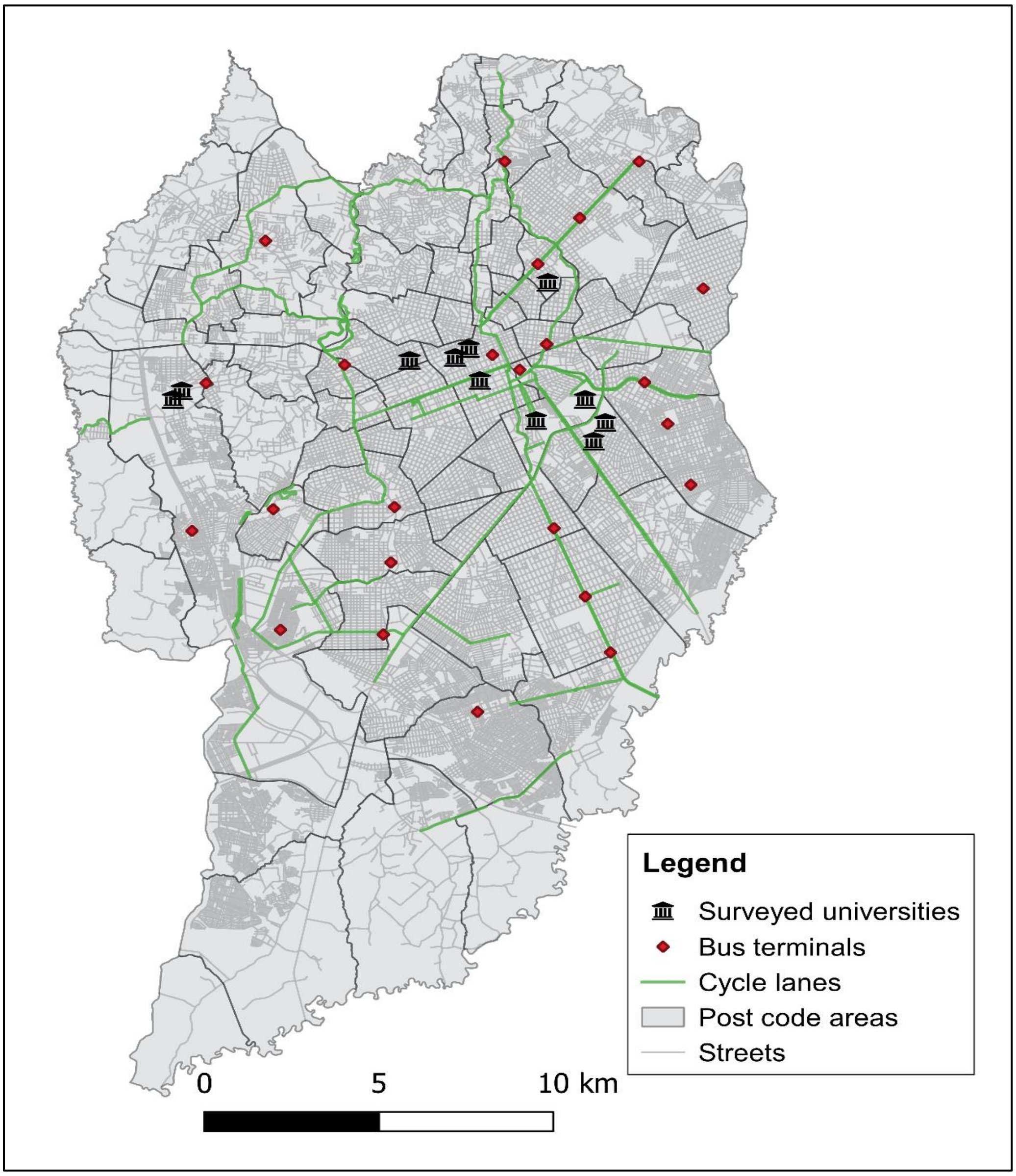

Figure 3.5 - Mobility infrastructure of Curitiba

3.4.1 Qualitative assessment

PhD students from the Institute for Transport Studies (ITS) at the University of Leeds received an invitation to examine a first version of the survey critically. A copy was sent to four researchers who agreed to participate. Each section of the questionnaire was followed by a space for comments, where the researchers provided detailed feedback. The assessment of this feedback resulted in a refined new version. The following sections report activities that, as opposed to the examination process detailed above, were conducted locally in Curitiba, Brazil.

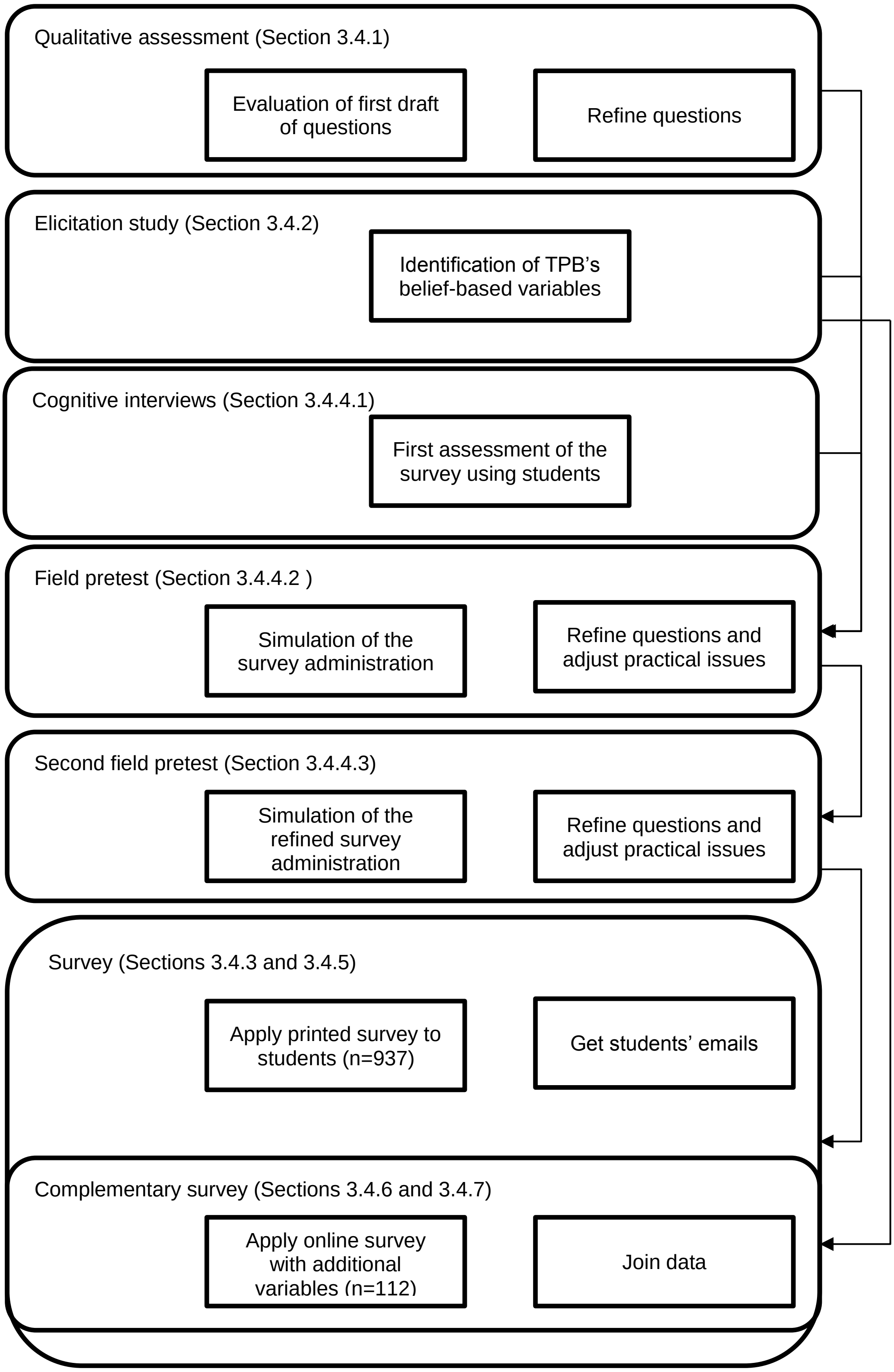

Figure 3.6 – Chronology of survey development and administration phases

3.4.2 Elicitation study

The author of the TPB states that the items used to measure the constructs of "Behavioural beliefs", "Control beliefs", and "Normative beliefs" which are indirect predictors of intentions (through attitudes, perceived behavioural control and subjective norms, respectively), vary across different populations and behaviours (Fishbein and Ajzen, 2010). Thus, arbitrarily selecting questions or adapting from other studies might not always ensure validity and reliability. In respect to these belief-based constructs of the TPB, Fishbein and Ajzen (2010) state that in order to construct a measure for them, a prior study can be made to identify which are the accessible beliefs of a sample related to a given behaviour. For example, behavioural beliefs refer to the beliefs about the advantages and disadvantages (good and bad characteristics) of performing the behaviour. If the example of 'going to the university by car' is taken, the beliefs could be the notion that it would be fast and comfortable but also expensive. Once that is acknowledged, a measurable indicator of behavioural beliefs can be constructed according to what was elicited and added to the final survey. However, each person may have (and probably have) different beliefs about the same behaviour, which makes the task of summarizing a set of beliefs of a given population difficult. For this reason, the authors recommend the identification of a set of beliefs that are held with the greatest frequency in the population of interest, that is, a *modal set* of accessible beliefs (Fishbein and Ajzen, 2010). This is accomplished by running a qualitative study, on which a sub-sample of the study's sample is selected. Participants are asked to individually list the beliefs they hold about the behaviour. With all the responses in hand, the researcher analyses the content and selects the mostly mentioned beliefs, to be further assessed in the whole sample (Fishbein and Ajzen, 2010).

The open-ended questionnaire (Appendix B) covered only behavioural and control beliefs. Normative beliefs were not part of this activity since *personal* salient beliefs, instead of *modal* beliefs, were considered for this case. Personal beliefs can be directly evaluated in each participant with a specific question for that purpose. The participant is then invited to consider this belief in the question that evaluates its intensity. It was assumed that collecting a set of modal normative referents from the sample would not be appropriate to evaluate the influence of the judgement of other people on the participant's behaviour. The most elicited people could potentially include persons that may not be part of a particular individual's social circle, turning the question difficult to respond or embarrassing to the student.

25 undergraduate students, coursing the final year of Business administration at a local university were selected. An e-mail contact was made with professors from different institutions. Two other classes were rejected due to having an incompatible number of students (less than 20) and a third group was rejected as it was composed of first-year undergraduates, who sometimes do not have legal permission to use privately-owned motorised forms of transport.

Participants were given a few minutes to list the good and bad characteristics of each transport mode (to assess behavioural beliefs) and the factors that would enable or obstruct the use of each mode (to assess control beliefs). Figure 3.7 displays the most cited characteristics of each transport mode (behavioural beliefs). A content analysis was performed to identify and group items with a semantic difference but clearly referring to the same concept. Items having something clearly in common were also grouped (e.g. 'slow' and 'time-consuming'). The four most frequently cited characteristics were included in the main questionnaire as standardised questions.

Most of the elicited characteristics converge with the literature on determinants of transport mode choice. The two exceptions are 'Overcrowded' and 'Practicality', which do not appear in any of the European-based empirical studies that are described in Section A.1.2, in Appendix A. 'Practicality' was the fourth most listed attribute of the motorcycle. This method of transport is used by a considerable portion of Brazil's population. The term 'overcrowded', cited as a bus attribute, might not have appeared in the reviewed literature due to a terminology issue. This characteristic can be implicitly included in feelings of comfort and convenience, which were revealed by the studies. Additionally, cultural and linguistic differences between this study's and the literature population might underlie these differences.

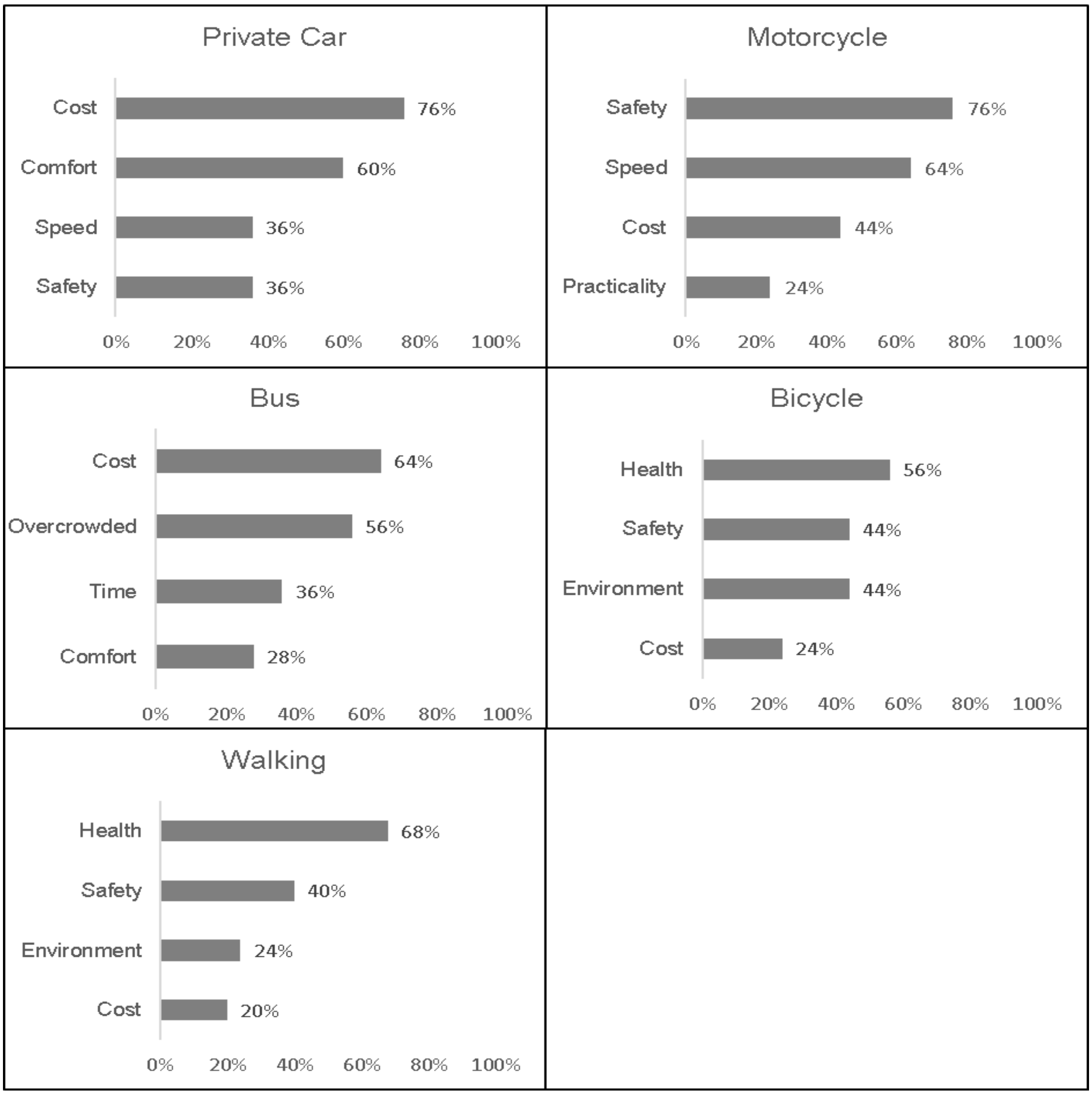

Figure 3.7 - Good or bad characteristics of each transport mode elicited by participants.

The predominance of ‘cost’ as a cited characteristic (cheap or expensive) of all transport modes needs to be highlighted. This can be a result of a country where transportation significantly affects people’s living costs, especially students. Cultural particularities of middle-income countries might also explain why ‘safety’ appears amid the most listed characteristics (safe or unsafe) in all transport modes, except bus. While safety might refer to accidents when it is listed as an attribute of riding a motorcycle, it may also refer to urban violence when it comes to walking.

Figure 3.8 demonstrates the elicited restricting and facilitating factors of each transport mode (control beliefs).

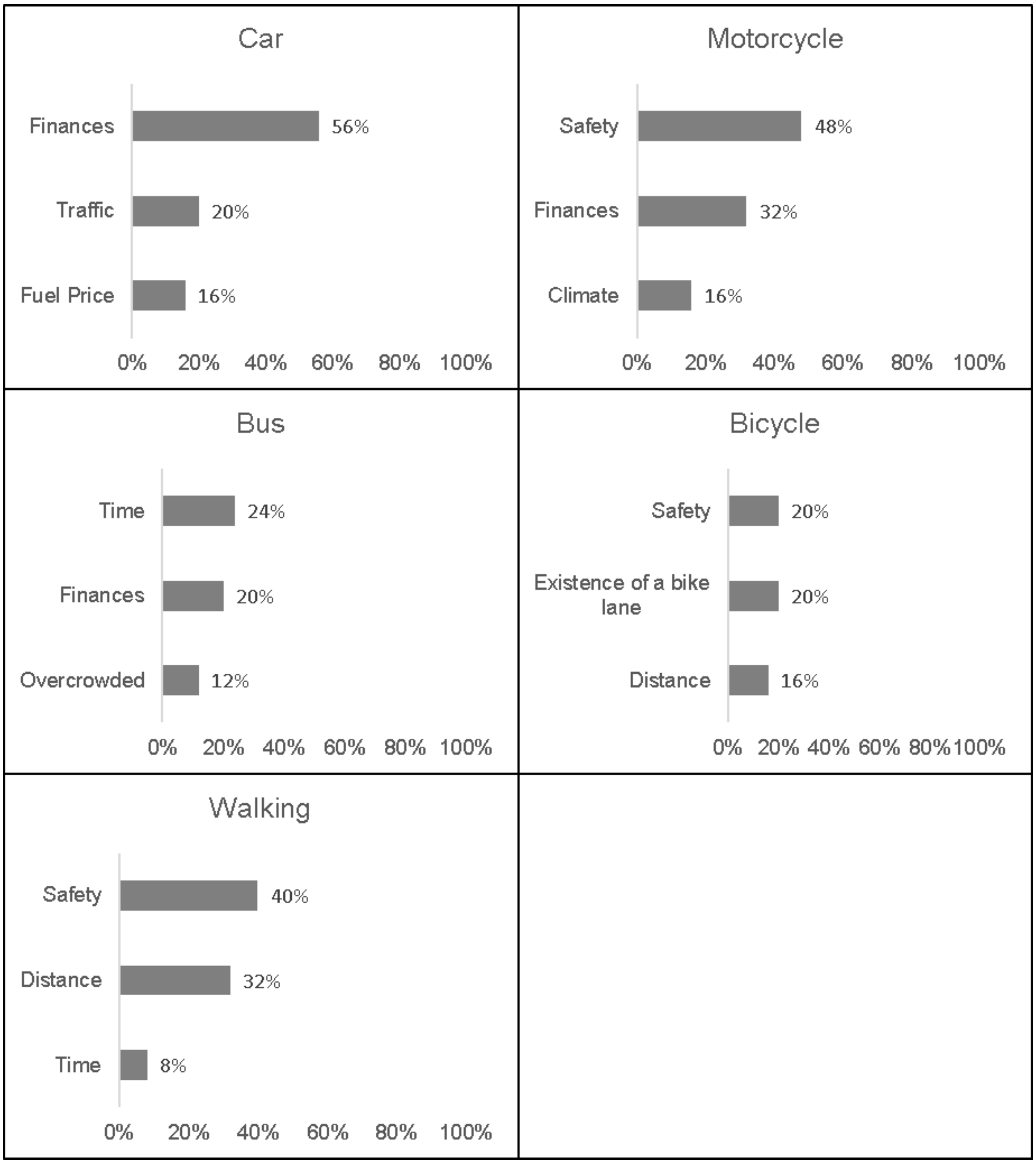

Figure 3.8 – Restricting of facilitating factors of transport modes elicited by participants

For control beliefs, the two most cited barriers or facilitators of each transport mode were introduced as Control Beliefs factors. Section 3.4.6 shows more details of the questions originated from the elicitation study.

3.4.3 Main Survey Questionnaire design

The questionnaire was set up to examine the relations between the variables of each of the main concepts of research. This type of design is defined as analytic (Albuam and Oppenheim, 1993) or correlational (Punch, 2005).

The first step on the questionnaire development was to observe the potential issues concerning survey responses that may lead to data-collection errors, causing bias and poor validity and reliability. Table 3.5 provides a summary of these aspects along with the adopted coping strategies.

Table 3.5 – Possible response issues and correspondent coping strategies

Response issue	Definition	Coping strategy
Satisficing	The respondent offers the first answer that he or she thinks is acceptable, without effectively thinking about the question (Krosnick and Presser, 2010).	Reducing the difficulty of the questionnaire completion and motivating the respondent with respect to how he or she might benefit from the results of the research.
Acquiescence	The endorsement of an attitude question without being fully aware of its content (e.g. be inclined to agree with a statement) (Krosnick and Presser, 2010).	Eliminating the agree/disagree scale, which is empirically known to cause acquiescence (Berg and Rapaport, 1954); Reducing the number of true/false scales as much as possible; Making the questions easy to understand.
Question order effects	People might respond to a certain question in different forms depending on the context of the questions that are presented before (Krosnick and Presser, 2010).	Present easy and pleasant questions first; Group questions on the same topic together; Proceed questions from general to specific; Place sensitive questions at the end.
Response order effects	The order in which responses are presented affects their selection (Krosnick and Presser, 2010).	Counterbalance the order in which choices are presented among respondents.
Social desirability bias	Respondents falsely report in a socially desirable direction when answering sensitive questions (Krosnick and Presser, 2010).	Use self-administration as the survey application method; Use introductory text before the sensitive question legitimating the undesired behaviour; Ensuring anonymity of responses.

After the acknowledgement of the issues above, research was done to identify how past authors have approached the operationalisation of such variables. As most of the concepts were extracted from relatively established theories of social psychology, their corresponding measures were usually supported by quite strong empirical assessment in past studies, even in the transport field.

Nevertheless, the questions used in past studies to address the concepts of the theories could not be simply transferred to this thesis' survey due to language issues. The literature consulted was in English and a translation to Portuguese was needed. It is acknowledged that a survey translation is often not a simple exercise as a literal translation sometimes is not sufficient due to cultural differences. This was examined during the translation process and the risks were minimised with the pilot studies described later in the Chapter.

Before that, a discussion is presented next about the different options of measuring psychological variables.

3.4.3.1 Scales for measuring psychological variables

Attitudes, beliefs, values or norms are individual attributes that have intensity and direction (Oppenheim, 1992). Thus, these variables are usually measured using rating scales, which will further represent numerical values or scores. Oppenheim (1992) defines attitude scales as an instrument of measure that evaluates the respondent's degree of agreement or disagreement with respect to an attitude topic.

One of the most used methods of measurement in behavioural research is the Likert Scale (Zhang et al., 2011). It usually consists of a 5 or 7-point scale where respondents are asked to position their opinion in regards to a certain topic. The options range from *strongly disagree* to *strongly agree,* including a neutral position. Kerlinger and Lee (2016) explain that the score of each measured attitude item is summed (or averaged) to compose a final individual attitude score. A weakness of this method that has to be taken into account is the response set variance. That is, different individuals may have different tendencies to use certain types of response (e.g. ones might be more inclined to use extreme responses while others might tend to be more neutral). Kerlinger and Lee (2016) minimise this issue and categorise it as a mild threat of which the research has to be conscious of. The authors also advocate that this method is the most useful for behavioural research.

In the Thurstone scale, different attitude statements are submitted to 'judges', which can be experts in a given field or simply participants of the study. In this phase, each evaluated variable is given a particular score by each judge, depending on how they perceive the item as a strong indicator of the general attitude to be studied. In a second phase, with these corresponding ‘weights’ assigned to each variable, respondents are presented with the statements and asked to expose their endorsement (or not) to each declaration. The previously calculated ‘relevance’ or ‘weight’ (in the judgement phase) is used as the final score for each item with which the respondent has agreed (Oppenheim, 1992).

Guttman scales concentrates on ranking the individuals according to their attitudes. The responses are organized and submitted to scalogram analysis. This type of analysis identifies the items that had the most convergence of response and the individuals with the highest attitudes towards a certain topic (Kerlinger and Lee, 2016).

In the semantic differential scales, respondents express their opinion about a concept or object using a rating scale (traditionally 7 points) containing contrasting adjectives or opinions at their end-points (Teddlie and Tashakkori, 2009). Oppenheim (1992) draws attention to the necessity of elaborating two descriptors at the extreme points of the scale that are really opposed and do have some kind of dimension between them.

Table 3.6 presents the strengths and weaknesses associated with each of the presented scales.

Table 3.6 - Scales for psychological variables measurement

Scale	Strengths	Weaknesses
Thurstone scale (Thurstone and Chave, 1929)	High reliability (Oppenheim, 1992)	Does not allow the measurement of the intensity of attitudes; Time-consuming and expensive.
Likert scale (Likert, 1932)	Easily understood by re-spondent; Easy to develop; Allows the measurement of intensity and direction of attitude expression; Allows good variance of the responses.	Individuals with the same attitude level might be inclined to respond in different manners; Different expressions are assumed to have the same attitude weight; The response might not reflect the real attitude intensity (e.g. a neutral response might actually mean mildly positive or negative).
Cumulative scale (Guttman, 1944)	Allows the prediction of an individual’s attitude by its score; High reliability (Oppenheim, 1992).	Does not allow the measurement of intensity; Laborious technique (Oppenheim, 1992); The attitude has to be unidimensional.

Semantic Differential scale (Holmes, 1942)	Simple and easy to apply; Allows the measurement of intensity; Allows good variance of the results.	The choice of one scale point between the adjective pairs can be more subjective and judgemental.

Since the intensity of the attitudes is of interest in this study, the Thurstone and the Guttman's scale were not suitable. Both Likert or the Semantic Differential scales could be used for most of the variables, but the semantic scale was preferred, mainly for two reasons: (1) the majority of the current evidence around the use of psychological measurements of concepts, such as those from the TPB, were done using this scale (Fishbein and Ajzen, 2010) and (2) The semantic scales better fill an important assumption that is necessary for some data analysis procedures performed in the study, which is the existence of equal intervals between the points on the scale (more details on this issue are provided in Section 3.8, about levels of measurement).

3.4.3.2 The use of travel modes

Studies have used divergent forms of measuring the use of transport modes. Anable (2005) asked the frequency of use of each mode in two ways: (1) all journey purposes combined and (2) work trips. Bamberg et al. (2007) used 'mobility-diaries', in which participants reported the used transport modes for a period of one day. The authors also assessed past use of public transport with a 5-point scale asking its frequency of use in the last four weeks. Bamberg et al. (2010), when assessing the frequency of use of different transport modes in the past six months, used this same 5-point scale self-report approach. Hunecke et al. (2001) used a different form: PT use was measured using the division of PT trips by the total number of trips in a certain period of time.

Measuring recurrent behaviour can often be difficult, especially concerning how to formulate the questions. In regards to the assessment of the frequency of car use, for example, four different question forms can be used (Albuam and Oppenheim, 1993):

- Did you use the car yesterday?
- Have you used your car within the past week?

- When did you last used your car?
- How often do you usually use the car?

As the use of different transport modes is assumed to be a frequent behaviour in urban areas, the first three questions stated above would not be sufficient to identify different levels of car use. Thus, questioning the *frequency of use* of each transport mode at a given period was the strategy used in this research. The measurement had to rely on self-reporting, as the handling of travel diaries would be technically difficult in terms of sample size and cost. Survey participants were asked to report their weekly average use of the travel modes, for university routes, considering the antecedent month of classes. The scale was fully labelled and had seven-points that ranged from '*1-3 trips a week'* to '*more than 18 trips a week'*, with equal intervals.

3.4.3.3 Variables of the Theory of Planned Behaviour

The measures of TPB-related variables were constructed based on the guidelines of Fishbein and Ajzen (2010).

Attitudes to the use of each travel mode were measured using two 7-point semantic differential scales from -3 to +3 (*dislike/like* and *pleasant/unpleasant*). Subjective norms were assessed in the same manner, with the following question: '*Thinking about the important people in your life, how they would react to you using the car/bus/bike to go to the university*?' The scales were labelled as: *would completely oppose/would completely support* and *think I should not use/think I should use*. Intention was measured using the following item: *during the next month of classes, how often do you intend to use the car/bus/bike/motorbike/walk?* A seven-point fully labelled scale was used, from '*1-3 trips a week'* to '*more than 18 trips a week'*, with equal intervals, like the one employed to measure the use of travel modes.

3.4.3.4 Variables of the Norm-activation Model and the Value-belief-norm Theory

All VBN and NAM constructs were measured using seven-point bipolar scales (*very true/very false*). These scales were adapted from previous publications that have used the NAM in transport-related research (Nordlund and Garvill, 2003). Personal norm was measured with the following two items: '*I feel morally obliged to use the car as less as possible'* and '*I feel obliged to use alternative modes to the car due to personal values'. '*Awareness of consequences' was measured using three indicators: '*Car-related pollution can lead to irreversible consequences to the planet'; 'Traffic noise decrease the quality of life in the cities'* and; '*The increasing level of cars is a threat to planet resources'*. The following statement was used to measure '*Ascription of responsibility'*: '*My decision about which transport mode to use makes me responsible for air pollution'*, whereas Perceived ability to reduce threat (PART) was assessed using: '*I have the ability to reduce the environmental and social threat associated with car use'.*

3.4.3.5 Variables of the Theory of Interpersonal Behaviour

Habits gain strength over time due to the frequency and repetition of behaviour (Ajzen, 2012). Therefore, measuring habit by asking respondents about how many times he or she adopted a certain behaviour might seem appropriate. However, in some cases, it might be difficult for the person to remember the frequency of a certain action (e.g. how many times a person took the car on the last month) (Verplanken and Orbell, 2003).

There are two alternatives to this type of measure which have been the most common and accepted in the literature (Klöckner, 2013b): the *response-frequency measure of habit (RFM)* introduced by (Lanken et al., 1994) and the *self-report habit index (SRHI)* (Verplanken and Orbell, 2003). The RFM method applied to transport, consists of asking respondents to pick which travel mode they would choose for different activities (e.g. going to a bar, visiting friends and going shopping). Participants are asked to respond quickly, without much deliberation. The strength of car use habit (for example) is then extracted from the number of times a person chose a car as the mode of transport among the several activities. On the SRHI method, habit strength is measured by directly asking participants to report if they have performed a certain action "by force of habit", for example. This measurement can be problematic as people might not be fully aware of their own habits and about what a habitual behaviour really means.

The habit of using each travel mode was measured in this study using the *response-frequency measure* (RFM). Six activities were presented to participants (visiting family/practice sports/go shopping/go to the park on a sunny day/go to the supermarket/go for a night out with friends). Thus, the habit score for each mode ranged from 0 to 6.

3.4.3.6 Other variables

Variables that are hypothesized to be influencers of mobility behaviour or positive incentives perception were included. Familiarity with 'mobility' smartphone applications was one of them. It was measured using a four-point categorical scale with the following labels: "I've never heard of it"; I've heard about it, but never used it"; I've used it in the past, but not anymore"; and "I currently use it" (Appendix C – Question 4). Seven different types of apps were presented, including taxi apps, journey-planners and ride-sharing apps. Car, motorbike and bicycle ownership were measured using a yes/no binary scales. The availability of these modes was measured similarly. Past experience with each mode was assessed with a semantic differential seven-point scale ranging from "*No experience at all*" to "*A lot of experience*" (Appendix C – Question 7). As detailed on the appropriate literature review chapter, past experience can be a significant predictor of mobility behaviour.

3.4.3.6.1 Sociodemographic variables

The sociodemographic variables were identified using literature analysis on travel behaviour, both on the context of developed and developing countries, to identify the demographic aspects that most influence mobility choices. As detailed earlier in Chapter 3, the attributes that considerably vary across different transport behaviours were the following: age; gender; income; education, household size and commuting trip distance. Age, travel distance and household size were assessed using open-ended questions, while income and gender were formatted as close questions. Educational level was not measured as the sample is formed by university students. The respondent's living neighbourhood was also assessed using an open-ended question.

3.4.3.7 Acceptability of positive incentives

This research will assume that the sample has never been in touch with any of the positive incentives initiatives, therefore the respondents will give answers with regards to incentives based only on textual information about the tools in the questionnaire. Asking for the preference of a potential consumer in regards to a hypothetical set of goods or services is widely used in Stated Preference (SP) surveys.

The list of the assessed incentives and correspondent descriptions that were offered in the survey are shown below:

- Maps: Having a digital or printed map containing information about cycle routes, bus lines/frequencies and walking paths;
- Money: Receiving cash prizes if you travel using alternative modes to the car or motorbike;
- Points and badges: Accumulating points and earning badges for travelling without the car or motorcycle (e.g. "you've earned 2000 points and have achieved 'Gold' status in cycling");
- Ranking: Participate in a ranking showing the people who most used the bus, bike or walking as means of transportation in Curitiba ("You are currently third on the ranking of sustainable travellers in Curitiba!");
- Discount Vouchers: Receiving discount vouchers that you can use to buy products or services (e.g. retail stores, cinema tickets, etc.);
- Journey Planner: Having access to a journey planner containing information about the trip you want to do (distance, duration, physical effort, price, emissions) on different types of transport modes in Curitiba;
- Real-time information: Have access to real-time information, including bus times, weather and traffic problems ("your next bus will arrive in 5 minutes"; "tomorrow will be a sunny day, why not cycle to campus?"; "Traffic is chaotic now, why not go on foot?");

- Personalized Feedback: Have access to a personalised report about my recent journeys and their consequences (kilometres travelled, total time on journeys, air pollutants emitted, calories burned, etc.);
- Social Media: Being able to share your journey habits with friends and family through social media (“ ’your name’ has just cycled 12 kilometres!”);
- Challenges: Receive periodical challenges to complete (e.g. “challenge for this week: cycle 10 kilometres!”);
- Buddying: Know about another person who may join you to cycle, walk or get the bus together (e.g. “Your friend goes to the university using a bus line that stops next to your house, how about joining him or her?”).

As previously detailed in Section 2.4, three different variables were used as indicators of acceptability, for each one of the eleven incentives: attitudes, intention to use and willingness to reduce private CFVs’ use in response to the incentive (perceived personal impact).

Personal attitudes were measured using seven-point semantic differential scales (*I don’t like it/I like it a lot*). The intention to use was also measured using a seven-point scale ranging from “*I wouldn’t use it*” to “*I would use it a lot*”. The perceived personal impact was assessed using a scale in the same format (“*This would **never/certainly** make me change trips by car or motorcycle to alternative modes*”).

As the last item of the survey, respondents were asked if they consent to receive a complementary questionnaire. Those who answered ‘*yes*’, were asked to provide their e-mails. A copy of the main questionnaire is displayed in Appendix C.

3.4.4 Pilot studies

After defining the measurements, steps were taken to uncover possible problems with respect to the questionnaire design and the administration protocol. Firstly, cognitive interviews were conducted, followed by two field pre-tests. These tests have the purpose of finding out how the survey instrument works in realistic conditions. In addition, they should be conducted using respondents who are drawn from the same population as the final experiment but who are not part of the sample. (Fowley Jr, 2009).

3.4.4.1 Cognitive interviews

Once the questionnaire has been designed and critically and systematically analysed for its content and layout, a first test was performed with 5 undergraduate students using the cognitive interviewing approach. This procedure, unlike field pilot studies, focuses more on the questionnaire itself instead of the whole survey process. It is concentrated on the mental processes behind survey responses, allowing problems to be identified. It is also qualitative in nature and complementary to traditional field testing (Collins, 2003). The main cognitive technique used on the test was ‘probing’, which refers to the researcher asking questions (or probes) that are designed to elicit how the respondent went on answering the questionnaire (Collins, 2003). The students were encouraged to verbalise any difficulty they might have faced during the survey completion. In addition, the researcher concurrently asked questions about how the respondent felt about answering each question. Response latency, or the time elapsed between the question presentation and the answer, was also measured. Collins (2003) states that questions that require more memory searching have longer response latencies.

Most of the issues revealed by this activity were regarding question interpretation issues which required small adequacies. The questionnaire was then ready for further tests.

3.4.4.2 First pilot study

Before official administration, the survey was subject to a pilot study in the form of a field pre-test. Babbie (1990) advocates that this type of test should be administered as nearly identical as possible to the final survey, only differing in scale, as the pre-test uses fewer cases. Following this consideration, the exact administration protocol was simulated using a classroom of 20 undergraduate students of ‘*Universidade Positivo’*. During the activity, completion times of every participant were recorded and notes were taken in respect to any practical issue that arose.

The analysis of the pre-test data followed the guidelines provided by Babbie (1990), which are mostly corroborated by De Vaus (2014). Both authors determine that the following items should be examined:

- Response variation in questions;
- Questions clarity (excessive' don't know' answers, multiple answers marked when this is not allowed, etc.);
- Questionnaire format (skipped questions).

In addition, the researcher paid attention to how the students behaved during the completion of the questionnaire. The first student to return the questionnaire did it after 14 minutes, while the last student took 27 minutes. The average time of completion was 19 minutes. These time lengths of completion were judged to be too long, especially as the activity involved a certain 'disruption' to university classes. The number of fundamental issues uncovered by this pre-test was also judged too high. Thus, a second pilot study was done before the final administration, in the same manner as the first, but using a different set of students. The list of issues and corresponding treatments are displayed in Appendix D.

3.4.4.3 Second pilot study

This time, 25 undergraduate students belonging to a different classroom were assessed. The average time of completion now was 16 minutes. The issues and resolutions of this second test are detailed in Appendix E. After the refinement of the questionnaire, it could finally be administered to the whole sample.

3.4.5 Main questionnaire implementation

The survey application followed a self-administration approach, in which respondents completed the questionnaire unaided by an interviewer. This approach has the advantage that respondents might be more thoughtful during the completion of the survey, as they can complete it at their own time (Andres, 2017). A potential disadvantage is that questions must be sufficiently clear to allow the participant to understand them adequately. In addition, there is often no guarantee that the intended individual will respond to the questionnaire (Andres, 2017). To minimise the issue related to the clarity of questions, the development of the survey passed through three different pilot studies (as explained earlier), to ensure the questions are clear and unambiguous. In addition, the researcher was available during the whole survey administration to personally answer any individual questions regarding interpretation. An organized group response using a pen-and-paper approach, under the supervision of the researcher, also ensured that all intended participants completed the questionnaire in an appropriate manner.

Students filled the survey in their respective classrooms, with previous authorization of the responsible professor, who was asked to provide at least a 20-minute time period of the class to be taken for the activity. This amount of time ensured that the survey was fully and thoughtfully completed. The students answered the questionnaire simultaneously and individually. Andres (2017) gives a warning about this survey application method, stating that the surveyor when explaining the survey's purpose, might influence respondents to answer on a specific way. To avoid this, minimum information about the survey's goals were revealed. The researcher only presented himself and explained the main topics covered in the questionnaire, avoiding to provide any judgmental information. Andres (2017) also points out that the group setting might create an atmosphere that affects responses. Indeed, this issue arose during pilot studies when respondents talked with each other or loudly expressed their answers to the whole group. Thus, the researcher clearly stated to the classroom that they should complete the questionnaire individually and in silence. An adequate distance among the respondents was also aimed to minimise mutual influences between students.

3.4.6 Complementary questionnaire design

A second survey (Appendix F) was administered to the same participants of the main study, upon their agreement. This version assessed the belief-based constructs of the TPB (behavioural, normative and control), which were excluded from the main instrument due to excessive questionnaire length.

Table 3.7 describes the measurement strategy adopted for each one of the three main constructs measured by this survey.

Table 3.7 - Measures of the complementary questionnaire

Concept	Indicator	Form of measure
Behavioural beliefs	Belief strength	A seven-point labelled scale was used to assess how likely the participant thinks that a trip to the university would have a specific attribute. The four most cited attributes on the previously administered elicitation questionnaire (Figures 2 to 6) were used. The scale ranged from 'extremely unlikely' to 'extremely likely' for each of the transport mode aspects.
	Attribute evaluation	A seven-point numerical scale ranging from 0 to 6 was provided, '0' meaning "not important at all" and 6 being "extremely important". Each one of the transport modes attributes described above were assessed.
Normative beliefs	Injunctive normative referents	Respondents were asked to provide two persons or groups, by which they might have been influenced when making choices related to the use of transport modes.
	Injunctive normative belief strength	Respondents were then asked what their individual referents would think about them using each transport mode for university routes. Separate questions were provided in regards to each of the two persons/groups that were mentioned by the student. A seven-point numerical scale was provided, being: '0' = think I should never use and; '6' = think I should always use.
	Motivation to comply	This question assessed the student's willingness to behave in the manner that each of the two referents thinks they should behave. The following statement was given: "In general, I want to do what (his referent) wants me to do", followed by a true/false scale. Separate questions were designed to each of the two referents.
Control beliefs	Control belief strength	Considering the control factors that were most cited by the sample of the students who participated in the elicitation study (Figures 7 to 11), questions were developed to assess the perceived likelihood that a trip to the university using each of the transport modes would have the specified control factor (e.g. "How likely is it that there will be traffic jams if I go to campus by car next month?"). A seven-point semantic differential scale (highly unlikely/highly likely) was provided.
	Power of control factor	Finally, respondents had to answer how strongly each control factor would impede (or facilitate) them to go to the university using each of the correspondent transport modes.

As discussed earlier in Section 3.4.2, the belief-based measures described in the table above need a specific form of measurement which follows a multiplicative model. This will be discussed in more detail later in the results chapter (Section 4.1). This section will be limited to showing how the belief-based variables were measured. Following the guidelines provided by

Fishbein and Ajzen (2010), each of the constructs was measured using multiplicative composite scores, where:

- Behavioural beliefs (A) in regards to a specific transport mode was scored as the sum of the multiplications of belief strength (b) and attribute evaluation(e), to each of the assessed travel mode attributes (i) (Equation 1):

$$A = \sum b_i e_i \qquad (1)$$

- Injunctive normative beliefs (N) were scored in the same manner as above, summing the multiplications of normative belief strength (n) and motivation to comply (m) with specific persons/groups (i) (Equation 2):

$$N = \sum n_i m_i \qquad (2)$$

- Control beliefs (C) were measured by summing the multiplications of control belief strength (c) and power (p) to each control factor (i) (Equation 3):

$$C = \sum c_i p_i \qquad (3)$$

3.4.7 Complementary questionnaire implementation

Different from the first part of the survey, this second part was administered online. This form of administration is more appropriate in the case of this research's design since reaching all of the previous respondents again would be costly, time-consuming and difficult. Classrooms also changed in the interval between the two survey administrations as the academic period had changed.

Coverage error might be a problem when using online surveys as not all portions of the population have access to the internet. Nevertheless, this form of administration works better when the survey sample is assumed to have the internet as part of everyday life, such as students (Andres, 2017).

An invitation email was sent to participants of the first survey using the *Onlinesurveys.ac.uk* server (former Bristol Online Surveys), which was also the website used for questionnaire completion. Participants received a link which redirected them to the web survey. Three follow-up emails were sent (one per week) and the survey remained open for 4 weeks (from 1st to 30th September 2018). 112 people answered from the 700 that have initially agreed to be invited (16% response rate). An equivalent amount to approximately £150 (one hundred and fifty pounds sterling) was offered as a prize draw in the form of 10 retail discount vouchers.

3.5 Data analysis strategy

Before any exploratory analysis has been conducted, the constructs assessed through the questionnaire were checked for measurement quality. Thus, reliability and validity analyses are initially presented. Next, some of the measured items will be subject to factor analysis, in an attempt to produce a smaller set of meaningful factors to be used on further examinations. The identification of a factorial structure among the evaluation of positive incentives, for example, will allow a more profound, yet easier to interpret analysis. Table 3.8 summarises the methods to be subsequently employed for each research question.

Table 3.8 - Statistical methods employed to research questions

RQ	Statistical method	Expected outputs
What determinants of travel behaviour can be used to underpin a segmentation approach? (RQ1)	Correlation analysis; cluster analysis; discriminant analysis; analysis of variance (ANOVA).	A first set of determinants was drawn from literature, forming this study's framework. Secondly, however, these variables will be examined in respect to the multiple statistical methods used to assess the other RQs, which will offer evidence to support an informed suggestion about the suitability of each variable for future segmentation approaches.
What behavioural factors are associated with individual acceptance of positive	Descriptive statistics	Relevant descriptive statistics such as measures of central tendency or frequency distributions of variables.

incentives to reduce the use of Private conventionally-fuelled vehicles (CFVs)? (RQ2)	Correlation analysis.	Relationships between behavioural, as well as sociodemographic variables and perceptions of positive incentives (attitudes, intention and willingness to change), both individually and across categories of incentives.
Which psychographic segments show higher acceptability of positive incentive schemes? (RQ3)	Descriptive statistics;	Measures of central tendency or frequency distributions of variables.
	Cluster analysis;	The discovery of travel-related psychographic groups across the sample.
	Analysis of variance (ANOVA) with *post-hoc* analyses.	Significant differences in the acceptability of incentives across the psychographic clusters.
What are the behavioural differences between distinct segments of the population that are created based on the acceptance of incentives? (RQ4)	Descriptive statistics;	Means and standard deviation of variables of interest will be presented.
	Cluster analysis.	The discovery of groups of incentives acceptability across the sample.
	Analysis of variance (ANOVA).	Significant differences in the behaviour and sociodemographic profile across the acceptability clusters.
What environmental benefits can be estimated (in general and considering population segments) from a hypothetical implementation of positive incentives in Curitiba? (RQ5)	Scenario estimation	The potential reduction in terms of kilometres travelled by private CFVs, private CFV-related carbon emissions and private CFV-related social costs of carbon.

Statistical techniques that are well established in literature, such as cluster analysis and analysis of variance, will be conducted according to guidelines suggested by authors like Tabachnick and Fidell(2007) and Hair et al. (2014). The scenario estimation analysis has followed a more specific, data-driven, methodology, which is described in detail below.

3.5.1 Scenario estimation

The evaluation of potential benefits coming from hypothetical future transport interventions is not new. It was applied to examine the impacts of Intelligent Speed Adaptation systems, for example (Lai et al., 2012) and structural travel demand management measures (Eriksson et al., 2006; Eriksson et al., 2008a; Eriksson et al., 2010). Even regarding positive incentives, the SUNSET project came close to empirically evaluating potential environmental benefits that would come from these initiatives, as it assessed public attitudes and intention to use certain types of incentives in the context of European cities (SUNSET, 2011). The aim of the scenario estimation in this study will be to demonstrate the possible impacts on a Brazilian city and also considering a wider range of positive incentives.

The scenarios will be created based on the stated intention reported by students to switch trips made by car or motorcycle to alternative modes of transport, that is, the perceived personal impact. Thus, this variable has to be transformed into a percentage of probability of change. The variable 'SWI_INCE' for the eleven incentives was ranged 1 to 7, where 1' represents "I would never switch in response to this incentive" and '7' refers to "I would certainly switch". The new percentage values will be calculated by dividing these scores by 7, resulting in a 7-point percentage scale from 0% to 100% likelihood of changing.

There are two main uncertainties on this scenario-building process, which are: (1) what does the stated likelihood of reducing private CFV's use represent in terms of a number of saved trips per week and; (2) what would be the alternative mode selected by participants in place of the private CFVs. Therefore, different scenarios will be built to accommodate a range of possibilities in regards to these uncertainties (e.g. a scenario where respondents started cycling for all their weekly trips to the university and other more conservative scenarios, where respondents started using public transport for just a single trip per week, for example).

It is also worth noticing that, as the nature of stated intention or stated preference surveys, the results can be influenced by 'policy response' bias, that is when a respondent deliberately bias his response to influence policy decisions (Bonsall, 1983). This leads to random errors because the decision-making protocol that generated the stated intention might differ from the one people would actually use (Ben-Akiva and Morikawa, 1990). When interpreting the results, therefore, care should be taken as the resulting impact of the incentives can be overestimated. The examination of mutual differences between incentives and psychographic clusters, however, are a more reliable source of information when it comes to the presence of this type of bias.

Three mathematical equations will be formulated to generate different scenarios representing three types of savings, in case positive incentives were implemented, which are:

- Savings in the total distance travelled by private conventionally-fuelled vehicles;
- Savings in the total carbon emissions derived from travelling by private conventionally-fuelled vehicles;
- Savings in terms of the social cost of these carbon emissions.

The distance savings will be calculated considering variables such as the kilometres between the student's house and the university campus, the reported likelihood of changing behaviour and the number of trips per week using private motorised vehicles. Carbon emission savings will be calculated as a function of the distance savings (considering the emission factors of different travel modes). The social cost of carbon, on its turn, will be assessed as a function of the emission savings (taking the average cost per tonne of carbon into account).

The development of the equations and their mathematical parameters will be presented with more detail later in the Results chapter (starting in Section 4.6).

3.6 Coding and data cleaning

With the surveys in hand, a set of codes was established for all the variables. The majority of the measures used 7-point scales, which were coded as a number from 1 to 7 (independently if the scale was unipolar or bipolar). Dichotomy variables (e.g. 'do you own a car?') were coded as 0 or 1. The question regarding familiarity with mobility apps was coded in a 1 to 4 format, while the question of habit, containing six different mobility scenarios, was coded using a different numerical score to each mode of transport (0 to 6). The neighbourhood and email were the only variables coded as text, while age, distance and household size were coded with the exact numerical response. De Vaus (2014) suggests that missing values should be coded as not to be confused with a valid answer and be given the same code to as many variables as possible. Thus, missing values were all allocated as blank values. Invalid responses (e.g. more than one value was marked on `single answer` questions) were coded as ‘x’, while ‘don’t know’ and ‘other’ answers were all coded as 0.

Next, a codebook was constructed, which refers to a document that “describes the locations of the variables and lists the code assignments of the attributes composing those variables” (Babbie, 1990, p.211). The codebook also contained instructions about the coding of each question, as suggested by De Vaus (2014). Subsequently, a transfer sheet was designed for data entry, with each column representing each response to be coded.

After the questionnaires have been coded, the data needed to be checked to ensure that only valid codes were entered (Fowler, 2009). De Vaus (2014) adds that data should be subject to valid range checks and logical checks. All variables were checked for their valid coding range. Age was checked to be within the range from 17 to 90 years old and doubtful values for household sizes were inspected (nine values higher than 10 were excluded). In respect to logical checks, answers referring to not having a bike available to use and reporting its use to the university had their respective variables treated as missing values (5 cases). Distances to the university were checked with respect to the reported living neighbourhood. Unrealistic distances were considered as missing values (26 cases).

Data from the complementary questionnaire was exported from the web survey system and was already in a proper spreadsheet format. This data was checked in the same manner as the main survey and joined (using the email as joining field) to form a unique dataset. Special attention was paid regarding the open-ended question used to define the respondent’s normative referents. Values were excluded whenever a text that did not refer to a real person was identified (two cases).

3.7 Missing data analysis

Virtually all surveys fail to collect complete datasets from all the sampled individuals (Fowler, 2009). Notwithstanding, missing data is one of the most prevalent problems in data analysis (Tabachnick and Fidell, 2007). Appendix

G presents a description of the patterns of missing data that may be present in a dataset.

In this research, 75% of all completed questionnaires had at least one question with a missing response. Considering all the data cells of the data matrix, 2% of items were missing.

The first step taken to deal with the missing data problem was to exclude 17 respondents who left more than 30% of questions blank, which was assumed to indicate an uncommitted response. The cases were also visually inspected to check if the pattern of omissions also indicated lack of commitment (e.g. the missing answers were predominantly at the end of the survey). This action dropped the valid sample from 937 to 920 participants.

There are generally two forms of dealing with missing data in a dataset: excluding these cases from the analysis or estimating (imputing) responses using systematic criteria (Tabachnick and Fidell, 2007). Missing data can pose problems to data analysis depending on its pattern and the amount that is missing. When the rate of non-response to a single question is fewer than 5% of cases, a bias in the results is highly unlikely (Fowler, 2009). Tabachnick and Fidell (2007) corroborates this idea and add that when fewer than 5% of values are missing, any imputation method would yield similar results, therefore they can just be ignored. Only two questions had more than 5% of non-response: three out of the six scenarios used to assess the variable “habit” (5.2%, 5.4% and 6.2%) and “distance to campus” (5.9%). It can be assumed that the above-average missing rate for habit is due to the more complex nature of the question, where the respondent had to choose just one transport mode for six different scenarios and a considerable amount of participants ended up choosing more than one, resulting in invalid responses. Missing responses to “distance to campus” are probably due to the lack of knowledge of the respondent about this distance and therefore missing cases will be excluded from the analysis. The relatively high amount of non-response (or invalid responses) across the habit scenarios implicated in 8.3% missing data on the resulting index of habit.

In this research, variables that had less than 5% of missing values had these values excluded pairwise. In this frequently used approach, all cases containing missing values on any variable that is being used in a particular analysis are ignored (de Vaus, 2014). Tabachnick and Fidell (2007) agree that this is a reasonable choice if the amount of missing data is few and its pattern appears random. In the case of ‘habit’, which had more than 5% of values missing, the pattern of missing data was examined and an imputation method was performed to minimise bias.

3.7.1 Data imputation

From the 8.32% of missing data in the “habit” variable, 4.91% were not computed because three or more out of six items in the scale were missing. As the amount of these cases represented less than 5% of the total respondents, they will be disregarded and imputation will be performed where only one or two trip scenarios (from the total of six) were omitted. For these cases, *hot-deck nearest neighbour* imputation method was performed. In this method, a donor variable is found by minimising some distance function (Huisman, 2000). Here, the donor variable was randomly selected among the non-missing items of the habit scale for the same respondent, which is referred to as ‘Random method’ (Huisman, 2000). Therefore, the higher the frequency that a certain transport mode was chosen by the respondent among the non-missing scenarios, the higher the probability that this mode was imputed in the missing trip scenarios. Chen and Shao (2000) argue that the imputed values using the nearest neighbour imputation are actually occurring variables, not constructed ones, which make them unlikely to be nonsensical. 32 respondents (3.29%) had values imputed using the *hot-deck nearest neighbour* imputation. This approach led the "Habit" variable to have a total of 4.91% of missing values, which was considered ignorable using the less-than-5% rule set out above.

3.8 Data levels of measurement

The definition of the level of measurement of the variables is crucial, as some statistical methods only can legitimately be applied to certain scale type (Stevens, 1946; Yusoff and Mohd Janor, 2014). Ordinal variables are ones in which the categories can be ranked from low to high, although it is impossible to define how much difference there is between the values. Interval (or continuous) variables, on the other hand, are ones in which categories are also ranked from low to high but the differences among the values are clearly defined. Categorical (or nominal) scales are ones where there is no specific ranking order between the categories (de Vaus, 2014). Some of the analyses conducted on this thesis (e.g. principal component analysis, confirmatory factor analysis) have the 'continuity' of variables as an assumption of the method. In other words, from a statistical point of view, ordinal variables could not be subject to these techniques. Thus, it is worth to examine the levels of measurement of the questionnaire variables and the discussions around the use of ordinal variables as continuous (violating the methods' assumptions) provided by literature, to evaluate the appropriateness of using such variables in these types of analysis.

The variables 'travel mode level of use' (question 3), 'app familiarity' (question 4) and 'travel mode intention to use' (question 11) were measured using fully-labelled scales and the differences among categories are impossible to be known, therefore they are considered naturally ordinal (for a list of all the observed variables, see Appendix H; for the main and complementary questionnaires, see Appendix C and Appendix F, respectively). 'Mode ownership' (question 1), 'mode availability' (question 2), 'mode habit' (question 12) and sociodemographic (question 15) are considered categorical since there is no clear order amongst the categories. All the other observed variables were measured using semantic-differential scales which, as is the case of Likert-type scales, are ordinal in nature but often are considered interval by researchers (Knapp, 1990). There are no agreed rules for determining if a particular scale that is ordinal in nature can be considered interval or not (Knapp, 1990) and this has indeed been subject to a lot of controversies (Jamieson, 2004). The numerical categories contained in semantic-differential scales can be assumed to have equal intervals (Heise, 1969), especially because they are not text-labelled (e.g. the commonly used strongly disagree/strongly agree) but numbered instead (-3 to 3, or 1 to 7). This makes it more prone to be assumed interval. The number of points that form a scale is also an important issue. A 10-point scale tends to be “more continuous” than a 5-point one (Knapp, 1990). The analytical study of Wu and Leung (2017) shows that, in fact, increasing the number of points on a scale makes the assumption of being an interval scale closer. For the purpose of this research analysis and following the arguments presented above, variables deriving from semantic-differential scales will be considered interval. Traditionally, transport researchers have used statistical methods that require continuous variables with ordinal variables without invalidating their results, such as factor analysis (Payre et al., 2014; Zailani et al., 2016; Javid et al., 2016) or structural equation modelling (Eriksson et al., 2006; Payre et al., 2014).

3.9 Research ethics

The research was subject to the evaluation and approval of a research Ethics Committee from the University of Leeds. Issues around data collection and storage were examined. The main risks were regarding the cooperation of intermediaries (professors) to gain access to research participants; the fieldwork conducted outside the United Kingdom and the consequent transfer of data outside the European Economic Area. Actions to ensure data protection and anonymization were established according to the ethics committee recommendations, as well as a protocol of informed consent for the questionnaire application. A favourable review from the ethical committee was received under the reference ‘AREA-16-073’.

This chapter highlighted the research methodology, especially the sample definition, the phases of the questionnaire design and implementation and the initial steps taken to ensure the data was ready to be analysed. The thesis now proceeds to the results chapter.

Chapter 4
Results

This chapter presents the results of the analysis of the questionnaires' data. The main goal here is to offer the research findings in a more descriptive manner. A more critical view of these results and their interactions with the related literature will be offered in the discussion chapter (Chapter 5). The chapter is divided into five main sections, the objectives of which and the research question associated (if applicable) are described in Table 4.1.

Table 4.1- Objectives of the results chapter

Section number	Section name	Objectives	Research question
4.1	Development of constructs	To describe the processes around the establishment of variables based on multiple items of the questionnaire (constructs), including the test of reliability and validity.	-
4.2	Sample characterisation	To give an overview of the characteristics of the sample: (1) its sociodemographic profile, (2) it's spatial distribution, (3) its travel behaviour patterns and (4) its general perceptions of positive incentives.	-
4.3	Associations between travel behaviour and acceptability of positive incentives	To find patterns of association between travel behaviour and individual acceptability of incentives.	RQ1/RQ2
4.4	Cluster analysis of travel behaviour variables	To get meaningful, statistically consistent segments of the sample regarding its travel behaviour. To investigate the groups' significant disparities in terms of background behavioural variables and acceptance of positive incentives.	RQ1/RQ3
4.5	Cluster analysis of positive incentives acceptability	To find meaningful, statistically consistent segments of the sample regarding its acceptance of positive incentives. To investigate the groups' significant differences in terms of travel behaviour patterns.	RQ4
4.6	Scenario estimation	To design scenarios where positive incentives are implemented in the area of study, focusing on the potential reduction of three different aspects: (1) total distance travelled by means of private conventionally-fuelled vehicles, (2) Co2 emissions and, (3) emission financial costs.	RQ5

4.1 Development of constructs

Variables that are directly-measured using surveys are sometimes not sufficient to assess certain concepts of interest to the study. In these cases, new indicators can be calculated based on the values of two or more questionnaire items that underlie a single concept. In this research, 25 composite variables were created based on two or more questions each.

This combination of variables has several advantages such as creating more valid, reliable and precise measures, apart from being able to measure more complex concepts in a more simplified manner (de Vaus, 2014). According to Blaikie (2008), reducing data to a single measure can be done by creating scales or indexes. While these terms are usually used interchangeably by authors, the conceptual difference is that a ‘scale’ is a combination of measures that have been tested for unidimensionality, while ‘indexes’ have not (Blaikie, 2008). The term used along this thesis to mention any variable that was created based on a composite score will be ‘construct’. On empirical terms, constructs are considered to be the cause of their underlying items (DeVellis, 2012). That is, the existence of a causal empirical relationship between the construct and the directly observed variables is implicit. Consequently, there is also a relationship between the items that compose the construct.

In this research, the formation of constructs followed two different methodologies. The travel-related and psychological variables were translated into constructs following what was already established in theories of social psychology. Although confirmatory factor analysis was performed to verify these relationships empirically. Variables dealing with incentives acceptability did not have such a solid empirical background and therefore the constructs had to be elucidated with the use of exploratory factor analysis. Figure 4.1 illustrates this process using a flow diagram which was constructed following a chronological order.

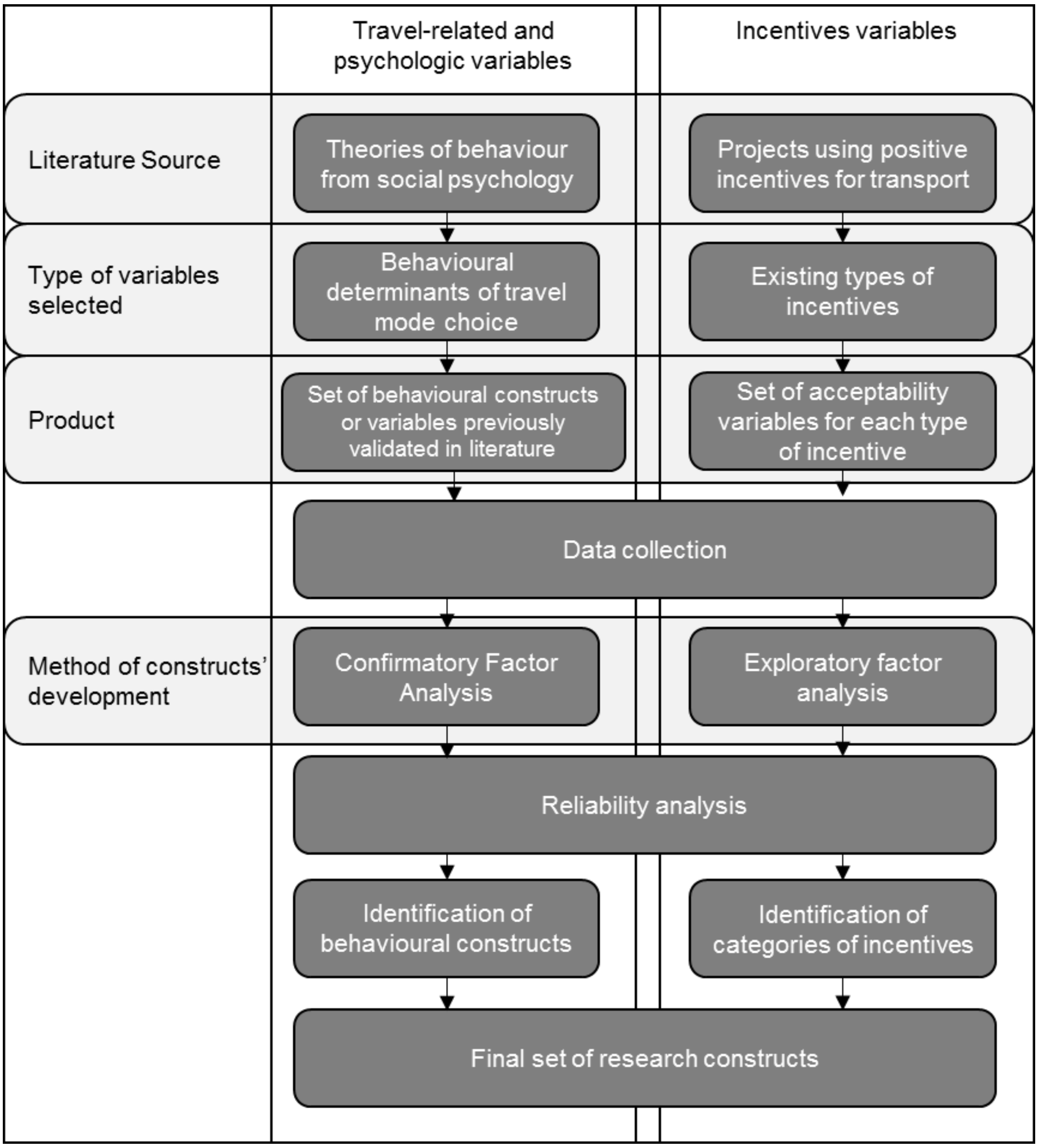

Figure 4.1 - Flow diagram of the process of constructs' development

Constructs that are built from the administration of multi-item attitude scales such as the Likert-type or semantic differential scales are usually assessed in a summated form (De Vaus, 2014). The final score of the constructs can also be averaged or combined in a non-linear fashion. Simply summing up (or averaging) scores of variables that load highly on a given factor is an adequate method for many researchers. The only potential problem is that variables with higher standard deviations will contribute more heavily to the sum. However, if the used scales of measurement are the same and the standard deviations among variables are roughly equal, this problem is considerably alleviated

(Tabachnick and Fidell, 2007). The strategy employed in this study (either to sum or average scores) depended on the ease of interpretation. For example, when comparing values between different behavioural constructs was a necessity, the averaging of scores was preferred to maintain the same range of values between the constructs and thus facilitate this assessment.

As already explained in the last chapter, a special case of composite variables is the Theory of Planned Behaviour's measures of Beliefs, where Fishbein and Ajzen (2010) advocate the use of a multiplicative model, which is discussed next.

4.1.1 TPB's belief-based constructs

Firstly, the decision on how to scale each composite of the multiplicative model used to measure beliefs in the TPB (called the expectancy-value model) is an issue. This model was previously conceptualised in Section 3.4.6. Items related to a person's beliefs can be scaled using unipolar or bipolar scores, but these choices can have substantial implications in the multiplicative composite as the scales lack a true rational zero point. For example, a '0' score in an "agree/disagree" bipolar scale does not necessarily mean complete neutrality. In addition, linear transformations of a single score implicate in a non-linear transformation of the product term of the multiplicative model of beliefs (Fishbein and Ajzen, 2010). Thus, from a measurement perspective, using either unipolar or bipolar scales can be equally justified (French and Hankins, 2003), but the construction of the multiplicative composite can significantly affect future correlation indexes to be calculated. However, this problem can be substantially minimised if a proper scoring system is employed. Different alternative empirical scaling methods to the multiplicative model were tested, such as hierarchical regression analysis (Schmidt, 1973), optimal scoring (Holbrook, 1977) and conjoint measurement (Bagozzi, 1985). French and Hankins (2003) offer a summary of each method and outline that there are no reasons to advocate the use of any of them. More recently, the use of open-ended measures (Esses and Maio, 2011), and dimensional salience (Newton et al, 2012) were tested. The use of both of these methods is also still not reliable, as they have not granted strong empirical support yet and require more substantial evidence. Fishbein and Ajzen (2010) also recognise that this ‘muddle’ has not been properly addressed by empirical research and no definite conclusion can be drawn. Nevertheless, the authors suggest that the use of empirical scaling methods (as described above) should be used only where there is no *a priori* basis for determining the proper score. Where this premise exists, they suggest the use of a psychological criterion. That is, scores are defined based on the psychological nature of the item. Taking the behavioural belief strength and outcome evaluation measurement for car use as an example, the unlikely/likely measure for ‘safety’ was scaled in a bipolar manner (-3 to 3), as denying the outcome ‘safety’ in respect to car use generally implies that the respondent thinks it is unsafe (thus being bipolar). On the other hand, if the example of the control belief measurement is taken, a unipolar scale (1 to 7) is more apparent. If a respondent disagrees with the statement “I having money would facilitate my ability to go to the university by car”, it usually does not mean that having money would impede one’s ability to use the car. Thus, this research used the above described psychological criterion proposed by Fishbein and Ajzen (2010) to create the scaling system for behavioural, injunctive normative and control beliefs.

It is important to highlight that these scales were built considering this study’s particularities and replication should be performed with caution. A decision on which type of criteria to use when calculating belief scores should be made considering the nature of the behaviour under study, the research’s population and the questionnaire items.

4.1.2 Factor analysis and the initial set of constructs

Factor analysis (FA) is a technique used to identify underlying factors present in the pattern of correlations among a set of measures. Where there is a large set of measures, factor analysis can determine whether there are subsets of items forming separate scales (Blaikie, 2008). This procedure can yield very useful results, making further analysis more profound and easier to interpret. What should be noted, however, is that the technique makes no reference to the conceptual meaning of a factor. This should be assessed by the researcher when looking at the empirical associations given by FA (Babbie, 1990). When there is no previous theory behind the structure of the items and when the goal of the analysis is just to look at the patterns of correlation and not to develop any kind of theory from the resulting factors then the appropriate technique is Principal Component Analysis (PCA) (Tabachnick and Fidell, 2007).

In this research, the eleven different types of incentives were subject to principal component analysis (PCA) to examine possibly correlated incentives that can be treated as a single category. The analysis was conducted separately for attitudes, intention to use and perceived personal impact. One may argue that the analysis should be conducted considering all variables (the three indicators for all eleven incentives), but as De Vaus (2014, p.186) states, “it is important to be able to assume that correlations between the variables will not be causal”. In this sense, attitudes is a causal determinant of intentions, as postulated by the Theory of Planned Behaviour (Ajzen, 1991), which might even be a predictor of perceived impact.

Before proceeding to the PCA itself, the ‘factorability’ of the variables was tested using *Barlett’s* test (Snedecor and Cochran, 1983), which showed significance ($p < 0.001$) and so can be considered adequate. In addition, the sampling adequacy was successfully obtained with the *Kaiser-Meyer-Olkin* (KMO) test (KMO > 0.800) (Kaiser, 1974). Oblique rotation (*Oblimin*) was performed, as the resulting factors of an orthogonal rotation (*Varimax*) were considered to be correlated ($r > 0.600$ for the three analyses). Tabachnick and Fidell (2007) suggest the use of an oblique rotation when correlation among factors is observed. Nevertheless, the factorial structure of the incentives derived from the orthogonal and oblique rotation was quite similar.

An initial, non-rotated solution, suggested the adoption of two components for all three analyses, following the criteria of *eigenvalues* greater than 1.0 and the examination of a *scree plot*. The number of components suggested by *eigenvalues,* according to Tabachnick and Fidell (2007), is probably right when the number of variables is fewer than 40 and the sample size is large. The scree plot shows eigenvalues plotted against the number of components. The appropriate number of factors is found looking for the point where the plotted line changes slope (Tabachnick and Fidell, 2007). Therefore, the solution was rotated considering two components.

For attitudes, the two components explained 52.64% of the variance and the 'Buddying' incentive did not load highly in any component (λ < 0.400) after rotation (this threshold value of 0.4 follows recommendations of Blaikie, 2008). With 'Buddying' excluded, the total explained variance increased to 56.2%. For intentions, two components were also extracted and the explained variance was 55.5%. Lastly, 'perceived personal impact' was subject to PCA and two components were extracted explaining 62.3% of the variance. 'Journey Planner' and 'Information' were excluded due to having high loadings in both components. This, according to Blaikie (2008) indicates the items contribute to more than one factor and exclusion is plausible. In addition, both incentives' loadings were between 0.4 and 0.5. So, if the inclusion criteria had been set up at 0.5 instead of 0.4, these incentives would have been excluded anyway. The final explained variance for 'perceived personal impact' was 64.1%.

Table 4.2 and Table 4.3 present the Pattern matrix (containing factor loadings) and the Structure Matrix (containing item-to-component correlations) derived from PCA.

Table 4.2 - PCA analysis of incentives (pattern matrix)

	Attitudes (λ)		**Intention (λ)**		**Perceived impact (λ)**	
Incentives	**Comp. 1**	**Comp. 2**	**Comp. 1**	**Comp. 2**	**Comp. 1**	**Comp. 2**
Map	-0.032	**0.736**	0.010	**0.751**	0.337	**0.496**
Money	-0.106	**0.744**	-0.111	**0.783**	-0.092	**0.925**
Points	**0.747**	0.050	**0.720**	0.090	**0.754**	0.089
Rankings	**0.773**	0.056	**0.784**	0.047	**0.819**	0.054
Vouchers	-0.011	**0.779**	-0.056	**0.815**	0.098	**0.812**
Journey Planner	0.150	**0.682**	0.184	**0.647**	-	-
Information	0.221	**0.575**	0.204	**0.592**	-	-
Feedback	**0.529**	0.270	**0.480**	0.307	**0.701**	0.126
Social Media	**0.824**	-0.106	**0.855**	-0.158	**0.920**	-0.215
Challenges	**0.790**	-0.037	**0.805**	-0.050	**0.804**	-0.029
Buddying	-	-	**0.441**	0.240	**0.583**	0.159

Note: factor loadings greater than 0.40 are highlighted.

Table 4.3 - PCA analysis of incentives (structural matrix)

	Attitudes (r)		Intention (r)		Perceived impact (r)	
Incentives	**Comp. 1**	**Comp. 2**	**Comp. 1**	**Comp. 2**	**Comp. 1**	**Comp. 2**
Map	0.305	**0.721**	0.363	**0.755**	**0.566**	**0.652**
Money	0.235	**0.695**	0.258	**0.731**	0.336	**0.883**
Vouchers	**0.770**	0.393	**0.762**	**0.429**	**0.795**	**0.437**
Journey Planner	**0.798**	0.410	**0.806**	**0.416**	**0.844**	**0.432**
Information	0.347	**0.774**	0.327	**0.788**	**0.474**	**0.858**
Feedback	**0.463**	0.751	**0.488**	**0.734**	-	-
Social Media	**0.485**	**0.676**	**0.483**	**0.689**	-	-
Challenges	**0.653**	**0.513**	**0.625**	**0.533**	**0.759**	**0.449**
Points	**0.775**	0.272	**0.780**	0.244	**0.820**	0.210
Rankings	**0.773**	0.326	**0.781**	0.329	**0.790**	0.342
Buddying	-	-	**0.554**	**0.448**	**0.656**	**0.428**

Note: correlations greater than 0.40 are highlighted.

More important than the identification of the factors themselves, is checking whether the factorial structure that resulted makes sense. Two different components showed up for the three analysis conducted: incentives related to competition or collaboration (points, rankings, feedback, social media, challenges and buddying), which will be future referred to as ‘Social incentives’, and incentives related to increasing value to the user (maps, money, vouchers, journey planner and information on consequences), referred to as ‘Value maximisation incentives’. As will be seen later in the chapter, both constructs showed good reliability. The factorial structure followed almost the same pattern across the three different indicators, except for the incentives that were excluded from a specific analysis due to not loading highly in any component ($\lambda < 0.400$), or loading highly in both components. This was the case of ‘Attitudes to Buddying’ and ‘Perceived personal impact’ using ‘Journey Planner’ and ‘Information’. These newly developed constructs (scales) were then calculated for each respondent using the mean of the scores of the incentives that compose each component found in PCA for attitudes, intention and perceived personal impact.

After the uncovering of incentives categories through PCA, a set of variables that have a previous theoretical justification was created. Before constructing the composite scores of the variables that were measured with more than one questionnaire item (constructs), however, they still had to be assessed in regards to their reliability and validity. With respect to the incentives categories, although the performance of the PCA may already have indicated the validity of these components, some additional tests also need to be performed to ensure their quality. Table 4.4 shows the conceptual details of all the preliminary variables, along with the questionnaire items they derived from (for a list of all the variables that constitute this research, see Appendix H).

Table 4.4 – Description of constructs used in this research before the assessment of validity and reliability

Construct	Measured concept.	Questionnaire items
USED_*MODE*[1]	Used mode previous week.	BEH_*MODE*[1]
MOSTUSED	Mostly used mode previous week.	BEH_*MODE*[1]
APPFAM	Level of familiarity with the set of mobility apps.	APP_1; APP_2; APP_3; APP_4; APP_5; APP_6; APP_7.
ATT_*MODE*[1]	Attitudes to each travel mode.	ATT_*MODE*1[1]; ATT_*MODE*2[1].
ATT_SOCIALINC	Attitudes to incentives related to competition.	ATT_*INCE*[4]
ATT_VALMAXINC	Attitudes to incentives related to maximising value.	ATT_*INCE*[5]
INT_SOCIALINC	Intention to use incentives related to competition.	INT_*INCE*[4]
INT_VALMAXINC	Intention to use incentives related to maximising value.	INT_*INCE*[5]
SWI_SOCIALINC	Likelihood to switch to sustainable modes due to incentives related to competition.	SWI_*INCE*[4]
SWI_VALMAXINC	Likelihood to switch to sustainable modes due to incentives related to maximising value.	SWI_*INCE*[5]
SNORM_*MODE*[1]	Subjective (social) norms in regards to each travel mode.	SNORM_*MODE*1[1]; SNORM_*MODE*2[1].
PNORM_CARS	Personal norms in regards to the use of cars.	PNORM_CARS1; PNORM_CARS2.
AWC_CARS	Awareness of consequences in regards to the use of cars.	AWC_CARS1; AWC_CARS2; AWC_CARS3.
ASCR_CARS	Ascription of responsibility in regards to the use of cars.	ASCR_CARS1; ASCR_CARS2.
HAB_*MODE*[1]	The number of times each travel mode was cited in the six habit scenarios.	HABIT1; HABIT2; HABIT3; HABIT4; HABIT5; HABIT6.
HABITMODE	Most habitual travel mode.	HAB_CAR; HAB_BUS; HAB_BIK; HAB_MOT; HAB_WAL.
CARHABIT	Habitual use of the car or other modes.	HAB_CAR

PBC_*MODE*[1]	Perceived behavioural control to use each travel mode.	PBC_*MODE*1[1]; PBC_*MODE*2[1].
AGEINT	Age collapsed into five categories.	AGE
DISTINT	Distance collapsed into five categories.	DIST
INCOMINT	Household income collapsed into five categories.	INCOM
BB_*MODE*[1]	Behavioural beliefs in regards to each travel mode.	BS*MODEATTR*[1,3]; OUTEVA_*ATTR*[3].
CB_*MODE*[1]	Control beliefs in regards to each travel mode.	CBS*MODEATTR*[1,3]; CPB*MODEATTR*[1,3].
INJNORMB_*MODE*[1]	Injunctive norms in regards to each mode.	INJREF1; INJREF2; INJS_*MODE*1[1]; INJS_*MODE*2[1]; MOTCOMP1; MOTCOMP2.
DESCNORM_*MODE*[1]	Descriptive norms in regards to each mode.	DESCREF1; DESCREF2; DESCS_*MODE*1[1]; DESCS_*MODE*2[1].

Notes: for a description of the questionnaire variables, see Appendix H. Terms formatted in italic refer to the measurement of that variables to different objects and were compacted to facilitate visualisation. Each case is detailed below.
[1] These variables were assessed for the five studied travel modes and the term 'MODE' was used for better visualisation. Thus, *MODE* refers to either car (CAR), bike (BIK), bus (BUS), motorcycle (MOT) or walking (WAL).
[2] These variables were assessed for each of the eleven different forms of incentives. For better visualisation, *INCE* was used in this table.
[3] These variables were assessed for each type of travel mode attributes (regarding behavioural or control beliefs). For better visualisation, *ATTR* was used in this table.
[4] These variables were assessed to each type of incentive that loaded highly ($\lambda > 0.500$) on the 'competition and collaboration' component found in PCA.
[5] These variables were assessed to each type of incentive that loaded highly ($\lambda > 0.500$) on the 'user value maximisation' component found in PCA.

4.1.3 Reliability assessment

Scale reliability refers to the "proportion of variance attributable to the true score of the latent variable" (DeVellis, 2012, p.31). Stated in a more simple form, it is how well a scale score reflects the true state of the variable being measured. Reliability can also be defined as the capacity of a measure to produce consistent results (Blaikie, 2008). Litwin (1995, p.6) defines it as "a statistical measure of how reproducible the survey instrument's data are". A common form of testing reliability is using a measure of internal consistency, namely the *Cronbach's* Alpha coefficient (Litwin, 1995). Other forms of assessing reliability such as test-retest or alternate-form require the same population sample to be targeted at two different points in time, which was not done in this study. In mathematical terms, *Cronbach's* Alpha is a coefficient that expresses the proportion of total variance among items that are due to the construct that they intend to measure and thus is communal (DeVellis, 2012). An alpha coefficient of 0.65 to 0.70 can be considered acceptable, while between 0.70 and 0.80 would be respectable and between 0.80 and 0.90 would be very good. Too long scales might be the case if the coefficient is much larger than 0.90 (Litwin, 1995).

Eisinga, Grotenhuis and Pelzer (2013) have argued that, for constructs composed by two items, the Spearman-Brown formula is more appropriate than the Cronbach's Alpha (in this case, Spearman-Browns is equivalent to a standardised Cronbach's alpha). This formula estimates the reliability of a whole scale by calculating the reliability of split halves of the scale (Litwin, 1995). Table 4.5 shows standardised Cronbach's alpha for the initial set of constructs developed for this research, along with inter-item correlations of constructs that were composed of two items. DeVellis (2012) explains that the higher the correlations among items that comprise a scale, the more reliable the individual items are.

Table 4.5 – Cronbach's alpha and inter-item correlations of constructs

Construct	Cronbach's Alpha (α)	Inter-item correlation (r)
APPFAM	0.616	-
ATT_CAR	0.749	0.599
ATT_BUS	0.807	0.676
ATT_BIK	0.866	0.764
ATT_MOT	0.908	0.832
ATT_WAL	0.900	0.818
ATT_SOCIALINC	0.817	-
ATT_VALMAXINC	0.774	-
INT_SOCIALINC	0.823	-
INT_VALMAXINC	0.802	-
SWI_SOCIALINC	0.870	-
SWI_VALMAXINC	0.742	-
SNORM_CAR	0.811	0.687
SNORM_BUS	0.861	0.756
SNORM_BIK	0.886	0.796
SNORM_MOT	0.889	0.801
SNORM_WAL	0.917	0.847
PNORM_CARS	0.675	0.510

AWC_CARS	0.818	-
ASCR_CARS	0.650	0.482
PBC_CAR	0.683	0.518
PBC_BUS	0.358	0.218
PBC_BIK	0.649	0.481
PBC_MOT	0.591	0.420
PBC_WAL	0.698	0.536

Note: for a description of each construct, see Table 4.4.

‘Familiarity with mobility apps’, which would be a construct composed by the sum of the scores of past user experience with each type of app showed a barely acceptable internal consistency ($\alpha_{standardised}$ = 0.616). This can be justified by the fact that each app is considerably different from each other in nature. Therefore, each variable might not often vary together across the sample. A PCA was performed in order to explore the existence of subsets of highly correlated apps but the resulting factors had unacceptable internal consistency as well ($\alpha_{standardised}$ < 0.65). Variables related to perceived behavioural control (PBC) of using the bus, motorcycle and bike showed unacceptable reliability coefficients as well ($\alpha_{standardised}$ < 0.65). These low coefficients might be explained by the fact that each item measured different components of the perceived behavioural control. In particular, one item evaluated "autonomy" while the other measured "capacity". These findings also somehow contrast with the argument of Fishbein and Ajzen (2010), who state that measures of capacity and autonomy should correlate with each other. Having just one-item to measure each subcomponent of PBC might have been critical for this low internal consistency coefficient.

Internal consistency was not measured for the belief measures of the TPB. As Ajzen (2018) explains, internal consistency is not a requirement for these constructs (normative, control and behavioural), because different beliefs might be inconsistent with each other.

Scales were also tested for unidimensionality. “A scale that is unidimensional is one in which each item measured the same underlying concept” (De Vaus, 2014, p. 184). Item-to-scale correlation coefficients were examined and only items with coefficients larger than 0.3 were retained to ensure unidimensionality (De Vaus, 2014). All calculated scales in this research showed item-to-scale coefficients larger than 0.3, except ‘bus PBC’, which had already shown low internal consistency, and three mobility apps from the ‘familiarity with apps’ scale (sharing-trip apps; journey-plan apps and public-transport apps). These apps were removed and the new calculated alpha coefficient did not substantially change as a result ($\alpha_{standardised} = 0.615$).

Even though the other constructs demonstrated good reliability, this alone does not mean that the constructs are qualified to be used in further analyses should not rely only on this assessment, but also on the examination of validity.

4.1.4 Validity assessment

Ghiselli, Campbell and Zedeck (1981) define validity as the extent to each a set of measures is appropriate to answer a specific question. More recently, Litwin (1995, p.33) defines validity as to how well a scale “measures what it sets out to measure”. There are essentially three types of validity to be assessed: content, criterion and construct validity (DeVellis, 2012). Litwin (1995) also adds a fourth type called face validity. Their definition and assessment strategies are presented in Table 4.6.

Table 4.6 – Types of validities and their assessment strategies in this research

Type of validity	Definition	Assessment strategy
Face validity	“A cursory review of items by untrained judges” (Litwin, 1995, p.35).	A first draft of the main survey was subject to an evaluation of PhD students from the Institute for Transport Studies of the University of Leeds (previously explained in Section 3.4.1). A more refined version was subject to cognitive interviews with undergraduate students (Section 3.4.4.1).
Content validity	“The extent to which a specific set of items reflect a content domain” (DeVellis, 2012, p.59). This is often assessed with the review of the survey by experts in the field (Litwin, 1995). But can also be determined by insights gained from literature review and constructs definition (DeVellis, 2012).	While the survey constructs were not subject to any evaluation by external experts in the field, most of the constructs that compose the independent variables were extracted from strongly established indicators within the transport research field (more details can be found in Chapter 3, section 3.1). Some exceptions apply, however. Measures of familiarity with apps, travel mode experience and the questions regarding positive incentives (dependent variables) were not constructed based on previously existing indicators and will have to rely on other validity measures. This is mostly due to the relative novelty of these measures.

Criterion-related validity	The extent to which a measure has an empirical association with some criterion that is considered “gold standard” (DeVellis, 2012).	Due to the lack of access to datasets that have used the same measures as this research, criterion-related validity could not be assessed. In addition, empirical studies using the same measures in Brazil are scarce, thus making it difficult to select one that could be assumed as “gold standard”.
Construct validity: convergent	Convergent validity means that a set of indicators represent the same construct (Henseler et al., 2009).	Confirmatory factor analysis was used to determine convergent validity for those constructs that were hypothesised based on previous theory. In these cases, the Average Variance Extracted (AVE) was used to determine this type of validity (Fornell and Larcker, 1981). Where constructs were not built on previous theories, convergent validity was assessed based on the factorial structure given by a Principal Component Analysis (PCA), in which the items should have loaded substantially on their underlying factor to confirm validity. (Tabachnick and Fidell, 2007).
Construct validity: discriminant	Discriminant validity is achieved when two different constructs, which supposedly measure different concepts, exhibit sufficient empirical differences (Henseler et al., 2009).	When the squared AVE of a given construct is higher than the correlations with all other constructs, discriminant validity is confirmed (Fornell and Larcker, 1981). When the factorial structure was determined by a PCA, cross-loadings were examined to see if there were any items with small differences in the loads between the factors.

Confirmatory factor analysis (CFA) can be used as evidence of the construct validity of theory-based instruments (Li, 2016). This type of analysis is used when a researcher wants to confirm a particular pattern of variables that are predicted based on theory or previous analytic studies (DeVellis, 2012). Namely, based on the knowledge of the theory, he or she assumes the underlying factor structure *a priori* and then test this hypothesised arrangement statistically (Byrne, 2016).

The use of Maximum likelihood (ML) estimator in CFA with ordinal data is not theoretically appropriate, as this type of model assumes variables to have multivariate normality (Li, 2016). The violation of this assumption may lead to downward biases of factor loadings (used to test convergent validity) and downward biases of inter-factor correlations (used to test divergent validity) (Li, 2016). The previous discussion of Section 3.8 has already argued about the adequacy of considering variables that are naturally ordinal as intervals for data analysis. In addition, some simulation studies addressing the use of ML for ordinal variables showed estimates to be essentially non-biased (Yang-

Wallentin et al., 2010). Another study found that the bias in parameter estimates when using ordinal-type variables was negligible for the maximum likelihood estimator (Lei, 2009). As the results from the simulation study by Li (2016) suggest, the relative bias is smaller when sample size and number of variable categories are higher, even when variables are moderately non-normal.

To test the validity of the constructs that derived from pre-established theories, a CFA model using Maximum Likelihood estimator was performed. Goodness-of-fit indicators were analysed, as well as factor loadings, Average Variance Extracted (AVE) and Composite Reliability (CR). AVE was calculated to examine convergent validity as recommended by Fornell and Larcker (1981), who established that its value should exceed 0.50. To assess discriminant validity, the square root of AVE for each construct should be higher than the correlation among this and all other assessed constructs (Fornell and Larcker, 1981). Composite reliability (CR) was calculated using the resulting factor loadings, as it is sometimes advocated as a more reliable form of measuring construct reliability than Cronbach's Alpha (Henseler et al., 2009).

The first tested CFA model contained all 45 variables pertaining to 19 constructs related to mobility behaviour. This first solution showed poor fit (χ^2 (209, N=920) = 238,26; $p < .001$; χ^2/df =3.199; NFI < 0.900). APP_FAM, PBC_MOT, PBC_BUS and ASCR_CARS constructs have not achieved convergent validity (AVE < 0.500) and were therefore excluded from the model. Although having slightly acceptable convergent validity (AVE = 0.626 and AVE = 0.569), PBC_CAR and PBC_BIK showed unacceptable factor loadings on item PBC_CAR2 ($\lambda < 0.600$) and PBC_BIK2 ($\lambda < 0.600$).

It is assumed that APP_FAM did not show convergent validity for the same reasons of its low reliability presented earlier (each app being very different in nature). Thus, personal familiarity with each mobility app was considered separately in subsequent analyses.

PBC was split into its two different components described by Fishbein and Ajzen (2010): autonomy and capacity. The relatively low reliability examined in Section 4.1.3 already raised suspicion about the non-convergent nature of

PBC in this study. For the same theoretical reasons, PBC_WAL was also excluded from the model, even though it showed slightly acceptable values of reliability and convergent validity in the second model. However, when a second model of CFA was conducted without the problematic constructs of the first model, but with PBC_WAL still included, the construct also failed to achieve convergent validity ($\lambda < 0.600$ in PBC_WAL2).

Another issue that demanded attention was the lack of validity displayed by the construct 'ascription of responsibility'. The influence of an individual's perception of own responsibility with respect to an environmental problem (in this case, the use of cars) in behaviour was postulated by Schwartz's Norm-activation theory (Schwartz, 1977). Stern et al. (1999) then, generalised this concept by considering 'ascription of responsibility' as also a manifestation of one's perception about his or her own ability to act against the environmental problem. Both of these concepts were used in an attempt to measure a single construct in this research (ASCR_CARS), but due to the demonstrated lack of convergence, they will be considered separately as 'personal responsibility for the problem of excessive car use' (RESP_CARS) and 'perceived ability to reduce the cars' environmental threat' (ABIRED_CARS). Although authors have often used both terms interchangeably (Han et al., 2017), the separation of these concepts is not new, since other studies have already done so (De Groot, 2008; Menzel and Bögeholz, 2010).

A third measurement model without all problematic factors showed good fit (χ^2 (209, N=920) = 238.26; $p < .001$; χ^2/df =3.199; RMSEA = 0.048; CFI = 0.961; NFI = 0.945). Chi-square test was significant, which would indicate poor fit, but this test was demonstrated to be sensitive to sample size and non-normality (Connell, 2012) and therefore the Root Mean Square Error of Approximation (RMSEA) was considered as a test for absolute fit instead. Table 4.7 presents the resulting factor loadings, AVE and CR for each construct present in the model.

Table 4.7 - Factor loadings, Average Variance Extracted (AVE) and Composite Reliability (CR) of research constructs.

Items	Construct	Factor loadings	AVE	CR
ATT_CAR1	ATT_CAR	0.872	0.619	0.762

ATT_CAR2		0.691		
ATT_BUS1	ATT_BUS	0.836	0.677	0.808
ATT_BUS2		0.810		
ATT_MOT1	ATT_MOT	0.908	0.831	0.908
ATT_MOT2		0.915		
ATT_WAL1	ATT_WAL	0.895	0.817	0.899
ATT_WAL2		0.913		
ATT_BIK1	ATT_BIK	0.858	0.764	0.866
ATT_BIK2		0.890		
SNORM_CAR1	SNORM_CAR	0.789	0.691	0.817
SNORM_CAR2		0.872		
SNORM_BUS1	SNORM _BUS	0.853	0.757	0.862
SNORM_BUS2		0.887		
SNORM_BIK1	SNORM _BIK	0.899	0.797	0.887
SNORM_BIK2		0.887		
SNORM_MOT1	SNORM _MOT	0.930	0.803	0.891
SNORM_MOT2		0.861		
SNORM_WAL1	SNORM _WAL	0.935	0.848	0.918
SNORM_WAL2		0.907		
AWC_CARS1	AWC_CARS	0.817	0.624	0.831
AWC_CARS2		0.665		
AWC_CARS3		0.873		
PNORM_CARS1	PNORM_CARS	0.649	0.520	0.682
PNORM_CARS2		0.787		

Discriminant validity was also successfully demonstrated for all constructs in this model, as the square root of AVE for any given construct was not lower than any estimated correlation between this and all other constructs (Table 4.8).

Table 4.8 - Discriminant validity of research constructs (related to mobility behaviour)

Constructs	1	2	3	4	5	6	7	8	9	10	11	12
ATT_CAR (1)	**0.787**											
ATT_BUS (2)	0.059	**0.823**										
ATT_BIKE (3)	-0.315	-0.068	**0.874**									
ATT_MOT (4)	0.002	-0.088	0.118	**0.912**								
ATT_WAL (5)	-0.386	-0.059	0.561	-0.082	**0.904**							

SNORM_CAR (6)	0.476	-0.046	-0.110	-0.002	-0.197	**0.832**						
SNORM_BUS (7)	0.199	0.462	0.001	0.104	-0.063	0.165	**0.870**					
SNORM_BIKE (8)	-0.244	-0.004	0.425	0.132	0.256	-0.198	0.215	**0.893**				
SNORM_MOT (9)	-0.127	-0.022	0.010	0.535	-0.050	0.043	0.118	0.286	**0.896**			
SNORM_WAL (10)	-0.313	-0.020	0.309	-0.019	0.543	-0.254	0.098	0.676	0.158	**0.921**		
AWC_CARS (11)	0.030	0.135	0.125	-0.034	0.127	0.077	0.131	0.002	-0.011	0.013	**0.790**	
PNORM_CARS (12)	-0.319	0.220	0.216	-0.044	0.180	-0.241	0.125	0.174	0.062	0.163	0.338	**0.721**

Note: Diagonal elements are the square root of AVE between the constructs and their respective items. Off- diagonal elements are correlations among factors.

For the incentives categories, the item factor loadings resultant from the PCA (Table 4.2) suggest convergent validity. The substantial differences in cross-loadings of both components also suggest discriminant validity, as calculated discrepancies were all above 0.20.

4.1.5 Final set of research constructs

Table 4.9 provides a summary of the scale quality tests performed along with the final decision to whether include each construct in subsequent analysis or not.

Table 4.9 – Summary of results from reliability and validity tests.

Construct	Reliability		Validity		Decision
	Alpha[1]	Composite Reliability[2]	Convergent	Discriminant	
APPFAM	Unacceptable	-	Not achieved[3]	Achieved[5]	Not included
ATT_CAR	Respectable	Achieved	Achieved[3]	Achieved[5]	Included
ATT_BUS	Very good	Achieved	Achieved[3]	Achieved[5]	Included
ATT_BIK	Very good	Achieved	Achieved[3]	Achieved[5]	Included
ATT_MOT	Very good	Achieved	Achieved[3]	Achieved[5]	Included
ATT_WAL	Very good	Achieved	Achieved[3]	Achieved[5]	Included
ATT_SOCIALINC	Very good	-	Achieved[4]	Achieved[6]	Included
ATT_VALMAXINC	Respectable	-	Achieved[4]	Achieved[6]	Included
INT_SOCIALINC	Very good	-	Achieved[4]	Achieved[6]	Included
INT_VALMAXINC	Very good	-	Achieved[4]	Achieved[6]	Included
SWI_SOCIALINC	Very good	-	Achieved[4]	Achieved[6]	Included
SWI_VALMAXINC	Respectable	-	Achieved[4]	Achieved[6]	Included

SNORM_CAR	Very good	Achieved	Achieved[3]	Achieved[5]	Included
SNORM_BUS	Very good	Achieved	Achieved[3]	Achieved[5]	Included
SNORM_BIK	Very good	Achieved	Achieved[3]	Achieved[5]	Included
SNORM_MOT	Very good	Achieved	Achieved[3]	Achieved[5]	Included
SNORM_WAL	Very good	Achieved	Achieved[3]	Achieved[5]	Included
PNORM_CARS	Acceptable	Achieved	Achieved[3]	Achieved[5]	Included
AWC_CARS	Very good	Achieved	Achieved[3]	Achieved[5]	Included
ASCR_CARS	Acceptable	Achieved	Not achieved[3]	Not achieved[5]	Not included
PBC_CAR	Acceptable	-	Not achieved[3]	-	Not included
PBC_BUS	Unacceptable	-	-	-	Not included
PBC_BIK	Unacceptable	Achieved	Not achieved[3]	-	Not included
PBC_MOT	Unacceptable	-	Not achieved[3]	-	Not included
PBC_WAL	Acceptable	Achieved	Not achieved[4]	-	Not included

[1] Unacceptable if: $\alpha < 0.65$; Acceptable if: $0.65 <= \alpha < 0.70$; Respectable if: $0.70 <= \alpha < 0.80$; Very good if: $\alpha >= 0.80$.
[2] Achieved if CR > 0.60 (CFA model).
[3] Achieved if AVE > 0.50 and $\lambda > 0.60$ (CFA model).
[4] Achieved if $\lambda > 0.60$ (Principal Component Analysis).
[5] Achieved if difference between square root of AVE and interfactor correlations higher than …
[6] Achieved if component cross-loadings higher than 0.20.

The principal component analysis performed in Section 4.1.2 (where similar groups of incentives were identified) , along with the results of the reliability and validity tests in Section 4.1.3 and 4.1.4 (where constructs of 'app familiarity', 'perceived behavioural control of travel modes' and 'ascription of responsibility' were problematic), led to the final set of constructs and variables to be used in further analysis (Table 4.10).

Table 4.10 - Final set of research variables and constructs

Variable/construct	Number of questionnaire items	Measured concept.
BEH_*MODE*[1]	1	Weekly frequency of use of each mode.
USED_*MODE*[1]	1	Used mode previous week.
MOSTUSED	1	Mostly used mode previous week.
EXP_*MODE*[1]	1	Past experience with each travel mode.
ATT_*MODE*[1]	2	Attitudes to each travel mode.
ATT_*INCE*[2]	1	The evaluation of each incentive type.
INT_*INCE*[2]	1	The intention to use each incentive type.

SWIT_*INCE*[2]	1	The perceived likelihood to switch to sustainable modes due to receiving each incentive type.
ATT_SOCIALINC[3]	5	Attitudes to incentives related to competition.
ATT_VALMAXINC[4]	5	Attitudes to incentives related to maximising value.
INT_SOCIALINC[3]	5	Intention to use incentives related to competition.
INT_VALMAXINC[4]	6	Intention to use incentives related to maximising value.
SWI_SOCIALINC[3]	6	Likelihood to switch to sustainable modes due to incentives related to competition.
SWI_VALMAXINC[4]	3	Likelihood to switch to sustainable modes due to incentives related to maximising value.
ATT_ALLINC[5]	11	Attitudes to all incentives combined
INT_ALLINC[5]	11	Intention to use all incentives combined
SWI_ALLINC[5]	11	Likelihood to switch to alternative modes in response to all incentives combined.
SNORM_*MODE*[1]	2	Subjective (social) norms in regards to each travel mode.
PNORM_CARS	2	Personal norms in regards to the use of cars.
AWC_CARS	3	Awareness of consequences in regards to the use of cars.
INT_*MODE*[1]	1	Intended frequency of use (weekly) of each travel mode in the following month of classes
RESP_CARS	1	Perceived personal responsibility on environmental problems caused by the use of cars.
ABIRED_CARS	1	Perceived ability to reduce environmental problems caused by the car.
HAB_*MODE*[1]	6	The number of times each travel mode was cited in the six habit scenarios.
HABITMODE	6	Most habitual travel mode.
CARHABIT	1	Habitual use of the car or other modes.
AUTO_*MODE*[1]	1	Perceived autonomy to use each travel mode.
CAPAC_ *MODE*[1]	1	Perceived capacity to use each travel mode.
AGEINT	1	Age collapsed into five categories.
DISTINT	1	Distance collapsed into five categories.
INCOMINT	1	Household income collapsed into five categories.
BB_*MODE*[1]	8	Behavioural beliefs in regards to each travel mode.
CB_*MODE*[1]	4	Control beliefs in regards to each travel mode.
INJNORMB_*MODE*[1]	4	Injunctive norms in regards to each mode.
DESCNORM_*MODE*[1]	2	Descriptive norms in regards to each mode.

[1]These variables were assessed for the five studied travel modes and the term ‘MODE’ was used for better visualisation. Thus, *MODE* refers to either car (CAR), bike (BIK), bus (BUS), motorcycle (MOT) or walking (WAL).

[2]These variables were assessed for each of the eleven different forms of incentives. For better visualisation, *INCE* was used in this table.
[3] These variables were assessed to each type of incentive that loaded highly ($\lambda > 0.500$) on the 'competition and collaboration' component found in PCA.
[4] These variables were assessed to each type of incentive that loaded highly ($\lambda > 0.500$) on the 'user value maximisation' component found in PCA.
[5] These variables were created to allow a more broad comprehension of the acceptability of incentives. They were not subject to an empirical validity test but showed very good reliability ($\alpha > 0.750$).

After coding and cleaning the dataset, dealing with missing data issues, setting the levels of measurement and defining the research variables, the dataset was ready to be analysed and the objectives of this chapter were achieved. The thesis now goes on to present the results of the analysis.

4.2 Sample characterisation

Before presenting the results of data analyses with a focus on the research questions, this section provides descriptive statistics of all variables under study. Apart from presenting general descriptive indicators of the sample, some comparisons were made between different profiles in respect to travel behaviour and incentives' acceptability indicators.

4.2.1 Sociodemographic profile

Table 4.11 presents the general sociodemographic characteristics of the sample (n = 920). The majority of the sample is male and below 22 years old (average age is 21.8). 57.1% of the sample share their household with 2 or 3 other persons.

Table 4.11 - Frequency distribution of sociodemographic variables

Gender	**%**
Male	54.0
Female	46.0
Age	**%**
17	3.3
18	9.7
19	14.6
20	18.3
21	15.1
22	9.0

23	6.6
24	4.3
25	3.1
26 or more	4.3
Household Size	**%**
1	8.3
2	18.9
3	26.5
4	30.6
5	11.8
5 or more	4.0
Income	**%**
<= 3 minimum wages	24.7
> 3 <= 6 minimum wages	29.6
> 6 <= 9 minimum wages	19.9
> 9 <= 15 minimum wages	14.9
> 15 minimum wages	10.9

Different levels of financial income are represented in the sample. Approximately half of the sample earns below six times the Brazilian national minimum wage, while more than 10% have reported earning more than fifteen minimum wages, considering monthly family income. The minimum wage in Brazil at the time of data collection was 937 BRL (Brazilian *Reais*) per month, equivalent to 256 USD (American Dollars), 218 EUR (Euros) or 193 GBP (British Pounds)[2].

4.2.2 Spatial distribution

Figure 4.2 shows a map containing information about the respondent's distribution across all postcode areas of Curitiba (in Brazil called '*Bairros*'), along with the location of each of the surveyed universities (the number on the side of each campus mark indicates their respective number of questionnaire participants).

[2] Average rates of 2018 according to OFX (www.ofx.com). Access in 21st January 2019.

Almost all postcode areas of Curitiba were covered, except nine regions that are all on the administrative limits of the city. As can be seen on the map, there is a relatively higher amount of participants living on the universities' surrounding areas, although none of the universities offers on-campus accommodation. This map considers 726 respondents since 33 students did not report their postcode areas and other 161 live in different cities, usually part of the Curitiba's metropolitan region.

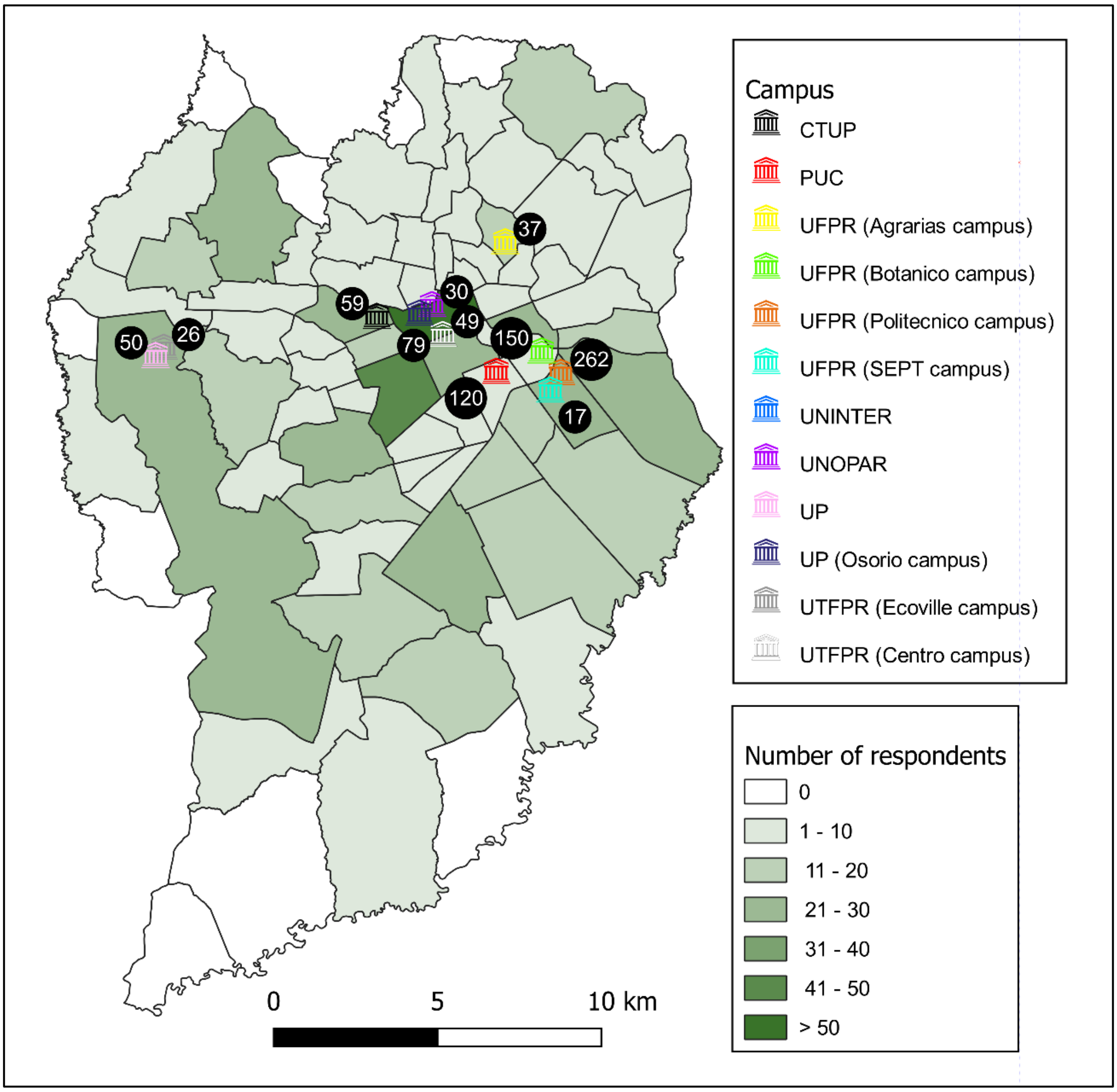

Figure 4.2 - Choropleth map of respondents by post-code area and universities of Curitiba

4.2.3 Aspects of mobility

With regard to indicators of mobility, Table 4.12 demonstrates that a considerably high proportion of the sample has used either the car (66.5%) or the bus (61%) to travel to the university at least one time in the preceding week of the questionnaire application. Considering the most used mode of transport in the same week, the bus (41%) and the car (40.4%) are highly predominant, while non-motorised forms of transport, such as the bike or walking, are only the preferred mode among fewer people (4.7% and 9.3% of the sample, respectively). Comparing these fixtures with the research by FONAPRACE (2014), which surveyed Brazilian undergraduate students, it can be seen that car use is higher among this study's sample (40.4% versus 20.1%) and bus use is lower (41% versus 54%). Cycling to the university is a more popular choice among students in Curitiba (4.7% versus 2.9%) and walking, on the other hand, is less popular (9.3% compared to 15.4%) (FONAPRACE, 2014). These differences could be a reflection of the time period between both studies and also particularities of the urban context of Curitiba, as the study by FONAPRACE considered a much wider national context.

Table 4.12 - Frequency distribution of transport-related observed variables

Vehicle ownership	**%**
Car	37.1
Bicycle	32.8
Motorcycle	4.6
Vehicle availability to commute	**%**
Car	65.4
Bicycle	39.1
Motorcycle	8.0
Used transport mode at least once during the week	**%**
Car	66.5
Bus	61.0
Bicycle	9.0
Motorcycle	5.9
Walking	17.2
Primary transport mode (mostly used)	**%**
Car	40.4
Bus	41.0
Bicycle	4.7
Motorcycle	3.0
Walking	9.3
Distance to campus	**%**
Less than or equal to 5km	24.5

Between 5km and 7.5km	12.8
Between 7.5km and 10km	18.2
Between 10km and 15km	19.2
More than 15km	25.3

Despite the availability rate of bicycles being relatively high (39.1%), only 9% of the sample reported using this form of transport to commute to the university. This can be an indication that bikes are mostly used for leisure.

The car was utilised by 66.5% of the students. This proportion seems to be really associated with the rate of car availability (65.4%), indicating that having a car available might be an important barrier to active transport within the sample.

The reported rates of mode-availability somewhat converge with secondary data gathered from a much larger sample of Curitiba (details in Section 3.2.1). The percentage of households of Curitiba owning at least one car is 71%, while the bike is present in 41% of houses and motorcycles in 15% (IPPUC, 2017)[3].

The sum of students that have non-motorised modes as their primary mode is relatively low (12.3%). Especially compared to studies carried with university students in cities such as Los Angeles - USA (24.8%) (Zhou, 2012), Hamilton - Canada (55.2%) (Whalen et al., 2013) or Giessen–Germany (44.2%) (Bamberg and Schmidt, 2003).

The sample is nicely heterogeneous in terms of distance to campus as 24.5% of students live less than 5 kilometres away from campus and roughly the same proportion lives more than 15 kilometres away. The Brazilian study by FONAPRACE (2014) shows that 39.4% of students live less than 10 kilometres away from campus. In this study’s sample, 55.5% of the participants live under this circumstance. Fonaprace’s study considered not only urban areas but also rural ones, which might be one of the reasons for this difference.

Lastly, to visualise more information in respect to the sample’s travel behaviour, the number of trips of each individual was estimated by means of a

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[3] This is based in a sample of 45.067 people surveyed as part of an origin-destination study (covered previously in the methodology chapter).

transformation of the original variable that measured the frequency of travelling with each travel mode. This variable was originally assessed using a seven-point scale referring to an interval of trips that the respondent has made on the preceding week of the survey (i.e. 1 to 3 trips, 4 to 6 trips, etc.) The correspondent median value was extracted from each option (e.g. 2 for the '1 to 3' option) and used as a rough estimation of the number of trips made by each transport mode. For the top end of the scale (more than 18 trips), a number of 20 trips was considered. From this new transformed variable (referring to the number of trips made in a week), the following information resulted (Table 4.13).

Table 4.13 – Results of variables derived from the estimated number of trips

Percentage of private CFV users that used other modes in the same week	69.5%
Percentage of students who used multiple travel modes during the week	54.0%
Total kilometres travelled by private CFVs (% of total)	63,563 (46.14%)
Total kilometres travelled by Non-motorised transport (% of total)	13,195 (9.58%)
Total kilometres travelled by Bus (% of total)	61,003 (44.28%)
Percentage of total trips made by car	40.4%
Percentage of total trips made by motorbike	2.9%
Percentage of total trips made by bus	40.5%
Percentage of total trips made by bike	4.9%
Percentage of total trips made walking	11.2%
Average amount of weekly trips to the university per person	13.78
Average total weekly kilometres per person	149.74

Perhaps the most curious information is that more than half of the sample did not just use one mode of travel in the week of the survey (54%). Almost 70% of private CFV users also use some alternative form to commute to the university. In terms of total distance travelled on the given week, more than 90% is covered by motorised forms of transport (car, bus or motorbike). 80.9% of the total amount of trips were performed by car or bus.

4.2.4 Perceptions of positive incentives

Participants rated each type of incentive in respect to three different indicators of acceptability: attitudes to the use (how strongly they like the incentive), intention to use (perceived probability of using the incentive) and perceived likelihood of switching from cars or motorcycles to alternative modes (bus, bike or walking) with the use of the incentive, in this thesis called 'perceived personal impact'. As expected, average scores on these three variables followed a descending pattern from attitudes to the perceived personal impact, for all incentives. Figure 4.3 shows mean scores on these variables for the eleven assessed incentives (displayed in descending order of perceived personal impact).

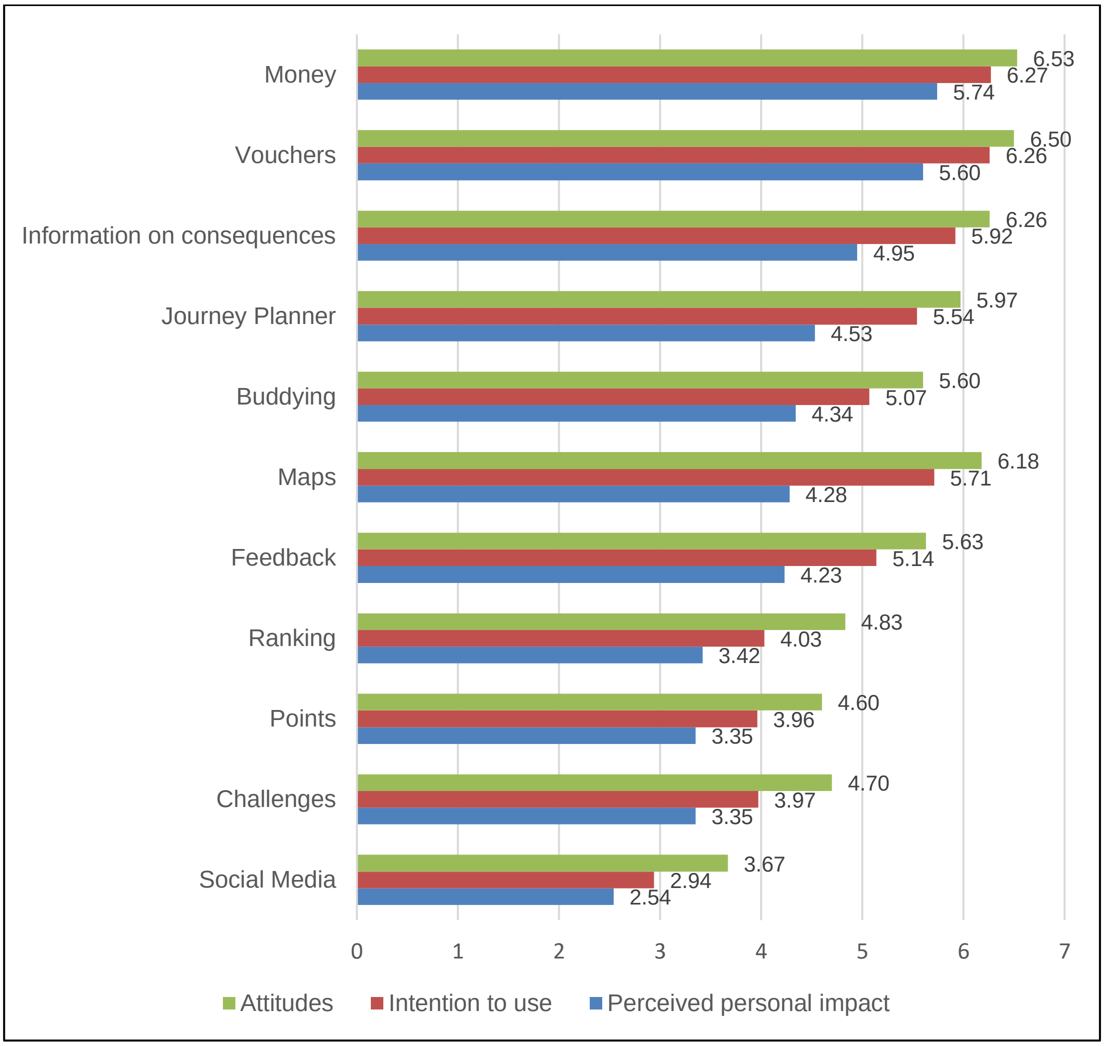

Figure 4.3 - Attitudes, intention to use and perceived personal impact (by type)

Notes: lines on top of each bar represent standard errors. Incentives are displayed in descending order of 'likelihood to switch'. All scales range from 1 to 7.

Financial incentives (money and vouchers) perform greater on the three indicators of acceptance. Ranking, Points, Challenges and Social Media do not appear to play an important role (compared to other forms) when it comes to incentivising people to change travel behaviour, as their average scores on 'perceived personal impact' all fall within the first half of the scale (less than 3.5 points).

Some incentives have a wider gap between scores on attitudes and perceived personal impact (meaning that attitudes do not translate into the perceived likelihood of behaviour change so often for these cases). Maps, in particular, is the incentive that this discrepancy is more salient (values drop from 6.18 to 4.28). In contrast, the lowest change can be seen in the 'Money' incentive.

Average values were also calculated considering categories of incentives and all incentives combined (Table 4.14). A considerable difference in scores shows up in favour of value maximisation incentives, for all three indicators of acceptability.

Table 4.14 - Mean scores (overall and by category of incentives)

Types of incentives[1]	Attitudes		Intention to use		Likelihood to switch	
	M	SD	M	SD	M	SD
Social Incentives	4.69	1.39	4.19	1.40	3.53	1.44
Value maximisation incentives	6.30	1.00	5.95	1.12	5.21	1.26
All incentives	5.50	0.87	4.98	1.07	4.21	1.27

[1] Social incentives: social media, challenges, points, rankings, buddying and social media. Value maximisation incentives: maps, money, vouchers, journey planner and information about consequences.

4.2.5 Behavioural and control beliefs

Participants of the complementary survey (n = 112) reported their beliefs about the experience of using each mode of transport and rated the importance of certain attributes of travelling (behavioural beliefs). In addition, they rated the probability of facing certain barriers (or facilitators) associated with each mode on a trip to campus and the extent to which these aspects impede or facilitate their ability to use each one of the modes. First, the scores of behavioural beliefs strengths are displayed in Table 4.15. Table 4.16 shows the importance given to the attributes of a trip to the university (outcome evaluations).

Table 4.15 - Strength of behavioural beliefs in relation to a trip to the university (n=112)

Beliefs	Mean[1]	Std. Deviation
A trip to the university using the *car* would be...		
Safe	2.18	1.28
Cheap	-1.16	1.67
Comfortable	2.67	0.86
Fast	1.91	1.28
A trip to the university using the *bus* would be...		
Cheap	0.70	1.73
Crowded	1.59	1.68
Comfortable	-1.13	1.50
Fast	-0.93	1.77
A trip to the university using the *bike* would be...		
Fast	-0.41	2.23
Good for the environment	2.45	1.40
Safe	-1.61	1.58
Healthy	2.22	1.43
A trip to the university using the *motorbike* would be...		
Cheap	0.95	1.96
Practical	1.04	2.13
Fast	1.73	1.72
Safe	-1.69	1.83
A trip to the university *walking* would be...		
Fast	-2.14	1.57
Good for the environment	2.16	1.68
Healthy	1.69	1.91
Safe	-1.72	1.83

[1] All variables were measured in a scale from -3 to 3.

Table 4.16 - Outcome evaluations of a trip to the university (importance of attributes)

Outcomes	Mean (in descending order)[1]	Std. Deviation
Speed	6.02	1.22
Practicality	5.99	1.22
Safety	5.93	1.15
Cost	5.52	1.43
Comfort	4.98	1.49
Not Crowded	4.91	1.72
Good for the environment	3.88	1.74
Healthy	3.70	1.79

[1] All variables were measured on a scale from 1 to 7.

The results show that participants, generally, see the car as a safe, comfortable and fast mode of transport, despite not being cheap. This quite positive image was not replicated when students assessed the bus, as this mode was perceived as being crowded, uncomfortable and slow. However, students see it as being somewhat cheap.

Walking and cycling appear to have the same general pattern of perception. Students judge that a trip to campus using these modes would be good for the environment and health, but unsafe and slow. The motorbike is considered a cheap, practical and fast mode of transportation, despite being also viewed as unsafe.

In fact, safety was one of the most valued attributed to travelling according to the students, alongside speed and practicality. Interestingly, these outcomes are more valued than financial cost and comfort. Environmental and health issues do not seem to play an important role in the decision of which travel mode to use.

The interpretation of the strength of behavioural beliefs together with the outcome evaluations can be an indication of the reasons why motorisation rates are high in Curitiba, particularly across the studied sample. The attributes that students perceive to be associated with using the car or the motorcycle are among the most important ones for them. While the attributes of riding a bicycle or walking are not seen with equal importance.

Finally, the strength and power of control beliefs were assessed. The control belief *strength*, in this case, refers to the perceived probability of a controlling factor to be present during a trip using a certain mode (e.g., the existence of bicycle paths or traffic jams). The belief *power* means the extent to which students perceive this particular factor as a real barrier or facilitator for them. Table 4.17 provides the results on these indicators.

Table 4.17 - Strength and power of control beliefs

Control attributes	Mean[1]	Std. Deviation
Car trips to the university		
I would have enough money[2]	-0.53	2.394
Having sufficient money is a facilitator[3]	1.31	2.148
Would have traffic jams	1.03	1.684
Traffic jams are a barrier	-0.58	2.078
Bus trips to the university		
I would have enough money	2.30	1.413

Having enough money is a facilitator	0.43	2.249
Would take too much time	1.53	1.698
The time spent is a barrier	0.83	2.207
Bike trips to the university		
Would have cycle lanes	-0.83	1.845
The existence of cycle lanes is a facilitator	0.00	2.238
Would have safety problems	1.18	1.875
Safety issues are a barrier	0.84	2.314
Motorbike trips to the university		
I would have an accident	0.13	1.984
Safety issues are a barrier	0.54	2.42
I would have enough money	-1.08	2.271
Having enough money is a facilitator	-1.11	2.116
Walking trips to the university		
Would be too distant	1.91	1.966
Distance is a barrier	2.14	1.812
I would have a safety problem	1.69	1.611
Safety issues are a barrier	1.14	2.172

[1] All variables were measured on a scale from -3 to 3.
[2] Control belief strength
[3] Control belief power

The table above is revealing in several ways. The use of non-motorised forms of transport is generally viewed as dangerous (in terms of accidents and violence) and insecurity is, indeed, a strong barrier to the use of these modes according to the data. Another Brazilian study revealed that lack of safety was perceived as the most significant barrier to cycle among students in three different cities (de Sousa et al., 2014). Cycle lanes are generally not expected, but students do not see their existence as a strong facilitator to cycle. These two observations also replicate the findings of de Sousa, Sanches and Ferreira (2014), who indicated that lack of infrastructure was expected by students but was the least strong barrier to cycle among a total of six factors. Distance is seen as a barrier to walking, as one could expect. This could be a reflection of the relatively large area of Curitiba and its metropolitan area and the relatively high average commuting distance of the surveyed students (around 11 km).

Using the bus is seen as something that takes too much time and this is a considerable barrier for the students. Interestingly, students do not perceive money as a barrier to take the bus, although they generally don’t think that having money actually facilitates their use of the public transport system.

From the data about car use, it is apparent that heavy traffic is not really seen as an inhibitory factor. In contrast, money appears to be a strong barrier, both in regards to the use of the car and the motorcycle.

4.2.6 Statistical comparison of means

Perhaps as important as looking at general scores for the survey variables, it is to compare them across different individual profiles. Although this will be done more intensively on the cluster analysis section (with more focus on psychographic segments, however), here variables are compared in respect to more easily accessible, groups, defined *a priori* (e.g. in terms of gender, primary travel mode, etc.).

The appropriate statistical test when aiming to compare two groups is the *t-test*. When the compared samples are independent observations, the test is often called 'independent t-test'. When more than two means are compared, then analysis of variance (ANOVA) can be used (Blaikie, 2008). *Post-hoc* analyses were performed using either Tukey's test (Tukey, 1949) (when variable variances were equal) or Tamhane's test (Tamhane, 1979) (when they were not). Thus, Levene's test for equality of variance (Levene, 1961) was performed prior to the *post-hoc* tests.

4.2.6.1 Comparison of variables related to travel behaviour

Firstly, measures of central tendency (in these cases, the mean) for travel behaviour variables were compared among different sociodemographic profiles (gender, age, income and distance to campus).

With respect to gender, 29 out of 44 variables related to travel behaviour showed significant differences between genders on the 5% significance level ($p < 0.05$). The full table containing this analysis is in Appendix I, while the main highlights are shown in Table 4.18, below.

Table 4.18 - Highlights of significant differences in travel behaviour among sociodemographic profiles and different distances to campus

Variable	Highlights
Gender	Men are more behaviourally inclined to cycle as they exhibit higher scores of cycling habit, bike experience and higher perceived capacity and autonomy to use it. They also use it more often than women.
	Women are usually more aware of the harmful environmental consequences of using the car, they also have a greater perception of their personal ability to deal with the problems that come from excessive car use and are more aware of their own responsibility in this issue.
	Women are more behaviourally inclined to use the bus, as they have higher experience with this mode, as well as a higher habit, social norms and actual use of this mode.
	Men have more positive attitudes to motorised forms of transport.
Age	Younger students tend to use the bus more often.
	Older students use the motorcycle more than the younger do.
	Younger students have more positive attitudes to the car and the bus, and more negative attitudes to cycling and walking.
Income	Wealthier students use the car more than the poor do, while poorer students use the bus and walk more frequently. The same discrepancy is observed in terms of experience, social norms and perceived control over these modes.
	Wealthier students have lower feelings of moral obligations to reduce car use.
Distance to campus	Students living closer to the university do not display differences to those living further in terms of the use of cars, motorbikes and even cycling.
	Those living near the university have less positive attitudes to the car and more positive attitudes to cycling and walking.

4.2.6.2 Comparison of variables related to positive incentives

Another form of describing the population is illustrated here. Different sociodemographic and travel behaviour profiles were compared in terms of indicators of acceptability of positive incentives. The full table containing the data is displayed in Appendix J (sociodemographic variables) and Appendix K (transport-related variables) and the highlights presented here (Table 4.19).

Table 4.19 - Highlights of significant differences in acceptability of incentives among sociodemographic profiles and users of travel modes

Variable	Highlights
Gender	Women are significantly more responsive to positive incentives. The only types of incentives where this difference is not demonstrated are money, points, rankings and social media.
Age	Older students demonstrate less positive attitudes to incentives overall, particularly maps, money, vouchers, feedback, challenges and buddying.
Income	Wealthier students have less perceived likelihood of switching travel modes due to incentives, in general.

Distance to campus	No differences exist on the acceptability of the majority of incentives with respect to distance travelled. Differences were only significant for Points, Maps and Social Media. Students living farther to campus have significant higher acceptability of social media. It can be assumed that this is because travelling longer distances with non-motorised modes could be viewed as an 'accomplishment' worth of sharing. On the other hand, points and maps are more accepted by those living closer to the university.
Use vs non-use of different travel modes	Car users are less inclined to switch to alternative travel modes, for all types of incentives, compared to non-car users.
	Bus users intend to use incentives more than non-users (other than challenges). They are more prone to switch travel modes in response to all types of incentives.
	Bike users do not display significant differences in attitudes to incentives compared to non-users. They also do not show differences in likelihood to switch due to maps, money, vouchers, journey planner, information, challenge nor buddying.
Travel mode mostly used	People that have the car as the main mode of transport are particularly less responsive to incentives, in general. They mostly discriminate from bus users, who are more susceptible to all incentives in terms of perceived personal impact, almost all incentives in terms of intention to use and five different incentives with respect to attitudes. They also differ considerably from walkers and cyclists, with respect to potential switch (higher scores on five out of eleven incentives).
	Bus users, cyclists and walkers have more positive attitudes than car users to the Points incentive. They have a higher intention to use maps, points and rankings. In addition, they have a higher likelihood of changing behaviour due to maps, money, points, rankings and vouchers.

4.2.7 Test of assumptions about the relationship of variables

Before proceeding to analyses that look to explore answers to the research questions of this thesis, this section aims to perform tests concerning some basic assumptions that were made prior to the construction of the questionnaire and the research design. For example, the structure of the Theory of Planned Behaviour (where attitudes, norms and perceived control are predictors of behaviour) was assumed to be true for this study's population. Also, a relationship between the three indicators of acceptability (attitudes, intention to use and potential switch) was assumed to exist. Thus, the aim of this section is to empirically check these hypotheses made *a priori*.

Although the analysis of causal relationships was not performed due to not being the scope of this research, it was judged prudent to conduct a correlational analysis[4] of these indicators, aiming to test general associations

[4] A correlation coefficient can be calculated using a variety of methods. When dealing with interval-level data, Pearson's 'r' is used. However, this method is not appropriate for data that are not normally distributed. In this case, Spearman's 'rho' (ρ) is the preferable method (de Vaus, 2014).

between the variables. A conceptualisation of this technique is presented next, before the presentation of its results.

4.2.7.1 Correlation analysis

When a change in the values of one variable means the existence of a change in the values of another variable, in a predictable form, it means these two variables are correlated and not independent (Dancey and Reidy, 2014). Thus, correlation analysis is a proper test to be performed here, as it seeks to find out if there is a relationship between variables, and what is the size and direction of that relationship (positive, negative or zero).

While it is common to categorise the strength of correlation coefficients as weak, moderate or strong based on the value of the correlation coefficient, De Vaus (2014) states that these definitions are relative. According to the author, in social sciences, for example, no two variables are likely to be strongly correlated, as typically there are many causes for outcomes in this particular field. The author further emphasises that a correlation of 0.30 might be considered as relatively strong in this field of science.

Within the domain of behavioural research, Cohen (1988) suggests that coefficients around 0.1 are ‘small’, those of 0.3 are ‘medium’ and 0.5 would be considered ‘large’. More recently, Hemphill (2003) created empirical guidelines for coefficient interpretation. In a review of 380 meta-analytical studies in the field of psychology, the author has found that the lower third portion of all correlations resides between 0.0 and 0.2, while the middle third is represented by coefficients between 0.2 and 0.3 and only the upper third portion contain coefficients larger than 0.3. For the sake of this research, we will consider coefficients between 0.1 and 0.2 as ‘small’, between 0.2 and 0.5 as ‘medium’ and larger than 0.5 will be considered ‘large’.

4.2.7.2 Test of assumptions of the independent variables

The first assumption to be tested is related to the constructs and psychological variables being associated with the use of modes of travel (and the intention to use). This analysis was done using variables that are theoretically associated with either intention or behaviour (for a list describing all the variables of this research, see Appendix H). Table 4.20 shows correlation coefficients calculated between the behavioural variables.

Table 4.20 - Correlation analysis of independent variables

Independent variables	Behaviour (ρ)					Intention (ρ)				
	Car	Bus	Bike	Moto	Walk	Car	Bus	Bike	Moto	Walk
INT_CAR[1]	8	-0.4***	-0.08*	-0.16***	-0.21***					
INT_BUS	-0.38***	0.79***	0.04	-0.03	-0.01					
INT_BIK	-0.02	0.03	0.53***	0.11***	0.08*					
INT_MOT	-0.1**	-0.05	0.21***	0.65***	0.04					
INT_WAL	-0.18***	-0.03	0.1**	0.03	0.72***					
ATT_CAR[2]	0.23***	0.05	-0.11***	-0.17***	-0.21***	0.28***	0.01	-0.14***	-0.13***	-0.22***
ATT_BUS	-0.11**	0.31***	0	-0.15***	-0.05	-0.16***	0.34***	0	-0.15***	-0.03
ATT_BIK	-0.01	-0.08*	0.2***	-0.02	0.11***	-0.01	-0.11**	0.3***	0	0.13***
ATT_MOT	-0.09**	0.04	0.1**	0.25***	-0.1**	-0.08*	-0.02	0.07	0.3***	-0.05
ATT_WAL	-0.07*	-0.07*	0.01	-0.05	0.33***	-0.08*	-0.07*	0.05	-0.04	0.38***
EXP_CAR[3]	0.33***	-0.25***	-0.07*	-0.02	-0.06	0.27***	-0.2***	-0.07*	-0.02	-0.09*
EXP_BUS	-0.19***	0.3***	0.03	0.09**	-0.08*	-0.2***	0.27***	0.04	0.06	-0.07
EXP_BIK	-0.11***	-0.04	0.24***	0.05	0.07*	-0.07*	-0.04	0.28***	0.09**	0.1**
EXP_MOT	-0.2***	-0.02	0.05	0.32***	-0.01	-0.18***	-0.03	-0.01	0.3***	0.04
EXP_WAL	-0.15***	0.05	0.05	-0.05	0.23***	-0.15***	0.06	0.05	-0.04	0.29***
SNORM_CAR[4]	0.28***	-0.11***	-0.05	-0.09**	-0.21***	0.33***	-0.18***	-0.06	-0.04	-0.17***
SNORM_BUS	-0.15***	0.36***	-0.04	-0.05	-0.07*	-0.2***	0.39***	-0.03	-0.05	-0.06
SNORM_BIK	-0.1**	-0.02	0.16***	0.04	0.16***	-0.13***	-0.02	0.27***	0.05	0.18***
SNORM_MOT	-0.16***	0.04	0.1**	0.27***	0.01	-0.15***	0.02	0.07	0.29***	0.05
SNORM_WAL	-0.11**	-0.09**	0.1**	0.01	0.36***	-0.12***	-0.06	0.1**	0.02	0.39***
PNORM_CARS[5]	-0.19***	0.14***	0.09**	0.03	0.12***	-0.23***	0.2***	0.13***	0.04	0.13***
AWC_CARS[6]	-0.03	0.01	-0.03	-0.03	-0.02	-0.04	0.03	-0.03	-0.02	-0.04
RESP_CARS[7]	0.01	-0.07*	-0.01	0.01	-0.03	0	-0.03	-0.05	-0.01	-0.02
ABIRED_CARS[8]	-0.07*	0.04	0.05	-0.04	0.02	-0.11***	0.08*	0.08*	0.01	0.04
HAB_CAR[9]	0.43***	-0.22***	-0.13***	-0.13***	-0.17***	0.45***	-0.2***	-0.15***	-0.12***	-0.2***
HAB_BUS	-0.31***	0.33***	0.05	-0.03	0.14***	-0.34***	0.35***	0.01	-0.03	0.16***
HAB_BIK	0	-0.04	0.25***	-0.03	-0.08*	0.02	-0.09*	0.32***	0.02	-0.08*
HAB_MOT	-0.21***	0.14***	-0.1**	-0.05	0.21***	-0.25***	0.15***	-0.07*	-0.07*	0.24***
HAB_WAL	-0.18***	-0.06	-0.01	0.53***	-0.07*	-0.16***	-0.11**	-0.02	0.51***	-0.05
CAPAC_CAR[10]	0.6***	-0.39***	-0.09**	-0.1**	-0.17***	0.59***	-0.39***	-0.07*	-0.05	-0.15***
CAPAC_BUS	-0.18***	0.44***	-0.03	-0.09**	-0.09*	-0.21***	0.4***	-0.06	-0.12***	-0.12***
CAPAC_BIK	-0.02	-0.1**	0.27***	0.01	0.09**	-0.05	-0.13***	0.34***	0.06	0.07*
CAPAC_MOT	-0.09**	-0.05	0.05	0.43***	-0.03	-0.07	-0.08*	0.05	0.43***	0.01

Independent variables	Behaviour (ρ)					Intention (ρ)				
	Car	Bus	Bike	Moto	Walk	Car	Bus	Bike	Moto	Walk
CAPAC_WAL	-0.17***	-0.11***	0.1**	-0.01	0.5***	-0.17***	-0.09**	0.08*	0	0.49***
AUTO_CAR[11]	0.41***	-0.31***	-0.07*	0	-0.1**	0.37***	-0.31***	0	0.04	-0.11**
AUTO_BUS	-0.01	0.03	0	0.03	-0.01	0.02	-0.01	0.03	0.07	-0.01
AUTO_BIK	-0.08*	-0.07	0.18***	0.04	0.14***	-0.11***	-0.08*	0.22***	0.08*	0.1**
AUTO_MOT	-0.11***	-0.11***	-0.01	0.32***	0.02	-0.08*	-0.12***	0.03	0.31***	0.03
AUTO_WAL	-0.15***	-0.08*	0.07*	0.01	0.36***	-0.17***	-0.04	0.07*	0.01	0.34***
BB_CAR[12]	0.37***	-0.18	0.04	-0.09	-0.21*	0.2*	-0.24*	0	-0.1	-0.21*
BB_BUS	-0.17	0.32***	-0.02	0.16	-0.01	-0.16	0.25**	0.04	0.05	0.07
BB_BIK	-0.07	0.07	0.24*	0.01	0.21*	-0.11	-0.12	0.37***	0.03	0.16
BB_MOT	-0.08	0.12	-0.07	0	-0.13	-0.05	-0.11	0.11	0.11	-0.11
BB_WAL	-0.25**	0.14	0.06	0.03	0.27**	-0.23*	0.02	0.13	0.02	0.36***
CB_CAR[13]	0.57***	-0.41***	-0.13	-0.07	-0.15	0.41***	-0.34***	-0.09	-0.07	-0.18
CB_BUS	-0.28**	0.44***	0.01	0.13	0.01	-0.3**	0.39***	-0.01	0.05	-0.07
CB_BIK	-0.21*	0.04	0.24*	-0.07	-0.04	-0.23*	0.05	0.09	-0.09	0.01
CB_MOT	0.19*	-0.16	-0.04	-0.02	-0.05	0.24*	-0.24*	-0.14	-0.02	-0.12
CB_WAL	-0.1	-0.13	0.11	-0.04	0.32***	-0.08	-0.09	-0.02	-0.01	0.29**
INJNORMB_CAR[14]	0.27**	-0.06	-0.03	0	-0.05	0.34***	0	0.11	0.1	0.01
INJNORMB_BUS	-0.16	0.38***	-0.13	0.01	0.02	-0.14	0.34***	0.01	0.02	0
INJNORMB_BIK	-0.13	0.08	0.2*	0.1	0.35***	-0.19	0.06	0.36***	0.1	0.36***
INJNORMB_MOT	-0.14	0.17	0.03	0.08	0.18	-0.09	0.18	0.07	0.25*	0.3**
INJNORMB_WAL	-0.08	-0.01	-0.14	-0.04	0.44***	-0.09	0.07	-0.08	-0.03	0.39***

Notes: cells containing significant correlations are highlighted in a shaded scale proportional to the correlation strength (*** (p <0.001, darkest shading), ** (p < 0.01, intermediate shading), * (p < 0.05, light shading). Values represent Spearman's correlation coefficient (ρ).
[1]Intention [2]Attitudes [3]Experience [4]Social Norms [5]Personal Norms [6]Awareness of Consequences [7]Perceived responsibility [8]Perceived ability to reduce threat [9]Habit [10]Capacity [11]Autonomy [12] Behavioural beliefs [13]Control Beliefs [14]Injunctive normative beliefs.

The numbers displayed above demonstrate a considerably high amount of correlations between intention or behaviour and their theoretical predictors, which serve as general evidence that it is still plausible to assume these relationships exist in the studied sample. A lower amount of correlations is seen between behavioural and control beliefs and Injunctive normative beliefs and intention/behaviour. This is probably caused by twofold: (1) them not being a direct theoretical cause of intention nor behaviour according to the TPB and (2) the sample size used to measure these variables was considerably lower (112 students).

4.2.7.3 Testing assumptions of the dependent variables

Apart from that, another assumption was done regarding the association between attitudes, intention and likelihood to change travel behaviour due to the use of incentives. While the association between attitudes and intention has strong theoretical and past empirical evidence (from the Theory of Planned Behaviour), perceived likelihood to change behaviour (or perceived personal impact) was a variable created without solid support from theory. Values are presented in Table 4.21 (for the relationships between attitudes and intention), Table 4.22 (for the association between potential switch and attitudes) and Table 4.23.

Table 4.21 - Correlation analysis for attitudes and intention to use incentives

Incentives		Intention to use (ρ)										
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Attitudes	Maps	0.69	0.29	0.22	0.26	0.37	0.39	0.33	0.26	0.17	0.21	0.27
	Money	0.26	0.69	0.17	0.18	0.44	0.21	0.18	0.18	0.11	0.17	0.19
	Points	0.30	0.28	0.83	0.59	0.34	0.30	0.30	0.36	0.37	0.43	0.28
	Rankings	0.29	0.25	0.58	0.79	0.34	0.33	0.31	0.38	0.39	0.43	0.35
	Vouchers	0.31	0.42	0.24	0.27	0.77	0.36	0.37	0.29	0.16	0.23	0.26
	Journey Planner	0.38	0.30	0.27	0.28	0.36	0.80	0.46	0.45	0.23	0.28	0.29
	Information	0.31	0.21	0.22	0.25	0.34	0.49	0.76	0.40	0.20	0.27	0.29
	Feedback	0.27	0.22	0.30	0.34	0.26	0.43	0.40	0.84	0.28	0.36	0.30
	Social Media	0.20	0.14	0.43	0.43	0.25	0.27	0.25	0.35	0.79	0.51	0.34
	Challenges	0.17	0.14	0.37	0.38	0.24	0.30	0.31	0.38	0.43	0.82	0.35
	Buddying	0.24	0.17	0.22	0.30	0.29	0.30	0.31	0.30	0.27	0.34	0.84

Note: all correlations are significant at $p < 0.05$. Diagonal elements (representing the same incentives) are highlighted.

Table 4.22 - Correlation analysis for attitudes and likelihood to switch due to the use of incentives

Incentives		Potential to switch (ρ)										
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Attitudes	Maps	0.37	0.26	0.17	0.17	0.28	0.30	0.25	0.20	0.13	0.16	0.24
	Money	0.16	0.53	0.12	0.12	0.35	0.15	0.17	0.12	0.07	0.12	0.15
	Points	0.31	0.32	0.71	0.53	0.36	0.30	0.30	0.33	0.37	0.41	0.30
	Rankings	0.30	0.29	0.53	0.66	0.34	0.34	0.30	0.36	0.40	0.40	0.35
	Vouchers	0.24	0.40	0.17	0.21	0.58	0.27	0.29	0.22	0.12	0.17	0.21
	Journey Planner	0.30	0.25	0.24	0.22	0.29	0.59	0.38	0.34	0.19	0.22	0.26

Incentives		Potential to switch (ρ)										
		1	2	3	4	5	6	7	8	9	10	11
	Information	0.22	0.18	0.18	0.19	0.28	0.38	0.55	0.30	0.16	0.22	0.24
	Feedback	0.23	0.20	0.27	0.30	0.23	0.37	0.36	0.61	0.28	0.29	0.26
	Social Media	0.21	0.13	0.39	0.41	0.22	0.27	0.26	0.34	0.67	0.44	0.32
	Challenges	0.25	0.16	0.34	0.34	0.22	0.28	0.29	0.31	0.40	0.67	0.32
	Buddying	0.15	0.17	0.22	0.26	0.21	0.26	0.28	0.24	0.21	0.26	0.67

Note: all correlations are significant at $p < 0.05$. Diagonal elements (representing the same incentives) are highlighted.

Table 4.23 - Correlation analysis for intention to use and likelihood to switch due to the use of incentives

Incentives		Potential to switch (ρ)										
		1	2	3	4	5	6	7	8	9	10	11
Intention to use	Maps	0.51	0.35	0.28	0.29	0.36	0.38	0.36	0.30	0.19	0.19	0.28
	Money	0.28	0.65	0.23	0.21	0.45	0.26	0.26	0.23	0.11	0.17	0.20
	Points	0.36	0.31	0.82	0.63	0.37	0.38	0.35	0.40	0.46	0.46	0.32
	Rankings	0.39	0.30	0.65	0.83	0.37	0.42	0.38	0.47	0.50	0.48	0.43
	Vouchers	0.31	0.48	0.25	0.28	0.70	0.35	0.34	0.28	0.18	0.22	0.31
	Journey Planner	0.38	0.26	0.31	0.29	0.33	0.70	0.48	0.41	0.25	0.29	0.30
	Information	0.30	0.25	0.26	0.26	0.36	0.45	0.66	0.39	0.20	0.28	0.31
	Feedback	0.29	0.25	0.34	0.38	0.30	0.45	0.44	0.72	0.37	0.36	0.33
	Social Media	0.25	0.14	0.46	0.50	0.24	0.35	0.30	0.41	0.80	0.50	0.36
	Challenges	0.31	0.20	0.44	0.45	0.27	0.37	0.35	0.43	0.52	0.82	0.38
	Buddying	0.26	0.22	0.28	0.34	0.27	0.35	0.36	0.34	0.29	0.32	0.80

Note: all correlations are significant at $p < 0.05$. Diagonal elements (representing the same incentives) are highlighted.

From the outputs of the analysis presented above, it is evident to suggest that attitudes, intention and potential to switch are related, indeed. These three indicators displayed mainly large correlations between the same incentives ($\rho > 0.5$). Although more complex analyses would have to be performed to explore the nature of these relationships more deeply.

With the assumptions successfully tested using survey data, further analyses can be performed safely, keeping these assumptions in place.

4.3 Association between perceptions of incentives and mobility-behavioural aspects

The second research question of this thesis had to do with the existence of patterns of association between indicators of acceptability of incentives and travel behaviour variables: *what behavioural factors are associated with individual acceptance of positive incentives to reduce private CFVs use?* Correlation analysis was performed to investigate this issue. The resulting correlation coefficients are shown in Table 4.24, for the two categories of incentives and for all incentives combined.

Table 4.24 - Correlation analysis of acceptability of incentives and travel behaviour variables

Variables	Attitudes (ρ)			Intention to use (ρ)			Perceived impact (ρ)		
	Social	Value Max.	All	Social	Value Max.	All	Social	Value Max.	All
BEH_CAR[1]	-0.13	-	-0.11	-0.19	-0.18	-0.15	-0.25	-0.24	-0.21
BEH_BUS	0.13	0.09	0.14	0.18	0.13	0.21	0.22	0.17	0.24
BEH_BIK	-	-	-	0.09	0.08	0.09	0.10	0.09	0.09
BEH_MOT	-	-0.07	-	-	-	-	-	-	-0.07
BEH_WAL	0.08	0.11	0.09	0.10	0.07	0.13	0.14	0.10	0.16
ATT_CAR[2]	-0.07	-	-	-0.13	-0.11	-0.09	-0.20	-0.18	-0.17
ATT_BUS	0.12	0.17	0.16	0.19	0.15	0.21	0.19	0.16	0.21
ATT_BIK	0.21	0.19	0.22	0.29	0.26	0.24	0.24	0.21	0.23
ATT_MOT	0.13	-	0.08	0.08	0.11	-	-	0.08	-
ATT_WAL	0.10	0.14	0.12	0.19	0.16	0.18	0.17	0.14	0.19
EXP_CAR[3]	-0.09	-	-0.08	-0.10	-0.11	-	-0.17	-0.17	-0.13
EXP_BUS	0.10	0.13	0.12	0.17	0.14	0.20	0.17	0.13	0.20
EXP_BIK	0.12	-	0.09	0.15	0.16	0.10	0.11	0.12	0.10
EXP_MOT	-	-	-	-	-	-	-	-	-
EXP_WAL	0.11	0.18	0.13	0.19	0.14	0.25	0.16	0.12	0.22
PNORM_CARS[4]	0.29	0.21	0.29	0.34	0.32	0.27	0.35	0.32	0.29
AWC_CARS[5]	0.21	0.29	0.26	0.28	0.22	0.29	0.25	0.19	0.27
RESP_CARS[6]	0.16	0.19	0.20	0.21	0.19	0.20	0.19	0.15	0.20
ABIRED_CARS[7]	0.20	0.24	0.23	0.28	0.22	0.28	0.27	0.22	0.27
INT_CAR[8]	-0.16	-	-0.15	-0.23	-0.20	-0.20	-0.27	-0.25	-0.24
INT_BUS	0.13	0.11	0.14	0.21	0.15	0.24	0.27	0.21	0.31
INT_BIK	0.12	0.08	0.12	0.18	0.16	0.13	0.19	0.16	0.15
INT_MOT	-	-0.08	-	-	-	-	-	-	-

Variables	Attitudes (ρ)			Intention to use (ρ)			Perceived impact (ρ)		
	Social	Value Max.	All	Social	Value Max.	All	Social	Value Max.	All
INT_WAL	0.09	0.10	0.10	0.14	0.11	0.13	0.17	0.14	0.17
HAB_CAR[9]	-0.21	-0.18	-0.23	-0.29	-0.25	-0.26	-0.28	-0.25	-0.29
HAB_BUS	0.10	0.13	0.13	0.17	0.12	0.20	0.19	0.16	0.25
HAB_BIK	0.14	0.10	0.15	0.17	0.17	0.12	0.13	0.12	0.12
HAB_MOT	0.09	0.12	0.12	0.15	0.12	0.17	0.17	0.15	0.18
HAB_WAL	-	-0.09	-	-	-	-0.09	-0.08	-	-0.12
SNORM_CAR[10]	-0.09	-	-0.07	-0.11	-0.08	-0.11	-0.15	-0.12	-0.16
SNORM_BUS	0.12	0.20	0.16	0.14	0.24	0.20	0.14	0.24	0.20
SNORM_BIK	0.12	-	0.12	0.19	0.14	0.19	0.20	0.17	0.21
SNORM_MOT	0.09	-0.08	-	0.10	-	-	0.10	-	-
SNORM_WAL	0.10	0.09	0.11	0.18	0.15	0.18	0.20	0.18	0.22
CAPAC_CAR[11]	-0.10	-	-0.09	-0.14	-0.13	-0.11	-0.19	-0.16	-0.19
CAPAC_BUS	-	0.09	0.08	0.08	-	0.12	-	-	0.10
CAPAC_BIK	0.11	-	0.09	0.11	0.13	-	0.11	0.12	0.08
CAPAC_MOT	-	-0.07	-	-	-	-0.09	-	-	-
CAPAC_WAL	0.08	-	0.08	0.08	0.07	-	0.10	0.10	0.09
AUTO_CAR[12]	-	-	-	-0.11	-0.09	-0.11	-0.11	-0.10	-0.10
AUTO_BUS	-	-	-	-	-	-	-	-	-
AUTO_BIK	0.09	-	0.07	-	0.07	-	-	-	-
AUTO_MOT	-	-	-	-	-	-	-	-	-
AUTO_WAL	0.12	0.07	0.12	0.10	0.11	-	0.08	0.08	0.07
AGE	-0.12	-0.12	-0.14	-	-	-	-	-	-
DIST[13]	-	-0.07	-	-	-	-0.08	-	-	-
INCOM[14]_	-0.10	-	-0.09	-0.17	-0.17	-0.11	-0.21	-0.19	-0.21

Note: Only significant correlations are displayed. Positive correlations higher than +0.1 or -0.1 are formatted using a blue and red gradient, respectively.
[1]Behaviour [2]Attitudes [3]Experience [4]Personal Norms [5]Awareness of consequences of car use [6]Perceived own responsibility in problems of car use [7]Perceived ability to reduce car-associated problems [8]Intention [9] Habit [10] Subjective norm [11]Capacity [12]Autonomy [13]Distance from campus [14]Financial Income.

Frequency of car use (BEH_CAR), attitudes to using the car (ATT_CAR), intention to use the car in the near future (INT_CAR), car use habit (HAB_CAR), perceived capacity (CAPAC_CAR) and perceived autonomy (AUTO_CAR) to use the car showed negative correlations with indicators of acceptability of incentives, along with experience with this travel mode (EXP_CAR). Behavioural predictors of the use of alternatives such as the bus, the bike or walking displayed positive correlations with individual acceptance of incentives. That is, when the value of a predictor of bus use (e.g. attitudes to bus use) increases, the values of attitudes to incentives (or intention to use incentives) also increase, meaning there is a positive association between these factors.

The strongest negative associations appear to be between the frequency of car use and how likely students are to switch to alternative modes due to the use of incentives. Car use habit is also associated with attitudes toward incentives. Namely, the stronger the habit to use the car, the less a person likes the incentives tools.

The most prominent positive associations are seen for the variables related to the Norm-Activation Theory. For example, feelings of moral obligation to use the car less is positively correlated with intention to use and perceived personal impact of both incentives categories ($\rho > 0.3$).

Behavioural factors that determine a person's travel patterns are, indeed, associated with how they perceive incentive strategies to sustainable transport, mostly with a small or medium correlation strength.

Perhaps the most important information that can be extracted from this analysis is that the theoretical predictors of car use are negatively correlated with the acceptance of positive incentives.

4.4 Cluster analysis of travel behaviour variables

As already explained before, the data collected in this research is roughly divided into three blocks: variables related to travel behaviour, variables related to perceptions of positive incentives and sociodemographic variables. The next sections aim to identify homogeneous groups of survey participants and analyse significant differences in two different manners:

- Identification of psychographic segments of the sample and analysis of differences in incentives' preferences across the groups (addressing research question 3) (this section);
- Identification of incentives' preferences segments and analysis of differences in psychographic/sociodemographic profiles across the groups (addressing research question 4) (Section 4.5).

To analyse data in regards to RQ3, this section is structured as follows: first, the statistical technique to be used will be presented (Section 4.4.1). Next, critical alternatives regarding how the analysis parameters are set up are discussed in section 4.4.2. After these have been established, the analysis flows according to Figure 4.4.

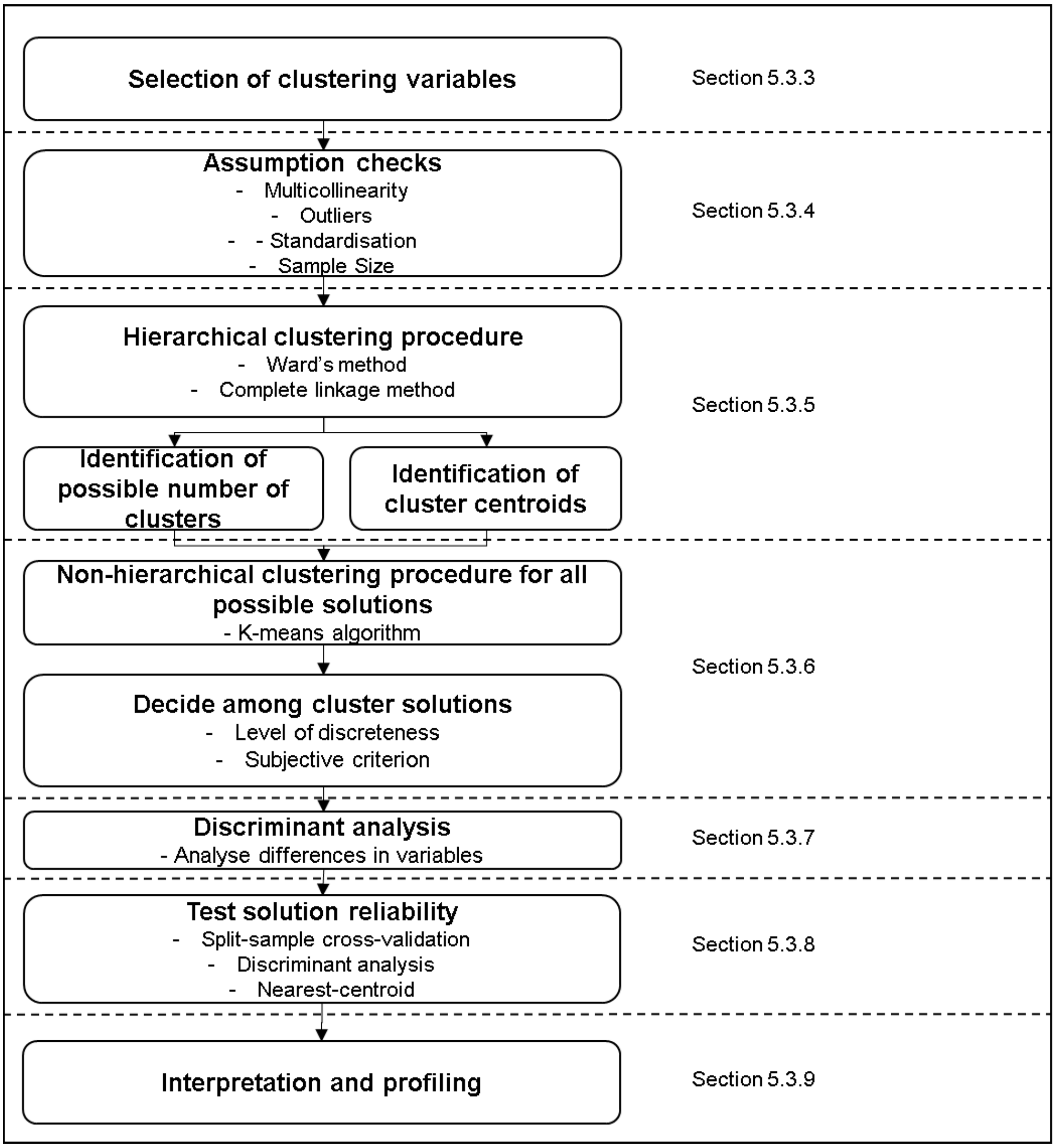

Figure 4.4 - Flow of cluster analyses (with respective sections in the text)

4.4.1 Definitions and objectives of the analysis

Cluster analysis is a technique to classify individuals into a smaller number of mutually exclusive groups, based on some sort of similarity between them. The goal is to maximise the homogeneity within groups (or clusters) while maximising the heterogeneity between them (Blaikie, 2008). This method allows the organisation of a large dataset so then it can be more easily understood and information can be retrieved more efficiently (Everitt et al., 2001). This method has been used in travel behaviour research to elaborate, for example, population target groups for the development of better-tailored policies (Anable, 2005; Mikiki and Papaioannou, 2012) or to identify relevant differences in attitudes between different groups of travellers in respect to mode choice (Molin et al., 2016).

The main objectives of a cluster analysis within the scope of this research are (based in Hair *et al.*, 2014):

- Classification of individuals: to create an empirically based classification of individuals with respect to their general transport behaviour profile (firstly) and their perceptions about positive incentives for sustainable travel (secondly);
- Data simplification: to define a structure among individuals in a simplified perspective, forming groups to be submitted to further analysis;
- Relationship identification: to be able to identify relevant differences or relationships between respondents that would otherwise not be possible with individual observations.

It is prudent to state that cluster analysis is a descriptive, non-inferential technique. The results are dependent on the variables that are used and therefore generalisation is usually not appropriate. The application of cluster analysis in this research can serve as evidence that the acceptance of positive incentives does (or does not) differentiate across different psychological profiles. Additionally, the examination of the variables that most discriminate among the groups and how they discriminate may serve as guidance to future policy development.

4.4.2 Clustering methods

Among the different methods of cluster analysis, there are hierarchical methods, non-hierarchical methods and two-step approaches. A two-step procedure is recommended when there are both categorical and continuous variables in the dataset to be segmented. At a hierarchical clustering method, the whole data set is partitioned in multiple steps, either following an *agglomerative* approach (where the initial number of clusters is equal the number of individuals and the data is progressively 'grouped') or a *divisive* approach (where a big cluster including all individuals is successively separated in smaller groups) (Everitt et al., 2001). Agglomeration methods can be performed using different algorithms and different forms that differ by how the 'distance' between individuals is calculated at each iterative step [5] (e.g. squared Euclidean distance). Nevertheless, the decision among different forms of assessing similarity is not critical (Punj and Stewart, 1983), and no one specific form can be recommended above others (Everitt et al., 2001). Finally, with respect to the algorithms used to define clusters, Ward's algorithm usually works well[6] (Everitt et al., 2001). Ward's method has been shown to outperform other methods if no significant outliers are present (Punj and Stewart, 1983).

Among non-hierarchical methods, the *K-means* algorithm is commonly used and generally performs well. It is generally less susceptible to outliers in the data and allows the reassignment of a case to a different, "more optimal", cluster during the iterative process. Hierarchical procedures, on the other hand, may lead to undesirable early combinations that may persist in the whole procedure (Hair et al., 2014).

The *K-means* algorithm requires the number of clusters to be specified *a priori*. It also needs a starting point, known as 'cluster seeds', or cluster centres (Hair et al., 2014). This can be specified in a random manner, but the *K-means* algorithm performs better and its benefits are only realised if a non-random starting point is used. (Punj and Stewart, 2012; Hair et al., 2014). The hierarchical clustering method can be used to identify structure in the data

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[5] Correlations can also be used as a 'measure of similarity', instead of distances, but distances represent the concept of proximity in the best way according to Hair et al (2014).

[6] In this approach, "the selection of which two clusters to combine is based on which combination of clusters minimizes the within-cluster sum of squares across the complete set of disjoint or separate clusters. At each step, the two clusters combined are those that minimise the increase in the total sum of squares across all variables in all clusters" (Hair et al, 2014, p. 442).

using cluster's geometrical centroids and use this information as the initial cluster centres for the *K-means* procedure (Clatworthy et al., 2005). This combination of methods, although more time consuming, enables the advantages of the hierarchical methods to be complemented by the ability of non-hierarchical techniques to refine the results by allowing the change of cluster memberships during the method (Hair et al., 2014). This research will use Ward's method first, and then the *K-means* algorithm to 'tune-up' the solution, using the cluster centres resultant from the hierarchical method as a starting point[7].

4.4.3 Selection of variables

The selection of which variables to be used to group observations has to follow theoretical, conceptual and practical considerations (Hair *et al.*, 2014). As it is the interest of this research to find groups that discriminate in a 'psychological' manner, all the psychological variables that are theoretically assumed to influence the use of (or the intention to use) each mode of transport were initially inserted. Variables that were not included in the analysis were:

- Categorical variables such as 'familiarity with apps', which were not inserted because (1) they are not metric variables (thus violating one of the method's assumption) and (2), their theoretical underpinning as a determinant of travel choices is not established in the literature[8].
- 'Intention to use each travel mode' was not included as this concept is theoretically and empirically strongly tied to the actual use of each transport mode (as can be seen in the correlational analysis in Section 4.2.7.2). Thus, only variables that predict travel behaviour with a "similar" level of influence were included.
- 'Behavioural beliefs', 'Control beliefs' and 'Normative beliefs' were not included as they can be considered reflecting virtually the same

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[7] For comparison purposes, the complete-linkage (or furthest neighbour) algorithm was also conducted to support the evaluation of the cluster solutions using two different methods. It also performs well according to Hair *et al* (2014). The cluster centres, however were extracted from the solution using Ward's method.

[8] Especially when compared to theories such as the Theory of Planned Behaviour or the Norm Activation Theory.

concepts of ‘Attitudes’, ‘Perceived behavioural control’[9] and ‘Subjective norms’ (Fishbein and Ajzen, 2010).

The variables that were not incorporated in the analysis were used posteriorly to enrich the description of the cluster’s characteristics. In some cases, they also served to establish a criterion validity of the cluster solution[10].

4.4.4 Assumption checks

This section outlines the critical issues to be assessed before conducting cluster analysis.

4.4.4.1 Outliers

An examination of outliers is crucial before performing cluster analysis, as they have the potential to distort results. An examination of multivariate outliers using the *Mahalanobis* distance showed no significant outliers across the sample. This significance test was performed dividing the distance by the number of variables (D^2/df). According to Hair *et al.* (2014), values exceeding three can be considered outliers, when having a large sample size. The higher value encountered in the whole sample was 2.94.

To build more evidence about the existence of outliers, a ‘dissimilarity value’ was calculated to each observation concerning the clustering variables (proposed by Hair et al. 2014). The idea is to evaluate any values that are relatively large compared to the others. The measure of dissimilarity is calculated by firstly subtracting the mean of each clustering variable from each respondent’s score on that same variable. Finally, the sum of the squared differences across the same respondent values is computed as the dissimilarity value. There are no values that stand out as being relatively large. Instead, the dissimilarity measure drops constantly and smoothly starting from the highest to the lowest value across the whole sample. This, along with the

[9] Measured separately as ‘capacity’ and ‘autonomy’ in this thesis.

[10] This can be done when variables that were not used to form the clusters are known to vary across the clusters (Hair *et al*, 2014). Here, intentions and actual behaviour in respect to different modes are assumed to vary across different psychographic profiles, for example.

Mahalanobis distances' calculation, gives evidence that there are no significant outliers to be excluded from the analysis.

4.4.4.2 Sample size

The issue of sample size in cluster analysis is not related to statistical inference, but rather if the sample is large enough so then small groups in the population can be represented. Some general guidelines indicate a sample of at least 500 observations to be very good, and 1000 to be excellent (Batool, 2012). Other authors state there are no strict guidelines in regard to sample size, which has to be large enough to ensure the representativeness of all different groups within the population (Hair et al., 2014). Here, a total sample of 920 is assumed to be of adequate size for cluster analysis to be performed.

4.4.4.3 Standardisation

The standardisation of variables is often critical for cluster analysis since variables with a larger dispersion (large standard deviation) have more impact on the final similarity value. Thus, in the case where variables were measured with quite different metrics, they should be standardised. However, if this is not the case, the need for standardisation is minimised (Hair et al., 2014). The variables to be used in segmentation were measured roughly with the same attitudinal scale (7 points), apart from the unique case of 'Habit', which has 6 points. Still, this 'small' variation in the scale does not implicate in substantial differences in standard deviations in comparison to other variables. In the case of constructs (a combination of variables), care was taken with regard to using an average score of the combined items instead of a sum (maintaining a 'relatively' equal standard deviation).

4.4.4.4 Multicollinearity

The composite variables that are part of this analysis have been subject to a prior factor analysis (previous chapter), where discriminant validity was assessed. This process ensures that these variables are not correlated to an extent that would pose a risk to segmentation. However, as there are variables that did not take part in this previous validation, a correlation matrix containing all selected segmentation variables was inspected. 98.9% of correlations coefficients in the matrix were lower than 0.50, which is considered an appropriate threshold for the purposes of analysing collinearity prior to cluster analysis (Sambamdam, 2003). The few cases of high correlations occur between constructs that notably have sufficient theoretical and empirical evidence from past research to show they represent distinct concepts and are not redundant (e.g. subjective norms and attitudes).

Further tests of multicollinearity (more statistically advanced) are performed in the validation stage of this analysis (discriminant analysis). Up to this point, no signs of multicollinearity were identified and the analysis can begin.

4.4.5 Hierarchical analysis (part 1)

This first part of the analysis aims to examine a range of possible cluster solutions in terms of the number of clusters and their centroids, to be used in the non-hierarchical subsequent analysis. Hierarchical clustering requires a complete dataset, thus observations with a missing value in any variable were excluded at this stage, reducing the sample to 637.

As first evidence of the number of clusters to be retained, the agglomeration schedule table can be examined. This schedule shows all the stages of agglomeration, from stage 1 (where there were 636 clusters) to stage 636 (where there is just one large single group). The agglomeration coefficients represent a measure of the increase in heterogeneity[11]. Thus, large differences in these coefficients when moving from one cluster solution to the other demonstrate that this stage is joining quite distinct clusters (Hair *et al*. 2014). When examining the bottom of Table 4.25, a large increase in heterogeneity can be seen from the two-cluster solution to the one-cluster solution (which is normally expected). Moving up on the table, there is a relatively large increase in heterogeneity from two to three clusters, from three to four and from four to five clusters (between 4% and 4.50%). This percentage drops to 2.48%

[11] This coefficient is the distance between the two closest observations of the clusters being combined (Hair et al., 2014).

between five and six clusters and remains stable onwards. This suggests that the five-cluster solution be applied as a stopping rule since further solutions increase heterogeneity in a quite ‘stable’ and ‘constant’ manner. The solution of three, four and five clusters are examined further.

Table 4.25 - Agglomeration schedule (Ward's method) for psychographic clusters (n = 637)

Stage	Cluster Combined		Coefficients	N. clusters	Coefficients Diff	% increase in heterogeneity
	Cluster 1	Cluster 2				
1	357	795	7	636	10.01	143.06%
2	156	564	17.014	635	10.25	60.24%
3	305	727	27.264	634	10.63	38.97%
4	133	636	37.889	633	11.25	29.69%
5	452	724	49.139	632	51,594.09	24.45%
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
627	12	94	51,643.23	10	1,011.39	1.96%
628	7	26	52,654.62	9	1,134.23	2.15%
629	58	85	53,788.85	8	1,270.86	2.36%
630	2	6	55,059.7	7	1,330.33	2.42%
631	5	7	56,390.03	6	1,396.78	2.48%
632	22	58	57,786.81	5	2,401.24	4.16%
633	12	53	60,188.05	4	2,678.84	4.45%
634	2	5	62,866.89	3	2,826.85	4.50%
635	12	22	65,693.74	2	7,503.23	11.42%
636	2	12	73,196.97	1	-	-

Another relevant check is to examine the generated cluster sizes. Table 4.26 shows the cluster sizes for the three different possible solutions. Cluster 5 represents only 5.7% of the sample and this has to be taken into account when examining the solutions. More specifically, this cluster has to be checked to determine if it represents a genuine portion of the population or not. This cluster has high mean values in variables assessing perceptions of motorcycle use, which can, indeed, be a significant particularity of a few people. The other cluster solutions contain substantial cluster sizes (more than 20% of the sample). Therefore, all cluster solutions remain plausible.

Table 4.26 - Cluster sizes generated by Ward's method for psychographic clusters (n = 637)

Ward's Method								
5-cluster solution			**4-cluster solution**			**3-cluster solution**		
Cluster	**Size**	**% of total**	**Cluster**	**Size**	**% of total**	**Cluster**	**Size**	**% of total**
1	132	20.7	1	132	20.7	1	355	55.7
2	223	35	2	223	35	2	130	20.4
3	94	14.8	3	130	20.4	3	152	23.9
4	152	23.9	4	152	23.9			
5	36	5.7						

A further examination to ensure the range of plausible solutions is to run an F-test (ANOVA). This test can provide evidence of the magnitude of dissimilarities across clusters in different solutions as well as the number of significant differences. The higher the F-ratio, the higher the variability within clusters for this particular solution. Table 4.27 displays these ratios. This test was conducted using also the results of the *furthest neighbour* clustering method, in an attempt to strengthen the conclusions.

Table 4.27 - F-test of clustering variables after the performance of hierarchical methods (n = 637)

Clustering variables	**Ward's Method**			**Furthest Neighbour Method**		
	5 cluster	**4 clusters**	**3 clusters**	**5 cluster**	**4 clusters**	**3 clusters**
	F	**F**	**F**	**F**	**F**	**F**
ATT_CAR	26.41***	24.81***	34.47***	29.52***	39.36***	48.49***
ATT_BUS	6.41***	2.84*	1.43	9.59***	8.39***	4.88**
ATT_BIK	31.38***	41.07***	59.22***	14.19***	18.63***	25.35***
ATT_MOT	23.42***	12.2***	17.19***	27.68***	32.9***	47.65***
ATT_WAL	24.64***	32.83***	41.08***	44.08***	51.31***	68.24***
EXP_CAR	12.46***	16.51***	8.8***	11.09***	13.2***	15.84***
EXP_BUS	5.45***	6.69***	0.06	3.18*	4.24**	2.12
EXP_BIK	21.35***	22.33***	31.19***	12.04***	15.84***	23.68***
EXP_MOT	60.1***	20.5***	29.48***	91.15***	112.82***	161.14***
EXP_WAL	15.65***	20.67***	20.33***	21.53***	27.89***	39.74***
SNORM_CAR	19.37***	25.07***	23.72***	17.76***	23.71***	34.86***

Clustering variables	Ward's Method			Furthest Neighbour Method		
	5 cluster	4 clusters	3 clusters	5 cluster	4 clusters	3 clusters
	F	F	F	F	F	F
SNORM_BUS	6.17***	6.51***	2.12	8.05***	6.62***	3.36*
SNORM_BIK	34.48***	40.97***	50.88***	30.55***	36.79***	55.2***
SNORM_MOT	41.93***	13.68***	18.04***	42.78***	54.51***	81.5***
SNORM_WAL	28.6***	38.06***	45.66***	66.42***	88.7***	102.57***
PNORM_CARS	9.73***	11.86***	13.12***	15.41***	19.91***	28.81***
AWC_CARS	1.74	2.07	0.41	4.68***	5.46***	7.14***
RESP_CARS	0.65	0.51	0.59	5.11***	4.57**	5.88**
ABIRED_CARS	3.25*	4.16**	3.45*	13.96***	14.87***	21.41***
HAB_CAR	31.11***	32.72***	31.15***	24.41***	32.46***	48.53***
HAB_BUS	16.26***	21.55***	13.45***	12.37***	16.52***	24.61***
HAB_BIK	7.54***	9.99***	14.58***	2.72*	3.63*	1.47
HAB_MOT	7.78***	8.15***	4.59**	10.96***	14.13***	18.92***
HAB_WAL	101.21***	19.61***	29.34***	54.04***	72.02***	108.19***
CAPAC_CAR	82.33***	108.44***	13.35***	47.98***	56.51***	73.78***
CAPAC_BUS	9.55***	7.39***	2.97	16.73***	5.89***	0.49
CAPAC_BIK	72.65***	89.54***	128.18***	7.98***	8.88***	12.84***
CAPAC_MOT	131.5***	25.11***	35.97***	94.19***	113.49***	170.3***
CAPAC_WAL	102.94***	136.48***	204.35***	62.93***	83.85***	87.96***
AUTO_CAR	30.48***	40.68***	1.17	45.25***	27.06***	26.49***
AUTO_BUS	11.34***	15.1***	22.04***	38.95***	4.21**	6.31**
AUTO_BIK	101.08***	129.38***	188.33***	20.15***	9.5***	12.51***
AUTO_MOT	92.8***	78.5***	117.89***	78.4***	100.05***	147.44***
AUTO_WAL	273.46***	302.42***	454.22***	44.65***	43.93***	52.63***
Sum of F	**1445.19**	**1368.41**	**1662.78**	**1030.47**	**1171.83**	**1570.31**
N. of non-significant	**2**	**2**	**7**	**0**	**0**	**3**

*: p < 0.05;
**: p < 0.01;
***: p < 0.001.

The sum of the F-ratios is higher for the three-cluster solution for both methods. However, the number of non-significant variables increase substantially in this option. This suggests that the three-cluster solution is more heterogeneous but this disparity is based on fewer variables. The solutions of four and five clusters, despite having a little less total variability, discriminate groups using more psychological aspects.

Although the solutions of four and five clusters appear to be relatively better, especially considering that a solution with a higher number of groups might have more practical significance to represent more meaningful groups, the three distinct solutions will still be examined further using a non-hierarchical analysis.

4.4.6 Non-hierarchical analysis (part 2)

The cluster centroids determined by Ward's method of hierarchical clustering were used as a starting point for the performance of the *K-means* algorithm. The whole sample was used in this analysis as *K-means* allows the use of *pairwise* exclusion of cases (n = 920). The outputs of these analyses were subject to two examinations: the level of distinctiveness between segments using F-tests, and a subjective criterion using the profile of the generated clusters, in search of an interpretation that is relevant to the objectives of this thesis. Table 4.28 shows the results of an F-test across clustering variables after the *K-means* clustering algorithm. In fact, the algorithm appears to have improved the initial solutions given by the hierarchical methods, as the sum of F-ratios is substantially higher. Still, the three-cluster solution shows the higher variability, although clusters did not discriminate in terms of 'attitudes to using the bus', while the other two solutions did.

Table 4.28 - F-test of clustering variables after the performance of K-means algorithm (n = 920)

Clustering variables	5 clusters	4 clusters	3 clusters
	F	F	F
ATT_CAR	30.583***	41.308***	53.022***
ATT_BUS	8.096***	6.331***	2.228
ATT_BIK	62.873***	68.2***	62.443***
ATT_MOT	49.098***	16.282***	14.018***
ATT_WAL	170.81***	100.79***	69.21***
EXP_CAR	23.854***	31.22***	37.566***
EXP_BUS	9.914***	12.498***	22.507***
EXP_BIK	43.444***	62.683***	81.666***

Clustering variables	5 clusters	4 clusters	3 clusters
	F	F	F
EXP_MOT	120.211***	24.271***	17.186***
EXP_WAL	35.128***	31.854***	53.757***
SNORM_CAR	26.936***	36.211***	54.204***
SNORM_BUS	6.003***	8.589***	8.11***
SNORM_BIK	80.698***	102.308***	125.275***
SNORM_MOT	75.684***	22.634***	19.528***
SNORM_WAL	148.733***	124.612***	136.976***
PNORM_CARS	8.37***	11.774***	14.509***
AWC_CARS	2.172	0.472	0.256
RESP_CARS	2.231	2.528	2.433
ABIRED_CARS	5.286***	5.064**	4.408*
HAB_CAR	36.45***	47.459***	85.824***
HAB_BUS	21.488***	23.741***	37.016***
HAB_BIK	12.724***	8.077***	12.68***
HAB_MOT	9.688***	6.12***	11.68***
HAB_WAL	61.076***	5.944***	3.829*
CAPAC_CAR	128.171***	215.094***	286.351***
CAPAC_BUS	14.816***	27.588***	16.169***
CAPAC_BIK	132.518***	104.134***	149.221***
CAPAC_MOT	153.574***	17.26***	10.288***
CAPAC_WAL	115.347***	169.915***	302.024***
AUTO_CAR	123.995***	191.701***	325.587***
AUTO_BUS	34.49***	94.585***	50.175***
AUTO_BIK	154.811***	167.572***	189.187***
AUTO_MOT	112.016***	27.204***	28.474***
AUTO_WAL	96.923***	216.299***	302.927***
N. of non-significant	**2**	**2**	**3**
Sum of F	**2118.211**	**2032.322**	**2590.734**

*: $p < 0.05$;
**: $p < 0.01$;
***: $p < 0.001$.

As none of the solutions considered so far can be disregarded with strong statistical justification, an initial profile of the clusters was examined to check for meaningfulness and interpretability. As Hair *et al* (2014) explain, even though there are statistical methods to evaluate possible cluster solutions, it still falls to the researcher to decide about the number of clusters to be retained.

A careful examination of the three different solutions was undertaken. Mean values of all clustering variables were explored and judgements were made in respect to their differences across clusters. Substantive differences resulting from the four-cluster and five-cluster solutions did not show up on the three-cluster solution, resulting in a significant loss of information in this case. For example, the three clusters were divided into people displaying high scores on car use determinants, people more prone to the use of non-motorised forms of transport and people with low control and attitudes to all travel modes, except having higher control over bus use. The four-cluster solution adds a group that is generally more prone to the use of the motorbike and the bicycle, together. The five-cluster solution appeared to be a more meaningful grouping. Specifically and yet generally, this solution isolated a cluster which represented people having positive perceptions of the motorbike only. The motorbike is a travel mode that represents more than 21% of total trips in Brazil (IPEA, 2016) and assessing the characteristics of a group that is more 'psychologically-inclined' to use this type of mode is worth it. It was assumed, therefore, that the five-cluster solution would generate more significant results for the purpose of this research.

4.4.7 Discriminant analysis

Before moving to a final validation and interpretation of the clusters, multiple discriminant analysis[12] was performed, mainly for three reasons: (1) to determine if the variables used to find the clusters perform well in being able to assign people to different segments, (2) the relative contribution of each variable in this assignment process and (3), to build evidence in respect to the reliability of the cluster solution. Firstly, the first two objectives are presented. Next, the reliability check is demonstrated.

[12] The correct term when more than two dependent variables are involved.

4.4.7.1 Estimating discriminant functions and assessing the discriminatory power

Discriminant analysis works by deriving discriminant functions used to predict the membership of a particular case (in this case, a survey participant) to a certain category (in this case, the identified psychographic segments). The method always calculates 'NS -1 'functions, where 'NS' is the number of segments (Hair et al., 2014).

In this analysis, all the clustering variables were entered simultaneously in the procedure, as there was no *a priori* knowledge about their discriminatory weights[13]. As the method uses *listwise* deletion of missing values, they were imputed using *mean-substitution* to avoid a significant loss of cases[14]. AWC_CARS (awareness of consequences of car use) and RESP_CARS (perceived responsibility in the problems derived from car use) did not discriminate significantly. This was somehow expected, as these variables did not show significant mean differences across groups after cluster analysis either. Thus, groups cannot be interpreted concerning these indicators.

Initially, the overall significance of the discriminatory model was assessed through Wilk's Lambda statistic (Hair et al., 2014). Results show the model is statistically significant ($\lambda < 0.001$). Secondly, to identify the relative contributions of each variable to the derivation of each discriminant function (and thus assessing their 'discriminatory power'), discriminant loadings can be inspected[15]. These values can be interpreted just like factor loadings in factor analysis. Table 4.29 displays these loadings alongside a measure of overall discriminant power called Potency index, which is useful when more than two functions are computed. The potency index is calculated as a relative measure considering the variable's loadings and the contribution of each function to the overall solution (Hair et al., 2014).

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[13] When this is not the case, a *stepwise* method is preferable (Hair et al., 2014).

[14] This method of imputation was demonstrated to be best form of treating missing values in discriminant analysis (Chan and Dunn, 1972).

[15] These are linear correlations between each independent variable and the discriminant functions (Hair et al., 2014).

Table 4.29 - Discriminant loadings and potency index of each psychographic variables (n = 920)

Clustering variables	Discriminant functions				Potency index (in descending order)
	1 [1]	2	3	4	
ATT_WAL	**0.376**	0.371	-0.092	-0.52	0.150
AUTO_BIK	**0.409**	-0.178	0.327	0.43	0.133
SNORM_WAL	**0.446**	0.228	-0.026	-0.398	0.126
CAPAC_MOT	0.17	**-0.545**	-0.257	-0.132	0.111
CAPAC_BIK	**0.403**	-0.031	0.319	0.362	0.111
CAPAC_CAR	-0.161	-0.121	**0.58**	-0.378	0.109
AUTO_CAR	-0.069	-0.248	**0.578**	-0.289	0.101
EXP_MOT	0.205	**-0.448**	-0.273	-0.171	0.094
CAPAC_WAL	**0.448**	0.152	0.096	-0.063	0.090
AUTO_MOT	0.20	**-0.496**	-0.047	-0.042	0.085
AUTO_WAL	**0.405**	-0.014	0.19	0.131	0.076
SNORM_BIK	**0.39**	0.055	0.045	-0.06	0.063
SNORM_MOT	0.189	**-0.356**	-0.2	-0.037	0.058
ATT_BIK	**0.305**	0.182	0.072	-0.089	0.049
HAB_WAL	0.082	**-0.355**	-0.175	-0.112	0.047
ATT_MOT	0.166	**-0.281**	-0.158	0.04	0.038
EXP_BIK	**0.285**	0.016	0.008	0.096	0.034
HAB_CAR	**-0.212**	-0.05	0.191	-0.143	0.030
AUTO_BUS	0.036	-0.142	**0.313**	0.105	0.028
EXP_WAL	**0.205**	0.19	-0.037	-0.025	0.027
EXP_CAR	-0.051	-0.063	0.166	**-0.3**	0.025
ATT_CAR	**-0.226**	0.001	0.103	0.1	0.025
SNORM_CAR	**-0.184**	-0.079	0.159	-0.083	0.022
HAB_BUS	0.069	0.144	-**0.183**	0.138	0.018
CAPAC_BUS	-0.083	0.081	-0.028	**0.236**	0.016
HAB_BIK	0.124	0.006	0.056	**0.162**	0.012
EXP_BUS	0.024	0.056	-0.132	**0.163**	0.010
HAB_MOT	0.071	**0.131**	-0.056	-0.001	0.007
ATT_BUS	-0.061	0.104	-0.012	**0.116**	0.007
PNORM_CARS	**0.121**	0.024	-0.034	0.057	0.007
SNORM_BUS	-0.001	0.039	-0.093	**0.144**	0.006
ABIRED_CARS	0.064	**0.087**	0.032	-0.036	0.004
RESP_CARS	-0.007	-0.007	0.062	**-0.089**	0.002
AWC_CARS	-0.01	**0.066**	0.03	-0.041	0.002

[1] Discriminant loadings. Values that are highlighted represent the highest absolute loading of a given variable.

The most relevant variables concerning their overall ‘power’ to form groups are, in general, relative to people’s *perception of control* over some forms of transport, particularly the non-motorised ones. Additionally, attitudes and norms with respect to walking appear to be strongly associated with how the groups were determined by cluster analysis. On the other hand, indicators belonging to the Norm-activation theory such as PNORM_CARS, ABIRED_CARS, RESP_CARS and AWC_CARS do not seem to influence the formation of clusters overall. A hypothesis is that all the population segments equally value these components.

To demonstrate the results in a graphical perspective, the group centroids for the first two discriminant functions are displayed in Figure 4.5.

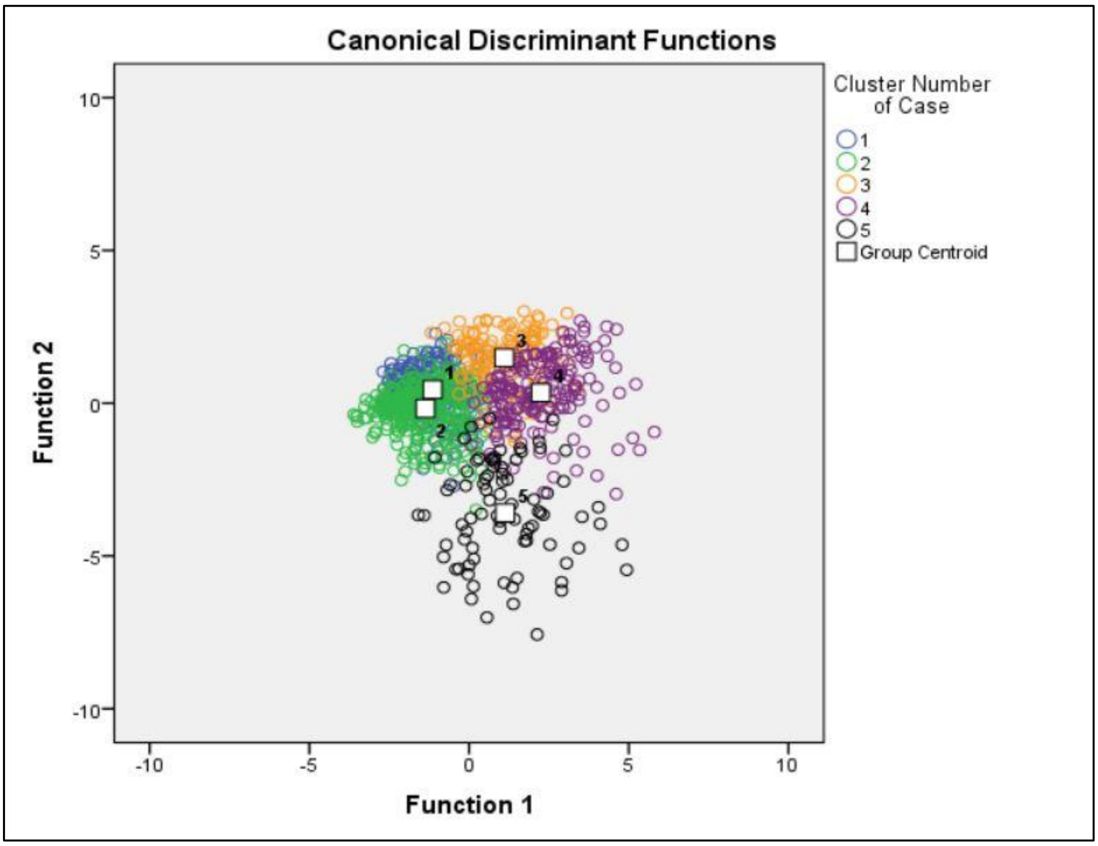

Figure 4.5 - Representation of clusters according to the first two discriminant functions

As can be seen in the graphical representation above, Cluster 5 seems to differentiate mostly from the other four groups with respect to Function 2 (where variables about the perception of the motorcycle load relatively higher). Whereas cluster 1 and 2 appear to distinguish from clusters 3 and 4 by means of function 2 (where variables regarding perceptions of non-motorised forms of transport load higher). In fact, mainly people with positive perceptions of a motorcycle are represented in cluster 5. The proximity of the centroids of cluster 1 and 2 indicate that these clusters do not discriminate much in respect to both of these functions. Cluster 1 is defined mostly by people having relatively higher perceptions about bus use while cluster 2 represents the more 'car-dependent' people (as will be seen later in the profiling section of this chapter). The discrimination between both of these groups probably comes by means of functions 3 and 4 (where variables concerning both of these modes of transport load highly).

4.4.8 Cluster solution cross-validation

As a final step before moving to the interpretation of these groups, however, this solution still needs to be validated through the test of its reliability (or stability). This validation serves as an indication that the solution is generalizable and stable over time (Hair *et al.*, 2014). This is an essential part of the analysis as cluster analysis always creates clusters, regardless of the actual existence of groups across the studied sample. A common way of assessing this is conducting a discriminant analysis (as done previously) in a random part of the sample (usually 70% or 65% of cases), and then using functions derived from this analysis to classify the remaining individuals that were excluded from the initial examination (holdout sample) (Punj and Stewart, 1983)[16]. After classifying, the predicted group for each case is compared with the segmentation solution of the cluster analysis. Table 4.30 shows the classification matrix (where the diagonal represents the percentage of cases correctly classified for each cluster).

Hair *et al.* (2014) establish that the percentage of corrected classified cases overall should be 25% higher than if cases were grouped by chance. As there are five different clusters, the correct classification is expected to occur by chance in around 20% of cases. Thus, a correct ratio of at least 25% (1.25x20)

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[16] The function used to do this classification is the Fisher's classification function (Hair et al., 2014).

is expected. The solution demonstrated to be reliable as 88.5% of cases were assigned correctly by the classification function.

Table 4.30 - Classification matrix for psychographic clusters using discriminant analysis (n = 270)

	Clusters from K-means				
Predicted cluster from classification function	**1**	**2**	**3**	**4**	**5**
1	**92.5%**	0.0%	1.9%	0.0%	5.7%
2	7.1%	**88.9%**	2.0%	0.0%	2.0%
3	5.4%	0.0%	**81.1%**	10.8%	2.7%
4	1.8%	0.0%	0.0%	**92.7%**	5.5%
5	0.0%	3.8%	3.8%	11.5%	**80.8%**
Cases correctly classified: 88.5%					

In addition, Cohen's kappa coefficient (Cohen, 1960) was calculated to evaluate the agreement between the two sources of classification[17]. The result indicated almost perfect agreement between both classifications ($\kappa = 0.857$), using the thresholds established by Cohen (1960).

Using only discriminant analysis to test reliability was indicated to have some drawbacks, as discriminant coefficients may be poor estimates of population values (Punj and Stewart, 1983). Thus, to strengthen the evidence of reliability, an alternative test was conducted.

4.4.8.1 An alternative approach of validation: the nearest-centroid reliability test

In this test, cluster analysis was performed in a random half-split of the sample. The final cluster centroids were extracted and each participant of the second (holdout) sample was assigned to a particular cluster based on the smallest Euclidean distance to each one of these firstly generated cluster centroids. K-means was then performed in the second sample and the cluster memberships were compared among all the cases. This method of cross-validation was

[17] The kappa coefficient measures the degree of a non-random agreement between measurements for the same nominal-level variable. Its values can range from 0.0 (disagreement) to 1.0 (perfect agreement) (Simpson, 2015).

created by McIntyre and Blashfield (1980) and later recommended by Hair *et al.* (2014) and Punj and Stewart (2014). It represents good evidence that the cluster solution is reliable and has external validity. Table 4.31 shows the resulting classification matrix.

Table 4.31 - Classification matrix for psychographic clusters using nearest-centroid (n = 270)

	Clusters from K-means				
Predicted cluster	**1**	**2**	**3**	**4**	**5**
1	**78.4%**	8.0%	8.0%	2.3%	3.4%
2	7.1%	**81.9%**	3.9%	0.0%	7.1%
3	16.7%	1.9%	**79.6%**	1.9%	0.0%
4	0.8%	3.3%	19.5%	**68.3%**	8.1%
5	5.0%	0.0%	2.5%	5.0%	**87.5%**
Cases correctly classified: 77.8%					

Cohen’s kappa coefficient (Cohen, 1960) was calculated again, and the result indicated substantial agreement between both classifications ($\kappa = 0.714$).

With the 5-cluster solution adequately tested for its internal consistency and external validity, the interpretation and profiling of the cluster can be performed.

4.4.9 Interpretation and profiling

A cluster solution, even after being tested for reliability and statistical significance, is useless without an interpretation that is meaningful to the research objectives. Here, the goal is to contribute to the understanding of the key psychological differences across the population under study and, more importantly, to assess how these dissimilarities translate into how they perceive a range of incentives for sustainable mobility.

This section is organised as follows:

– Firstly, a summary of each group’s profile is presented using variables that were used to discriminate clusters and other variables that were not part of the analysis. These previously not included data may help to visualise relevant differences among the clusters, especially regarding sociodemographic and additional travel behaviour characteristics.

– Secondly, differences in terms of acceptance of incentives are explored, both considering incentives individually and overall.

A careful comparison of the clusters was performed to identify their unique psychological characteristics when compared to others. This was done examining mean differences and the results of the discriminant analysis described earlier (which provided information about what variables contribute more to differentiate the groups[18]).

A label was assigned to each cluster to facilitate future references. The labels were created taken the most significant and unique attributes of a given cluster in consideration. However, care should be taken when interpreting clusters considering only these labels, as they represent a strong 'simplification' of a rather more complex profile. Figure 4.6 presents these labels and the percentage size of each segment.

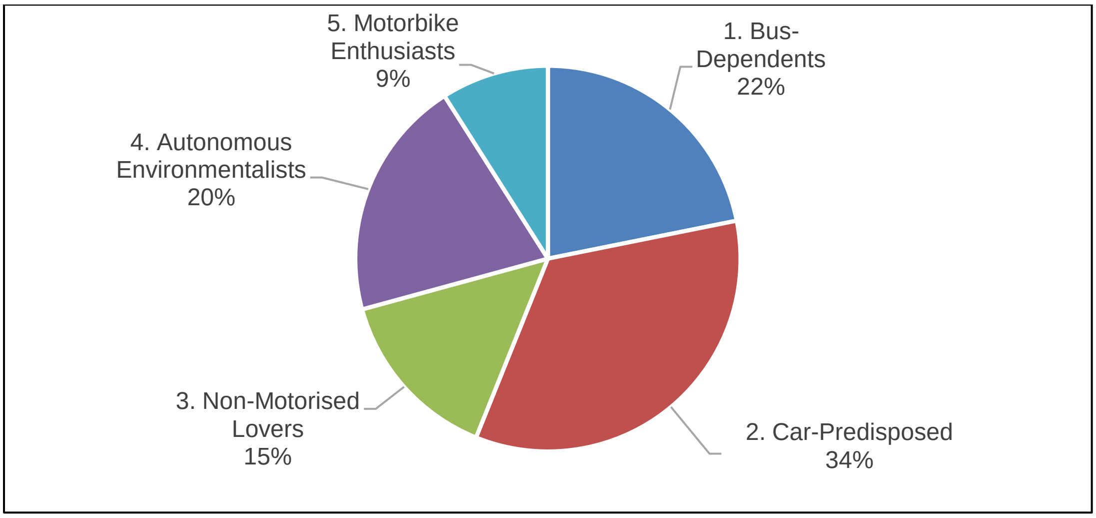

Figure 4.6 - Psychographic clusters names and sizes (n = 920)

To understand the origin of these labels, mean-centred scores of each cluster with respect to the clustering variables are presented in Table 4.32[19]. The interpretation of these values has to be done in relative terms only as they do

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[18] Throughout this section 'cluster', 'segment' and 'group' are terms that refer to the same concept and will be used interchangeably.

[19] Considering the variable mean across the whole sample.

not represent absolute scores on the variables. Thus, the profiling of the clusters took the absolute scores into consideration as well.

Table 4.32 - Mean-centred scores of clustering variables for psychographic clusters (n = 920)

Variable	Bus Dep.[1]	Car Pred.	N-Mot. Lov.	Aut. Env.	M'Bike Enth.	F [2]
ABIRED_CARS	-0.24 ^{34}	-0.14 ^{3}	0.37 ^{125}	0.28 ^{15}	-0.52 ^{34}	5.415***
ATT_BIK	-0.82 ^{34}	-0.63 ^{34}	1.24 ^{125}	1.34 ^{125}	-0.65 ^{34}	62.873***
ATT_BUS	0.36 ^{35}	0.02 ^{5}	-0.1 ^{15}	-0.03 ^{5}	-0.75 ^{1234}	8.096***
ATT_CAR	0.27 ^{345}	0.45 ^{345}	-0.6 ^{12}	-0.4 ^{12}	-0.5 ^{12}	30.583***
ATT_MOT	-0.15 ^{25}	-0.7 ^{145}	-0.26 ^{5}	0.34 ^{25}	2.68 ^{1234}	49.098***
ATT_WAL	-1.08 ^{34}	-0.79 ^{34}	2.94 ^{1245}	0.79 ^{1235}	-0.98 ^{34}	170.81***
AUTO_BIK	-1.07 ^{45}	-0.68 ^{345}	-1.42 ^{245}	2.86 ^{1235}	1.13 ^{1234}	153.746***
AUTO_BUS	-0.92 ^{245}	0.56 ^{13}	-1.4 ^{245}	0.88 ^{13}	0.4 ^{13}	34.419***
AUTO_CAR	-2.18 ^{2345}	1.68 ^{1345}	-1.24 ^{1245}	0.13 ^{123}	0.7 ^{123}	123.858***
AUTO_MOT	-0.7 ^{245}	-0.29 ^{145}	-0.64 ^{45}	0.39 ^{1235}	3.52 ^{1234}	108.558***
AUTO_WAL	-1.31 ^{345}	-0.91 ^{345}	0.11 ^{124}	2.63 ^{1235}	0.58 ^{124}	96.249***
AWC_CARS	-0.05	0.06	0.14	-0.01	-0.34	2.172
CAPAC_BIK	-0.9 ^{45}	-0.61 ^{4}	-0.73 ^{45}	2.53 ^{1235}	0.14 ^{134}	131.463***
CAPAC_BUS	0.78 ^{2345}	-0.03 ^{15}	-0.54 ^{1}	0 ^{15}	-0.92 ^{124}	14.593***
CAPAC_CAR	-2.03 ^{2345}	1.96 ^{1345}	-0.83 ^{12}	-0.36 ^{12}	-0.4 ^{12}	128.186***
CAPAC_MOT	-0.28 ^{5}	-0.4 ^{5}	-0.21 ^{5}	-0.15 ^{5}	3.33 ^{1234}	146.276***
CAPAC_WAL	-1.19 ^{345}	-1 ^{345}	1.36 ^{125}	2.12 ^{125}	-0.2 ^{1234}	113.959***
EXP_BIK	-0.44 ^{345}	-0.77 ^{345}	0.36 ^{124}	1.35 ^{1235}	0.39 ^{124}	43.444***
EXP_BUS	0.46 ^{235}	-0.33 ^{14}	0.01 ^{1}	0.11 ^{2}	-0.15 ^{1}	9.914***
EXP_CAR	-0.72 ^{235}	0.53 ^{14}	0.17 ^{14}	-0.33 ^{23}	0.19 ^{1}	23.854***
EXP_MOT	-0.38 ^{5}	-0.64 ^{345}	0.12 ^{25}	-0.12 ^{25}	3.34 ^{1234}	114.671***
EXP_WAL	-0.23 ^{34}	-0.63 ^{34}	1.07 ^{125}	0.87 ^{125}	-0.8 ^{34}	35.467***
HAB_BIK	-0.05 ^{4}	-0.16 ^{4}	-0.13 ^{4}	0.42 ^{1235}	-0.01 ^{4}	12.724***
HAB_BUS	0.31 ^{25}	-0.3 ^{134}	0.25 ^{25}	0.13 ^{25}	-0.28 ^{134}	21.488***
HAB_CAR	-0.23 ^{2}	0.76 ^{1345}	-0.43 ^{2}	-0.61 ^{2}	-0.29 ^{2}	36.45***
HAB_MOT	0.05 ^{5}	-0.2 ^{34}	0.38 ^{25}	0.17 ^{25}	-0.38 ^{134}	9.688***
HAB_WAL	-0.08 ^{5}	-0.11 ^{5}	-0.06 ^{5}	-0.11 ^{5}	0.96 ^{1234}	61.076***
PNORM_CARS	-0.06 ^{4}	-0.4 ^{34}	0.24 ^{2}	0.54 ^{12}	0.11	8.37***
RESP_CARS	-0.23	0.13	0.07	-0.05	-0.06	2.12
SNORM_BIK	-0.94 ^{345}	-0.84 ^{345}	0.95 ^{12}	1.5 ^{125}	0.39 ^{124}	80.698***
SNORM_BUS	0.43 ^{235}	-0.23 ^{1}	-0.09 ^{1}	0.06	-0.17 ^{1}	6.003***
SNORM_CAR	-0.14 ^{2}	0.54 ^{1345}	-0.45 ^{2}	-0.44 ^{2}	-0.07 ^{2}	26.936***
SNORM_MOT	-0.23 ^{5}	-0.54 ^{345}	-0.1 ^{25}	0.13 ^{25}	2.47 ^{1234}	75.684***
SNORM_WAL	-1.29 ^{2345}	-0.91 ^{1345}	2.37 ^{1245}	1.27 ^{1235}	-0.2 ^{1234}	148.733***

Notes: the neutral point is displayed as a white cell and represent the value of zero. Positive values are formatted using a gradient green colour and negative values are formatted as a gradient of red.

Superscript values represent groups with which the cluster differ significantly ($p < 0.05$) (ANOVA post-hoc Tukey's test if equal variances and Lamhane's test if not).
[1] Cluster labels were shortened for better visualisation.
[2] F-value resultant from ANOVA test (*** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$)).

The *'Bus-Dependents'* group shows relatively low scores on autonomy to use all travel modes. Perceived capacity to use modes apart from the bus is also evident. They have more experience with the bus than other groups as well as perceived norms to use this type of transportation, which means they generally perceive other people to be bus users. Their attitudes to using the bus and to the car are relatively high, despite this is the group with the lowest relative perceived capacity and autonomy to use a car as a mean of transport.

People pertaining to the *'Car-Predisposed'* group perform greater than average on all behavioural predictors of car use. They have much better-than-average feelings of autonomy and capacity to use the car, despite they also feel relatively autonomous to use the bus. This indicates that they probably could use the bus if they really wanted to. Using the car is more habitual for them and they think other people think they should use the car.

The '*Non-Motorised Lovers'* group shows very low relative scores of capacity to use any transport mode other than walking. They also have more experience when it comes to commuting on foot. They have more positive attitudes and perceived social pressure to the use of non-motorised forms of transport, although riding a bicycle is just as unusual for them as for the *Car-Predisposed* group. They are more aware of their ability to help reduce the bad effects of car use and have higher feelings of moral obligation to avoid car use when compared to the '*Car-Predisposed*'. Surprisingly, their score on perceived autonomy to walk is just average, significantly lower than the '*Autonomous Environmentalists',* for example. This could indicate that, although they feel capable of walking to campus, this choice is not made entirely based on their will, but is also constrained by external factors (e.g. not having access to any other form of transport).

The fourth group, the '*Autonomous Environmentalists'*, show relatively high scores on 'moral obligation to reduce car use' (compared to the '*Car-Predisposed*' and the '*Bus-Dependents*' groups). They have more positive attitudes to and previous experience with non-motorised forms of transport overall. When it comes to having control over travel modes, they have a very high perceived capacity and autonomy to walk and cycle. They differentiate themselves to the '*Non-Motorised Lovers*' in the sense that they feel they have the autonomy to pick other transport modes such as the car, the bus or the motorcycle. Cycling is more habitual for them than to any other cluster. They also feel that important others think they should use non-motorised forms of transport.

Finally, the '*Motorbike Enthusiasts'* is perhaps the group with the clearest profile. They present clear patterns of preference to use the motorbike. Attitudes, norms, habit, past experience and perceived control regarding the motorcycle are all significantly higher among them. They have significantly more negative attitudes to use the bus when compared to every other group. They also have more negative attitudes to the car when compared to the first two groups and more negative attitudes to cycling and walking if compared to the third and fourth groups (those that are more prone to non-motorised transportation). Overall, they have lower than average attitudes to all travel modes other than the motorbike. Feelings of autonomy are generally higher for all the modes. Curiously, they display a relatively high perceived capacity to cycle as well. When it comes to habit, however, walking is actually more habitual for them. This can indicate that they view the motorbike as a mean to go to the university, but not necessarily to perform other activities related to leisure or shopping. Social norms are positively inclined towards using the motorcycle and the bike. In general, therefore, this group demonstrates to have some positive scores on behavioural determinants related to other modes (particularly social norms and autonomy to cycle), but they appear to not like the idea as much as other groups.

4.4.9.1 Sociodemographic differences

Apart from looking at the variables used to form the clusters, the groups were also compared with respect to general sociodemographic variables (Table 4.33). When variables were categorical, the test used to evaluate the significance of differences was the Chi-Square test (χ^2). In this test, the observed frequencies of responses are compared to an expected frequency. Large differences between these two implicate in a large Chi-square value, which in turn, is more likely to represent a significant divergence.

Table 4.33 - Sociodemographic characteristics of psychographic clusters (n = 920)

Variable (mean)	(1) Bus Dep.	(2) Car Pred.	(3) N-Mot. Lov.	(4) Aut. Env.	(5) M'Bike Enth.	F
Age (years)	21.33$^{3\ 5}$	21.65^{5}	23.21^{1}	22.25^{5}	24.72$^{1\ 2\ 4}$	8.56***
Household Size (persons)	3.40	3.44^{3}	2.96^{2}	3.43	3.19	3.68**
Commuting distance (km)	14.34^{4}	12.1^{4}	11.66^{4}	7.91$^{1\ 2\ 3\ 5}$	14.68^{4}	11.10***
Variable (count)	**(1) Bus Dep.**	**(2) Car Pred.**	**(3) N-Mot. Lov.**	**(4) Aut. Env.**	**(5) M'Bike Enth.**	**X^2 [1]**
Male	89 (18.2%)[2]	143 (29.2%)	65 (13.3%)	135 (27.6%)	57 (11.7%)	63.97***
Female	108 (26%)	166 (40%)	70 (16.9%)	48 (11.6%)	23 (5.5%)	
MWs[3] <= 3	59 (34.7%)[4]	27 (11.3%)	33 (28.7%)	52 (32.7%)	16 (21.6%)	68.70***
3 < MWs <= 9	83 (48.8%)	113 (47.1%)	55 (47.8%)	77 (48.4%)	47 (63.5%)	
9 < MWs	28 (16.5%)	100 (41.7%)	27 (23.5%)	30 (18.9%)	11 (14.9%)	

Superscript values represent groups with which the cluster differ significantly (p < 0.05) (ANOVA *post-hoc* Tukey's test if equal variances and Lamhane's test if not).
[1]Chi-square test values (*** (p <0.001), ** (p < 0.01), * (p < 0.05)).
[2]Here, percentages are shown in relation to the total amount of people corresponding to the sociodemographic indicator and not to the total cluster size. In this case, 18.2% of men.
[3] MW = Minimum monthly wage.
[4] Here, percentages are relative to the cluster total size.

The groups displayed significant differences on all indicators. Particularly, the *Motorbike Enthusiasts* are significantly older and the *Autonomous Environmentalists* do live significantly closer to the university. When it comes to gender, a higher amount of women belong to the *Bus-Dependents* and *Car-Predisposed* clusters, while significantly more men belong to the *Autonomous Environmentalists* and *Motorbike Enthusiasts*. People earning more than nine times the Brazilian national minimum monthly wage represent a higher percentage of the *Car-Predisposed* group, while the *Bus-Dependents* and the clusters more inclined to non-motorised forms of transport have a higher concentration of poorer people.

4.4.9.2 Differences on intentions and actual use of transport modes

Another fruitful examination is to explore differences in actual travel behaviour in terms of frequency of use of each travel mode and intentions across the groups. This also serves as an indicator of the predictive validity of the cluster solution[20], since it is expected that clusters showing a higher predisposition to the use of a certain travel mode do show significantly higher intentions and use of this same mode. Nevertheless, as the goal was to find clusters that differ psychologically, the composition of the clusters is not expected to be limited to *users* of one particular mode of transport. Table 4.34 presents these indicators.

Table 4.34 - Behaviour and intention to use travel modes of psychographic clusters (n = 920)

Variable	Bus Dep.	Car Pred.	N-Mot. Lov.	Aut. Env.	M'Bike Enth.	F
BEH_CAR	1.01 $^{2\,3}$	**3.44** $^{1\,3\,4\,5}$	1.67 $^{1\,2}$	1.42 ^{2}	1.63 ^{2}	62.679***
BEH_BUS	**3.62** $^{2\,3\,4\,5}$	1.37 $^{1\,3}$	2.05 $^{1\,2}$	1.9 ^{1}	1.36 ^{1}	40.219***
BEH_BIK	0.13 ^{4}	0.06 ^{4}	0.16 ^{4}	**0.77** $^{1\,2\,3}$	0.3	16.431***
BEH_MOT	0.03 ^{5}	0.01 ^{5}	0.06 ^{5}	0.05 ^{5}	**1.37** $^{1\,2\,3\,4}$	75.335***
BEH_WAL	0.21 $^{3\,4}$	0.11 $^{3\,4}$	**1.47** $^{1\,2\,5}$	**1.26** $^{1\,2\,5}$	0.23 $^{3\,4}$	35.613***
INT_CAR	1.29 ^{2}	**3.48** $^{1\,3\,4\,5}$	1.62 ^{2}	1.51 ^{2}	1.79 ^{2}	53.893***
INT_BUS	**3.61** $^{2\,3\,4\,5}$	**1.31** $^{1\,3\,4}$	**2.19** $^{1\,2\,5}$	1.91 $^{1\,2}$	1.19 $^{1\,3}$	41.153***
INT_BIK	0.33 ^{4}	0.2 ^{4}	0.29 ^{4}	**1.21** $^{1\,2\,3\,5}$	0.31 ^{4}	20.492***
INT_MOT	0.07 ^{5}	0.06 ^{5}	0.12 ^{5}	0.16 ^{5}	**2.01** $^{1\,2\,3\,4}$	93.403***
INT_WAL	0.24 $^{3\,4}$	0.21 $^{3\,4}$	**1.8** $^{1\,2\,5}$	**1.45** $^{1\,2\,5}$	0.37 $^{3\,4}$	39.73***

Note: values with significant differences with three or more other groups are highlighted.
Superscript values represent groups with which the cluster differ significantly ($p < 0.05$) (ANOVA post-hoc Tukey's test if equal variances and *Lamhane's* test if not).

Bus and car users dominantly populate the *Bus-Dependents* and the *Car-Predisposed* clusters, respectively. The other three clusters do have nice representability on the use of the car and the bus. The weekly walking frequency is significantly higher among the *Non-Motorised Lovers* and the

20 To assess predictive validity, a researcher examines variables that have theoretical relationships with the variables used in cluster analysis. If significant differences are demonstrated, one can conclude that the clusters depict groups that have predictive validity (Hair *et al.* 2014).

Autonomous Environmentalists (p < 0.001) (who also have significantly higher levels of cycling to the university). *Motorbike Enthusiasts* have significantly higher usage of the motorbike, as well as an intention to use it (p < 0.001). The differences that are seen on intentions across the groups somewhat replicate the differences found in actual behaviour, which would be expected as both concepts are strongly related according to the Theory of Planned Behaviour. Interestingly, the mean scores of the frequency of car and bus use are somewhat high for all the groups (despite the very high relative scores of the '*Car-Predisposed*' and the '*Bus-Dependents*'). This confirms that the generated clusters represent groups that differ mainly in a *psychological* manner, rather than in behaviour exclusively. Thus, every group found has the potential to be positively influenced by incentives when it comes to switching to non-motorised forms of transport, for example.

Considering the reported weekly frequency of use of each transport mode, the 'primary' mode of each survey respondent was identified. Figure 4.7 shows the modal-split of each cluster with respect to this indicator.

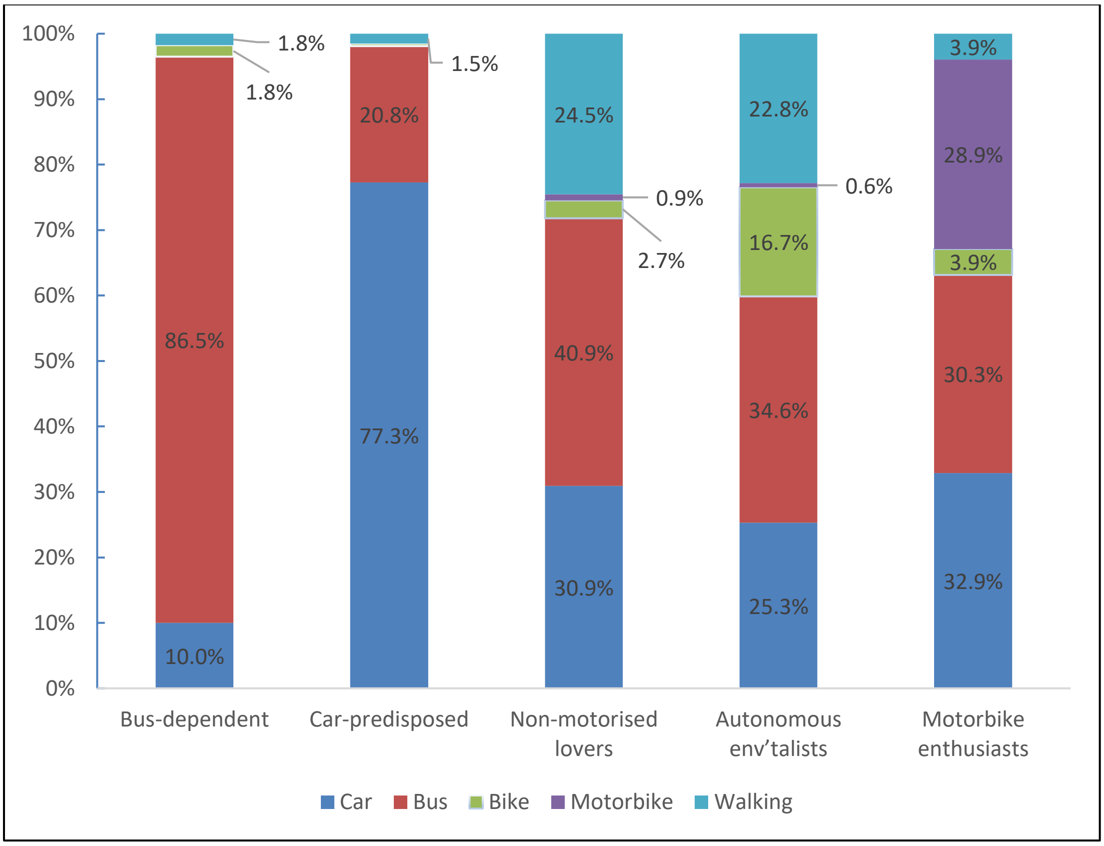

Figure 4.7 - Most used travel modes by psychographic clusters (n = 920)

The results of this analysis somewhat converge with what was found in Table 4.34. The *Non-Motorised Lovers*, *Autonomous Environmentalists* and the non-motorbike crusaders present a more heterogeneous pattern of use of travel modes, where the *Bus-Dependents* group is more concentrated towards having the bus as the main mode of transport. The same pattern appears to exist for the *Car-Predisposed*.

4.4.9.3 Differences in ownership and availability of transport modes

Figure 4.8 presents rates of bike, motorbike and car ownership and availability. Availability, here, means the participant has the travel mode available to use *in general*, and not specifically to go to the university. As sometimes can be the case for university students in Brazil, they might be living with someone who owns a car, for example, but are not able to use it frequently. The variables used to form clusters, on the other hand, were assessed in the context of trips to the university.

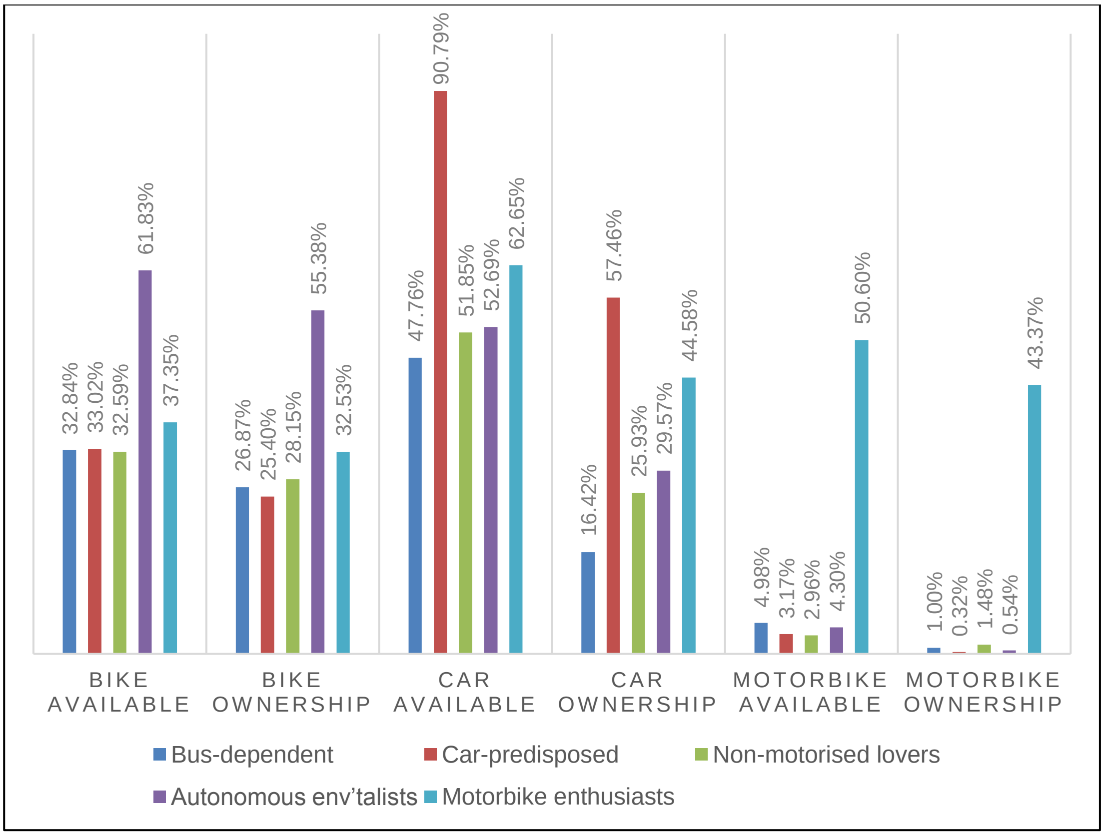

Figure 4.8 - Availability and ownership of travel modes by psychographic clusters (n = 920)

The *Bus-Dependents* cluster shows the lowest percentages of ownership and availability of cars, which are both large among the *Car-Predisposed* group. Bike owning and availability are quite constant across groups, except for the *Autonomous Environmentalists* who show a higher percentage on this indicator. Quite high percentages of ownership and availability of all the modes are displayed among the *Motorbike Enthusiasts*. Interestingly, a high car-owning rate is shown even among the clusters that are more psychologically prone to walking or cycling. The *Bus-Dependents* group appears to be the most 'excluded' when it comes to having a motorised vehicle available.

4.4.9.4 Differences in the behavioural, normative and control beliefs

To allow a better comprehension of the underlying beliefs that form attitudes, subjective norms and perceived behavioural control across the different mobility groups, F-tests were conducted for these variables. As the assessment of these indicators was done using a second survey, the sample is reduced to 112 individuals. The data are presented in Table 4.35. The interpretation of these results has to be done with care due to the small sample (especially in the case of the '*Motorbike Enthusiasts*' group, with only four respondents). Statistical significance of the differences is not present on the majority of the tests possibly because of this issue. The results might also be biased as some groups can be underrepresented by this smaller sample, considering that the members of each group might have had different levels of motivations to engage in the second online survey.

Table 4.35 - Differences in behavioural, normative and control beliefs among clusters (n=112)

Variables	1. Bus-Dep (n=30)	2. Car-Pred. (n=35)	3. Non-Mot Lov. (n=25)	4. Aut. Env. (n=18)	5. M'Bike Enth. (n=4)	F
Belief Strength – Cars[1]						
Safe	2.33	2.31	1.83	2.06	2.5	0.734
Cheap	-1.1 [5]	-1.06 [5]	-1.65	-0.67	-2 [1,2]	1.184
Comfortable	2.63	2.83	2.39	2.78	2.75	0.974
Fast	1.97	2.06	1.61	2	1.5	0.557
Belief Strength – Bus[1]						

Variables	1. Bus-Dep (n=30)	2. Car-Pred. (n=35)	3. Non-Mot Lov. (n=25)	4. Aut. Env. (n=18)	5. M'Bike Enth. (n=4)	F
Cheap	0.63	1.06	0.04	0.94	1	1.42
Crowded	1.8	1.8	1.42	1.17	1.25	0.631
Comfortable	-1.23	-1.31	-1.08	-0.72	-0.75	0.559
Fast	-0.8	-1.31	-1	-0.5	0	0.996
Belief Strength – Bike[1]						
Fast	-0.85 [4]	-0.97 [4]	-0.22	1.11 [1 2]	-0.5	3.185*
Good for the environment	2.57	2.46	1.83	2.94	3	1.991
Safe	-1.54	-1.83	-1.7	-1.06	-2.25	0.906
Healthy	2.07 [5]	2.23 [5]	1.79	2.83	3 [1 2]	1.792
Belief Strength – Motorbike[1]						
Cheap	0.88	1.2	0.28	1.07	2	0.949
Practical	1.26	0.8	0.65	1.19	2.75	0.993
Fast	2.07	1.63	1.1	2.07	2.25	1.266
Safe	-1.67	-1.94	-1.63	-1.63	-0.5	0.561
Belief Strength - Walking[1]						
Fast	-2.63 [3]	-2.62 [3]	-1.08 [1 2]	-1.89	-2	5.187***
Good for the environment	1.53 [5]	2.24 [5]	2.29	2.71	3 [1 2]	1.843
Healthy	0.7 [4 5]	1.79 [5]	2.08	2.35 [1]	3 [1 2]	3.577**
Safe	-1.97	-1.82	-1.56	-1.24	-2	0.519
Outcome Evaluations[2]						
Cost	6.07 [2]	4.94 [1]	5.54	5.83	5	3.047*
Comfort	4.43 [2]	5.51 [1]	4.79	4.89	6	2.881*
Safety	5.45 [2]	6.37 [1]	5.96	5.67	6.5	3.272*
Speed	5.69	6.43	5.84	5.94	6.25	1.745
Not Crowded	4.4 [2]	5.54 [1]	4.67	4.5	6.5	3.316*
Healthy	3.4	3.23	4.28	4.22	4	1.937
Good for environment	3.7	3.49	4.24	4.44	3.75	1.289
Practical	5.73	6.26	5.96	5.94	6	0.747
Behavioural beliefs – Composite score[3]						
Cars	28.64	38.46 [3]	23.73 [2]	33.44	33.75	2.277
Bus	3.59	-0.91	-0.09	3.44	10.75	0.494
Bike	3.4 [4]	-1.54 [4]	7.14 [4]	26 [1 2 3]	7.25	5.248***
Motorbike	16.22	9.8	7.31	20.92	37.75	1.593
Walking	-16.75 [3 4]	-15.44 [3 4]	4.79 [1 2]	2.65 [1 2]	-1.5	6.192***
Control beliefs						
Car trips to the university…						
I would have enough money[1]	-1.5 [2]	1.23 [1 3 4]	-1.32 [2]	-1.33 [2]	0	9.358***

Variables	1. Bus-Dep (n=30)	2. Car-Pred. (n=35)	3. Non-Mot Lov. (n=25)	4. Aut. Env. (n=18)	5. M'Bike Enth. (n=4)	F
Having enough money is a facilitator[2]	4.77 [2]	6.54 [1,4]	5.24	3.67 [2,5]	6.5 [4]	7.874***
Would have traffic jams[1]	1.3	0.97	0.96	0.89	0.5	0.336
Traffic jams are a barrier[2]	3.17 [5]	3.17 [5]	3.52 [5]	3.78	5.25 [1,2,3]	1.167*
Bus trips to the university…						
I would have enough money[1]	2.6	2.37	2.16	2.17	1	1.323
Having enough money is a facilitator[2]	5.13 [2]	3.6 [1]	5	3.94	5	2.766*
Would take too much time[1]	1.27	2.03	1.12	1.33	2.5	1.731
The time spent is a barrier[2]	3.57 [2,5]	6.09 [1,3]	4.56 [2]	4.53	6.25 [1]	7.202***
Bike trips to the university…						
Would have safety problems[1]	1.13	1.74 [4]	1.32	-0.06 [2]	1.25	2.981*
Safety issues are a barrier[2]	4.45	5.8 [4]	5.08 [4]	3.17 [2,3]	5.25	4.73***
Would have cycle lanes[1]	-0.93	-1.06	-0.8	0.11	-2.5	2.245
The existence of cycle lanes is a facilitator[2]	3.4	3.74	4.68	4.44	4.5	1.484
Motorbike trips to the university…						
I would have an accident[1]	-0.33	0.43	-0.68	0.00	-0.75	1.388
Safety issues are a barrier[2]	4.00 [5]	5.29 [4]	4.76	3.22 [2,5]	6.5 [1,4]	3.545**
I would have enough money[1]	-1.57	-0.54	-1.44	-1.17	0.5	1.509
Having enough money is a facilitator[2]	3.21	2.4 [5]	2.88 [5]	2.67 [5]	6 [2,3,4]	3.053*
Walking trips to the university…						
I would have a safety problem[1]	1.87	2.26 [4]	1.36	0.72 [2]	1.75	3.318*
Safety issues are a barrier[2]	5.03	5.97 [4]	4.72	4.06 [2]	6.25	3.142*
Would be too distant[1]	2.6 [3]	2.51 [3]	0.36 [1,2]	1.78	1.75	6.856***
Distance is a barrier[2]	6.57 [3]	6.66 [3]	4.68 [1,2,5]	6.29	6.75 [3]	6.375***
Control beliefs – Composite score[3]						
Cars	-12.13 [2]	4.83 [1,3,4]	-10.2 [2]	-11.44 [2]	-2.75	7.546***
Bus	7.83 [2]	-4.86 [1]	3.52	2.18	-10.25	4.674**
Bike	-10.14	-16.23 [4]	-10.68	-0.67 [2]	-15	4.45**
Motorbike	-6.93	-0.63	-9.04	-4.11	-0.75	1.849
Walking	-28.37 [3]	-31.66 [3,4]	-13.8 [1,2]	-16.65 [2]	-21.75	5.702***
Injunctive normative beliefs[3]						
Cars	46.31	63.06	44.79	46.59	47.5	2.538*
Bus	58.03	46.7	45.29	45.06	40.5	1.475
Bike	23.39	18.18 [3,4]	32.75 [2]	44.94 [2]	20.75	6.179***
Motorbike	20.46	13.48	18.58	15.94	16	1.065

Variables	1. Bus-Dep (n=30)	2. Car-Pred. (n=35)	3. Non-Mot Lov. (n=25)	4. Aut. Env. (n=18)	5. M'Bike Enth. (n=4)	F
Walking	15.34	12.18 [3]	30.08 [2]	21.35	16.25	5.106***

[1] Measured using a '-3 to +3' scale. [2] Measured using a '1 to 7' scale. [3] Measured using the TPB's multiplicative approach (expectancy-value model) (Fishbein and Ajzen, 2010).

Despite the interpretation issues in Table 4.35, it also reveals insightful information. Considering only statistically significant results, several conclusions can be drawn. Cycling is considered to be a fast mode of transportation to a higher extent by the *Autonomous Environmentalists*. In addition, walking is best evaluated by groups that are more prone to non-motorised transport, as they consider this mode healthy and fast to a greater degree compared to other groups. With regards to the relative importance of attributes of a trip to the university, the *Bus-Dependents* group considers cost as the most important aspect, while comfort, safety and not being crowded is more important to the *Car-Predisposed*, especially if compared to the *Bus-Dependents*. Although lacking statistical significance due to the reduced sample size, the *Car-Predisposed* tend to evaluate car trips better than the other groups. Similarly, groups more prone to non-motorised modes also have a better perception of the experience with these types of transportation.

Looking at control beliefs, it can be seen that the high PBC of car use that is demonstrated by the *Car-Predisposed* might be explained by the belief that they have enough money to use the car. They also tend to see money as a facilitator to use the car to a higher extent than other groups. The *Car-Predisposed* also display a higher belief that bus trips would take too much time of their days. This possible under evaluation of alternative modes by car users has already been demonstrated in past research (Beirão and Sarsfield Cabral, 2007). The autonomous-environmentalists evaluate non-motorised modes better than other groups, especially with respect to safety issues around cycling or walking.

Injunctive normative beliefs in regards to cycling or walking are significantly lower among the *Car-Predisposed*, as well. This indicates that they generally think that other people think they should not use these travel modes.

4.4.9.5 Differences in the familiarity with mobility smartphone applications

The level of individual familiarity with mobility apps was assessed in this thesis under the assumption that it might be an indicator of incentives acceptability. Thus, using the differences across the behavioural groups with respect to this variable (if any) to enrich the profile description of the groups can be useful for further conclusions in regard to the acceptance of incentives. Table 4.36 presents the response proportions for multiple types of smartphone applications among the groups, along with the results of Chi-Square tests (χ^2).

Table 4.36 – Familiarity with mobility apps, by psychographic cluster

Smartphone application	Level of knowledge	Bus Dep.	Car Pred.	N-Mot. Lov.	Aut. Env.	M'Bike Enth.	All
Trip-sharing (carpooling) apps χ^2 = 28.849 (12) p = 0.004	Never heard of it	**94 (47.2%)**	137 (43.9%)	50 (37.9%)	61 (33.9%)	24 (30%)	366 (40.5%)
	Know a little	86 (43.2%)	135 (43.3%)	51 (38.6%)	76 (42.2%)	**42 (52.5%)**	390 (43.2%)
	Know reasonably well	12 (6%)	27 (8.7%)	21 (15.9%)	**31 (17.2%)**	10 (12.5%)	101 (11.2%)
	Know very well	7 (3.5%)	13 (4.2%)	**10 (7.6%)**	12 (6.7%)	4 (5%)	46 (5.1%)
Ride source apps (e.g. Uber) χ^2 = 12.227 (12) p = 0.428	Never heard of it	1 (0.5%)	2 (0.6%)	1 (0.7%)	1 (0.5%)	0 (0%)	5 (0.6%)
	Know a little	13 (6.5%)	14 (4.4%)	8 (6%)	7 (3.8%)	7 (8.5%)	49 (5.4%)
	Know reasonably well	40 (20%)	58 (18.4%)	13 (9.7%)	34 (18.3%)	18 (22%)	163 (18.1%)
	Know very well	146 (73%)	241 (76.5%)	112 (83.6%)	144 (77.4%)	57 (69.5%)	700 (77.5%)
Mode-sharing apps c = 31.190 (12) p = 0.002	Never heard of it	151 (75.5%)	**241 (77.2%)**	89 (67.4%)	128 (71.1%)	42 (53.2%)	651 (72.1%)
	Know a little	45 (22.5%)	64 (20.5%)	36 (27.3%)	45 (25%)	**30 (38%)**	220 (24.4%)
	Know reasonably well	4 (2%)	5 (1.6%)	5 (3.8%)	2 (1.1%)	**5 (6.3%)**	21 (2.3%)
	Know very well	0 (0%)	2 (0.6%)	2 (1.5%)	**5 (2.8%)**	2 (2.5%)	11 (1.2%)
Trip planning/tracking apps (e.g. Waze, HereWeGo) χ^2 = 46.434 (12) p = 0.000	Never heard of it	**15 (7.5%)**	6 (1.9%)	7 (5.3%)	6 (3.3%)	3 (3.8%)	37 (4.1%)
	Know a little	36 (18.1%)	27 (8.7%)	15 (11.4%)	**42 (22.8%)**	10 (12.5%)	130 (14.4%)
	Know reasonably well	**72 (36.2%)**	94 (30.2%)	42 (31.8%)	63 (34.2%)	23 (28.8%)	294 (32.6%)
	Know very well	76 (38.2%)	**184 (59.2%)**	68 (51.5%)	73 (39.7%)	44 (55%)	445 (49.3%)

Smartphone application	Level of knowledge	Bus Dep.	Car Pred.	N-Mot. Lov.	Aut. Env.	M'Bike Enth.	All
Bus scheduling/tracking apps $\chi^2 = 27.194$ (12) $p = 0.007$	Never heard of it	33 (16.5%)	**73 (23.5%)**	21 (15.8%)	28 (15.3%)	16 (20.3%)	171 (18.9%)
	Know a little	48 (24%)	86 (27.7%)	**51 (38.3%)**	62 (33.9%)	29 (36.7%)	276 (30.6%)
	Know reasonably well	46 (23%)	**82 (26.4%)**	31 (23.3%)	41 (22.4%)	19 (24.1%)	219 (24.3%)
	Know very well	**73 (36.5%)**	70 (22.5%)	30 (22.6%)	52 (28.4%)	15 (19%)	240 (26.6%)
Taxi-hiring apps (e.g. EasyTaxi) $\chi^2 = 31.957$ (12) $p = 0.001$	Never heard of it	18 (9%)	16 (5.1%)	8 (6%)	**19 (10.4%)**	4 (5%)	65 (7.2%)
	Know a little	**93 (46.7%)**	104 (33.2%)	50 (37.6%)	64 (35%)	30 (37.5%)	341 (37.8%)
	Know reasonably well	54 (27.1%)	97 (31%)	34 (25.6%)	44 (24%)	**32 (40%)**	261 (28.9%)
	Know very well	34 (17.1%)	96 (30.7%)	**41 (30.8%)**	56 (30.6%)	14 (17.5%)	241 (26.7%)
Incentive-based exercise apps (e.g. Strava, Endomondo) $\chi^2 = 45.685$ (12) $p = 0.000$	Never heard of it	**60 (29.9%)**	57 (18.3%)	21 (15.8%)	42 (22.8%)	14 (17.5%)	194 (21.5%)
	Know a little	89 (44.3%)	**159 (51.1%)**	57 (42.9%)	58 (31.5%)	29 (36.3%)	392 (43.4%)
	Know reasonably well	29 (14.4%)	52 (16.7%)	35 (26.3%)	42 (22.8%)	**26 (32.5%)**	184 (20.4%)
	Know very well	23 (11.4%)	43 (13.8%)	20 (15%)	**42 (22.8%)**	11 (13.8%)	139 (15.4%)

Notes: percentages are shown with regard to the cluster sizes. Highlighted values represent the highest percentage for a particular response category.

Only Ride source apps like Uber® and Cabify® did not show significant differences in levels of familiarity among the clusters ($p > 0.05$). The *Bus-Dependents* group is naturally more familiarised with bus scheduling/tracking apps, while less familiarised with trip sharing and trip planning apps. Incentive-based exercise apps are more known by *Non-Motorised Lovers* and *Autonomous Environmentalists*. *Car-Predisposed* people are overall more familiar with trip-planning apps and less familiarised with bus scheduling/tracking applications. The *Car-Predisposed* and the groups more prone to the use of non-motorised modes had a better knowledge of taxi hiring apps. The *Motorbike Enthusiasts* cluster displays less knowledge about types of application that are associated with travel modes other than the bike (taxi hiring and bus scheduling apps).

4.4.9.6 Acceptability of positive incentives

As a last point of consideration and aiming to answer research question 3 of this thesis, differences corresponding to the individual acceptability of positive incentives are examined across the five clusters. After establishing the profile of the segments in relation to their travel behaviour patterns, sociodemographic aspects and familiarity with mobility applications, the analysis of the levels of acceptability of incentives may lead to useful conclusions. Especially about whether differences on acceptability do exist among the groups, in the first place, and the magnitude of these differences, in the second place.

Initially, Table 4.37 brings the mean values of attitudes, intention to use and perceived likelihood to switch to alternative travel modes to each one of the eleven assessed incentives.

Table 4.37 - Mean comparison of incentives acceptability among psychographic clusters (n = 920)

Variables	Clusters					F[1]
	Bus Dep. (1)	Car Pred. (2)	N-Mot. Lov. (3)	Aut. Env. (4)	M'Bike Enth. (5)	
Maps						
Attitudes	6.16	6.17	6.43^{5}	6.18	5.81^{3}	2.904*
Intention to use	$5.88^{2\,3}$	$5.38^{1\,3\,4}$	$6.3^{1\,2\,5}$	5.87^{2}	5.27^{3}	11.569***
Likelihood to switch	4.40^{2}	$3.89^{1\,3\,4}$	$4.81^{2\,5}$	$4.6^{2\,5}$	$3.9^{3\,4}$	11.05***
Money						
Attitudes	6.48	6.46^{4}	6.67	6.71^{2}	6.28	3.398**
Intention to use	6.35	$6.04^{3\,4}$	$6.57^{2\,5}$	$6.55^{2\,5}$	$5.8^{3\,4}$	9.687***
Likelihood to switch	5.86^{2}	$5.45^{1\,3\,4}$	$5.97^{2\,5}$	$6.18^{2\,5}$	$5.26^{3\,4}$	10.706***
Points						
Attitudes	4.75^{2}	$4.06^{1\,3\,4}$	5.14^{2}	4.98^{2}	4.52	11.952***
Intention to use	4.12^{2}	$3.25^{1\,3\,4\,5}$	4.63^{2}	4.53^{2}	3.94^{2}	18.668***
Likelihood to switch	3.48^{2}	$2.77^{1\,3\,4}$	3.93^{2}	3.81^{2}	3.32	14.188***
Rankings						
Attitudes	4.90	$4.52^{3\,4}$	5.12^{2}	5.11^{2}	4.77	4.206**
Intention to use	4.09^{2}	$3.54^{1\,3\,4}$	4.49^{2}	4.45^{2}	4.00	8.725***
Likelihood to switch	3.60^{2}	$2.91^{1\,3\,4}$	3.79^{2}	3.89^{2}	3.32	10.551***

Variables	Clusters					F[1]
	Bus Dep. (1)	Car Pred. (2)	N-Mot. Lov. (3)	Aut. Env. (4)	M'Bike Enth. (5)	
Vouchers						
Attitudes	6.55	6.44	6.57	6.64^{5}	6.16^{4}	3.52**
Intention to use	6.5$^{2\,5}$	5.99$^{1\,3\,4}$	6.43$^{2\,5}$	6.54$^{2\,5}$	5.8$^{1\,3\,4}$	10.855***
Likelihood to switch	5.85$^{2\,5}$	5.26$^{1\,3\,4}$	5.75^{2}	6.02$^{2\,5}$	5.1$^{1\,4}$	11.414***
Journey Planner						
Attitudes	5.87	5.95	6.21^{5}	6.06	5.67^{3}	2.487*
Intention to use	5.54	5.38^{3}	5.92^{2}	5.64	5.36	3.228*
Likelihood to switch	4.67^{2}	4.2$^{1\,3\,4}$	4.91^{2}	4.72^{2}	4.44	5.663***
Information (conseq.)						
Attitudes	6.27	6.2	6.4	6.44^{5}	5.87^{4}	3.806**
Intention to use	6.01	5.68$^{3\,4}$	6.21$^{2\,5}$	6.17$^{2\,5}$	5.55$^{3\,4}$	6.935***
Likelihood to switch	5.08^{2}	4.59$^{1\,3\,4}$	5.31$^{2\,5}$	5.31$^{2\,5}$	4.57$^{3\,4}$	8.542***
Feedback						
Attitudes	5.55	5.63	5.62	5.81	5.43	1.067
Intention to use	5.06	5.01	5.31	5.44	4.95	2.245
Likelihood to switch	4.28	3.99$^{3\,4}$	4.51^{2}	4.54^{2}	3.91	4.022**
Social Media						
Attitudes	3.65	3.36^{4}	3.77	4.05^{2}	3.84	4.203**
Intention to use	2.98	2.55$^{3\,4}$	3.08^{2}	3.37^{2}	3.16	6.387***
Likelihood to switch	2.61^{2}	2.14$^{1\,3\,4}$	2.78^{2}	2.97^{2}	2.53	8.634***
Challenges						
Attitudes	4.59	4.6	4.79	4.99	4.61	1.598
Intention to use	3.8^{4}	3.73^{4}	4.21	4.38$^{1\,2}$	4	4.228**
Likelihood to switch	3.26^{4}	3.05$^{3\,4}$	3.64^{2}	3.84$^{1\,2}$	3.2	6.353***
Buddying						
Attitudes	5.51	5.63	5.78	5.73	5.17	1.39
Intention to use	5.12	4.8^{3}	5.51^{2}	5.23	4.93	4.099**
Likelihood to switch	4.38	3.94$^{3\,4}$	4.76^{2}	4.7^{2}	4.23	6.787***

Notes: Superscript numbers represent groups with which values differ significantly at $p < 0.05$ (ANOVA post-hoc Tukey's test if equal variances and Lamhane's test if not).
Values above the 50 percentile were formatted using a green gradient of colours, while a red gradient was used to show values below that threshold.
Values that differ significantly from two or more groups are highlighted in bold.
[1] F values resulting from analysis of variance where: *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$).

The F-values indicate significant differences ($p < 0.05$) in acceptability among clusters with respect to the majority of incentives. Maps and vouchers showed the highest amount of significant differences across clusters (24 and 22). In contrast, Feedback and Buddying are the categories that demonstrated the least differentiation (4 and 6 significant differences at $p < 0.05$). The following paragraphs provide details about the results of each particular incentive.

Maps are generally more accepted by the *Non-Motorised Lovers* and less accepted by the *Car-Predisposed*, especially considering intention to use and the perceived personal impact[21].

The acceptance of *money* is significantly different when comparing the *Car-Predisposed* together with the *Motorbike Enthusiasts* and the *Non-Motorised Lovers* together with *Autonomous Environmentalists*. Differences between these 'pairs' of clusters are also observed when looking at the acceptance of *vouchers* and *information* about the consequences of travelling. In these cases, the clusters more prone to the use of private CFVs (the first two) are generally less responsive to these types of incentives, in contrast to the clusters more apt to non-motorised forms of transport.

Points and *rankings* are substantially less accepted by the *Car-Predisposed*. The other groups do not display significant differences among themselves on these same incentive types.

Journey-planner is an incentive that is equally well-received by all the clusters. Only when it comes to switching travel modes, the *Car-Predisposed* show significantly lower scores regarding this incentive. *Feedback* on past travel behaviour follows the same acceptance pattern as the journey-planner.

Social media is the incentive with the lowest overall scores on all acceptance indicators. However, the '*Non-Motorised Lovers*' and '*Autonomous Environmentalists*' are particularly less resistant to it when compared to the *Car-Predisposed*, who show significantly lower scores even when compared to the *Bus-Dependents* cluster.

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[21] All the significances reported on the text of this sub-section consider the 5% significance level.

The *Autonomous Environmentalists* show the higher acceptance scores of *challenges* and are significantly more responsive to this incentive if compared to the *Bus-Dependents* and the *Car-Predisposed*.

Finally, people generally have the same positive attitudes to *buddying*, but the *Car-Predisposed* have inferior intentions and perceived personal impact, in comparison to the clusters more prone to non-motorised forms of transport.

Another form of visualising the variability on the acceptance of incentives is through a graph. Figure 4.9 presents the mean scores of all the clusters that showed any significance with any other cluster within the same incentive for the specific indicator of ‘perceived personal impact’. This indicator was chosen as it is assumed to represent the most relevant indicator of potential behaviour change resulting from the incentives.

To allow a comparison between groups relative to their level of dissimilarity with others and an assessment of the number of significant differences in terms of different indicators of acceptability, Table 4.38 was constructed. It contains the number of significant differences between groups for the three indicators of acceptability and for all the indicators combined (considering $p < 0.05$).

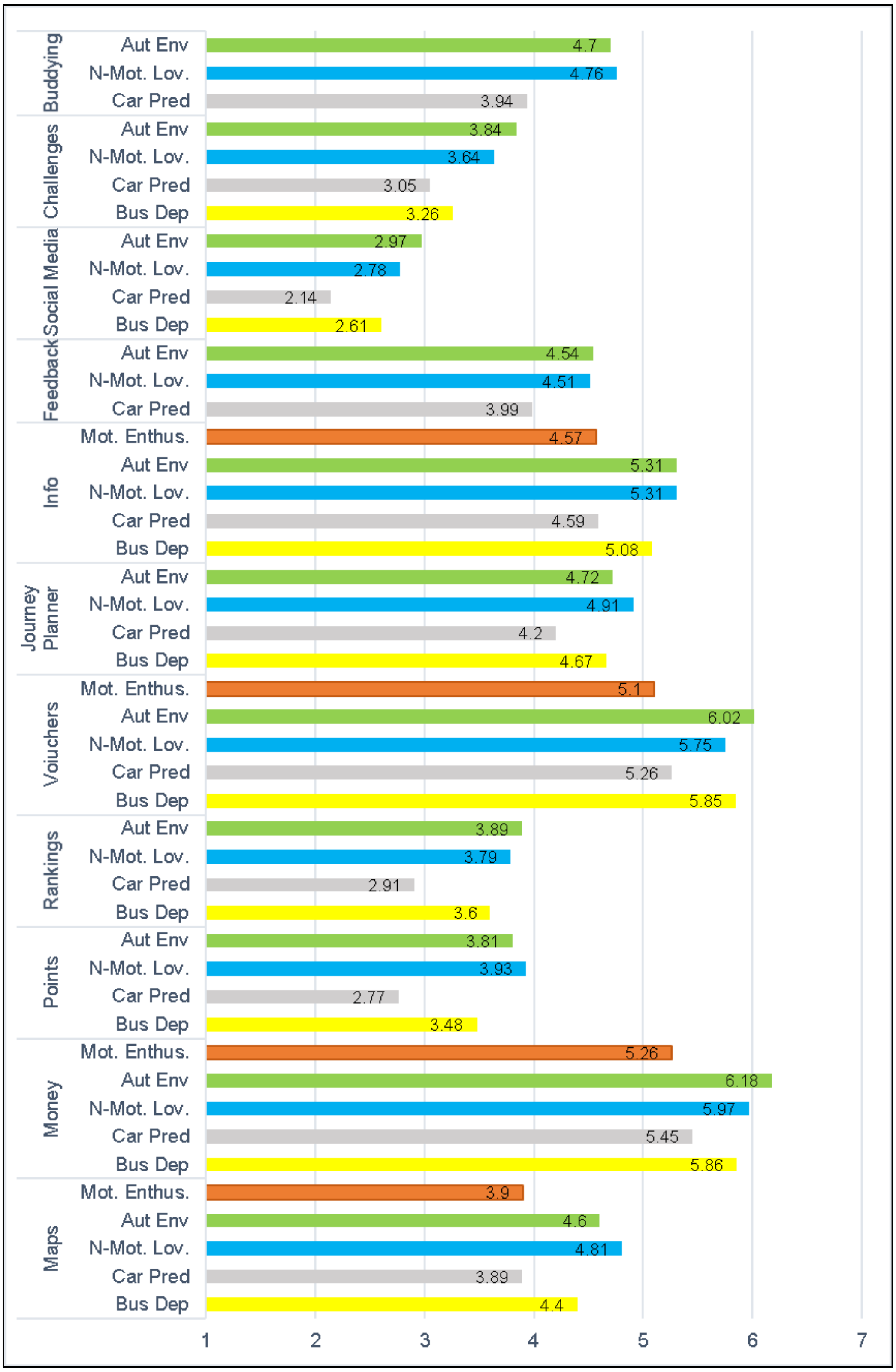


Figure 4.9 - Mean values of the perceived personal impact of incentives (n = 920)

Note: Only groups with significant differences ($p < 0.05$) to at least one other group are displayed.

Table 4.38 - Number of significant differences between clusters ($p < 0.05$), by indicator of acceptability ($n = 920$)

Attitudes to incentives						
Clusters	**Bus Dep.**	**Car Pred.**	**N-Mot. Lov.**	**Aut. Env.**	**M'Bike Enth.**	**Total**
Bus Dep.	-	1	0	0	0	1
Car Pred.	1	-	2	4	0	7
N-Mot. Lov.	0	2	-	0	2	4
Aut. Env.	0	4	0	-	2	6
N-Mot. Reluc.	0	0	2	2	-	4
Total	1	7	4	6	4	22
Intention to use incentives						
Clusters	**Bus Dep.**	**Car Pred.**	**N-Mot. Lov.**	**Aut. Env.**	**M'Bike Enth.**	**Total**
Bus Dep.	-	4	1	1	1	7
Car Pred.	4	-	9	8	1	22
N-Mot. Lov.	1	9	-	0	4	14
Aut. Env.	1	8	0	-	3	12
N-Mot. Reluc.	1	1	4	3	-	9
Total	7	22	14	12	9	64
Perceived personal impact						
Clusters	**Bus Dep.**	**Car Pred.**	**N-Mot. Lov.**	**Aut. Env.**	**M'Bike Enth.**	**Total**
Bus Dep.	-	8	0	1	1	10
Car Pred.	8	-	11	11	0	30
N-Mot. Lov.	0	11	-	0	3	14
Aut. Env.	1	11	0	-	4	16
N-Mot. Reluc.	1	0	3	4	-	8
Total	10	30	14	16	8	78
All indicators combined						
Clusters	**Bus Dep.**	**Car Pred.**	**N-Mot. Lov.**	**Aut. Env.**	**M'Bike Enth.**	**Total**
Bus Dep.	-	13	1	2	2	18
Car Pred.	13	-	22	23	1	59
N-Mot. Lov.	1	22	-	0	9	32
Aut. Env.	2	23	0	-	9	34
N-Mot. Reluc.	2	1	9	9	-	21
Total	18	59	32	34	21	164

Looking at the data in Table 4.38, it is noticeable that the discrepancy between psychographic groups is not very apparent in terms of attitudes, but is progressively more evident looking at intentions and perceived personal impact. Furthermore, the *Car-Predisposed* is noticeably the group displaying the higher amount of differences on acceptability concerning all indicators and with all other groups, but predominantly with the '*Non-Motorised Lovers*' and the '*Autonomous Environmentalists*'. These two groups, in their turn, do not differentiate between themselves in any indicator for any type of incentive. Similarly, the '*Motorbike Enthusiasts*' and the '*Car-Predisposed*' only differ in terms of one indicator of acceptance to one incentive: intention to use vouchers (*Car-Predisposed* are less inclined to use). The '*Bus-Dependents*' group has the fewest number of significant differences and these are mainly to the '*Car-Predisposed*' group. It only differs from the '*Autonomous Environmentalists*', for example, in terms of intention to use and perceived personal impact of *challenges*. The '*Motorbike Enthusiasts*' also exhibit more differences when compared to the groups more prone to non-motorised forms of transport, but not in the same extent as the '*Car-Predisposed*' people do.

Finally, the differences were explored considering categories of incentives previously validated by principal component analysis (Section 4.1.2). Table 4.39 shows that the *Bus-Dependents*, *Autonomous Environmentalists* and *Non-Motorised Lovers* are significantly more responsive to value maximisation incentives when compared to the *Car-Predisposed* and the *Motorbike Enthusiasts*. The *Car-Predisposed*, however, are not different from the other groups when it comes to having attitudes to this incentive component. In other words, they apparently like these incentives as much as the other groups, but when it comes to really use them or changing behaviour, the differences arise. For social incentives, the *Car-Predisposed* demonstrate to have lower scores for all indicators of acceptance when compared to other groups other than the *Motorbike Enthusiasts*.

Table 4.39 - Mean comparison of acceptability to categories of incentives among psychographic clusters (n = 920)

F-TEST	Clusters					F
Variable	**Bus Dep.**	**Car Pred.**	**N-Mot. Lov.**	**Aut. Env.**	**N-Mot. Reluc.**	
Social Incentives						
Attitudes	4.68	**4.44** $^{3 4}$	4.89 ^{2}	4.99 ^{2}	4.64	5.533***
Intention to use	4.19 ^{2}	**3.81** $^{1 3 4}$	4.54 ^{2}	4.57 ^{2}	4.17	11.553***
Perceived personal impact	3.60 ^{2}	**3.13** $^{1 3 4}$	3.89 ^{2}	**3.94** $^{2 5}$	3.41 ^{4}	12.773***
Value maximisation incentives						
Attitudes	6.28	6.24	6.46 ^{5}	6.42 ^{5}	**6.00** $^{3 4}$	4.827***
Intention to use	**6.07** $^{2 5}$	**5.70** $^{1 3 4}$	**6.29** $^{2 5}$	**6.16** $^{2 5}$	**5.57** $^{1 3 4}$	13.466***
Perceived personal impact	**5.37** $^{2 5}$	**4.87** $^{1 3 4}$	**5.5** $^{2 5}$	**5.61** $^{2 5}$	**4.78** $^{1 3 4}$	15.944***
All incentives						
Attitudes	5.48	**5.36** $^{3 4}$	5.68 ^{2}	**5.71** $^{2 5}$	5.33 ^{4}	5.225***
Intention to use	5.04 ^{2}	**4.67** $^{1 3 4}$	**5.34** $^{2 5}$	**5.29** $^{2 5}$	**4.8** $^{3 4}$	14.343***
Perceived personal impact	4.31 ^{2}	**3.82** $^{1 3 4}$	**4.55** $^{2 5}$	**4.59** $^{2 5}$	**3.99** $^{3 4}$	15.532***

Notes: Superscript numbers represent groups with which values differ significantly at $p < 0.05$.
Values that differ significantly from two or more groups are highlighted in bold.
[1] F values resulting from the analysis of variance where: *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$).

A second segmentation analysis was performed to identify significant groups in terms of preferences to incentives. This will be done not by considering the absolute scores of acceptance to each incentive, but values will be *standardised* by the individual. An analysis structured in that way avoids that the resulting clusters are a mere reflection of response-styles (Hair et al., 2014). That is, the resulting clusters could be formed by people who are more inclined to respond positively, those who respond more negatively and some other groups in the middle. Standardisation by observation is done by subtracting each incentive score by the respondent's average score on all eleven incentives. Thus revealing what are the most and least preferred incentives and avoiding the influence of response-style effects (Schaninger and Buss, 1986). This method is especially suited for attitudinal data (Hair et al., 2014).

4.5 Cluster analysis of positive incentives acceptability variables

This analysis aimed at finding a meaningful segmentation structure with respect to the acceptability of positive incentives within the sample. The author's expectation was that clusters would have relative differences in the type of incentives that were more or less accepted by each group. However, after checking the assumptions of the method and performing a combination of hierarchical and non-hierarchical methods for a range of different solutions (similar to what was done earlier in the chapter), the solutions were judged to be not meaningful and will not be reported. In summary, there were two clusters found who were similar in terms of the types of incentives that they viewed positively and negatively. Their differences were just in regards to the intensity of this difference. Both clusters showed higher acceptability to incentives related to the user's value maximisation and lower acceptability to social incentives. While one cluster showed larger absolute differences between these two categories, the other showed smaller ones. This result shows that the whole sample displays the same level of *relative preference* to the incentives. The analysis was stretched to create a higher amount of clusters and also considering absolute scores, without standardisation, but these also led to meaningless results for the sake of this study.

4.6 Scenario estimation

This section is dedicated to designing scenarios where positive incentives are implemented in the area of study. The analysis focuses on the potential reduction of three different aspects: (1) total distance travelled by means of private conventionally-fuelled vehicles, (2) Carbon dioxide (Co2) emissions and, (3) emissions costs. These will be developed both by considering the sample as a whole and also by looking at the relative difference on the estimated impacts by each psychographic cluster.

The objectives of this analysis are twofold:

1. To support the decision-making process of future policy interventions that are based on positive incentives, especially in Curitiba, Brazil, with

an estimation of the environmental and financial benefits coming from the implementation of such strategies.

2. To compare the resulting scenarios to past research that addressed the impact of other policies aimed at travel behaviour change using similar methods (further presented in the Discussion chapter).

The analysis is described in detail, for the three different levels, in the sections below.

4.6.1 The decrease in distance travelled by private CFVs

Firstly, the scenarios were estimated in respect to variations on the weekly distance travelled by private CFVs (in kilometres), for the implementation of each type of incentive. Since the scenarios will be hypothesised in terms of the number of trips reduced per week and to give context to the analysis, Figure 4.10 shows a histogram illustrating the number of respondents by intervals of weekly trip amounts. The average amount of weekly trips among the sample's private CFV users was 8.58. The highest average was observed for the *Car-Predisposed* (10.28) and the lowest for the *Bus-Dependents* (5.43).

Additionally, the sample size for this analysis was reduced as only respondents who used a private CFV on the preceding week of the survey were considered (n=614).

The variation on the trip distances (ΔD) was calculated as a function of the reported distance (in kilometres) of the students' journeys to the university (d) and the perceived personal impact of a given incentive (p). The resulting value of this combination, in turn, was multiplied by the number of weekly trips that are hypothetically reduced (k), for each studied scenario (k = 1, k = 2…). For the cases where the number of total weekly trips made by a respondent (T) is less than the number of reduced trips being evaluated (k), the total possible reduced distance for this respondent (for his total trips) is added to the equation ($\Delta DMAX$). This was done as it is impossible for a student that makes 4 trips in a week to reduce 6 car journeys on the same week, for example, so the reduced distance related to 4 trips is inserted on the sum. The formula is shown below (Equation 1).

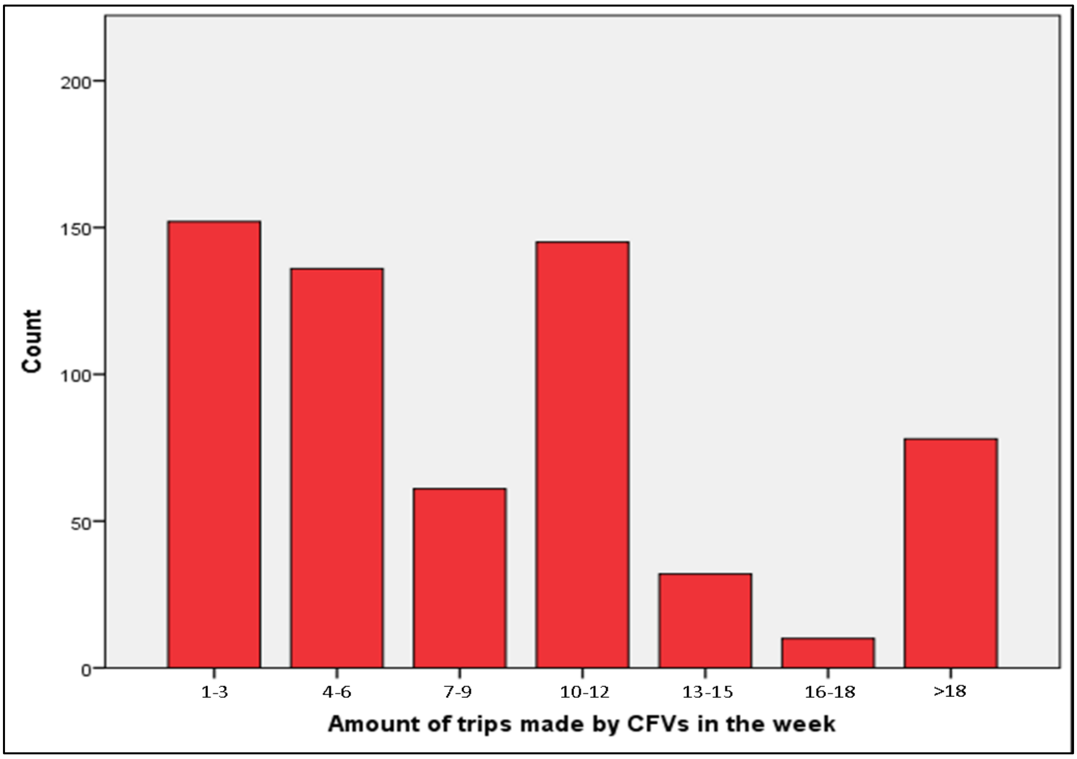


Figure 4.10 - Histogram with the number of respondents per different intervals of quantities of private CFV trips made in the preceding week of the survey

$$\Delta D_{jk} = \Delta S_j \times k + \begin{cases} 0, & k = 1 \\ \Delta DMAX_{jq}, & k > 1 \end{cases} \tag{1}$$

Where,

$$\Delta S_j = \left[\sum_{m=1}^{M} \left(p_{mj} \times d_m \right) \right] \tag{2}$$

$$\Delta DMAX_{jq} = \sum_{q=1}^{Q} \left(p_{qj} \times d_q \; x \; T_q \right) \tag{3}$$

j = type of incentive;

k = number of weekly trips reduced, with $k \in \mathbb{N}^*$[22];
ΔD = total variation on the weekly travelled distance;
ΔS = variation on the weekly travelled distance for a single trip;
$\Delta DMAX$ = maximum variation on the weekly travelled distance;
p = stated likelihood of switching from cars to alternatives;
d = kilometres travelled to the university on a single trip;
T = total weekly trips to the university;
m = participants whose total amount of weekly trips (T) is higher than or equal to k;
M = total amount of participants whose total amount of weekly trips (T) is higher than or equal to k;
q = participants whose total amount of weekly trips (T) is lower than k;
Q = total amount of participants whose total amount of weekly trips (T) is lower than k.

Alternatively, another approach was used to calculate the sum of the distance variation. In this case, the perceived personal impact of an incentive (p) was used to estimate a dummy variable representing the switch to alternative forms of transport (P). This was estimated via the generation of a random number between 0 and 1. If this number was lower than the reported perceived impact (p), the resulting values would be '1' (switched), and '0' (did not switch), otherwise. This approach allows, for example, a student who reported a 90% chance of switching to be considered an individual who actually remained using the car (with a 10% chance).

The formula of this second approach (with P replacing p) is expressed as follows (Equation 4).

$$\Delta D_{jk} = \Delta S_j \times k + \begin{cases} 0, & k = 1 \\ \Delta DMAX_{kj}, & k > 1 \end{cases} \tag{4}$$

Where,

$$\Delta S_j = \left[\sum_{m=1}^{M} \left(P_{mj} \times d_m \right) \right] \tag{5}$$

[22] The set of natural numbers above 0.

$$\Delta DMAX_j = \sum_{q=1}^{Q} \left(P_{qj} \times d_q \; x \; T_q \right) \tag{6}$$

and,

$$P_{mj} = \begin{cases} 1, & R < p_{mj} \\ 0, & R > p_{mj} \end{cases} \tag{7}$$

$$P_{qj} = \begin{cases} 1, & R < p_{tj} \\ 0, & R > p_{tj} \end{cases} \tag{8}$$

R = randomly generated number between 0 and 1, where $R \in \mathbb{R}$.

P = dummy 'switch' variable considering the individual's probability of switching in response to a certain incentive j.

To be able to have a value representing the sum of kilometres travelled in private CFVs in response to all incentives combined, a total variation (ΔD) was calculated as a function of the 'switch' variable (P), which resulted from an average of the perceived personal impact (p) for all the eleven incentives. This composite variable ('perceived personal impact of all incentives') showed very good reliability (α = 0.906). The resulting equation is shown below (Equation 9).

$$\Delta D_k = \left[\sum_{i=m}^{m} (P_m \times d_m) \right] \times k + \begin{cases} 0, & k = 1 \\ \Delta DMAX, & k > 1 \end{cases} \tag{9}$$

Where,

$$\Delta DMAX = \sum_{q=1}^{Q} \left(P_q \times d_q \; x \; T_q \right) \tag{10}$$

P = dummy 'switch' variable considering the average probability of switch in response to all incentives combined.

The two calculation approaches of likelihood to switch (considering stated likelihood directly or indirectly, via the new dummy variable) yielded approximately similar results, especially regarding scenarios that stipulate a maximum of 10 reduced trips (an average of 1.0% absolute differences in distance reduction).

The second approach (Equation 4) was used to tabulate results. It was judged to be a more ‘realistic’ methodology in comparison with the first approach, although it could be less reliable for smaller sample sizes.

The estimation was done for car and motorbike users, separately. Finally, car and motorbike users were considered together to generate indexes representing a reduction of distance travelled by private CFV’s.

First, the potential impacts are examined for both travel modes separately. The studied sample travelled a total of roughly 58,000 kilometres by car and 5,300 kilometres by motorbike on the week preceding the survey. Considering these distances, the potential impact of incentives were analysed and compared in percentage terms.

As an example, the implementation of all incentives combined, in the event that a reduction of two trips per week (one return trip) would have been seen in accordance with the declared intentions of the participants, could potentially reduce the weekly distance travelled by cars in 11.6% and by motorcycles in 13.6%[23]. This is probably due to the fact that even though motorcycle users are more reluctant to change in general (average value of perceived likelihood to change-p is 0.425 compared to 0.505 for car users), they generally travel longer distances in one week (average of 161km compared to 100km of car users).

From this point on, however, the focus will be on the examination of the potential benefits in terms of private CFVs use (cars and motorbikes combined). Therefore, Table 4.40 shows the potential kilometre reduction for

[23] This was calculated using the first approach (Equation 4), as the sample size of motorbike users were judged to be too small (n=54), thus increasing the errors of the dummy variable estimation (switch or no switch).

each type of incentive and also considering all incentives combined. A graphical representation of the same data is displayed in Figure 4.11.

The method of analysis used here has some limitations. The distance measures taken into account were reported by the students and might not reflect the real trip distances, as sometimes answers to this question can be just a rough estimate. Furthermore, this scenario estimation exercise does not take in consideration participants who might have shared trips with other surveyed student(s) during that week. Instead, every student is assumed to travel on their own or with people that are not part of the studied sample. More limitations are discussed further in the Discussion chapter.

The results show quite a substantial decrease in kilometres travelled by private CFVs in response to incentives. Even considering the most conservative scenario (where just one private CFV trip per week is replaced), the travelled distance reduction rate for all incentives is 5.4% and reaches 8.3% when looking at money rewards in isolation. A most probable scenario, perhaps, would be a two-trip reduction, which would represent a single return trip to the university, in a week. This scenario shows a decrease of 10.8% on the total distance.

Table 4.40 - Estimation of total kilometres travelled in one week by private CFVs for each reduction scenario (n = 614)

k[1]	D_{tot}[2]	D_{maps}	D_{money}	D_{points}	D_{rank}	D_{vouc}	D_{jour}	D_{info}	D_{feed}	D_{socm}	D_{chal}	D_{budd}
0	63,563 (0%)	63,225 (0%)	62,815 (0%)	62,875 (0%)	62,926 (0%)	63,096 (0%)	63,096 (0%)	62,976 (0%)	63,096 (0%)	63,296 (0%)	63,136 (0%)	63,046 (0%)
1	60,123 (-5.4%)	59,928 (-5.2%)	57,595 (-8.3%)	60,489 (-3.8%)	60,740 (-3.5%)	58,308 (-7.6%)	59,239 (-6.1%)	58,684 (-6.8%)	59,611 (-5.5%)	61,769 (-2.4%)	60,546 (-4.1%)	59,390 (-5.8%)
2	56,684 (-10.8%)	56,631 (-10.4%)	52,375 (-16.6%)	58,104 (-7.6%)	58,554 (-6.9%)	53,519 (-15.2%)	55,382 (-12.2%)	54,392 (-13.6%)	56,125 (-11%)	60,241 (-4.8%)	57,955 (-8.2%)	55,735 (-11.6%)
3	54,170 (-14.8%)	54,280 (-14.1%)	48,471 (-22.8%)	56,473 (-10.2%)	56,987 (-9.4%)	50,070 (-20.6%)	52,637 (-16.6%)	51,309 (-18.5%)	53,628 (-15%)	59,289 (-6.3%)	56,174 (-11%)	53,193 (-15.6%)
4	51,657 (-18.7%)	51,929 (-17.9%)	44,566 (-29.1%)	54,841 (-12.8%)	55,420 (-11.9%)	46,620 (-26.1%)	49,891 (-20.9%)	48,226 (-23.4%)	51,130 (-19%)	58,337 (-7.8%)	54,393 (-13.8%)	50,652 (-19.7%)
5	49,143 (-22.7%)	49,579 (-21.6%)	40,662 (-35.3%)	53,210 (-15.4%)	53,854 (-14.4%)	43,170 (-31.6%)	47,145 (-25.3%)	45,143 (-28.3%)	48,633 (-22.9%)	57,385 (-9.3%)	52,612 (-16.7%)	48,111 (-23.7%)
6	47,347 (-25.5%)	47,844 (-24.3%)	37,843 (-39.8%)	52,037 (-17.2%)	52,743 (-16.2%)	40,741 (-35.4%)	45,092 (-28.5%)	42,969 (-31.8%)	46,833 (-25.8%)	56,751 (-10.3%)	51,245 (-18.8%)	46,274 (-26.6%)
7	45,550 (-28.3%)	46,108 (-27.1%)	35,023 (-44.2%)	50,863 (-19.1%)	51,633 (-17.9%)	38,312 (-39.3%)	43,040 (-31.8%)	40,795 (-35.2%)	45,033 (-28.6%)	56,117 (-11.3%)	49,879 (-21%)	44,437 (-29.5%)
8	43,754 (-31.2%)	44,373 (-29.8%)	32,203 (-48.7%)	49,690 (-21%)	50,522 (-19.7%)	35,883 (-43.1%)	40,987 (-35%)	38,621 (-38.7%)	43,234 (-31.5%)	55,483 (-12.3%)	48,512 (-23.2%)	42,600 (-32.4%)
9	42,299 (-33.5%)	43,010 (-32%)	29,905 (-52.4%)	48,689 (-22.6%)	49,605 (-21.2%)	33,962 (-46.2%)	39,302 (-37.7%)	36,872 (-41.5%)	41,774 (-33.8%)	54,996 (-13.1%)	47,414 (-24.9%)	41,039 (-34.9%)
10	40,844 (-35.7%)	41,647 (-34.1%)	27,606 (-56.1%)	47,688 (-24.2%)	48,688 (-22.6%)	32,040 (-49.2%)	37,617 (-40.4%)	35,122 (-44.2%)	40,314 (-36.1%)	54,509 (-13.9%)	46,317 (-26.6%)	39,477 (-37.4%)

[1] Reduced trips in response to incentives.
[2] Kilometres travelled by private CFVs in one week, with percentage reduction over the total.
Note: The total distance travelled in kilometres (first row) is different between incentives due to a different number of missing values for each variable.

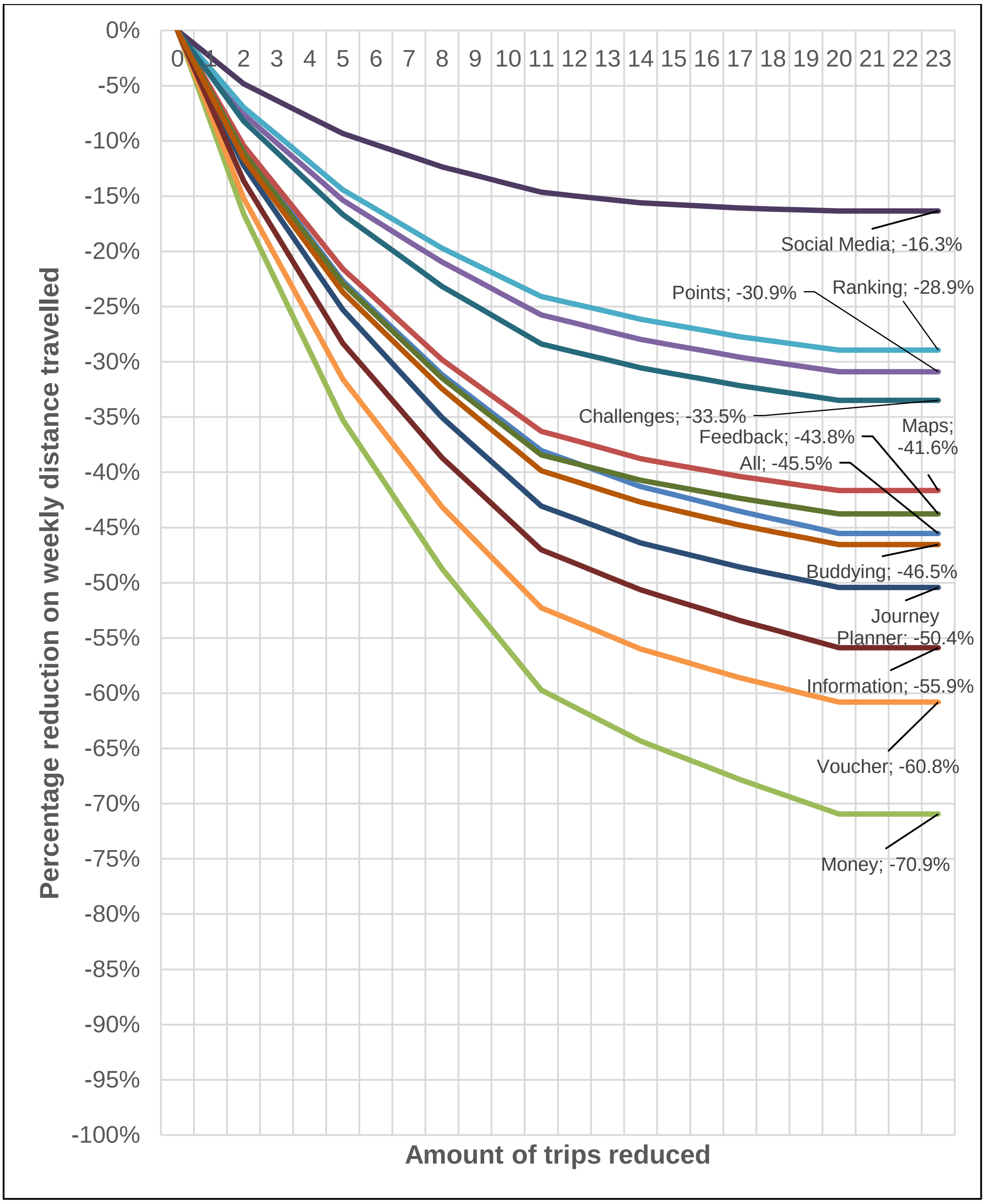


Figure 4.11 - Percentage reduction on weekly distance travelled by private CFVs in response to positive incentives, per trip reduction scenario (k) (n = 614)

As the participant with the largest amount of trips to the university travels about 22 times in a week, the end of the lines presented in Figure 4.11 (reduction of 22 or more trips) represents the most optimistic scenario (where students would make the switch on all their weekly trips to the university). Considering this scenario, the implementation of incentives is estimated to achieve a 45.5%

reduction in total distance travelled by private CFVs in Curitiba, in a week (28,944 kilometres avoided).

Financial rewards are the most impactful incentives, while incentives linked with collaboration and competition (social media, rankings, challenges) are among the least effective tools. This is tied to the better acceptance that financial incentives demonstrated. Informative incentives (information on consequences of travelling, journey planner) are also more effective than the average performance of all incentives and could lead to an approximate 13% reduction on private CFV travelling, considering two trips avoided in a week.

Overall, the potential benefits coming from the implementation of incentives are quite significant. Later on this thesis, more discussions will be presented in terms of the comparison of these results to other studies that looked to positive incentives and a more detailed argument in terms of policy implementation will be presented.

For now, the analysis proceeds to the examination of the potential environmental and (consequently) financial benefits.

4.6.2 The decrease in carbon emissions

Another form of looking at the outputs presented in the previous section is to examine how these potential benefits translate to the emission of pollutant gases. Thus, the variation in emissions related to the use of private CFVs was calculated using emission parameters of different vehicles established in the literature. In this case, the parameters regarding the use of cars or motorcycles (c) were used to multiply the previously calculated reduced distance (ΔD) to each reduction scenario (*k*)*,* resulting on the estimated reduction in emissions for each scenario (ΔC). These values, in turn, were compensated by the carbon emissions of travelling by the alternative modes (cycling, walking or taking the bus). As the alternative choice was not specifically assessed in the sample, scenarios in regards to this choice were also developed. In addition, since it would not be possible to know if a respondent who had used both types of private CFVs would have chosen to avoid the car or the motorcycle trips, participants who had used both modes were not considered, for simplification purposes (2.9% of the sample).

The calculation was performed as follows: the total variation in terms of emissions of a particular travel mode ($\Delta \boldsymbol{C}car, \Delta \boldsymbol{C}bus$, etc.) was calculated by multiplying emission parameters of this mode ($\boldsymbol{c_{car}}, \boldsymbol{c_{moto}}$, etc.) to the variations in terms of the distance of a single trip (ΔS), expressed earlier. This result, in turn, was multiplied by the number of reduced trips (k), depending on the scenario to be studied. Similarly to the method described earlier, for the respondents whose amount of reduced trips (k) exceeded the total trips made in a week, the maximum variation of emissions was added to the formula ($\Delta CMAX$), which is also a function of the maximum variation of distance ($\Delta DMAX$).

The emission parameters used for each travel mode are shown below (Table 4.41). As travelling activities emit multiple gases that are harmful to the environment (carbon dioxide, carbon monoxide, methane, etc.), studies often report emission parameters in terms of 'carbon dioxide-equivalent' (Co2-eq), which refers to a weighted sum of the pollutant gases in terms of their global warming potential (Duffy and Crawford, 2013). The studies consulted to get the emission parameters have used 'Co2-eq' and this unit will be considered here too.

These emission parameters are an estimation. Even with the effort to minimise these errors by choosing parameters that were calculated in similar contexts to this study, the real parameters for the sample are unknown. It is thus suggested that results are examined considering these aspects.

For practical purposes and also considering that the values assumed are quite similar, the emission coefficients of cycling and walking were averaged, to form a single value that could be considered as a coefficient for 'non-motorised forms of transport'. This simplification enables the investigation of 'bi-dimensional' scenarios in terms of which travel mode is chosen as an alternative to private CFVs (bus or non-motorised modes). As a result, various scenarios were estimated, not only in terms of the number of reduced trips, but also in terms of the proportion of these trips that would have been replaced by bus trips (b), and non-motorised trips (1-b).

Table 4.41 - Emission parameters of travel modes

Travel mode	gCo2-eq/pass.km (fuel/food)[1]	Data source (fuel/food)	gCo2-eq/pass.km (non-fuel/food)[2]	Data source (non-fuel/food)	Total emissions (gCo2-eq/pass.km)
Car	190	Brazil (Henrique and Carvalho, 2011)	72.3	Europe (Duffy and Crawford, 2013)	262.3
Motorcycle	70	Brazil (Henrique and Carvalho, 2011)	72.3[3]	No data source[3]	145.4
Bus	13.2[4]	Brazil (Henrique and Carvalho, 2011; URBS, 2017)	81.2	Europe (Duffy and Crawford, 2013)	94.4
Bike	19.1	Europe (Duffy and Crawford, 2013)	67.3	Europe (Duffy and Crawford, 2013)	86.4
Walking	47	Europe (Duffy and Crawford, 2013)	36.7	Europe (Duffy and Crawford, 2013)	83.7

Note: Emissions expressed in grams of carbon dioxide equivalent per kilometre per passenger (gCo2-eq/pass.km).
[1] These values refer to direct emissions (related to fuel or food consumption).
[2] These values refer to indirect emissions, which can take the form of aspects related to a vehicle`s life cycle (e.g. maintenance, manufacture) or the purchase of footwear and cycling equipment.
[3] To the best of the researcher's knowledge, no reliable data exists to determine non-fuel related emissions of motorbikes. For practical purposes, the value related to cars is considered.
[4] This value was calculated based on the government`s official data from Curitiba in relation to the average bus occupancy rate, which can be considered to be relatively high (96.7 passengers/trip).

The equation used to calculate the variation in total emissions due to positive incentives is demonstrated below (Equation 11).

$$\begin{aligned} \Delta Ctot_{kb} &= \Delta Ccar + \Delta Cmoto + \Delta CMAXcar + \Delta CMAXmoto \\ &- \begin{cases} (\Delta Cbus \times b) + [\Delta Cnmot \times (b-1)], & k = 1 \\ (\Delta Cbus \times b) + [\Delta Cnmot \times (b-1)] + \\ (\Delta CMAXbus \times b) + [\Delta CMAXnmot \times (1-b)], & k > 1 \end{cases} \end{aligned} \tag{11}$$

Where,

$\Delta Ctot$ = variation in tons of CO_2-equivalent weekly emissions in response to all incentives combined;

k = number of weekly trips reduced, with $k \in \mathbb{N}^*$;

b = percentage of trips originally made by private CFV estimated to be switched to the bus;

$\Delta Ccar = (\Delta S_k \times c_{car}) \times k$

$\Delta Cmoto = (\Delta S_k \times c_{moto}) \times k$
$\Delta Cbus = (\Delta S_k \times c_{bus}) \times k$
$\Delta Cnmot = (\Delta S_k \times c_{nmot}) \times k$
$\Delta CMAXcar = \Delta DMAXcar \times c_{car}$
$\Delta CMAXmoto = \Delta DMAXmoto \times c_{moto}$
$\Delta CMAXbus = \Delta DMAXbus \times c_{bus}$
$\Delta CMAXnmot = \Delta DMAXnmot \times c_{nmot}$

Where,

$\Delta Ccar$ = variation in tons of CO_2 equivalent weekly emissions related to travelling by car;
$\Delta Cmoto$ = variation in tons of CO_2 equivalent weekly emissions related to travelling by motorcycle;
$\Delta Cbus$ = variation in tons of CO_2 equivalent weekly emissions related to travelling by bus;
$\Delta Cnmot$ = variation in tons of CO_2 equivalent weekly emissions related to travelling using non-motorised forms of transport (walking or cycling);
ΔS = variation on the weekly travelled distance for a single trip;
$\Delta CMAXcar$ = maximum variation in tons of CO_2 equivalent weekly emissions related to travelling using the car;
$\Delta CMAXmoto$ = maximum variation in tons of CO_2 equivalent weekly emissions related to travelling using the motorcycle;
$\Delta CMAXbus$ = maximum variation in tons of CO_2 equivalent weekly emissions related to travelling using the bus;
$\Delta CMAXnmot$ = maximum variation in tons of CO_2 equivalent weekly emissions related to travelling using non-motorised forms of transport (cycling or walking);
c_{car} = tons of CO_2 equivalent per kilometre travelled by car;
c_{moto} = tons of CO_2 equivalent per kilometre travelled by motorcycle;
c_{bus} = tons of CO_2 equivalent per kilometre travelled by bus;
c_{nmot} = tons of CO_2 equivalent per kilometre travelled by non-motorised forms of transport (cycling or walking).

Table 4.42 shows the estimated tons of carbon dioxide-equivalent emissions for the scenarios. Emission savings would range from 0.55 to 5.11 tons per week, depending on the scenario.

As a matter of estimating a potential impact of incentives if a wider population of private CFV users in the city behaved in the same manner as the surveyed students, the values presented above were extrapolated considering the total amount of undergraduate students of Curitiba. The reported number by the official government census data is 127,422 students (INEP, 2017). The rate of private CFV users in the sample (66.7%) was used to estimate the value of private CFV users in the city’s population (which came down to 85,050). Table 4.43 displays the calculated values.

Table 4.42 - Estimated carbon emission savings (tons) of the sample due to positive incentives, for different scenarios of reduced trips per week and different alternative choices (n = 614).

Estimated savings (tons of Co2-eq)					
Reduced trips per week (k)	The proportion of trips switched to the bus and non-motorised modes (b)/(1-b)				
	100%/0%	75%/25%	50%/50%	25%/75%	0%/100%
0 (baseline scenario)	15.53 (0%)	15.53 (0%)	15.53 (0%)	15.53 (0%)	15.53 (0%)
1	-0.55 (-3.6%)	-0.56 (-3.6%)	-0.57 (-3.7%)	-0.58 (-3.7%)	-0.58 (-3.8%)
2	-1.11 (-7.1%)	-1.12 (-7.2%)	-1.14 (-7.3%)	-1.15 (-7.4%)	-1.17 (-7.5%)
3	-1.52 (-9.8%)	-1.65 (-10.6%)	-1.78 (-11.5%)	-1.91 (-12.3%)	-2.04 (-13.1%)
4	-1.94 (-12.5%)	-2.13 (-13.7%)	-2.32 (-14.9%)	-2.51 (-16.1%)	-2.70 (-17.4%)
5	-2.36 (-15.2%)	-2.61 (-16.8%)	-2.86 (-18.4%)	-3.1 (-20%)	-3.35 (-21.6%)
6	-2.66 (-17.1%)	-2.89 (-18.6%)	-3.13 (-20.1%)	-3.36 (-21.6%)	-3.59 (-23.1%)
7	-2.96 (-19.1%)	-3.24 (-20.8%)	-3.51 (-22.6%)	-3.79 (-24.4%)	-4.07 (-26.2%)
8	-3.26 (-21%)	-3.58 (-23.1%)	-3.9 (-25.1%)	-4.22 (-27.2%)	-4.54 (-29.3%)
9	-3.5 (-22.6%)	-3.81 (-24.5%)	-4.11 (-26.5%)	-4.42 (-28.4%)	-4.72 (-30.4%)
10	-3.75 (-24.1%)	-4.09 (-26.3%)	-4.43 (-28.5%)	-4.77 (-30.7%)	-5.11 (-32.9%)

Notes: First row represents total carbon emissions due to the use of private CFVs (baseline scenario). Subsequent rows represent absolute reductions from the total. Values are expressed in tons of Co2 equivalent (TonsCo2-eq).

Table 4.43 - Extrapolation of estimated carbon savings to the total population of undergraduate students of Curitiba, due to positive incentives, for different scenarios of reduced trips per week and different alternative choices (N = 85,050).

Estimated savings (tons of Co2-eq)					
Reduced trips per week (k)	The proportion of trips switched to the bus and non-motorised modes (Pb)/(1-Pb)				
	100%/0%	75%/25%	50%/50%	25%/75%	0%/100%
0 (baseline scenario)	2151.3 (0%)	2151.3 (0%)	2151.3 (0%)	2151.3 (0%)	2151.3 (0%)
1	-76.6 (-3.6%)	-77.7 (-3.6%)	-78.8 (-3.7%)	-79.9 (-3.7%)	-81.0 (-3.8%)
2	-153.2 (-7.1%)	-155.4 (-7.2%)	-157.6 (-7.3%)	-159.7 (-7.4%)	-161.9 (-7.5%)
3	-210.9 (-9.8%)	-228.9 (-10.6%)	-246.8 (-11.5%)	-264.8 (-12.3%)	-282.7 (-13.1%)

Estimated savings (tons of Co2-eq)					
Reduced trips per week (k)	The proportion of trips switched to the bus and non-motorised modes (Pb)/(1-Pb)				
	100%/0%	**75%/25%**	**50%/50%**	**25%/75%**	**0%/100%**
4	-268.6 (-12.5%)	-294.9 (-13.7%)	-321.1 (-14.9%)	-347.4 (-16.1%)	-373.6 (-17.4%)
5	-326.4 (-15.2%)	-360.9 (-16.8%)	-395.4 (-18.4%)	-430. (-20%)	-464.5 (-21.6%)
6	-368.1 (-17.1%)	-400.5 (-18.6%)	-432.8 (-20.1%)	-465.2 (-21.6%)	-497.6 (-23.1%)
7	-409.9 (-19.1%)	-448.3 (-20.8%)	-486.7 (-22.6%)	-525. (-24.4%)	-563.4 (-26.2%)
8	-451.7 (-21%)	-496.1 (-23.1%)	-540.5 (-25.1%)	-584.9 (-27.2%)	-629.3 (-29.3%)
9	-485.4 (-22.6%)	-527.5 (-24.5%)	-569.6 (-26.5%)	-611.7 (-28.4%)	-653.8 (-30.4%)
10	-519.2 (-24.1%)	-566.2 (-26.3%)	-613.2 (-28.5%)	-660.1 (-30.7%)	-707.1 (-32.9%)

Notes: First row represents total carbon emissions due to the use of private CFVs (baseline scenario). Subsequent rows represent absolute reductions from the total. Values are expressed in tons of Co2 equivalent (TonsCo2-eq).

The values presented above consider a 100% penetration rate of positive incentives in this population, which is a very optimistic scenario. It could lead to emission savings of around 77 to 162 tons per week (considering a more conservative ‘switch rate’ of 1 to 2 trips per week). When just the sample is examined, in a more realistic approach, this same scenario would lead to savings of around 0.5 to 1.2 tons of carbon dioxide-equivalent per week.

4.6.2.1 The decrease in emission-related costs

The third type of estimation scenario was created considering the savings in terms of the financial costs of carbon emissions. The cost per unit of carbon was extracted from the study of Ricke *et al.* (2018), who estimated the value to be $24 (twenty-four American dollars) per tonne of carbon dioxide, in Brazil. That is, for every tonne of carbon dioxide that is expelled in the atmosphere, $24 is spent, on average, due to the environmental damage that is associated with this emission. This is often referred to as the ‘social cost’ of carbon (Ricke *et al.* 2018). Having established the average value of $24 dollars per tonne, Table 4.44 presents the total cost (in dollars), per person, that would be saved in case positive incentives were to be implemented. Thus, different situations can be estimated from these individual values in regards to the potential financial impact if more people adopt the incentives (by multiplying these individual values to the desired number of impacted people)[1].

Table 4.44 - Estimated carbon emission financial savings (dollars) per person, based on the sample (n=614), due to the implementation of positive incentives, for different scenarios of reduced trips per week and different alternative choices.

Estimated savings per adopter of positive incentives (tons of Co2-eq)					
Reduced trips per week (k)	**The proportion of trips switched to the bus and non-motorised modes (Pb)/(1-Pb)**				
	100%/0%	**75%/25%**	**50%/50%**	**25%/75%**	**0%/100%**
0 (baseline scenario)	$0.61 (0%)	$0.61 (0%)	$0.61 (0%)	$0.61 (0%)	$0.61 (0%)
1	-$0.02 (-3.6%)	-$0.02 (-3.6%)	-$0.02 (-3.7%)	-$0.02 (-3.7%)	-$0.02 (-3.8%)
2	-$0.04 (-7.1%)	-$0.04 (-7.2%)	-$0.04 (-7.3%)	-$0.05 (-7.4%)	-$0.05 (-7.5%)
3	-$0.06 (-9.8%)	-$0.06 (-10.6%)	-$0.07 (-11.5%)	-$0.07 (-12.3%)	-$0.08 (-13.1%)
4	-$0.08 (-12.5%)	-$0.08 (-13.7%)	-$0.09 (-14.9%)	-$0.10 (-16.1%)	-$0.11 (-17.4%)
5	-$0.09 (-15.2%)	-$0.10 (-16.8%)	-$0.11 (-18.4%)	-$0.12 (-20%)	-$0.13 (-21.6%)
6	-$0.10 (-17.1%)	-$0.11 (-18.6%)	-$0.12 (-20.1%)	-$0.13 (-21.6%)	-$0.14 (-23.1%)
7	-$0.12 (-19.1%)	-$0.13 (-20.8%)	-$0.14 (-22.6%)	-$0.15 (-24.4%)	-$0.16 (-26.2%)
8	-$0.13 (-21%)	-$0.14 (-23.1%)	-$0.15 (-25.1%)	-$0.17 (-27.2%)	-$0.18 (-29.3%)
9	-$0.14 (-22.6%)	-$0.15 (-24.5%)	-$0.16 (-26.5%)	-$0.17 (-28.4%)	-$0.18 (-30.4%)
10	-$0.15 (-24.1%)	-$0.16 (-26.3%)	-$0.17 (-28.5%)	-$0.19 (-30.7%)	-$0.20 (-32.9%)

Notes: First row represents weekly financial costs per person due to the use of private CFVs (baseline scenario). Subsequent rows represent absolute reductions from the total due to the use of positive incentives. Values are expressed in American dollars ($).

Taking the scenario where students would replace two trips that they would originally have made by private CFVs on a single week (on average), the

[1] Nevertheless, care should be taken as these values at the individual-level resulted from a simple division of the values for the entire sample, which were generated considering its heterogeneity. Any kind of extrapolation would be more realistic by multiplying these values to at least the number that represents the sample size (614), to avoid significant distortions.

implementation of positive incentives could lead to a reduction of carbon costs of around $27 per week, considering that the whole sample would be using the incentives tools. If incentives were to be used by the whole population of undergraduate students in the city, the weekly savings could reach around $3,700 per week (from $3,677 to $3,886), also considering a two-trip reduction.

4.6.3 The decrease in carbon emissions and costs by psychographic segment

The aim of this section is to evaluate the impact of a positive incentive scheme implementation for each psychographic group identified previously in Section 4.4. These results have the potential to shed some light not only on which type of behavioural profile would be responsible for greater emissions savings and carbon costs in this context, but also to compare the relative extent to which each segment would be impacted by such initiatives. Thus, serving as a general guideline for better-tailored policies.

Initially, one might think that clusters such as the "*Bus-Dependents*" or the "*Autonomous Environmentalists*" would be worthless to assess as they do not use private CFVs at all. As detailed in Section 4.4, the segments were formed based exclusively on psychological characteristics. Although it is expected that the "*Car-Predisposed*" or the "*Motorbike Enthusiasts*" clusters, for example, display a higher weekly frequency of private CFV use, all the other groups also contain individuals who drive a car or ride a motorbike, as can be seen in Table 4.45.

Table 4.45 - Use of private CFVs of psychographic clusters

	Bus Dep. (n=201)	**Car Pred. (n=315)**	**N-Mot. Lov. (n=135)**	**Aut. Env. (n=186)**	**N-Mot. Reluc. (n=83)**	**All (n = 920)**
Amount of private CFV users (% of total cluster size)	90 (44.8%)	283 (89.8%)	74 (54.8%)	104 (55.9%)	63 (75.9%)	614 (66.7%)
Average car trips per week	5.4	10.3	7.9	6.3	5.2	8.0
Average motorbike trips per week	0.0	0.0	0.2	0.0	4.1	0.6
Average private CFV trips per week	5.4	10.3	8.1	6.4	9.3	8.6
Average trip distance of private CFV users	13.9	11.5	11.9	7.8	15.1	11.6

The *Bus-Dependents* cluster has the lowest proportion of private CFV users among its total members. Even though, this represents almost half of the students (44.8%). The average amount of trips made by private CFVs by them, nonetheless, is low (5.4). The *Non-Motorised Lovers*, on average, have a relatively high amount of weekly trips by private CFVs (8.1). The average distance of 11.9 kilometres between their home and the university indicates that distance should be one of the main causes. The weekly use of the motorbike is almost an exclusive characteristic of the *Motorbike Enthusiasts*. Other groups display a very low frequency of use of this mode.

The second step of the analysis aimed at examining the differences in terms of absolute values of emissions (tons of CO2-eq) for one week, per each cluster. From this point on, only emissions that are related to the use of private CFVs (cars or motorbikes) are considered, as these are the modes that are being treated as less 'environmental-friendly' or 'sustainable' in this thesis. Figure 4.12 presents the baseline parameters of these emissions.

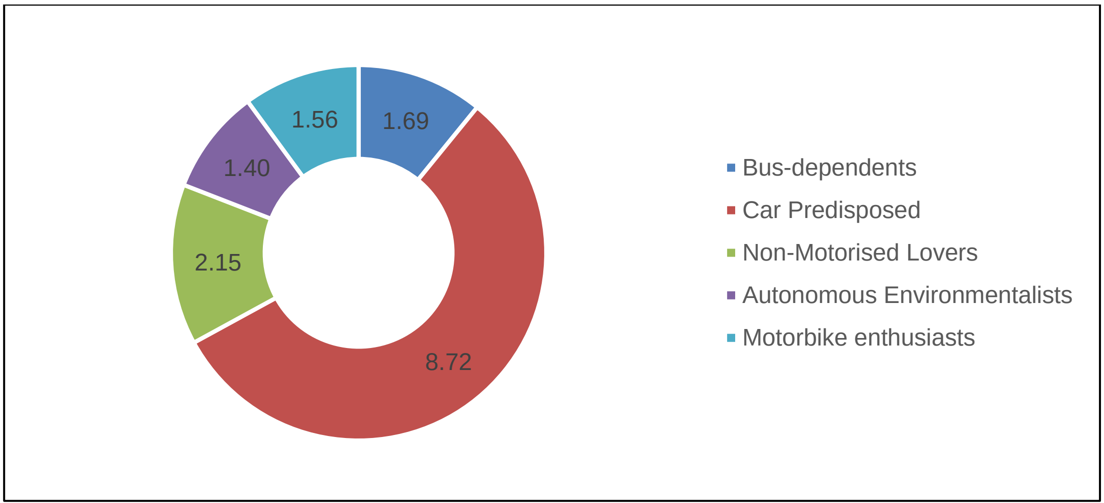
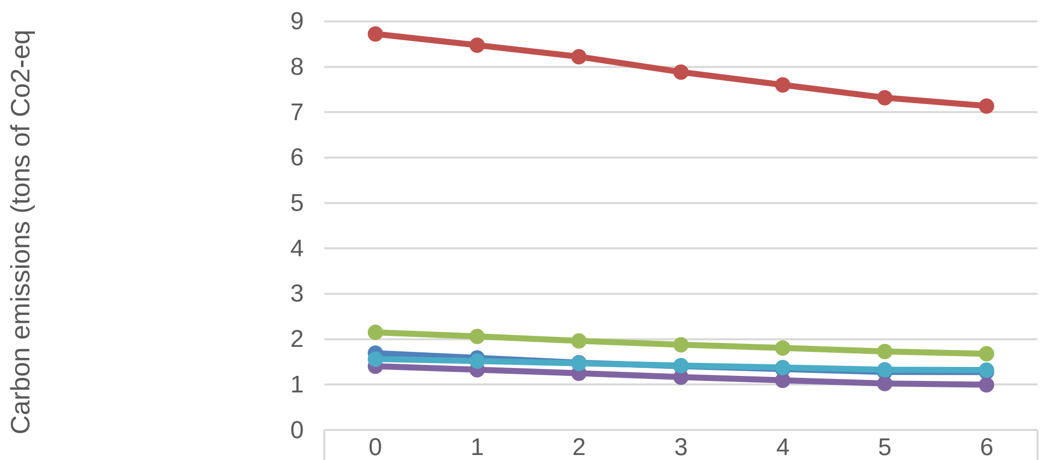


Figure 4.12 - Total tons of carbon dioxide equivalent emissions, per psychographic cluster (n = 614)

The *Car-Predisposed* cluster is responsible for more than half of the total weekly private CFV-related carbon emissions of the sample (8.72 tons), while the other clusters share roughly similar amounts of pollutants.

Figure 4.13 shows a graph representing the number of total emissions for a given cluster for different reduction scenarios, starting from the baseline (without any incentives intervention) and subsequently increasing until the scenario where six trips would be replaced due to incentives, in a week. The data shown in the graph considers the scenario where 50% of the trips made by private CFVs are replaced by bus trips and the other 50% by non-motorised trips. This uncertainty arises from the lack of detailed data about which travel mode the respondent would pick as an alternative to the private CFV (and the fact that non-motorised travel modes have different levels of emissions per trip per person, compared to the bus).



	0	1	2	3	4	5	6
Bus-dependents	1.69	1.59	1.48	1.41	1.34	1.28	1.27
Car Predisposed	8.72	8.47	8.22	7.88	7.60	7.32	7.14
Non-Motorised Lovers	2.15	2.06	1.97	1.88	1.80	1.73	1.68
Autonomous Environmentalists	1.40	1.33	1.25	1.16	1.09	1.02	1.00
Motorbike enthusiasts	1.56	1.52	1.47	1.42	1.37	1.33	1.32

Number of trips reduced in a week (k)

Figure 4.13 - Baseline of emissions and potential reduction (tons of CO_2-eq) for each psychographic segment, per different scenarios of reduced trips (n = 614)

Note: the data used on this graph assumes the replacement rate of 50% to buses and 50% to non-motorised transport.

In absolute terms of carbon emission reductions, the *Car-Predisposed* people would be responsible for the greatest benefits for the environment when using positive incentives. Possibly because they are the ones liable for the most emissions related to mobility in the first place, so their behaviour change tends to produce higher benefits. The *Car-Predisposed* group also contains a higher number of people who use the car more regularly than the other groups (they make an average of 9.3 private CFV trips in a week while the *Bus-Dependents*, for example, make 2.5). *Motorbike Enthusiasts* are the ones with the lowest environmental impact coming from the use of positive incentives. This can probably be explained by them being less prone to positive incentives in general, while also being a relatively small group (63 private CFV users).

Table 4.46 shows the emission reductions in relative terms. Here, the segments more prone to individual motorised forms of transport demonstrate a lower percentage variation in emissions in response to incentives, while the *Bus-Dependents* would be responsible for better relative environmental outcomes when looking at the most conservative scenarios.

Table 4.46 - Percentage reduction in carbon emissions for each psychographic cluster, per different scenarios of reduced trips (n = 614)

Amount of reduced trips per week	Bus Dep.	Car Pred.	N-Mot. Lov.	Aut. Env.	N-Mot. Reluc.
0 (baseline)	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
1	-6.1%	-2.9%	-4.3%	-5.5%	-2.9%
2	-12.3%	-5.7%	-8.6%	-10.9%	-5.9%
3	-16.8%	-9.6%	-12.7%	-17.1%	-9.3%
4	-20.6%	-12.8%	-16.1%	-22.2%	-12.1%
5	-24.4%	-16.1%	-19.5%	-27.3%	-14.9%
6	-24.6%	-18.1%	-22.0%	-29.0%	-15.5%

Lastly, these differences were transformed into emissions-related financial costs (Table 4.47).

Table 4.47 - Weekly financial costs and savings related to carbon emissions, per psychographic cluster (n = 614)

Amount of reduced trips per week	Bus Dep.	Car Pred.	N-Mot. Lov.	Aut. Env.	N-Mot. Reluc.
0 (baseline)	*$40.58*	*$210.20*	*$51.60*	*$33.72*	*$37.51*
1	$38.10 (-$2.49)	$204.20 (-$6.0)	$49.38 (-$2.22)	$31.87 (-$1.85)	$36.41 (-$1.10)
2	$35.61 (-$4.97)	$198.2 (-$12.0)	$47.16 (-$4.44)	$30.02 (-$3.69)	$35.31 (-$2.19)
3	$33.76 (-$6.82)	$190.05 (-$20.15)	$45.05 (-$6.55)	$27.96 (-$5.76)	$34.02 (-$3.49)
4	$32.22 (-$8.37)	$183.25 (-$26.95)	$43.29 (-$8.31)	$26.24 (-$7.48)	$32.98 (-$4.53)
5	$30.67 (-$9.91)	$176.45 (-$33.76)	$41.53 (-$10.08)	$24.51 (-$9.20)	$31.93 (-$5.58)

6	\$30.59 (-\$9.99)	\$172.14 (-\$38.06)	\$40.25 (-\$11.35)	\$23.93 (-\$9.79)	\$31.70 (-\$5.81)

Note: values are expressed in American dollars per week and are based on the cost per ton of Co2 of \$24.00, established by Ricke et al. (2018).

As one could expect, the *Car-Predisposed* are the ones with the highest weekly 'carbon cost' among the sample (\$210), while the *Autonomous Environmentalists* have the lowest impact in terms of emissions-related costs (\$34). An important reduction would be observed with the use of incentives in all groups though. *Motorbike Enthusiasts* perform worse in this aspect. They would be responsible for savings of around \$4.50 per week if four trips were to be reduced, as opposed to almost \$27 of the *Car-Predisposed*, for instance.

4.6.4 The decrease in carbon emissions and costs by private CFV user of each psychographic segment

To allow a deeper understanding of the differences among segments, the absolute reductions on emissions were also calculated for a single private CFV user that is part of each cluster (Table 4.48).

Table 4.48 – Emissions and potential savings per private CFV user, considering each cluster and the entire sample (n = 614)

	Bus Dep.	**Car Pred.**	**N-Mot. Lov.**	**Aut. Env.**	**N-Mot. Reluc.**	**All**
Average emissions per private CFV user per week (CO_2-eq)	18.8	30.8	29.1	13.5	24.8	25.3
Carbon savings per week per private CFV user, when one trip is replaced (KgCO_2-eq)[1]	1.1	0.9	1.2	0.8	0.8	0.9
Total carbon cost per week per private CFV user (Dollars)	\$0.45	\$0.74	\$0.70	\$0.32	\$0.60	\$0.61
Carbon cost savings per week per private CFV user, when one trip is replaced (Dollars)[1]	- \$0.03	-\$0.02	-\$0.03	-\$0.02	-\$0.02	-\$0.02

[1] This index was calculated considering a scenario where 50% of private CFV trips were replaced by non-motorised modes and 50% to public transport.

The *Car-Predisposed* continue to be the cluster with higher emissions per individual in a week of commuting (30.8 kilograms of CO_2-eq), followed by the *Non-Motorised Lovers* (29.1 Kgs of CO_2-eq) and the *Motorbike Enthusiasts* (24.8 Kgs of CO_2-eq). The clusters with the lowest carbon footprint in the context of private CFV use are the *Bus-Dependents* (18.8 Kgs of CO_2-eq) and the *Autonomous Environmentalists* (13.5 Kgs of CO_2-eq). It is worth remembering that these indicators are a function of multiple variables such as trip distance, trip frequency, mode choice and perceived personal impact.

In this aspect, the *Non-Motorised Lovers* are instead the group where individual use of incentives would lead to better environmental outcomes per incentive user (a reduction of 1.22 kgCO_2-eq/person while the other groups show an average of 0.89 kgCO_2-eq/person). This can be explained by the combination of higher levels of acceptability of incentives in general, with a relatively higher number of private CFV trips in a week and higher travelled distances, on average (compared to the *Autonomous Environmentalists* who also show good acceptability but do not travel that much using private CFVs). Targeting incentives to people who belong to the same psychological profile as the *Non-Motorised Lovers* may have the best incremental environmental benefit in terms of carbon savings and in terms of the associated financial cost savings.

This concludes the results chapter. The chapter to follow presents discussions around the findings, including a summary of the results, the study limitations and suggestions for future work.

Chapter 5
Discussion

This chapter aims to examine the significance of the findings of this study in light of the current state-of-the-art. Also, it looks to explore the general relevance of the research.

First, the sections are devoted to exploring the results of the four major phases of the research: the development of a theoretical model (Section 5.1); the correlation analysis (Section 5.2); the psychographic segmentation (Section 5.3) and; the scenario estimation (Section 5.4). These sections begin by providing a summary of the findings, which are followed by an assessment of the similarities or contrasts with the current literature. These critical comparisons are expected to lead to broader and more insightful conclusions, thus strengthening the finding of this thesis reported in Chapter 5. Next, the adequacy of the results to meet the main contributions that were predicted at the beginning of this research is also discussed, along with the assessment about how the findings perform in respect to answering the associated research questions. The chapter follows with a synthesis of the findings in Section 5.5, with emphasis on the practical contributions of the thesis. The chapter ends with the research limitations and directions for future work (Section 5.6).

5.1 The theoretical framework

Several theories of behaviour were identified as being used to explain transport behaviour in past studies (i.e. TPB, GST, NAM, VBN, TIB, SLT, etc.). A theoretical review of how the concepts of these theories relate to transport, with a focus on transport mode choice, was done (Section 2.1). After a review about the strategies of public segmentation and positive incentives (Sections 2.2 and 2.3), a set of competency questions was developed with the aim to select those theoretical constructs that best serve the purpose of this research (Section 2.4). The resulting theoretical framework is expected to contribute to the current literature by offering concepts that are suitable inputs for a market segmentation approach to travel behaviour. In summary, the concepts that formed the framework were those that: (1) were subject to past empirical tests in regards to their efficacy to influence the use of travel modes (car or other alternatives); (2) had their validity and reliability successfully assessed in travel behaviour research and; (3) could be operationalised within the methodological spectrum of this research. That is, could be represented as survey variables. Four factors that are not related to behaviour theories were also added to the framework as they were assumed to influence travel mode choice to a significant degree or to influence the acceptability of persuasive technologies, in a similar manner.

Future transport interventions aimed at fostering sustainable travel behaviour can be guided by the behavioural factors outlined in the theoretical framework. For example, by increasing someone's attitudes, norms and perceived control over cycling or even the feelings of moral obligation to help the environment (personal norms), a given policy would consequently increase bike use, according to the theoretical relationships established by the framework.

Three concepts were included to represent the concept of 'acceptability' of positive incentives: attitudes, intention to use and likelihood to change in response to the incentive (perceived personal impact). The reviewed literature does not define 'acceptance' in a particularly unique manner. In addition, measuring acceptance of a new product or service depends on factors such as whether the products have already been released or not. Despite these issues, it was assumed that assessing: (1) to what extent the participants like the proposed incentives; (2) their intention to use the incentives if they were implemented and; (3) the extent to which they believe these incentives would make them adopt the desired behaviour, would satisfactorily meet the objective of assessing acceptability.

The theory-derived variables of the resulting framework (Figure 2.4) can be compared to three different meta-analyses studies that aimed to identify correlates of car and non-car use (Gardner and Abraham, 2008; Hoffmann et al., 2017; Lanzini and Khan, 2017). All the theory-derived constructs that were selected to form the framework of this research are significant influencers of travel behaviour according to the meta-analysis of Lanzini and Khan, who assessed the use of multiple travel modes. The authors of the other two meta-analyses were more concerned to explain car use only. They also demonstrated that all the concepts considered in our framework are significant determinants of car use, apart from past experience in the case of the study by Gardner and Abraham (2008). Hoffmann *et al.* (2017) also assessed non-car use to a certain extent, but only found TPB-related variables due to examining just a small number of studies. The synthesis of the meta-analyses results was presented in Section 2.1.5.

Notwithstanding, some contrasts could also be spotted between the above-cited reviews and this thesis framework. Table 5.1 offers some discussion about the variables that were used in a variety of past studies but were not part of the framework.

Table 5.1 - Comments on variables that are influential of car or non-car use according to recent literature, but are not part of this research framework

Variable (car or non-car use)	Definition	Comment
Descriptive norm [1,2,3]	Perception's about other people's behaviour.	This variable was not included since the versions of the TPB assessed on the literature review only had injunctive norm as a direct predictor of behaviour.
Problem awareness (car use) [1,3]	A more broad view of the existence of environmental problems. This concept was also called 'ecological worldview' in the VBN theory.	These variables were not added due to not passing the criteria imposed by one of the competency questions that formed this study's framework. Namely, these constructs are not direct predictors of behaviour nor they are mediated by two or fewer constructs.
Problem awareness (non-car use) [1]		
Environmental concern (car use) [1,3]	The authors do not define this concept clearly. However, it might be associated with the concept of problem awareness, as described above.	
Environmental concern (non-car use) [1]		
Environmental values (non-car use) [1]	General pro-environmental values.	
Altruistic values (car use) [2]	An individual's principle that motivates individuals to contribute to the wellbeing of others.	
Attitudes to the environment and health (car use) [2]	Concerns about environmental protection and public health.	There is a terminology issue that should be addressed here. 'PBC- Environment', for example, is conceptually related to the concept of the ascription of responsibility (VBN theory). Other factors were not assessed by this research because either they are not part of any of the selected theories (e.g. identity pro-car and social comparison), or they violate the TPB's principle of compatibility, which dictates that all predictors of behaviour must be measured
Attitudes to travelling (car use) [2]	General personal evaluations about the activity of travelling.	
Attitudes to transport environment (car use) [2]	Perceptions about the built environment (e.g. cyclability or walkability).	

PBC – Environment (car use) [2]	Beliefs about the capability of reducing environmental problems.	in respect to the same action (i.e. the predictors of *car use* should be measured in regards to *car use*, mandatorily).
Identity Pro-car and Anti-car (car use) [2]	The authors do not provide a clear explanation of the variables.	
Social Comparison (car use) [2]	Consider driving as a mean of self-enhancement.	

[1] (Lanzini and Khan, 2017);
[2] (Hoffmann et al., 2017);
[3] (Gardner and Abraham, 2008).

Some of the variables on the table above showed very low effects according to their corresponding studies ($r < 0.1$ and $r > -0.1$): ‘PBC – Environment’, ‘Identity Pro-car’ and ‘Identity anti-car’. The pooled effect of ‘Descriptive Norms’ in car use was not significant in two of the studies ($p > 0.05$), while the concepts of ‘Environmental Values’ and ‘Attitudes to Travel’ showed no significant pooled effect on car use in their respective meta-analyses ($p > 0.05$).

Another point of consideration is that some variables that were included in the framework were shown to have none or weak pooled effects in car or non-car use according to one or more of these studies, namely: ‘Ascription of Responsibility’ (AR), ‘Awareness of Consequences’ (AC) and ‘Subjective norms’ (SN). In this study, ‘Perceived responsibility’ and ‘Perceived ability to reduce the problems of car use’, as well as AC, did not show many significant associations with the use of (or intention to use) travel modes (see Section 4.2.7, on the results chapter). AC and ‘Perceived responsibility’ also showed weak discriminatory power on the formation of clusters, besides not being variables that have actually discriminated between the formed groups (see Table 4.28 and Table 4.32). Nonetheless, these variables showed relatively high correlations with the acceptability of positive incentives on this study. Subjective norms, on the other hand, and in contrast with Gardner and Abraham (2008), were demonstrated to have a strong association with travel behaviour and relatively strong discriminatory power.

5.1.1 The answering of RQ1

RQ1: What determinants of travel behaviour can be used to underpin a segmentation approach?

The initial systematic selection of variables to compose the theoretical framework of this research offered a list of variables that are notably related to travel mode choices, according to the criteria stipulated by the competency questions that are shown in Section 2.4. The discussion presented above provides additional justification for the use of such variables, as it compares them with related literature and examines other variables that could have taken part in the initial structure. However, the discriminant and cluster analysis performed on this research revealed that some variables might not be suitable for the purpose of segmenting people according to their travel behaviour. Namely, 'Perceived Responsibility' and 'Awareness of Consequences' not only were the variables that contributed the least to form the groups (Table 4.29), but the five groups didn't display any significant differences in respect to them (Table 4.32).

With the aim of answering RQ1, Table 5.2 provides a synthesis of the relevance of each psychological variable that was included on the original theoretical framework, in terms of being adequate to the use on a market segmentation approach focused on travel behaviour.

Considering the variables that were previously selected as influencers of mode choice, 'perceived responsibility' and 'awareness of consequences' did not demonstrate to have strong empirical support to be considered useful for a segmentation approach. All other determinants were considered adequate for segmentation, according to theoretical and empirical examination.

Table 5.2 - Evidence of adequacy of psychological variables for segmentation approaches

Variable	**Association with the use of travel modes (ρ)[1]**	**Discriminatory power to form clusters[2]**	**Significant variation among clusters[3]**	**Adequate for segmentation[4]**
Theory of planned behaviour				
Intention to use	[0.53***, 0.81***]	Not used on cluster analysis	Yes: all modes	Yes

Variable	Association with the use of travel modes (ρ)[1]	Discriminatory power to form clusters[2]	Significant variation among clusters[3]	Adequate for segmentation[4]
Attitudes	[0.20***, 0.33***]	Strong: walk Medium: bike, car, moto Weak: bus	Yes: all modes	Yes
Subjective norms	[0.16***, 0.36***]	Strong: walk Medium: bike, moto Weak: bus, car	Yes: all modes	Yes
Capacity	[0.27***, 0.60***]	Strong: bike, car, moto, walk Medium: none Weak: bus	Yes: all modes	Yes
Autonomy	[0.03, 0.41***]	Strong: bike, car, moto, walk Medium: none Weak: bus	Yes: all modes	Yes
Normative beliefs	[0.08, 0.44***]	Not used on cluster analysis	Yes: Car, bike, walk No: Bus, moto	Unknown[5]
Control beliefs	[0.02, 0.57***]	Not used on cluster analysis	Yes: Car, bike, walk, bus No: Moto	Unknown[5]
Behavioural beliefs	[0.01, 0.37***]	Not used on cluster analysis	Yes: Bike, walk No: Car, bus, moto	Unknown[5]
Theory of Interpersonal Behaviour				
Habit	[0.05, 0.43***]	Strong: none Medium: car, walk Weak: bike, bus moto	Yes: all modes	Yes
Past Experience	[0.23***, 0.33***]	Strong: moto Medium: bike, car, walk Weak: bus	Yes: all modes	Yes
Norm-activation Model				
Perceived responsibility	[0.01, 0.07*]	Weak	No	No
Norm-activation Model / Value-Belief-Norm theory				
Awareness of consequences	[0.01, 0.03]	Weak	No	No
Personal norms	[0.03, 0.19***]	Weak	Yes	Yes
Value-Belief-Norm theory				
Perceived ability to reduce threat	[0.02, 0.07*]	Weak	Yes	Yes

[1] Interval of the correlations related to the five travel modes (Spearman correlation coefficients), in absolute values.
[2] Strong: the potency index (PI) is within the first tercile of all the clustering variables ranked in descending order. Medium: PI is within the second tercile. Weak: PI is within the third tercile.
[3] Yes: results of the F-test are significant at $p < 0.01$. No: results of the F-test are not significant at $p < 0.05$.
[4] Recommendation based on a subjective evaluation of the three indicators present on the table.
[5] No recommendation is given due to the small sample size used to assess these variables.

The theoretical concepts of attitudes, intention to use and perceived personal impact of incentives have also demonstrated to be adequate to represent the concept of acceptability. The correlation between the variables was considerably high (Section 4.3) and theoretical support was provided in Section 2.4. However, the use of these variables to support a segmentation analysis was not supported by the data, as the results of the segmentation analysis were considered meaningless (Section 4.5).

5.2 The correlation analysis

All psychological variables were subject to correlation analysis, with the aim of identifying patterns of association between these and the acceptability indicators of ‘value maximisation incentives’, ‘social incentives’ and all the incentives combined in a single index (Section 4.3). To the best of this author’s knowledge, this is the first study to test the association between a set of multi-theory behavioural determinants of mode choice and the acceptability of a ‘soft’ measure aimed at voluntary travel behaviour change. The acceptability of hard measures like road pricing schemes has been linked to variables like problem perception, social norms and the perceived ‘fairness’ of the measure (Schade and Schlag, 2003). Quite similarly, past studies that looked at soft measures have related acceptability of them to their perceived effectiveness among the population (Gärling and Schuitema, 2007), and to variables such as personal norms, problem awareness, fairness and willingness to reduce car use (Eriksson et al., 2006). Comparing these findings with this study, the relevance of some NAM variables on the acceptability of soft measures was also found here. ‘Personal norm’, ‘problem awareness’ and general pro-environmental orientation were found to be causal determinants of acceptability by Eriksson, Garvill and Nordlund (2006). Although this study did not look for causal relationships, a relatively strong association was found between the NAM and VBN variables: ‘personal norm’; ‘perceived responsibility’; ‘awareness of consequences’ and ‘ability to reduce threat’, when compared to the rest of the variables. This might indicate that the findings of the previous authors were successfully replicated on a different socioeconomic context and in relation to a different intervention.

Nevertheless, almost all the variables pertaining to the TPB and the TIB theories have demonstrated to have at least one significant correlation with either attitude, intention to use or perceived personal impact of incentives. The only exceptions were the predictors of motorbike use: 'past experience' and 'autonomy', as well as perceived autonomy to use the bus. Actually, a visual examination of Table 4.24 makes it evident that predictors of motorbike use (e.g. attitudes, intention, and capacity), along with motorbike's current use itself, are poorly associated with acceptability of incentives[2]. As will be seen later in the chapter, the motorbike-inclined psychological profile is much less attracted by incentives, overall, in comparison to other groups. This combination of findings seems to be relevant evidence that people that are inclined to the use of motorcycles are relatively bad targets for a positive incentive intervention. Future policy designs are also encouraged to focus on NAM-related variables, as these factors were shown to be particularly more correlated with the acceptance of incentives overall, although the variables from the TPB and TIB should not be ignored.

5.2.1 The answering of RQ2

RQ2: What behavioural factors are associated with individual acceptance of positive incentives to reduce private CFVs use?

Several medium-sized correlation coefficients could be observed, especially among the variables of the NAM and VBN theories. Table 5.3 provides a synthesis of the associations found in Section 4.3, not only with respect to behavioural variables (the focus of the RQ), but also sociodemographic aspects.

A worthy point of consideration is that the identification of these patterns of association does not mean that a causal relationship exists between the variables, which would require further analyses.

[2] It is worth noticing that these poor results in regards to the motorcycle were not due to inadequate sample size (n = 920).

Table 5.3 - Strength of correlations between individual factors and perceived personal impact of all incentives combined

Construct	Non-significant	Weak (ρ < |0.2|)	Moderate (|0.2| ≤ ρ < |0.5|)	Strong (ρ ≥ |0.5|)
Theory of planned behaviour				
Current use		Bike (+) Motorbike (-) Walking (+)	Car (-) Bus (+)	
Intention	Motorbike	Bike (+) Walking (+)	Car (-) Bus (+)	
Attitudes	Motorbike	Car (-) Walking (+)	Bus (+) Bike (+)	
Subjective Norm	Motorbike	Car (-)	Bus (+) Bike (+) Walking (+)	
Capacity	Motorbike	Car (-) Bus (+) Bike (+) Walking (+)		
Autonomy	Bus Bike Motorbike	Car (-) Walking (+)		
Norm-activation Model				
Perceived Responsibility			(+)	
Value-Belief-Norm theory				
Ability to reduce threat			(+)	
Norm-activation Model / Value-Belief-Norm theory				
Personal norm			(+)	
Awareness of consequences			(+)	
Theory of Interpersonal Behaviour				
Past Experience	Motorbike	Car (-) Bike (+)	Bus (+) Walking (+)	
Habit		Bike (+) Motorbike (+) Walk (-)	Car (-) Bus (+)	
Other				
Age	Non-Sig.			
Commuting distance	Non-Sig.			
Income			(-)	

Note: a '+' sign means that a positive correlation was observed between the theoretical construct and the perceived personal impact of incentives, while a '-' sign represents a negative correlation.

In regards to the direction of the association, the determinants of car use were always negatively related to the perceived impact of incentives. That is, the higher the experience someone has with the car, the lowest his perceived impact of positive incentives, for example. Apart from the car, the vast majority of the determinants of the use of non-motorised modes and the bus are positively associated with perceived impact. Although the data is not shown on the table above, it is worth noticing that they are also positively associated with attitudes and intention to use positive incentives.

5.3 The psychographic segmentation

Motivated by the literature's suggestion that there are different types of 'mobility profiles' among the population and that they should be targeted in different manners by policy interventions, a psychographic segmentation was performed in this study. While the specific aim was to evaluate the significant differences in terms of incentives acceptability, the identification of homogeneous groups who distinguish themselves in terms of their 'mobility behaviour' profile, alone, already extends the findings of previous segmentation studies. Specifically, the use of systematically selected, theory-based, empirically validated and multimodal behaviour variables represents a novelty of this work.

Three of the five segments identified are strongly related to a particular travel mode (*Car-Predisposed*; *Bus-Dependents* and the *Motorbike Enthusiasts*). This relationship, however, is more psychological than behavioural. Apart from the *Bus-Dependents* and the *Car-Predisposed*, who have the respective travel modes as their primary form of travel in 86.5% and 77.3% of the cases, respectively, the modal split on the other segments is quite heterogeneous. The *Motorbike Enthusiasts*, for example, who are psychologically resistant to all modes except the motorbike, have this mode as the primary form of travel in only 28.9% of cases. The groups that are more psychologically identified with non-motorised transport, only have the bike or walking as a primary mode among 27.2%-39.5% of their members. While the other three groups display a more clear inclination to a particular travel mode, the *Autonomous Environmentalists* and the *Non-Motorised Lovers* are quite similar in several ways. Environmental-related variables such as personal norm and perceived ability to reduce problems of excessive car use are equally higher among them.

The UK-based study of Anable (2005) reports that Perceived Behavioural Control was an essential construct to define her psychographic segments related to leisure travel. This study strongly corroborates with this finding, as feelings of capacity and autonomy were powerful discriminators of the groups. The identification of this similarity in a population with geographic and socioeconomic profiles very different from those of Anable (2005), besides the focus on students' commuting trips, reinforces the evidence that groups of travellers are distinguished mainly by feelings of control over the modes of travel.

The relationship between attitudes and behaviour was found to be inconsistent by past travel behaviour research. Mobility groups found by other studies (Anable, 2005; Magdolen et al., 2019) report this contradiction. Anable's 'Aspiring Environmentalists', for example, display a high feeling of enjoyment of travelling by car, while members of the car-inclined cluster do not necessarily express positive attitudes to using the mode. This dissonance is not present in this study as the attitudinal differences between clusters are generally linked with their behaviours, as demonstrated by the interpretation of the segments in Section 4.4.9. In fact, this research can be considered as very supportive of the use of the TPB in travel behaviour, as very few inconsistencies were found between the TPB variables and the behaviour of the clusters' members. The only case was related to perceived autonomy, as the *Bus-Dependents* displayed lower feelings of autonomy to use the bus compared to other clusters. One possible explanation is that bus users do not think using this mode is actually their choice, but rather the only option they have.

Age, gender, income and household size varied significantly among the psychographic clusters. These findings contrast with two past UK-based studies that did not find the same differences (Anable, 2005; Prillwitz and Barr, 2011). This suggests that socio-demographic aspects might be determinant in the formation of a 'psychological profile' in terms of mobility in Brazil. Richer people were more concentrated on the *Car-Predisposed*, while poorer people were more likely to be included on the *Bus-Dependents* or the groups related to non-motorised travel. A significant discrepancy in gender was also identified. While men were the majority among the *Autonomous Environmentalists* and *Motorbike Enthusiasts*, women were heavily concentrated on the *Car-Predisposed* or *Bus-Dependents* clusters (66% of all women). Lemos, Harkot and Santoro (2017) provide some empirical evidence of the reasons why women don't cycle as much as men in Brazil. Lower perceived capacity to cycle and lower availability of the bike are among the discovered factors. This study's data reinforce these hypotheses as women do have a significantly lower perceived capacity to cycle ($F = 85.53$. $p < 0.001$) and lower availability of bikes ($\chi^2 = 28.03$, $p < 0.001$). However, this pair of factors is probably not sufficient to explain gender differences in cycling behaviour. As Lemos, Harkot and Santoro (2017) explain, there are several cultural and moral reasons that have perpetuated in history and explain why women have considerably different mobility patterns compared to men. One of the background factors might be linked to the historical role assigned to women in their domestic space, restricting outdoor activities in general (Lemos et al., 2017). Further examinations about gender issues in mobility are still needed to provide further clarification and are strongly encouraged.

In regards to the general travel behaviour profile of the clusters, some similarities were observed with past studies based in European countries. Particularly, the 'Public transport dependents' group found by Semanjski et al. (2016) share some profile characteristics with our study's '*Bus-Dependents*', except that, in our case, this group does not have much positive attitudes to using the bus and have much higher positive feelings to the car, instead. The personality traces of our '*Car-Predisposed*' group was also discovered by Semanjski and colleagues and Anable (2005) ('Devoted Drivers' and 'Die Hard Drivers'). The '*Motorbike Enthusiasts*' was not found by any previous study probably as a reflection of the study context. The increasing levels of motorbikes in the modal-split in Brazil might not be particularly observed in European countries. These studies also found groups that have relatively more positive attitudes to non-motorised transport like the "*Autonomous Environmentalists*". These similarities indicate that even populations of countries with substantial differences in their socioeconomic and mobility scenarios can be divided into somewhat similar 'behavioural' groups.

Among the segmentation-based studies reviewed in this paper, this was the first to include the Norm-activation model variables ‘awareness of consequences’ and ‘ascription of responsibility’ as clustering variables. But these indicators did not distinguish significantly between the groups, demonstrating that the awareness of problems associated with the use of private CFVs and the perception of one’s own responsibility in these problems are cut uniformly across different psychographic groups. ‘Personal norm’, on the other hand, along with VBN theory’s ‘Ability to reduce’ the problems of car use, were consistently associated with the clusters that are more inclined to non-motorised transport. This provides extra evidence of the association of these constructs with sustainable travel behaviour.

Our findings support the suggestion of Hunecke et al. (2010) about the use of psychological variables to assign an individual to a particular target group *a priori*, as long as theory-driven measures are employed. The studies of Anable and Hunecke used extended versions of the TPB and came to quite similar conclusions with respect to the groups’ constituent variables.

The interpretation of the cluster provided in Section 4.4.9 can be useful for future transport interventions. Although the focus of this thesis was to highlight differences in the acceptance of a specific type of measure, other types of policy can build upon its results. The relative importance given to each attribute of a journey is relevant information. Safety, speed and cost appear to be the most important variables overall. Although some groups such as the *Car-Predisposed* seem to overestimate safety, compared to others. Another useful finding is that the formation of psychographic clusters (and also, to some extent, the use of each mode) was strongly associated with the degree of perceived capacity and autonomy that people have over the modes. Thus, messages designed to improve these feelings toward non-motorised modes, for example, can be an effective strategy for behaviour change.

5.3.1 The acceptability of positive incentives

The groups that are more psychologically oriented to non-motorised transport showed overall greater acceptability of incentives in our study. This finding corroborates with Semanjski et al. (2016), who found that the provision of informational incentives incites behaviour change to a larger extent among those who have attitudes or other motivators related to this type of persuasive information. Eriksson et al. (2008b) also reported that personal norm is a significant predictor of the acceptability of transport policy measures. Indeed, this indicator is more salient among the groups that are more responsive to incentives in our study (‘*Non-Motorised Lovers*’ and ‘Aspiring Environmentalists’).

After reviewing the state-of-the-art of the application of persuasive technologies, Anagnostopoulou *et al.* (2018) advise system designers to do not expect that all users can change behaviour and completely switch to sustainable forms of transport. The author further suggests that studies aiming at understanding the relative impact of these technologies on different traveller profiles are needed. This research offers evidence that a psychological segmentation based on theories of behaviour is suitable for this purpose.

Without yet evaluating the relative environmental impacts coming from the delivery of incentives to each group of this study, it is notable that all clusters have somewhat similar positive attitudes towards incentives. The strategies with the lowest scores on this acceptance variable, which are Rankings, Points and Social Media are the only ones that are especially not attractive to the *Car-Predisposed* cluster. Nevertheless, when it comes to the translation of such positive attitudes into the desire of using the systems or changing behaviour accordingly, some critical differences appear. ‘Maps’ is the incentive that shows the greatest average drop between the scores of attitudes and perceived personal impact, especially in the ‘*Car-Predisposed*’ cluster. Perhaps this is due to the familiarity that the sample has with this type of incentive. Trip-planning apps such as Waze, for instance, are reported to be acknowledged by 98.1% of the *Car-Predisposed* members. The incentives in which these effects are less notable are the financial rewards (cash or vouchers), which are also the two incentives with the highest acceptability scores overall. Informational incentives like journey-planners or maps also had a relative higher evaluation compared to other strategies. Incentives related to gamification such as rankings or challenges had lower acceptability scores, alongside social media tools.

Despite their good acceptability demonstrated here, the use of rewards alone to stimulate car use reduction has demonstrated to have effects on the short term which were not maintained once the incentives were removed (Foxx and Schaeffer, 1981). Although the study of Foxx and Schaeffer was done using a very small sample, this is still a relevant point of considerations as other authors state that rewards may lead to positive outcomes in the short term, but may actually weaken individual intrinsic motivations to a point even lower than it was before the intervention (Gneezy et al., 2011). Thus, the implementation of a positive incentive scheme should consider the use of a variety of different strategies to avoid these unwanted outcomes.

Practical guidelines for future policies are given later in the chapter (Section 5.5).

5.3.2 The answering of RQ3

RQ3: What psychographic segments show a higher acceptability of positive incentive schemes?

The *Bus-Dependents*, *Non-Motorised Lovers* and *Autonomous Environmentalists* display higher acceptability of social incentives, especially when compared to the *Car-Predisposed* and considering intention to use and perceived personal impact. These same clusters also show the same higher acceptance regarding the value maximisation incentives, but now also in contrast with the non-motorbike-reluctant.

To allow more practical guidance with respect to how the different groups perceive the incentives, each incentive strategy was inspected separately to assess the groups that are more and less responsive to them. Table 5.3 shows the groups that are *less* susceptible to each type of incentive (groups that show significantly lower scores on at least two acceptability indicators for a given incentive), groups that are *more* susceptible (similarly, groups that present significantly higher scores in at least two indicators of acceptability) and groups that are *slightly more* susceptible (in the case of segments that are significantly more responsive than some other group and at the same time are less responsive than a third group).

Table 5.4 - Summary of acceptability levels of incentives by the psychographic groups.

Incentive	Less accepted by	Slightly more accepted by	More accepted by
Maps	*Car-Predisposed*; *Motorbike Enthusiasts*	*Bus-Dependents*; *Autonomous Environmentalists*	*Non-Motorised Lovers*
Money	*Motorbike Enthusiasts*	*Car-Predisposed*	*Non-Motorised Lovers* ; *Autonomous Environmentalists*
Points	*Car-Predisposed*	-	*Bus-Dependents*; *Non-Motorised Lovers* ; *Autonomous Environmentalists*; *Motorbike Enthusiasts*.
Rankings	*Car-Predisposed*	-	*Bus-Dependents*; *Non-Motorised Lovers* ; *Autonomous Environmentalists*.
Vouchers	*Car-Predisposed*; *Motorbike Enthusiasts*	-	*Bus-Dependents*; *Non-Motorised Lovers* ; *Autonomous Environmentalists*.
Journey-planner	-	-	-
Information	*Car-Predisposed*; *Motorbike Enthusiasts*	-	*Non-Motorised Lovers* ; *Autonomous Environmentalists*.
Feedback	-	-	-
Social Media	*Car-Predisposed*	-	*Non-Motorised Lovers* ; *Autonomous Environmentalists*.
Challenges	*Bus-Dependents*; *Car-Predisposed*	-	*Autonomous Environmentalists*
Buddying	*Car-Predisposed*	-	*Non-Motorised Lovers*
Social incentives	*Car-Predisposed*	-	*Non-Motorised Lovers* ; *Autonomous Environmentalists*.
Value maximisation incentives	*Car-Predisposed*; *Motorbike Enthusiasts*	-	*Bus-Dependents*; *Non-Motorised Lovers* ; *Autonomous Environmentalists*.
All incentives	*Car-Predisposed*; *Motorbike Enthusiasts*	-	*Bus-Dependents*; *Non-Motorised Lovers* ; *Autonomous Environmentalists*.

Incentives related to maximising value to the user are less accepted by both the *Car-Predisposed* and the motorbike-inclined group while being more accepted by the other three clusters. Notwithstanding, the *Motorbike Enthusiasts* and the *Bus-Dependents* do not show significant differences in acceptability compared to any other clusters with regard to social incentives. Indeed, the *Motorbike Enthusiasts* are relatively averse to money, vouchers, information and maps, but do not display these differences for gamification strategies like rankings and are even relatively more attracted by points.

Interestingly, Journey Planner and Feedback on travel behaviour are viewed by the different groups in a roughly similar way. The discrepancy shown in respect to other incentive tools is not shown for both these incentives. The absolute scores on the acceptability indicators were also quite high. Perhaps these strategies would be particularly good to offer to the groups that display a clear relative aversion to other types of incentives (i.e. the *Car-Predisposed*).

5.3.3 The answering of RQ4

RQ4: What are the behavioural differences between distinct segments of the population that are created based on the acceptance of incentives?

To allow more broad conclusions of the significant differences of the sample in terms of incentives' acceptance, a segmentation analysis was attempted with a focus on the acceptability indicators of each positive incentive. The main objective was to find groups that differed in terms of the types of incentives to which they are most responsive. Nevertheless, as demonstrated in Section 4.5, a meaningful cluster structure was not found in this respect and the answer to this question remains unclear.

5.4 The scenario estimation

To extend the findings of the psychological acceptability of incentives and provide an estimation about what would be the impacts of the implementation of such schemes on the study's sample, a scenario estimation was performed (Section 4.6). Using data regarding the individuals' stated willingness to reduce car use in response to each type of incentive, alongside their current mobility patterns (mode choice, travel distance, trips per week), scenarios could be estimated in terms of the potential reduction in distance travelled by private CFVs and the consequent reduction in carbon emissions (CO_2-eq). The reduction in carbon emissions used the emission parameters of different types of vehicles that are established in past literature. The estimation of the environmental benefits of a soft measure represents a novelty of this work, as all the reviewed papers that address the impact of interventions aimed at voluntary travel behaviour change only report differences in terms of distance travelled in private CFVs or amount of trips on a given period (Taniguchi et al., 2007; Friman et al., 2013; Bamberg and Rees, 2017).

5.4.1 Estimated reduction of the distance travelled by private CFVs and associated carbon emissions

If the individuals' stated willingness to change behaviour in response to incentives was translated into the avoidance of just one return-trip to the university per week (a more conservative scenario), a distance reduction of 4.8% would be seen if they had used only the social media incentive (the least preferred incentive). In contrast, a reduction of 16.6% would be seen if they had used only the cash incentive (most preferred). Taking a combination of all incentives into consideration, an average reduction of 10.8% is estimated if two one-way trips were to be avoided, which represents almost 7,000 kilometres in a week. If the scenario of just one trip avoided in a week is considered, a reduction of 5.4% would be seen (exactly half of the two-trip saved scenario). The subsequently estimated scenarios for cases where more than two journeys are saved in a week do not follow a linear reduction on the distance. The reason is because there are individuals in the sample who undertake few trips to the university per week (two to four, for example) and, as a result, their respective calculated reductions for the less conservative scenarios (many trips saved in week) are less impactful in comparison to the people who perform more weekly trips.

Past meta-analytical research has indicated that the use of personalised travel planning reduced car use by 5% (Bamberg and Rees, 2017). The effect of an awareness campaign and public transport marketing reached a similar reduction percentage (Möser and Bamberg, 2008) and the application of Travel Feedback programs reduced car use by 7.3% (Taniguchi et al., 2007). The percentage reduction observed on these more traditional 'soft' interventions is approximately the same as what would be observed upon the implementation of smartphone-based positive incentives if the intended switch to alternative modes of transport were materialised into the avoidance of just a single private CFV trip in a week. This similarity represents an argument in favour of smartphone-based positive incentives as their capacity to reach larger audiences is greater than the traditional ‘face-to-face’ interventions.

The calculated reductions in terms of distance would represent a reduction of between 0.55 and 1.17 tons of carbon dioxide that would be emitted on the atmosphere on a single week of travelling, just as a result of the sample’s acceptance of positive incentives. If these results were extrapolated to the whole population of undergraduate students in Curitiba, the savings could reach up to 161.9 tons of Co2 per week. These substantial numbers are assumed to be relatively high mainly because the average number of private CFV trips per week of the whole sample (including those that do not use the car) is quite high (8.6 trips) and the average commuting distance of the students is also considerably high (11.6 km). The associated average weekly emissions per private CFV user was also found to be quite high (25.3 kg of CO_2-eq).

The combination of such a bad context in terms of travel-related emissions with the great acceptability of positive incentives that was shown in this research leads to the conclusion that such an initiative could, indeed, produce a positive change in the quality of life in Curitiba.

5.4.2 Estimated reduction of financial costs

The ‘social cost of carbon’ refers to the monetary value associated with the damage done by emitting one tonne of carbon in the atmosphere (Pearce, 2003). The findings of this research revealed that, on average, a single individual of the sample emits carbon dioxide during a week of travel relative to the amount of $0.61 (61 cents of American Dollars). For each trip that is avoided due to the use of positive incentives, around $0.02 (two cents of American Dollars), would be saved, per each adopter of the technology (see Section 4.6.2.1 for more details). Apart from carbon-related costs, there would also be savings on the costs associated with operating a private CFV (fuel consumption, etc.).

It is assumed that the above information can serve as an input for future cost-benefit analysis on the implementation of a positive incentive scheme. Preliminarily, the data can be confronted with the information provided by the EU-based SUNSET project, which offered insights about the financial costs of a one-year implementation of positive incentives (Grant-Muller et al., 2013). This allows an initial visualization of the costs and benefits in case such a project would be implemented. Table 5.5 shows the costs and benefits associated with the implementation of positive incentives. Most of the data was generated based on the SUNSET project report (Grant-Muller et al., 2013), but was adapted to the Brazilian context or based on the empirical findings of this research. The original values were transformed into American dollars[3] and adjusted for inflation.

Table 5.5 - Costs and benefits associated with the implementation of positive incentives

Implementation Costs	Description	Sum
Integration costs	IT employee to integrate the managing authority with the incentive provider organisation (Grant-Muller et al., 2013).	$543
Installation costs	Software and hardware related costs (Grant-Muller et al., 2013).	$1,403
Operating costs	Hardware and software maintenance, energy costs, system hosting, data storage/maintenance/analysis (Grant-Muller et al., 2013).	$3,847
Incentive design and management	Templates, interface with third-party providers (Grant-Muller et al., 2013).	$12,023
Marketing costs	Social media advertising, launch event, online advertising (Grant-Muller et al., 2013).	$11,542
Support costs	Technical support on the incentives platform (Grant-Muller et al., 2013).	$6,733
Total costs (Jul 2013)	Sum of costs at the time of publication	$36,090
Total costs (Oct 2018)	Sum of costs adjusted for inflation (OECD, 2019).	$37,756
Implementation Benefits	**Description**	**Sum**
Carbon social cost savings (dollars per return trip)	The value extracted from the scenario estimation (Table 4.44).	$0.04

[3] 1 EUR = 1.13153 USD according to www.xe.com on 12th June 2019.

Trip costs (dollars per return trip)	Value extracted based on the average Brazilian monthly salary ($575.5) (IBGE, 2019), the average percentage that is spent for transport in Brazil (15.8%) (Henrique Carvalho and Henrique Pereira, 2012), the average percentage reduction on the monthly number of trips of the sample, when one return trip is replaced per week (23.3%) and the average amount of weekly trips of the sample (8.58).	(575.5 * 23.3% * 15.8%) / (8.58 * 4) = $0.58
Private CFV operating costs (dollars per return trip)	Value extracted based on the estimated distance reduction in response to incentives for a return trip for the whole sample (6789 km), the number of private CFV users in the sample (614) and the estimated average operating cost of a private CFV per km ($0.44) (Grant-Muller et al., 2013)	(6789 / 614) * 0.44 = $4.94
Total benefits (dollars per return trip)	Sum of benefits	$5.56
Number of return trips (break-even point)	Total costs and total benefits per return trip	37,756 / 5.56 = 6,791

The information presented on the table offers a simplistic cost-beneficial view about the real implementation of incentives. The costs that were gathered by the SUNSET project were based on European services and might not be the same in Brazil. It also does not take into account the costs on the user's perspective (e.g. smartphone battery consumption). Additionally, it does not consider the operating costs that would be associated with the chosen alternative mode (e.g. bus ticket costs). Nevertheless, the information presented above represents an advance towards closing a relevant knowledge gap. That is, it offers technical insights to be used by future transport planners or institutions which might be interested in launching a positive incentives scheme, especially in Brazil.

In this simulation, a total of 6,791 return trips to the university using private CFVs would have to be switched to reach the break-even point between the implementation costs and benefits, considering a period of one year. If it is assumed that a single user would switch one private CFV return trip per week in response to incentives in a whole year, for example, a total of 131 users would be needed to reach the break-even point (6,791 / 52).

5.4.3 The answering of RQ5

RQ5: What environmental benefits can be estimated (in general and considering population segments) from a hypothetical implementation of positive incentives in Curitiba?

The findings discussed in the earlier sections focus on the general impacts of positive incentives. However, some insights can be drawn if the differences among clusters are observed, with a potential to inform policy about which groups of users would lead to the greatest environmental impacts.

The '*Car-Predisposed*' group is responsible for 56% of the emissions of greenhouse gases of our sample in a week of commuting (8.72 tons of CO_2-eq), although they represent only 34% of all students. All the other clusters emit around 1.5 to 2 tons of CO_2-eq in a week of commuting. As one could expect, the absolute reduction on emissions due to the use of positive incentives, considering the clusters as a whole, is greater for the *Car-Predisposed* (0.5 tons for one weekly return trip, as opposed to around 0.2 for the other groups). However, the *Car-Predisposed* are also the group which contains almost half of the sample's private CFV users (46%). So if the scenario is estimated considering emissions per person, the *Bus-Dependents* and the *Non-Motorised Lovers* are, indeed, the profiles who display the largest estimated savings (1.11 and 1.22 $KgCO_2$-eq per trip per person, respectively). This is a combination of multiple factors such as a relatively higher stated likelihood to change in response to incentives and a relatively higher trip distance, on average. Finally, if a *relative* reduction on emissions is calculated, considering the total amount of emissions that a cluster is responsible for (baseline scenario), the *Bus-Dependents* display the highest rate (6.2% reduction with the replacements of a single private CFV trip).

5.5 Synthesis of the findings

Having presented the descriptive results, the correlation analysis, the segmentation and the scenario estimation, the thesis now proceeds to the exploration of the results in a more practical and synthesised form, aiming to inform the implementation of future policies focusing on psychographic segmentation and positive incentives. One of the practical contributions of this research is to offer evidence about the relationship between specific behavioural profiles and positive incentives. Nevertheless, findings regarding the public segmentation approach and the acceptance of positive incentives may also be interpreted independently. That is, a policymaker who are interested in implementing positive incentives on a given context, but not particularly on psychographic segmentation, could take advantage of the descriptive results regarding positive incentives alone (Section 4.2.4), the evaluation of the acceptability of different incentives across different genders, ages, travel mode users, etc.(Section 4.2.6.2), or the estimation of the implementation scenarios (Section 4.6.1 and 4.6.2). Similarly, a transport planner who is not interested in positive incentives, but rather on how the population is divided in terms of mobility preferences, could use the results that deal with this subject alone (Sections 4.2.3, 4.2.6.1, 4.2.7.1 and 4.4).

With the results of this thesis, it is not possible to suggest a unique and "optimal" way of providing incentives to different people. In a more exploratory way, however, it provides a substantial amount of information, derived from multiple methods of analysis, in an attempt to make the reader familiar with the phenomenon of acceptance of positive incentives and psychographic segmentation, consequently being able to draw their own conclusion on how to design and deliver a certain type of intervention to a given population.

It is now appropriate to recall the main research question of this thesis, which is the following: *How can positive incentive schemes discourage the use of private conventionally-fuelled vehicles be targeted, considering acceptability factors of the population and their estimated environmental impacts?*

Although the answer to this question is dismembered in different parts of the results and discussion chapters, a more ‘condensed’ answer is given in Table 5.6. The table displays the highlights of the findings with a focus on each type of incentive assessed in this thesis. The content is based on the differences observed across sociodemographic profiles and the individual’s primary travel mode (Appendix J and Appendix K); the correlation analysis (Section 4.3); the public segmentation (Section 4.4) and the descriptive analysis (Section 4.2); the estimation of implementation scenarios (Section 4.6).

Table 5.6 - Synthesis of the thesis findings

Maps	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women; - Lower perceived personal impact by the wealthier; - Intention to use and perceived impact greater among bus users, bike users and walkers. **Particular association with psychological variables**[2]: - Attitudes to walking and habit of using the bus (positively). **Acceptability: generally and by clusters**[3]: - Medium acceptance across the sample (4th preferred incentive in terms of attitudes and intention to use, 6th in terms of perceived impact); - Particularly better accepted by the *Non-Motorised Lovers* and less accepted by the *Car-Predisposed*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -6,594 km (-10.4%); - -1.7 tons of CO_2-eq (-10.9%).
Money	**Differences across sociodemographic and mobility attributes**[1]: - Higher perceived personal impact by women; - Higher attitudes among the younger; - Lower intention to use and perceived impact among the wealthiest group; - Less perceived impact among the car and motorcycle users. **Particular association with psychological variables**[2]: - Attitudes to walking, experience with the bus and walking and habit of using the bus (positively). **Acceptability: generally and by clusters**[3]: - Good acceptance across the sample (Most preferred incentive in terms of all acceptance indicators); - Particularly even better accepted by the *Non-Motorised Lovers* and the *Autonomous Environmentalists*, in comparison to the *Motorbike Enthusiasts* and the *Car-Predisposed*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -10,441 km (-16.6%); - -2.7 tons of CO_2-eq (-17.7%).
Points	**Differences across sociodemographic and mobility attributes**[1]: - No differences across genders and age groups; - Better accepted by the poorer; - Less accepted by car users in comparison to cyclists, walkers and bus users. **Particular association with psychological variables**[2]: - Frequency of bus use and walking; attitudes to walking; cycling experience; intention to use the bus, bike and walking; habit of using the bus and cycling (positively); - Car use; attitudes to the car; experience with the car; intention to use the car; perceived capacity and autonomy to use the car, personal income and control beliefs of the car (negatively).

	Acceptability: generally and by clusters[3]: - Poor acceptance across the sample (10th preferred incentive in terms of all acceptance indicators); - Particularly even worse evaluated by the *Car-Predisposed*, compared to the *Bus-Dependents*, *Autonomous Environmentalists* and *Non-Motorised Lovers*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -4,771 km (-7.6%); - -1.2 tons of CO_2-eq (-7.8%).
Rankings	**Differences across sociodemographic and mobility attributes**[1]: - No differences across genders and age groups; - Higher intention to use and perceived personal impact among the poorest group. **Particular association with psychological variables**[2]: - Bus use; experience with the bike; intention to use the bus and habit of using the motorcycle (positively); - Car use and intention to use the car (negatively). **Acceptability: generally and by clusters**[3]: - Poorly accepted by the sample (8th preferred incentive in terms of all acceptance indicators); - Particularly even worse evaluated by the *Car-Predisposed*, compared to the *Bus-Dependents*, *Autonomous Environmentalists* and *Non-Motorised Lovers*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -4,373 km (-6.9%); - -1.1 tons of CO_2-eq (-7.3%).
Vouchers	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women; - Lower attitudes and less intention to use among the older; - Less perceived impact among the car and motorcycle users. **Particular association with psychological variables**[2]: - Frequency of bus use; experience with; intention to use the bus; perceived capacity and habit of using the bus; habit of using the motorbike (positively). **Acceptability: generally and by clusters**[3]: - Good acceptance across the sample (Most preferred incentive in terms of all acceptance indicators); - Particularly even better accepted by the *Non-Motorised Lovers* and the *Autonomous Environmentalists*, in comparison to the *Motorbike Enthusiasts* and the *Car-Predisposed*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -9,577 km (-15.2%); - -2.5 tons of CO_2-eq (-15.9%).
Journey Planner	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women. **Particular association with psychological variables**[2]: - Attitudes to walking (positively). **Acceptability: generally and by clusters**[3]:

	- Medium acceptance across the sample (5th preferred incentive in terms of attitudes and intention to use, 4th in terms of perceived impact); - Similarly liked and desired to be used by all groups, but the perceived impact for the *Car-Predisposed* in considerably lower than the *Bus-Dependents*, the *Autonomous Environmentalists* and the *Non-Motorised Lovers*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -7,714 km (-12.2%); - -2.0 tons of CO_2-eq (-12.8%).
Information	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women; - Older people like it less. **Particular association with psychological variables**[2]: - Frequency of use and habit of using the bus (positively). **Acceptability: generally and by clusters**[3]: - Good acceptance across the sample (3rd preferred incentive in terms of all acceptance indicators); - Particularly higher intention to use and perceived impact are shown among the *Non-Motorised Lovers* and *Autonomous Environmentalists*, compared to the *Car-Predisposed* and *Motorbike Enthusiasts*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -8,584 km (-13.6%); - -2.2 tons of CO_2-eq (-14.2%).
Feedback	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women. **Particular association with psychological variables**[2]: - Habit of using the motorbike (positively). **Acceptability: generally and by clusters**[3]: - Medium acceptance across the sample (6th preferred incentive in terms of attitudes and intention to use, 7th in terms of perceived impact); - Similarly liked and desired to be used by all groups, but the perceived impact for the *Car-Predisposed* in considerably lower than the *Autonomous Environmentalists* and the *Non-Motorised Lovers*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -6,971 km (-11.0%); - -1.8 tons of CO_2-eq (-11.5%).
Social Media	**Differences across sociodemographic and mobility attributes**[1]: - No relevant differences across genders and age, income and trip distance groups. **Particular association with psychological variables**[2]: - Intention to cycle and control beliefs regarding bus use (positively); - Car use; intention to use the car and control beliefs regarding the car (negatively). **Acceptability: generally and by clusters**[3]:

	- Poor acceptance across the sample (Least preferred incentive in terms of all acceptance indicators); - Particularly less accepted by the *Car-Predisposed*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -3,055 km (-4.8%); - -0.8 tons of CO_2-eq (-4.9%).
Challenges	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women. **Particular association with psychological variables**[2]: - No particular association observed. **Acceptability: generally and by clusters**[3]: - Poor acceptance across the sample (9th preferred incentive in terms of all acceptance indicators); - Particularly better accepted by the *Autonomous Environmentalists*, in terms of intention to use and perceived personal impact. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -5,182 km (-8.2%); - -1.3 tons of CO_2-eq (-8.7%).
Buddying	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women. **Particular association with psychological variables**[2]: - Bus use and experience with the bus. **Acceptability: generally and by clusters**[3]: - Medium acceptance across the sample (7th preferred incentive in terms of attitudes and intention to use, 5th in terms of perceived impact); - Particularly low perceived impact among the *Car-Predisposed*, compared to the *Autonomous Environmentalists* and *Non-Motorised Lovers*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -7,312 km (-11.6%); - -1.9 tons of CO_2-eq (-12.2%).
Social incentives	**Differences across sociodemographic and mobility attributes**[1]: - Higher perceived personal impact by women; - Higher intention to use and perceived impact among the poorer; - Lower perceived impact among car users in comparison to the walkers and the bus and bike users. **Particular association with psychological variables**[2]: - Intention to walk (positively). **Acceptability: generally and by clusters**[3]: - Lower acceptance when compared to value maximisation incentives; - Particularly less accepted by the *Car-Predisposed*; - Greater perceived impact among the *Autonomous Environmentalists*. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - Average of -5,277 km (-8.4%);

	- Average of -0.67 tons of CO_2-eq (-12.8%).
Value maximisation incentives	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women; - Less attractive to the older; - Lower perceived personal impact among the richer; - Lower intention to use and perceived impact among car users and motorcycle users. **Particular association with psychological variables**[2]: - Bus use and intention to cycle (positively); - Car use and intention to use the car (negatively). **Acceptability: generally and by clusters**[3]: - Greater acceptance when compared to social incentives; - Particularly better accepted by the *Bus-Dependents*, *Autonomous Environmentalists* and *Non-Motorised Lovers*, compared to the other two clusters. - The *Motorbike Enthusiasts* particularly dislike these types of incentives. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - Average of -8,582 km (-13.6%); - Average of -1.10 tons of CO_2-eq (-14.3%).
All incentives	**Differences across sociodemographic and mobility attributes**[1]: - Better accepted by women; - Less attractive to the older; - Lower perceived personal impact among the richer; - Lower intention to use among car users and lower perceived impact by car and motorcycle users. **Particular association with psychological variables**[2]: - Frequency of use of the car (negatively) and the bus (positively); - Attitudes to the bike and the bus (positively); - Experience with cycling and walking (positively); - All variables related to the NAM and VBN theories (personal norm, ability to reduce the threat, perceived responsibility and awareness of consequences); - Intention to use the car (negatively), the bus and the bike (positively); - Habit of using the car (negatively), the bus and the bike (positively); - Perceived capacity to use the car (negatively) and the bike (positively); - Financial income (negatively); - Control beliefs regarding the car (negatively). **Acceptability: generally and by clusters**[3]: - Considering attitudes, the *Car-Predisposed* are relatively less attracted by incentives, while the *Autonomous Environmentalists* like this category relatively more; - Intention to use and perceived impact is higher for the *Autonomous Environmentalists* and *Non-Motorised Lovers*, these indicators are lower for the *Motorbike Enthusiasts* and the *Car-Predisposed*. The *Bus-Dependents* are significantly better acceptors of the incentives if compared to the *Car-Predisposed*, only. **Estimated reduction on distance travelled by private CFVs and correspondent carbon emissions, per week**[4]: - -7,218 km (-11.8%);

	- -1.14 tons of CO_2-eq (-7.3%).

[1] Highlights were selected based on the significance of the t-test ($p < 0.05$) for gender, and on the significance of a post-hoc ANOVA test (Tukey or Tamhane's test), for income groups, age groups, distance groups and the primary travel mode (highlight is reported in the table if a certain group is significantly different from at least two other groups).
[2] Highlights were selected if a correlation above 0.100 was observed between the psychological attribute and all the three acceptance indicators (attitudes, intention to use and perceived personal impact). Only associations that were not observed on the majority of the other incentives (6 or more) are reported here.
[3] Highlights were selected based on the significance of a post-hoc ANOVA test (Tukey or Tamhane's test). Just segments with significant differences with at least two other segments are reported.
[4] Estimated reductions are reported considering that the perceived personal impact is materialised on the reduction of one return trip by private CFV in a week.

The summary of the main findings of this thesis can serve as technological guidance for future incentives implementations and also represents a theoretical provocation about the several personal factors that can be related to the acceptance of a transport intervention that aims at reducing private CFVs use. Thus, the argument made by Anable (2005), that interventions should not only consider using a market segmentation approach but that this should be done following an empirical approach rather than *a priori*, was strongly reinforced by this thesis. Especially because this research looked at a different type of travelling (to the university), a different type of population (students) and a different socioeconomic and transport context (Brazil).

Despite the insights presented in Table 5.6 cannot be generalised, some degree of transferability of the results may be assumed. As previously discussed in Section 5.3, the structure of the psychographic clusters found in this study shares some similarities with studies conducted in other cities and using different samples. Thus, the estimated environmental impacts in this study (and especially the relative differences in impacts between segments) can be assumed to be transferable to other contexts to some extent (where similar groups were found).

5.5.1 Policy implications

The findings also reiterate how the formation of target groups is an important issue when designing 'soft' measures'. That is, understanding the systematic differences across the population in regards to the response to a certain measure is crucial for the design of customised, and more effective, interventions (Richter et al., 2011).

A transport planner or any other individual interested in implementing positive incentives could build upon the knowledge summarised in Table 6.6 and, after identifying the sociodemographic profile of a new user, target him or her according to the incentives that perform better to that specific individual. For example, incentives that were shown to be better accepted by people in general (e.g. money) could be directed to people who are less responsive to incentives (older men who are car users, for example). An incentive developer can derive even more benefits from this study by assessing the psychographic profile of a new user. This could be done with questions that measure the psychological components measured in this study, which would allow a new user to be assigned to a specific group by estimate.

The thesis now proceeds to the discussion about its limitations and guidance for future research efforts.

5.6 Research limitations and guidance for future work

This section presents the limitations of the theoretical framework of this research, the method and the findings. Along with each sub-section, suggestions for future research and transport policies are given.

5.6.1 Limitations of the theory

5.6.1.1 The direction of causality

The theoretical framework used in this research considers the psychological factors that are theoretical *predictors* of travel mode choice. However, there is an ongoing debate in the literature as to whether these factors *cause* behaviour or people actually shape these factors according to their existing behaviour. This is especially more prominent for the relationship between attitudes and behaviour, within the TPB's framework.

The arguments are mainly based on the Theory of Cognitive Dissonance (Festinger, 1962), which summarily postulates that a dissonance between cognitions (i.e. attitudes, values, beliefs) and an actual behaviour activates a psychological tension on the individual, who starts to be motivated to reduce this dissonance, either by changing behaviour or changing cognitions accordingly. Although the empirical evidence about the influence of attitudes on intention and behaviour is currently more robust than the opposite, some studies on the transportation field have shown that this relationship is reciprocal, according to the review by Kroesen, Handy and Chorus (2017).

This research has found some inconsistencies between the general psychological profile of the segments and their general behaviours. For example, 30.9% of members of the '*Non-Motorised Lovers*' group mostly use the car on their travels to the university. Similarly, less than 20% of the '*Autonomous Environmentalists*' have the bike as a primary transport mode. As Anable (2002) points out, this dissonance is a theoretical problem and has little practical meaning, but future studies are encouraged to incorporate understandings and measurements of these processes. Particularly, studies could address whether or not people that show a higher dissonance between attitudes and behaviour would be better targets for behaviour change interventions.

5.6.1.2 The reliability and validity of constructs

The assessment of the reliability of the theoretical constructs used to define the segments had to rely on internal consistency tests. A more conclusive method would be the test-retest approach, which was not possible with the cross-sectional design used on this thesis. External validity is also difficult to assess when the use of a certain method on a certain context is new. In fact, the empirical scrutiny of theories such as the TPB, TIB, NAM and VBN within the Brazilian transport context is very limited, and so is the evaluation of positive incentives. Only with consistent repetitions of the measurements used here would a definite conclusion about the validity of the constructs be possible. In this research, however, the effect of these uncertainties was minimised by using theories with strong established validity and reliability over a high number of different behaviours and transport systems, although none of the studies was based in Brazil.

5.6.2 Limitations of the method

5.6.2.1 The coverage of a questionnaire

A survey questionnaire has the (perhaps natural) limitation of not being able to capture all the factors that reflect an individual’s decision-making process, either regarding the adoption of a behaviour or the acceptability of a technology. The operationalisation of this research had to be based on the reduction of an individual's complex psychological structure into unique and more "closed" concepts (i.e. the constructs of TPB, NAM, etc.), which may represent an oversimplification of reality.

5.6.2.2 The translation of the questionnaire items

The measures coming from the theories that underlie this research were originally in English and a translation to Portuguese was made. Past authors emphasise that a literal translation is often not sufficient to properly adapt a survey instrument to a different culture. A cultural translation can be necessary, where the cultural applicability of the measures is evaluated and relevant modifications are made (Mcgorry, 2000). After the literal translation of the measures used in this study, no relevant cultural inconsistencies were found. Some minor issues of interpretation were observed on the survey pre-tests, which were corrected accordingly (see Section 3.4.4 for details). Nevertheless, these actions still do not guarantee that the questionnaire is totally exempt from translation inadequacies.

5.6.2.3 Survey response bias

When using stated-intention surveys, the resulting data has a natural limitation because people do not always behave the way they want. A more problematic issue arises when using questions about socially desirable matters. In those cases, there are grounds to expect an intentional misreporting from the respondents (Krosnick and Presser, 2010). Section 3.4 details the actions that were undertaken on this research to minimise social desirability bias, which might be present on variables such as the NAM’s ‘awareness of consequences' and 'personal norm'. However, a similar type of bias, which is often called 'policy response' bias (Ben-Akiva and Morikawa, 1990) can exist when measuring the evaluation of a hypothetical transport intervention. Respondents could be inclined to answer positively to such questions, aiming to influence the implementation of future policies. This is a significant limitation that is present in this research, especially concerning the questions measuring the acceptability of positive incentives. In order to minimise the impact of this problem on the interpretation of results, much of the results and discussion chapters were directed to the examination of the results in relative rather than absolute terms. That is, a greater emphasis was placed on comparing the performance of one incentive with others, since the absolute value of acceptability of a given incentive is expected to have a greater bias. In the same way, the acceptance of incentives was analysed in a comparative way considering the different clusters. Policy response bias may also have occurred on the estimation of implementation scenarios. It is therefore suggested that the interpretation of absolute values (such as the estimated reduction of carbon emissions due to the use of incentives) should be done with caution.

In the case where an actual implementation of incentives is present in the research context, longitudinal studies are suggested. This type of study would not necessarily depend on stated intention surveys and the acceptance of incentives could be measured in relation to the actual use of each tool by the study participants.

5.6.2.4 Surveying students

Surveying undergraduate students is a limitation of this research since the psychological profile of this group can be quite particular in some ways. Thus, the results of this research are applicable only to this type of traveller. Most of the sample is composed by young adults and as the study by Pangbourne (2018) indicates, ageing is a relevant factor when it comes to the acceptance and use of mobility-oriented ICTs. The results of this study also demonstrate that attitudes to incentives among the older portion of the sample were lower (Section 4.2.6.2).

In addition, the psychological determinants of travel behaviour, the use of travel modes and the perceived impact of incentives were all assessed with respect to commuting journeys to the university. Perceptions of leisure trips, which can be quite distinct for example, were not covered. Interestingly, however, was that the travel segments found in this thesis were quite similar to those found in other studies that assessed trip purposes such as leisure (e.g. Anable, 2005), strengthening the argument that populations are systematically divided in roughly the same way when it comes to travel behaviour. The acceptability of positive incentives by students can also be quite particular, as young people are generally more familiar with smartphone-technologies. A fair amount of the past literature in travel behaviour and acceptance of sustainable transport interventions also uses university students as sample (Bamberg and Schmidt, 2003; Haustein et al., 2009; Kim et al., 2014; Javid et al., 2016). Therefore, future studies focusing on other individual profiles are encouraged.

5.6.3 Limitations of the findings

5.6.3.1 Generalisability and subjectivity of the cluster solution

Subjectivity is inherent to the cluster analysis method. While precautions were made to ensure that the most ‘optimal’ solution was retained (details on the corresponding chapter), it is still possible that the ‘real’ number of clusters in the sample is greater or smaller than what was determined. Additionally, knowing where one segment stops and the other one starts in relation to a certain variable is difficult to determine as clusters are not exclusive from each other in terms of the clustering variables. Thus, contrasting the cluster solution found here with those found in other Brazilian transport settings would be interesting to enhance the external validity of the results.

Generalisability was not a particular aim of this research. The focus was on surveying a variety of psychological and socioeconomic profiles and users of different travel modes. According to the descriptive results, that was successfully accomplished. Although a non-random sample was used, some degree of generalisability to the greater population of undergraduate students can be plausible to assume, as efforts were done to ensure that a variety of universities and undergraduate courses were covered in the city of Curitiba. In addition, some variables were compared to a larger sample of an origin-destination survey in Curitiba. The ownership of travel modes was quite similar between both samples (as shown in Section 4.2.3).

Although generalisability cannot be assumed as per the nature of the method, transferability of the findings to other contexts is plausible to assume. As discussed earlier in Section 5.3, the cluster solution found in this study has similarities with the findings with other studies in different socioeconomic and cultural contexts.

Nevertheless, future research efforts focusing on wider populations could explore the existence of additional mobility segments and different levels of acceptability of positive incentives. If so, a comparison could be made with this research, in regards to the sociodemographic and psychological profile of these ‘new’ segments, if any.

5.6.3.2 The calculation of carbon emissions

The estimation of scenarios of positive incentives implementation represents a first step to the understanding of the potential impacts of these initiatives in the context of a middle-income country. It has used imprecise sources of data to generate the scenarios, which represents a relevant limitation to the findings. One of the sources of error is the emission factors considered to each transport mode, which might not be accurate. Despite the efforts to approximate the coefficients to the area of the study, some coefficients had to be taken from studies conducted outside of Brazil due to the lack of national data. The use of stated intention survey data is also a limitation, as the respondents might have overstated their willingness to change behaviour in response to the incentives (policy response bias), consequently leading to scenarios that are too ‘optimistic’. Future studies that do not rely on stated intention data to estimate environmental scenarios would be particularly useful to extend the preliminary findings reported by this thesis.

5.7 Final conclusion

This study demonstrated that dividing the population into behavioural groups can be a useful strategy to increase the effectiveness of interventions based on Information and Communication Technologies (ICTs) such as smartphone apps using positive incentives. We showed that these technologies have the potential to induce voluntary travel behaviour changes (VTBC) to significantly different extents, depending on the type of strategy that is used and the user's behavioural profile. Original evidence was provided not only to how the population can be divided into distinct target groups in the context of a middle-income country, but how this population evaluates an innovative form of stimulating travel behaviour change and the potential impacts associated with such perceptions.

Positive incentives to discourage the use of private conventionally-fuelled vehicles can be targeted to different psychographic and sociodemographic profiles in different ways, considering their particular acceptability levels observed by this study. The estimated effects of these interventions, either generally or considering the relative impacts by population segments, serves as another useful guide to understanding how to target smartphone-based positive incentives. Recalling the main question posed in this research, which is '*How can positive incentive schemes to discourage the use of private conventionally-fuelled vehicles be targeted, considering acceptability factors of the population and their estimated environmental impacts?',* it is assumed that this study has answered it adequately and that it represents an original research contribution.

The author hopes to have presented here a comprehensive, valid and intellectually satisfying study, capable of aiding understanding about how an innovative form of fostering travel behaviour change can be operationalised in a more effective way. Furthermore, it is the author's personal desire that the public authorities of a country with a challenging urban transport reality, such as Brazil, be sensitised by the results presented here, and thus can be able to provide sustainable solutions to the country's citizens. With the belief that real change also begins at the individual level, the author aspires that people begin to look at their travel habits in a different manner, stimulated by scientific findings such as the ones presented here.

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Appendix A - Description of individual determinants for the use of different travel modes

A.1.1 Sociodemographic determinants

Table A.1 presents the relationships found between the level of private car use and different sociodemographic factors, followed by a more detailed review of the studies. The studies covered in the table used distinct samples and were conducted in different countries with different transport infrastructures, making the interpretation of the combined results limited somehow. Nevertheless the table is still useful to provide a broad overview of the prominent aspects that influence car use in a variety of contexts.

Table A.1 - Influence of sociodemographic variables to car use (Dargay, 2008)

Authors	Income	Male	Educa-tion	House-hold Size	Country
De Jong (1996)	+	+	+		Netherlands
Golob and Hensher (1998)			-	-	Australia
Steg et al. (2001)	+	+	+	-	Netherlands
Johansson-Stenman (2002)	+	+			Sweden
Asensio et al. (2003)	+		+	+	Spain
Nolan (2003)	+	+	0	+	Ireland
Simma and Axhausen (2003)		+			Austria
Fullerton et al. (2015)	+		-	0	Japan
Dargay and Hanly (2004)	+	+			United Kingdom
Fullerton (2005)	+	+	+	+	United States
e Silva et al. (2006)	+	+		+	Portugal

Note: (+) corresponds to a positive relationship between the factor and car use; (-) to a negative relationship and (0) to no significant relationship.

The studies presented above use levels of car use as dependent variables. There is divergence on the type of measurement to assess the amount of car use. While some studies consider distance travelled by car, others choose fuel expenditure or the personal choice to use the car as the main mode of transport.

Income and being male have a strong positive relationship with car use in the majority of the studies. Not surprisingly, other studies showed that the relationship between the use of public transport and income/male variables is negative (Johansson-Stenman, 2002; e Silva et al., 2006).

The level of education also relates positively with car use, exceptions are studies developed in Australia and Japan. The positive influence of household size on the level of car use was identified on five out of eight studies that examine this relationship.

It is worth noticing that all the studies presented were conducted in the context of developed countries. The research presented in this thesis has the potential to test if the same relationship patterns are observed in a middle-income country, with its cultural and socioeconomic particularities. For example, determinant factors for cycling that are not usually present in developed countries' studies are significant (or more significant) in Brazilian studies such as 'lack of infrastructure' and 'lack of public safety' (de Souza et al., 2014). Apart from travel behaviour, other relevant aspects that may vary across different cultures are the level of internet penetration (Internet World Stats, 2018) and Information Technology adoption and use (Phillips et al., 1994; Onofrei et al., 2004).

It is undeniable that sociodemographic variables have significant explanatory power on car use. However, the decision-making process for using the car also involves multiple psychological factors. As stated by Van Acker et al. (2016), different travel patterns are still found within homogeneous sociodemographic groups. With the exception of the studies of (Golob and Hensher, 1998) and (Steg et al., 2001), all the other researches presented in Table 6 do not address any behavioural component to explain mode choice. However, the use sociodemographic variables to explain car use often benefits from a significantly large sample (e.g. Asensio et al. (2003); Nolan (2003); Fullerton et al. (2015)), usually originating from government-owned datasets of large scale household surveys. This often allows more consistent results in comparison to behaviour-oriented research, often because studies addressing habits, attitudes, beliefs, etc. need to measure variables that are not present in large census datasets or travel surveys, therefore having to be based on primary data collection. Sociodemographic metrics are also more objective metrics than behaviour, which usually uses intensity scales to measure the respondent’s level of agreement with statements addressing attitudes and other behavioural components. Next section presents an overview of the types of psychological determinants that may be related to an individual’s behaviour.

A.1.2 Psychological determinants

One form of systematising the psychological motives that determine the use of transport modes is separating then as: instrumental, symbolic or affective (Steg et al., 2001; Steg, 2005; Beirão and Sarsfield Cabral, 2007; Gatersleben and Uzzell, 2007; Hunecke et al., 2010; Javid et al., 2016). In the past, the decision to use the travel modes was explained using models that focused only on instrumental factors, such as speed, convenience and cost. However, this utilitarian approach was complemented by subsequent studies who found that using the car, for example, can be something that brings feelings of power and superiority (affective aspects) and acts as a symbol of self-expression and status (symbolic) (Steg et al., 2001; Steg, 2005). A conclusive study by Mokhtarian and Salomon (2001) suggested that the act of travelling itself has a positive utility attached to it. That is, people do not travel just as a means to reach a destination, but it can also be something that brings enjoyment and pleasure or stress and boredom, for example. Empirical research has given support to these statements, especially concerning car use. Lois and López-Sáez (2009) found that affective factors, like enjoyment and excitement, explained as high as 12% of the car’s frequency of use among Spanish commuters. Surprisingly, the same study did not find any direct effects of instrumental and symbolic motives on car use but mediated by affective motivations instead. That is, the fact that a person evaluates the car as comfortable or fast (instrumental motives), would just produce an increase on the probability of using the car if these evaluations cause positive affective experiences like pleasure or excitement, for example. Another study, by Steg, Vlek and Slotegraaf (2001), shows that symbolic and affective motives for using the car are as significant as (or even more significant than) instrumental ones. Affective factors are also present when people evaluate other modes of transport such as bike, walking or taking the bus. Anable and Gatersleben (2005) demonstrate that affective aspects like freedom, excitement and relaxation were rated by people as almost equally important as instrumental ones like convenience and cost, when evaluating multiple travel modes. Nevertheless, research shows that the population of lower income countries give a significantly higher importance to symbolic-affective aspects of the car, whereas travellers of more developed countries tend to have more instrumental motivations when deciding among travel modes (Van and Fujii, 2011; Belgiawan et al., 2014).

Another tranche of research focuses on how established social psychology theories might be useful to explain the use of transport modes. Specifically, theories that explain either general behaviour adoption such as the Theory of Planned Behaviour (TPB) or pro-environmental behaviour like the Norm-Activation Model (NAM) are studied. Studying travel behaviour using such theories represent a much broader approach as it considers the adoption of behaviour as something more complex than just looking at symbolic, affective and instrumental reasons to use each travel mode. If we look at the application of the TPB in transport research, for example, these motives are not excluded but are specific predictors of only one of the three explanatory concepts of behaviour.

The theories of behaviour that were selected to be part of this study's theoretical framework were already outlined in Chapter 2. Here, additional theories that were reviewed but were not included in the research are described.

A.1.2.1 Social Learning Theory (SLT)

This theory emphasises that new behaviour patterns can emerge by observing the behaviour of others or through direct experience of new habits. In the travel behaviour context, learning by direct experience receives empirical support when giving free public transport tickets to non-users increases its regular use, for example (Taniguchi and Fujii, 2007). The learning by direct experience, according to the theory can be catalysed by informational reinforcement measures such as feedback and self-regulatory tools (Bandura, 1977).

The theory also states that positive external reinforcements (rewards) play an important role to increase the frequency of a given behaviour and that this is also true when an individual observes others being rewarded.

Self-reinforcement can also be determinant for behaviour. Bandura (1971) states that individuals tend to be constantly comparing their own behaviour to self-identified standards and adjust to that without the need of external interventions. In a later publication, Bandura (1977) introduces the concept of self-efficacy, which refers to an individual's perception of the ability to perform a certain action and to maintain that behaviour.

Anable et al. (2006) suggest three ways of increasing self-efficacy:

- Setting goals;
- Using a formalized process of setting goals and informing potential rewards; and
- Providing feedback from self-monitoring and encouraging record-keeping (rewarding progress, for example).

The concepts of the SLT are attached to some fundamental concepts of the use of positive incentives for behaviour change. Self-monitoring tools, rewards and using social media to compare behaviour were addressed in by projects like the SUNSET (SUNSET Project, 2014), for example. These provide an indication of the promising impacts that this kind of intervention may have on reducing car use.

A.1.2.2 The Goal-Setting Theory (GST)

The goal-setting theory was proposed by Locke and Latham (1991). This theory has a fundamental difference to the other theories reviewed so far. Its focus is more on the process of behaviour change or the accomplishment of one's desired behaviour.

According to the authors, the individual performance on a certain task designed to reach a specific goal depends on the perceived difficulty of the goal. Hard goals are perceived to require greater efforts by the individual. This perception leads to higher motivation and a higher feeling of success after the goal is achieved. Therefore, the higher the difficulty, the higher the individual's performance (Locke and Latham, 1991). This relationship between effort and performance can be moderated by four main aspects: receiving feedback on the progress towards the goal; increasing commitment to the goal, referring to the importance given to the goal by the individual; the complexity of the task, besides other situational constraints (Locke and Latham, 2006).

This theory has been modestly used in transport research. The study of Bamberg et al. (2011) shows a significant relationship between the intention to pursue a goal with the intention to voluntarily reduce car use. Goal intention, in turn, being determined by perceptions of goal feasibility and perceptions about goal progress, referred by Locke and Latham (1991) as 'task complexity' and 'feedback'.

Gärling et al. (2002) suggests that travel demand measures (such as road pricing, parking fees, improved bike paths, etc.) combined with determinant individual factors (income, attitudes, family structure, etc.) can determine the likelihood of an individual to set up a goal and form an implementation plan to reconsider his travel choices.

Positive incentives can directly influence individuals in the process of goal setting and task performance. When establishing a goal for the reduction of car use, for instance, incentives can facilitate the provision of feedback on goal progress, increasing the sense of commitment to the goal, reducing the perceived complexity of the tasks and diminishing situational constraints such as lack of information about alternatives, for example.

A.1.2.3 The Trans-theoretical Model of Behaviour Change (TTM)

This theory is focused on the process of behaviour change. The main concept behind the Trans-theoretical model (Prochaska and Di Clemente, 1982) is that behaviour change is acquired while an individual 'moves' towards different stages of change. Marcus et al. (1992) explain these different stages:

1. Pre-contemplation: individuals at this stage are not aware of a need to change a certain behaviour. They might assume the existence of bad behaviours but do not have any intention of changing.
2. Contemplation: At this stage, people start to consider that they might need to change unwanted behaviour, without having a serious commitment to act yet. They manifest the intention to change in the near future (e.g. six months). According to the authors, it is common to stay at this stage for a long time.
3. Preparation: This is one step closer to effectively taking action towards behaviour change. People at this stage have already tried to change without success and are considering taking action in a short period of time (e.g. one month).
4. Action: This stage is, according to (Marcus et al., 1992), where major changes occur. It represents the point where people have successfully changed their behaviour for a period lasting from one day to six months.
5. Maintenance: The aim at this stage is to maintain the gains of the recently adopted behaviour and avoid relapse, for at least six months.

People often move along all the stages until successfully maintaining a new behaviour. They might recurrently go back to the contemplation or preparation stages having learned from their failures and mistakes, suggesting that the movement along the stages follows a spiral pattern rather than a circle (Marcus et al., 1992).

This model views behaviour change as a process rather than a single event (Gatersleben and Appleton, 2007). It has been used especially in health psychology to study problem behaviours such as smoking and cocaine addiction (Prochaska, 1994). Evidence about the usefulness of the TTM when examining change in travel behaviour that occurs in response to interventions appears to be premature. The review by Friman et al. (2017) demonstrates that some changes in travel behaviour were observed in accordance to what is postulated by the TTM, but this is not sufficient to draw any protocols of transport interventions based on this theory, nor to make any recommendations for future policy development. Mainly due to the mall number of studies and the different methodologies applied by them (Friman et al., 2017).

Nevertheless, this does not mean that the trans-theoretical model does not serve as a general guideline for transport interventions. Intentions to use different positive incentives, for example, may vary across people in different stages of change. Considering the adoption of cycling for daily commuting, for example, research suggests that individuals in different stages of change have significant differences in terms of attitudes towards cycling and perceptions about the internal and external obstacles to cycle (Gatersleben and Appleton, 2007).

Apart from the factor coming from theories of behaviour, the next section explores the existence of significant relationships between additional factors like sociodemographic characteristics and the use of different transport modes. Car use, for example, has been found to be directly related to financial income and gender (male).

Appendix B - Elicitation questionnaire

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This questionnaire is part of a research being conducted in the Institute for Transport Studies of the University of Leeds, United Kingdom. Its results have the potential to help identifying innovative solutions to the urban mobility of Curitiba. The collected data will remain in possession of the research team, for research purposes only. Anonymity of the responses is guaranteed and the participation is totally voluntary and optional.
Please try to be as concise as possible in your answers.

1. List the good and bad characteristics (advantages or disadvantages) of each one of the transport modes below.

Private Car	Motorbike	Bus
- ______________ - ______________ - ______________ - ______________ - ______________	- ______________ - ______________ - ______________ - ______________ - ______________	- ______________ - ______________ - ______________ - ______________ - ______________
Bike	**Walking.**	**Other, specify:__________**
- ______________ - ______________ - ______________ - ______________ - ______________	- ______________ - ______________ - ______________ - ______________ - ______________	- ______________ - ______________ - ______________ - ______________ - ______________

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2. What factors, in your opinion, would facilitate or restrict the use of each transport mode?

Private Car	Motorbike	Public Transport
- ____________________ - ____________________ - ____________________ - ____________________ - ____________________	- ____________________ - ____________________ - ____________________ - ____________________ - ____________________	- ____________________ - ____________________ - ____________________ - ____________________ - ____________________
Bike	**Walking.**	**Other, specify:____________**
- ____________________ - ____________________ - ____________________ - ____________________ - ____________________	- ____________________ - ____________________ - ____________________ - ____________________ - ____________________	- ____________________ - ____________________ - ____________________ - ____________________ - ____________________

Thanks a lot for your participation! In case you have any queries about the research please contact email@email.ac.uk

Appendix C - Main questionnaire

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SURVEY QUESTIONNAIRE

You are being invited to participate in a research study titled: **Mobility in Curitiba: how to incentivise you to decrease the use of the car or motorcycle?** This study is being conducted by Rafael dos Reis, from the University of Leeds.

The purpose of this research study is to investigate your opinions in regards to mobility and your perception of a range of mobility solutions. It will take you approximately 15 minutes to complete. Your participation in this study is entirely voluntary and you can withdraw from this at any time prior to delivering the completed questionnaire. You do not have to answer any questions you do not want to.

We believe there are no known risks associated with this research study; however, as with any online related activity the risk of a security breach is always possible. To the best of our ability your participation in this study will remain confidential, and only anonymised data will be published. We will minimise any risks by not asking you to identify your-self at any point.

Many thanks for your help!

*******PLEASE RESPOND THE QUESTIONNAIRE USING AN "X" IN THE CHOSEN ANSWERS*******

1. **What transport modes do you currently own?** You may choose more than one.

Car	Motorcycle	Bike	None
☐	☐	☐	☐

2. **What transport modes do you have available to go to the university?** You may choose more than one.

Car	Motorcycle	Bike	None
☐	☐	☐	☐

3. **Thinking about the last month of classes, how frequent have you used each mode of transport TO GO TO THE UNIVERSITY, on average** *(please count a return trip as two trips)*? Leave blank if you haven't used the mode.

	Between 1 – 3 trips per week	4 – 6 trips per week	7 – 9 trips per week	10 – 12 trips per week	13 – 15 trips per week	16 -18 trips per week	18 or more trips per week
Car	___	___	___	___	___	___	___
Bus	___	___	___	___	___	___	___
Bike	___	___	___	___	___	___	___
Motorcycle	___	___	___	___	___	___	___
Walking	___	___	___	___	___	___	___

4. **Indicate how familiar you are with the following mobility apps.**

	I don't know	I've heard about, but have never used it	I've used it in the past, but not anymore	I currently use it
Apps that you can use to share a ride with someone going to the same destination *(e.g BlaBlaCar; Bynd).*	___	___	___	___
Apps that you can book a specific trip to be made by a privately owned car *(e.g UBER; Cabify).*	___	___	___	___
Apps that you can use to rent a car or bike owned by someone else *(e.g PegCar; Parpe).*	___	___	___	___
Apps you can use to plan a journey, check traffic status and navigate through GPS *(e.g Waze; HereWeGo; MapLink).*	___	___	___	___
Apps you can use to check real time bus location, bus routes or timetables *(e.g Itibus, Próximo ônibus Curitiba; Moovit).*	___	___	___	___
Apps you can use to take a Taxi *(e.g EasyTaxi, 99 Taxis).*	___	___	___	___
Apps that you can track your physical exercises and share your performance with friends *(e.g Endomondo; Nike+Run; Strava; Google Fit).*	___	___	___	___

5. **How would you like the experience of travelling to the university using each one of the modes during next month?** *Choosing an option to the right indicates agreement with the label on the right, and vice versa.*

Car	I would dislike it very much	___	___	___	___	___	___	___	I would like it very much	___DK
Bus	I would dislike it very much	___	___	___	___	___	___	___	I would like it very much	___DK
Bike	I would dislike it very much	___	___	___	___	___	___	___	I would like it very much	___DK
Motorcycle	I would dislike it very much	___	___	___	___	___	___	___	I would like it very much	___DK
Walk	I would dislike it very much	___	___	___	___	___	___	___	I would like it very much	___DK

6. Would going to the university next month using each transport mode be pleasant or unpleasant? Give your answer below.

Car	Very unpleasant	___	___	___	___	___	___	___	Very pleasant	___DK
Bus	Very unpleasant	___	___	___	___	___	___	___	Very pleasant	___DK
Bike	Very unpleasant	___	___	___	___	___	___	___	Very pleasant	___DK
Motorcycle	Very unpleasant	___	___	___	___	___	___	___	Very pleasant	___DK
Walk	Very unpleasant	___	___	___	___	___	___	___	Very pleasant	___DK

7. What is the experience you have with the use of each transport mode, considering your whole life? Give your answers below.

Car	No experience at all	___	___	___	___	___	___	___	A lot of experience	___DK
Bus	No experience at all	___	___	___	___	___	___	___	A lot of experience	___DK
Bike	No experience at all	___	___	___	___	___	___	___	A lot of experience	___DK
Motorcycle	No experience at all	___	___	___	___	___	___	___	A lot of experience	___DK
Walk	No experience at all	___	___	___	___	___	___	___	A lot of experience	___DK

8. Each topic below describes a form of incentive designed to reduce the use of conventional vehicles such as cars and motorcycles and, in turn, encourage the use of more sustainable forms such as walking, cycling or taking the bus. They are delivered over the internet, so imagine using them on a smartphone. Each incentive description is followed by three questions. Read the description of each incentive *carefully* and answer the questions that follow.

a. **Maps**: Having a digital or printed map containing information about cycle routes, bus lines/frequencies and walking paths

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

b. **Cash:** Receiving cash prizes if you travel using alternative modes to the car or motorbike.

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

c. **Points and Badges:** Accumulating points and earning badges for travelling without the car or motorcycle (e.g "you've earned 2000 points and have achieved 'Gold' status in cycling").

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

d. **Ranking and competition:** Participate in a ranking showing the people who most used the bus, bike or walking as means of transportation in Curitiba ("You are currently third on the ranking of sustainable travellers in Curitiba!").

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

e. **Vouchers:** Receiving discount vouchers that you can use to buy products or services (e.g retail stores, cinema tickets, etc).

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot

This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

f. **Journey Planner:** Having access to a journey planner containing information about the trip you want to do (distance, duration, physical effort, price, emissions) on different types of transport modes in Curitiba.

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

g. **Real-time information:** Have access to real-time information, including bus times, weather and traffic problems ("your next bus will arrive in 5 minutes"; "tomorrow will be a sunny day, why not cycle to campus?"; "Traffic is chaotic now, why not go on foot?").

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

h. **Personalized Feedback:** Have access to a personalised report about my recent journeys and their consequences (kilometres travelled, total time on journeys, air pollutants emitted, calories burned, etc.)

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

i. **Social Media:** Being able to share your journey habits with friends and family through social media ("'your name' has just cycled 12 kilometres!")

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

j. **Challenges:** Receive periodical challenges to complete (e.g. "challenge for this week: cycle 10 kilometres!")

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

k. **Buddying:** Know about other person who may join you to cycle, walk or get the bus together (e.g. "Your friend goes to the university using a bus line that stops next to your house, how about joining him?")

I don't like this	___	___	___	___	___	___	___	I like it very much
I would not use this	___	___	___	___	___	___	___	I would use it a lot
This would **never** make me change trips by car or motorcycle to alternative modes.	___	___	___	___	___	___	___	This would **certainly** make me change trips by car or motorcycle to alternative modes.

9. Thinking about the people you consider important in your life. What would be their opinions in respect to you using each one of the modes to go to the university? Answer the two questions that follow.

Car	Would completely oppose	___	___	___	___	___	___	___	Would completely support	___DK
Bus	Would completely oppose	___	___	___	___	___	___	___	Would completely support	___DK
Bicycle	Would completely oppose	___	___	___	___	___	___	___	Would completely support	___DK
Motorbike	Would completely oppose	___	___	___	___	___	___	___	Would completely support	___DK
Walking	Would completely oppose	___	___	___	___	___	___	___	Would completely support	___DK

Car	They think I should not use	___	___	___	___	___	___	___	They think I should use	___DK
Bus	They think I should not use	___	___	___	___	___	___	___	They think I should use	___DK
Bicycle	They think I should not use	___	___	___	___	___	___	___	They think I should use	___DK
Motorbike	They think I should not use	___	___	___	___	___	___	___	They think I should use	___DK
Walking	They think I should not use	___	___	___	___	___	___	___	They think I should use	___DK

10. About the use of cars or motorbikes and its consequences, give your opinion below.

I feel morally obliged to leave the car/motorbike unused as often as possible.									
Completely false	___	___	___	___	___	___	___	Completely true	___DK
I feel obliged to use more alternative modes such as public transport or bike due to personal values.									
Completely false	___	___	___	___	___	___	___	Completely true	___DK
The growing use of cars/motorbikes will lead to irreversible consequences to the planet.									
Completely false	___	___	___	___	___	___	___	Completely true	___DK
Traffic related air pollution and noise decrease the quality of life in the city.									
Completely false	___	___	___	___	___	___	___	Completely true	___DK
High levels of car/motorbike use is an environmental threat.									
Completely false	___	___	___	___	___	___	___	Completely true	___DK
My decision about what type of transport mode to use on a daily basis makes me responsible for the levels of traffic related pollution.									
Completely false	___	___	___	___	___	___	___	Completely true	___DK
I have the ability to help reducing the environmental and social threat attached to the use of cars/motorbikes.									
Completely false	___	___	___	___	___	___	___	Completely true	___DK

11. And what do you intend to do in the near future? Indicate the weekly frequency (Monday to Friday) that you plan to use each of the travel modes in your journeys TO THE UNIVERSITY during the next month of classes. If you don't intend to use a certain mode, leave the corresponding line blank. *Consider each one-way trip as one.*

	Between 1 – 3 trips per week	4 – 6 trips per week	7 – 9 trips per week	10 – 12 trips per week	13 – 15 trips per week	16 -18 trips per week	18 or more trips per week
Car	___	___	___	___	___	___	___
Bus	___	___	___	___	___	___	___
Bike	___	___	___	___	___	___	___
Motorcycle	___	___	___	___	___	___	___
Walking	___	___	___	___	___	___	___
Other? Which:________	___	___	___	___	___	___	___

12. **Considerando as seguintes atividades, indique qual o modo de transporte (APENAS UM) que você usaria para cada uma das atividades abaixo: UM MODO DEVE SER ASSINALADO POR ATIVIDADE.** *IMPORTANTE: Responda a primeira coisa que vem à sua cabeça, no menor tempo possível e sem muito raciocínio.*

Visiting family	Going to do sport/gym	Shopping clothes or accessories.
___Car ___Bus ___Bicycle ___Walking ___Motorcycle	___Car ___Bus ___Bicycle ___Walking ___Motorcycle	___Car ___Bus ___Bicycle ___Walking ___Motorcycle
Go to a park in a sunny day	**Going to the supermarket**	**Going for an night out with friends.**
___Car ___Bus ___Bicycle ___Walking ___Motorcycle	___Car ___Bus ___Bicycle ___Walking ___Motorcycle	___Car ___Bus ___Bicycle ___Walking ___Motorcycle

13. **If you really wanted to, could you use each one of the modes to go to the university next month?**

Car	Very unlikely that I could	___	___	___	___	___	___	___	Very likely that I could	___DK
Bus	Very unlikely that I could	___	___	___	___	___	___	___	Very likely that I could	___DK
Bicycle	Very unlikely that I could	___	___	___	___	___	___	___	Very likely that I could	___DK
Motorbike	Very unlikely that I could	___	___	___	___	___	___	___	Very likely that I could	___DK
Walking	Very unlikely that I could	___	___	___	___	___	___	___	Very likely that I could	___DK

14. **When deciding which type of transport mode to choose to go to the university in the next month, how much do you think that using each mode is really just up to your decision?**

Car	It is not up to my decision	___	___	___	___	___	___	___	It is entirely up to my decision	___DK
Bus	It is not up to my decision	___	___	___	___	___	___	___	It is entirely up to my decision	___DK
Bicycle	It is not up to my decision	___	___	___	___	___	___	___	It is entirely up to my decision	___DK
Motorbike	It is not up to my decision	___	___	___	___	___	___	___	It is entirely up to my decision	___DK
Walking	It is not up to my decision	___	___	___	___	___	___	___	It is entirely up to my decision	___DK

15. **Lastly, please let us know a little more about you.**

Age: ________	Gender: ___ Male ___Female ___Prefer not to say	Household Size*____ persons *number of people who have the accommodation you live as their main residence, including you.	Your home's city suburb (if different city, indicate its name): ______________________
Estimated distance between your house and the university campus: ______________ km	Household Income (estimated monthly salary):	☐ Less than 1 minimum wage (R$937) ☒ Between 1 and 3 minimum wages (R$937,01 and R$2811) ☐ Between 3 and 6 minimum wages (R$2811,01 and R$5622) ☐ Between 6 and 9 minimum wages (R$5622,01 and R$8433) ☐ Between 9 and 12 minimum wages (R$8433,01 and R$11224) ☐ Between 12 and 15 minimum wages (R$11224,01 and R$14055) ☐ More than 15 minimum wages (more than R$14055,01) ☐ Prefer not to say/Don't Know.	
Do you accept to receive a supplementary questionnaire by e-mail and compete for Submarino.com vouchers? ___No ___Yes - Email:______________________________			

*This email will just be used to send a follow up questionnaire to you. After that, it will be disregarded.

Many thanks for your participation! Should you have any questions about the research, please contact Rafael on email@email.ac.uk or *(xx) xxxxx-xxxx*.

Question number	Problem	Possible Cause	Treatment
General	Excessive time to complete	Painting options instead of crossing.	Asking the respondents to cross, also supervising it in person in the classroom.
		Confusion inverted scales.	Decrease the amount of scale endpoints inversions.
		Excessive reading.	Altering question statements to be more concise.
		Question 11.	I will group the subset of scales by transport mode instead of grouping them by control factor, reducing the amount of reading.
		Question 12	Same as above.
		Too many questions	Reduce the scales used to measure the following constructs: - Habit (Q14): Use 6 imaginary situations, instead of 9. - Behavioural Beliefs (Q5): change the criteria by which the salient beliefs were chosen from the qualitative pre-test, including the attributes cited by at least 30% of respondents (following suggestions of Ajzen and Fishbein (1980)). This will reduce some of the mode's variables from four to three or two; - Ecological Worldview (Q8): replace the 9-item NEP (New Ecological Paradigm) by the 5-item scale used by Stern el al. (1999), which showed reliability of .73 (Cronbach's Alpha).
General	Respondents being tired on the last questions and rushing to complete in time	Too many questions and a sort of "pressure" imposed by the classroom environment.	Define a maximum time for questionnaire completion. The students that do not finish on time will be asked to give the questionnaire back. The questionnaire will not be disconsidered. Putting tiring questions in the beginning of the questionnaire.
General	The last students to complete the questionnaire might impede the professor to start the class on time	Some students need a lot more time to complete the same questionnaire than others. The structure of the survey administration also imposes that all the students must complete the questionnaire before the professor is able to resume the class.	Same as above.
Q3	Many blank responses (35-50%)	People do not use the mode.	Consider blank answers as if the person do not use the mode at all.
Q4	Taxi apps = UBER?	Respondents did not pay attention to the UBER example.	Describing the apps types using only examples instead of stating the technical terms. Being present and open for queries during the questionnaire administration also minimises this.

Question number	**Problem**	**Possible Cause**	**Treatment**
Q5	Practicity - what is it?	Multiple meaning term.	Practicality' has multiple meanings in Portuguese that might be the same as 'velocity' when used in the context of transport. As this is just assessed in the question about motorbikes, I will replace it by the next most cited attribute (comfort).
Q5	High positive responses on bike and walking 'cheapness' and 'good for environment'	Bike and walking are notoriously good for the environment and cheap.	Adjust the scale endpoint from 'Good for the environment' to 'Extremely good for the environment' and use a unipolar scale. Replace the 'cost' attribute for these modes by the next most cited attribute on the previous pre-test (tiredness).
Q7	Me, society and the environment, what do you mean?	Question phrasing.	Emphasize that an average opinion is what is wanted, considering these three aspects. The solution to the problem below will also minimise this.
Q7	The two questions are highly correlated for 3 modes	Respondents do not differentiate 'good' and 'bad' from 'pleasant' and 'unpleasant'.	Replace the adjective pair 'good' and 'bad' by 'beneficial' and 'harmful'.
Q10	Many blank responses (10-15%)	People do not intend to use the mode at all.	Consider blank answers as if the person do not intend to use the mode at all.
Q13	Suspect response distributions (e.g. 'control and dominance over other people' was marked as not being a personal value by 15% of respondents'). In addition, respondents tended to mark answers on the positive side of the scale (0 to +3 instead of -1 and below).	The scale labels might me unclear and confusing.	Modify the scale. Will use the same scale of Schwartz (1992), replicated by Groot and Steg (2007). A 9-point scale ranging from -1 Opposite to my values, 0 not important to 7 extremely important. Respondents will rate he importance of the values as a "guiding principle in their lives".
Q13	Misunderstanding of the scale point 'neutral'		
Q14	Marked more than one answer	Question does not state that just one answer must be marked.	Clearly state that just one option must be marked.
Q15	Four respondents (20%) repeated ranks for different incentives	Questions statement is too long or not clear enough.	Make the text more concise and clearly state that they must not repeat any rank.
Q16	Do I consider myself when answering household size?	Not stated in the question.	Make it clear in the question.
Q16	What if I live in another city?	Not stated in the question.	Make it clear in the question.
BusWorkQuestion	Many blank responses (35%)	Question is in a bad position.	Reformat the question.

Appendix E - Outputs of the second pre-test

<table>
<tr><th>Question number</th><th>Problem</th><th>Treatment</th></tr>
<tr><td>General</td><td>Some students talked with each other about the questionnaire during completion, which might have influenced their responses.</td><td>State that the questionnaire must be completed alone.</td></tr>
<tr><td>General</td><td>Some students got confused as to what questions to consider only trips to campus and what questions to consider all trips.</td><td>Clearly state which trips we want them to consider when answering each question.</td></tr>
<tr><td>Q3</td><td>68% of respondents left blank the lines that correspond to a mode they don't use.</td><td>Remove the option "Don't use" and instruct respondents to leave blank the lines that correspond to a mode they do not use.</td></tr>
<tr><td>Q3</td><td>A considerable amount of respondents (6/25) chose the highest score (16 or more trips).</td><td>Adjust the high end of the scale.</td></tr>
<tr><td>Q5</td><td>Some students (4/25) answered just one from the two questions for each mode. 15 from 25 students gave the same score to good/bad and pleasant/unpleasant to all the modes. Correlation between both scales regarding car use was perfect (1,0).</td><td>Replaced the good/bad scale for like/dislike. Also separated this question in two different items, to avoid automaticity on responses.</td></tr>
<tr><td>Q8</td><td>Low Cronbach's alpha</td><td rowspan="2">Replace the measures of subjective norm</td></tr>
<tr><td>Q9</td><td>Low Cronbach's alpha;
Large concentration of responses at the high end of the scale for the car</td></tr>
<tr><td>Q11</td><td>16% of students left items blank for the same reason as Q3 above.</td><td>Same as Q3 above</td></tr>
<tr><td>Q13</td><td>Low Cronbach's alpha;
Large concentration of responses at the highest and lowest ends of the scale for the car</td><td rowspan="2">Replace the measures of perceived behavioural control. Putting more intensity in the adjectives of both endpoints of the scale.
Q14 lowest endpoint "depends highly on other people" was replaced by "Not up to my decision".</td></tr>
<tr><td>Q14</td><td>Low Cronbach's alpha</td></tr>
</table>

Appendix F - Complementary questionnaire

INVITATION EMAIL

Subject: Mobility in Curitiba: take part again and win up to R$1500.00

Message:

Dear undergraduate student,

You should remember to have participated in a study I did in your classroom on urban mobility. I invite you now to answer this brief second part, containing questions that will offer you the chance to point out the main limitations of Curitiba in relation to this theme. It will take you around 6 minutes to complete and we will draw 50 discount vouchers worth R$30.00 each from the *Submarino.com* store. Considering the reduced number of participants, there is a high chance to win! The questionnaire will remain open for a limited time, so do not waste time and participate now!

Click the link below to access the survey:

[link]

Your participation is entirely voluntary and there is no negative consequences on not taking part on this survey. Data will be temporary stored at onlinesurveys.com and the risk of breach is very low. We will minimize this risk by erasing all online stored data after collection.

Many thanks,

Rafael Alexandre dos Reis
Institute for Transport Studies - Universidade de Leeds/UK
tsradr@leeds.ac.uk

If you wish to unsubscribe from future emails, click the following link:
[link]

COMPLEMENTARY SURVEY – URBAN MOBILITY IN CURITIBA

PART 1

General instructions: the survey is divided in three sections and presents questions related to different types of transport modes. Every line must be marked.

1. Thinking about the last month of classes, how frequent have you used each mode of transport TO GO TO THE UNIVERSITY, on average (please count a return trip as two trips)? Leave blank if you haven't used the mode at all.

	Between 1 – 3 trips per week	4 – 6 trips per week	7 – 9 trips per week	10 – 12 trips per week	13 – 15 trips per week	16 -18 trips per week	18 or more trips per week
Car	○	○	○	○	○	○	○
Bus	○	○	○	○	○	○	○
Bike	○	○	○	○	○	○	○
Motorcycle	○	○	○	○	○	○	○
Walking	○	○	○	○	○	○	○
Van	○	○	○	○	○	○	○

In the next questions, indicate the likelihood that a trip to the university using each mode of transport has the following characteristics.

2. A trip to the university using the car would be…

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely
...safe?	○	○	○	○	○	○	○
...expensive?	○	○	○	○	○	○	○
...comfortable?	○	○	○	○	○	○	○
...quick?	○	○	○	○	○	○	○

3. A trip to the university using the bus would be…

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely
...cheap?	○	○	○	○	○	○	○
...crowded?	○	○	○	○	○	○	○
...comfortable?	○	○	○	○	○	○	○
...quick?	○	○	○	○	○	○	○

4. A trip to the university using the bike would be…

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely
...quick?	○	○	○	○	○	○	○
...very good for the environment?	○	○	○	○	○	○	○
...dangerous?	○	○	○	○	○	○	○
...very healthy?	○	○	○	○	○	○	○

5. A trip to the university using the motorbike would be…

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely
...cheap?	○	○	○	○	○	○	○
...practical?	○	○	○	○	○	○	○
...quick?	○	○	○	○	○	○	○
...dangerous?	○	○	○	○	○	○	○

6. Walking to the university would be…

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely
...quick?	○	○	○	○	○	○	○
...very good for the environment?	○	○	○	○	○	○	○
...very healthy?	○	○	○	○	○	○	○
...dangerous?	○	○	○	○	○	○	○

7. When choosing the transport mode to make the trip to the university, how important is each one of the factors below for your decision? Answer using the scale from 0 (not important at all) to 6 (extremely important).

	0	1	2	3	4	5	6
Has to be cheap							
Has to be comfortable							
Has to be safe							
Has to be quick							
Has to not be crowded (bus)							
Has to be healthy							
Has to be environmental-friendly							
Has to be practical							

PART 2

Note: On this page, some questions are in the form of statements. When this is the case, please indicate to what extent you think those statements are true or false, using the scale provided.

8. How likely is it that you will have enough money to go to campus by car next month?

Highly unlikely								Highly likely

8a. Me having enough money next month would facilitate my ability to go to campus by car.

Very false								Very true

9. How likely is it that there will be traffic jams if I go to campus by car next month?

Highly unlikely								Highly likely

9a. Traffic jams would impede me from going to campus by car next month.

Very false								Very true

10.How likely is it that you will be involved in an accident if you go to campus in a motorbike next month?

Highly unlikely								Highly likely

10a. The risks of an accident impedes me from going to campus by motorbike next month.

Very false								Very true

11.How likely is it that you will have enough money to go to campus by motorbike next month?

Highly unlikely								Highly likely

11a. Me having enough money next month would facilitates my ability to go to campus by motorbike.

Very false								Very true

12.How likely is it that you will have enough money to go to campus by bus next month?

Highly unlikely								Highly likely

12a. Me having enough money next month would facilitates my ability to go to campus by bus.

Very false								Very true

13.How likely is it that it will take too long to get to campus by bus during next month?

Highly unlikely							Highly likely

13a. The time spent impedes me to use the bus to go to campus next month.

Very false							Very true

14.How likely is it that you will have any safety issue (accident or violence) ifyou go to campus by bike during next month?

Highly unlikely							Highly likely

14a. Safety problems impede me to use the bike to go to campus next month.

Very false							Very true

15.How likely is it that there will be cycle lanes ifyou go to campus by bike during next month?

Highly unlikely							Highly likely

15a. The existence of cycle lanes facilitates my ability to go to campus by bike next month.

Very false							Very true

16.How likely is it that you will have any safety issue (accident or violence) ifyou go to campus walking during next month?

Highly unlikely							Highly likely

16a. Safety problems impede me to walk to campus next month.

Very false							Very true

17.How likely is it that you would have to walk too far to get to campus next month?

Highly unlikely							Highly likely

17a. The distance impedes me to walk to campus next month.

Very false							Very true

PART 3

18. When choosing what transport mode to use, there might be individuals or groups who would think you should or should not perform this behaviour. Please list two of these individuals or groups that come to mind when you think about which transport mode to use to go to campus.

Individual (group) 1 ___________
Individual (group) 2 ___________

19. Considering the individual (group) 1, that you outlined above, what do you think he (they) think about you using each one of the modes below to go to campus? Indicate using the scale from 0 (think I should never use) to 6 (think I should always use). Other numbers represent intermediary positions.

	0	1	2	3	4	5	6
Car							
Bus							
Bike							
Motorbike							
Walking							

20. Now answer in the same way considering individual (group) 2. Use the same scale from 0 (think I should never use) to 6 (think I should always use). Other numbers represent intermediary positions.

	0	1	2	3	4	5	6
Car							
Bus							
Bike							
Motorbike							
Walking							

Note: Indicate how true or false do you classify each statement below.

21. In general, I want to do what individual (group) 1 thinks I should do.

Very false								Very true

22. In general, I want to do what individual (group) 1 thinks I should do.

Very false								Very true

23. When we are not sure what to do, we can look to what others are doing. When it comes to choosing the transport mode to go to the university, list two individuals (groups) whose behaviour you might look for guidance.

Individual (group) 1 ___________
Individual (group) 2 ___________

24. Thinking about individual (group) 1, how much do you think he (they) uses each one of the modes? Answer on the scale from 0 (never uses) to 6 (always uses)?

	0	1	2	3	4	5	6
Car							
Bus							
Bike							
Motorbike							
Walking							

25. Thinking about individual (group) 2, how much do you think he (they) uses each one of the modes? Answer on the scale from 0 (never uses) to 6 (always uses)?

	0	1	2	3	4	5	6
Car							
Bus							
Bike							
Motorbike							
Walking							

Thanks for your participation! Please send any queries to tsradr@leeds.ac.uk

Appendix G - Patterns of missing data

With respect to the pattern of missing, three different forms can be characterised:

- MCAR (missing completely at random), where there are no systematic differences between people who responded and not responded, in respect to other variables (e.g. age, gender, etc.) (Huisman, 2000);
- MAR (missing at random), where the pattern of missing data is predictable from other variables in the dataset that are not the variables of interest (dependent variables) (Tabachnick and Fidell, 2007), or;
- NMAR (not missing at random), where the probability of missing data is systematically related to the values that are missing (Baraldi and Enders, 2010).

MCAR is the best possible pattern missing data can have, as it means that omissions are totally unsystematic (Baraldi and Enders, 2010). The MCAR type can be tested using Little's multivariate test (Little and Schenker, 1995), where non-significance would indicate there is no systematic pattern on the missing data whatsoever.

The pattern of MAR means that the values of one variable are not missing randomly but can be predicted by other variables in the same dataset (Bennett, 2001). One form of testing MAR is to consider two groups: one with values missing in a particular variable and other with valid responses in that same variable. Then, perform t-tests across all the other variables in the dataset to check whether there are any significant differences between these two groups in any variable. If significance is found in any variable, the assumption of MAR is plausible (Tabachnick and Fidell, 2007).

Taking the case of this research, if the amount of missing data in the variable "habit", for example, was not systematically related to any other variable, data would be MCAR. If, instead, it was directly related to the overall attitudes of the respondent towards the car, for example, data would be MAR. But if the pattern of omissions was related to habit itself, that is, a person who does not have a habit of using the car is more inclined to leave no response than a person who does, then data would be NMAR.

In respect to the pattern of missing data, the performance of Little's multivariate test (Little and Schenker, 1995) on all variables under study showed that data are not MCAR ($p<0.001$). Independent t-tests were done to evaluate the possibility that data missing in the variable "habit" can be predicted by other variables in the data set. This 'traceability' would configure the pattern of missing data as 'Missing at Random' (MAR). It is also important that missing data is not related to any dependent variable (Tabachnick and Fidell, 2007). The test showed significance ($p < 0.05$) in three other independent variables (age, motorcycle subjective norm and attitudes to the motorcycle). Huisman (2000) states that in the case data is assumed to be MAR, an imputation technique for missing values performs nicely if good estimates are done in regards to their values.

Appendix H - Variables measured on the surveys

Survey variable	Level of measurement	Measured concept	Questionnaire item
HAS_CAR	Dichotomous	Car ownership.	Q1[4]
HAS_MOT	Dichotomous	Motorcycle ownership.	Q1[4]
HAS_BIK	Dichotomous	Bike ownership.	Q1[4]
AVA_CAR	Dichotomous	Car availability.	Q2[4]
AVA_MOT	Dichotomous	Motorcycle availability.	Q2[4]
AVA_BIK	Dichotomous	Bike availability.	Q2[4]
BEH_*MODE*[1]	8-point ordinal	Weekly frequency of use of each mode.	Q3[4]
APPFAM	4-point ordinal	The level of familiarity with each of the seven types of mobility apps.	Q4[4]
ATT_*MODE*1[1]	7-point ordinal	The evaluation of the respondent in regards to using each transport mode to the university.	Q5[4]
ATT_*MODE*2[1]	7-point ordinal	The affective component of the respondent`s attitudes to the transport modes.	Q6[4]
EXP_*MODE*[1]	7-point ordinal	Past experience with each travel mode.	Q7[4]
ATT_*INCE*[2]	7-point ordinal	The evaluation of each incentive type.	Q8[4]
INT_*INCE*[2]	7-point ordinal	The intention to use each incentive type.	Q8[4]
SWIT_*INCE*[2]	7-point ordinal	The perceived likelihood to switch to sustainable modes due to receiving each incentive type.	Q8[4]
SNORM_*MODE*1[1]	7-point ordinal	The perceived support from important others in regards to using each transport mode.	Q9a[4]
SNORM_*MODE*2[1]	7-point ordinal	The perceived opinion of important others in regards to using each transport mode.	Q9b[4]
PNORM_CARS1	7-point ordinal	Feeling of moral obligation to use the car the least possible.	Q10a[4]
PNORM_CARS2	7-point ordinal	Feeling of moral obligation to use alternatives to the car due to personal values.	Q10b[4]
AWC_CARS1	7-point ordinal	Perceived likelihood of irreversible environmental damages caused by car-related air pollution.	Q10c[4]
AWC_CARS2	7-point ordinal	Perceived loss in general quality of life in the cities caused by traffic noise.	Q10d[4]
AWC_CARS3	7-point ordinal	Perceived environmental threat caused by excessive use of cars.	Q10e[4]
ASCR_CARS1	7-point ordinal	Perceived personal responsibility in respect to the pollution caused by car use.	Q10f[4]
ASCR_CARS2	7-point ordinal	Perceived ability to help tackling the environmental and social threats related to car use.	Q10g[4]
INT_*MODE*[1]	7-point ordinal	Intended frequency of use (weekly) of each travel mode in the following month of classes.	Q11[4]
HABIT1; HABIT2; HABIT3; HABIT4; HABIT5; HABIT6.	5-point categorical	The transport mode habitually used for six different mobility scenarios.	Q12[4]
PBC_*MODE*1[1]	7-point ordinal	Capacity to use each travel mode.	Q13[4]
PBC_*MODE*2[1]	7-point ordinal	Autonomy of using each travel mode.	Q14[4]
AGE	Interval	Age.	Q15[4]

Survey variable	Level of measurement	Measured concept	Questionnaire item
GENDER	Categorical	Gender.	Q15[4]
HHSIZE	Interval	Household Size.	Q15[4]
CITYAREA	Categorical	Neighborhood (or postcode area) that the respondent lives.	Q15[4]
DIST	Interval	Distance from home to the university.	Q15[4]
INCOM	7-point ordinal	Household income.	Q15[4]
ACC_EMAIL	Dichotomous	Willingness to receive an email with a complementary questionnaire.	Q15[4]
EMAIL	Categorical	Email address of respondent.	Q15[4]
BEH*MODE*2[1]	8-point ordinal	Weekly frequency of use of each mode.	Q1[5]
BS_*MODEATTR*[1,3]	7-point ordinal	The evaluation about using the transport modes in respect to four different types attributes for each (e.g. using the car would be comfortable/uncomfortable).	Q2; Q3; Q4; Q5; Q6.[5]
OUTEVA_*ATTR*[3]	7-point ordinal	The degree of importance given to each attribute assessed on the above questions.	Q7[5]
CBS_*MODEATTR*[1,3]	7-point ordinal	The evaluation about the existence of inhibit or facilitator factors to the use of each transport mode.	Q8; Q9; Q10; Q11; Q12; Q13; Q14; Q15; Q16; Q17.[5]
CPB_*MODEATTR*[1,3]	7-point ordinal	The power that each factor described above has to facilitate or impede the use of each travel mode.	Q8a; Q9a; Q10a; Q11a; Q12a; Q13a; Q14a; Q15a; Q16a; Q17a.[5]
INJREF1	Categorical	The respondent’s injunctive normative referent.	Q18[5]
INJREF2	Categorical	The respondent’s second injunctive normative referent.	Q18[5]
INJS_*MODE*1[1]	7-point ordinal	The perceived judgment of INJREF1 in respect to the participant using each travel mode.	Q19[5]
INJS_*MODE*2[1]	7-point ordinal	The perceived judgment of INJREF2 in respect to the participant using each travel mode.	Q20[5]
MOTCOMP1	7-point ordinal	The motivation to comply with what INJREF1 wants the participant to do.	Q21[5]
MOTCOMP2	7-point ordinal	The motivation to comply with what INJREF2 wants the participant to do.	Q22[5]
DESCREF1	Categorical	The respondent’s descriptive normative referent.	Q23[5]
DESCREF2	Categorical	The respondent’s second descriptive normative referent.	Q23[5]
DESCS_*MODE*1[1]	7-point ordinal	The perceived amount of use of each travel mode by DESCREF1.	Q24[5]
DESCS_*MODE*2[1]	7-point ordinal	The perceived amount of use of each travel mode by DESCREF2.	Q25[5]

[1]These variables were assessed for the five studied travel modes and the term ‘MODE’ was used for better visualisation. Thus, *MODE* refers to either car (CAR), bike (BIK), bus (BUS), motorcycle (MOT) or walking (WAL).
[2]These variables were assessed for each of the eleven different forms of incentives. For better visualisation, *INCE* was used in this table.
[3]These variables were assessed for each type of travel mode attributes (regarding behavioural or control beliefs). For better visualisation, *ATTR* was used in this table.
[4] Question belongs to main survey.
[5] Question belongs to complementary survey.

Appendix I - Mean comparison of mobility-related variables between sociodemographic profiles

Variables[4]	All	Gender			Age[1]					Income[2]					Distance to campus[3]				
		M	F	t [5]	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
BEH_CAR	2.08	2.04	2.13	-0.59	1.99	2.03	2.39	2.27^{5}	1.71^{4}	1.01^{2345}	1.83^{145}	2.04^{145}	2.81$^{1\ 23}$	3.64$^{1\ 23}$	1.77	2.31	2.34	2.34	1.86
BEH_BUS	2.07	1.90	2.25	-2.36*	2.82^{35}	2.19	1.83^{1}	2.06	1.65^{1}	2.71^{45}	2.13	2.00	1.65^{1}	1.35^{12}	1.47^{345}	2.03	2.37^{1}	2.27^{1}	2.29^{1}
BEH_BIK	0.26	0.38	0.12	3.94***	0.17	0.28	0.27	0.35	0.21	0.28	0.31	0.19	0.27	0.08	0.42^{2}	0.12^{1}	0.30	0.16	0.21
BEH_MOT	0.15	0.20	0.11	1.82	0.05^{5}	0.09^{5}	0.09^{5}	0.19	0.40^{123}	0.13	0.23	0.27	0.13	0.04	0.07	0.23	0.15	0.15	0.20
BEH_WAL	0.57	0.65	0.49	1.6	0.75	0.58	0.66	0.37	0.46	1.11^{2345}	0.47^{1}	0.36^{1}	0.35^{1}	0.26^{1}	1.62^{2345}	0.36^{1}	0.19^{1}	0.22^{1}	0.22^{1}
ATT_CAR	4.35	4.14	4.58	-2.61*	4.84^{5}	4.59^{5}	4.29	4.37	3.64^{12}	4.10	4.20	4.56	4.28	4.76	3.66^{234}	4.50^{1}	4.81^{1}	4.69^{1}	4.35
ATT_BUS	-1.59	-1.73	-1.39	-1.66	-0.91^{45}	-1.31^{5}	-1.62	-2.15^{1}	-2.21^{12}	-1.25	-1.58	-1.91	-1.51	-1.61	-1.67	-1.25	-1.14^{5}	-1.60	-2.01
ATT_BIK	-0.51	-0.08	-0.97	3.24**	-1.34^{3}	-0.74	0.03^{1}	0.15^{1}	-0.57	-0.58	-0.44	-0.31	-0.50	-0.48	1.00^{2345}	-0.89^{1}	-0.92^{1}	-0.66^{1}	-1.35^{1}
ATT_MOT	-1.57	-0.71	-2.60	6.50***	-1.31	-1.43	-1.97	-1.74	-1.40	-1.38	-0.67	-1.80	-2.47^{2}	-1.63	-2.05	-2.17	-1.49	-1.49	-0.95
ATT_WAL	-2.45	-2.48	-2.35	-0.45	-3.20^{5}	-2.88	-2.03	-2.31	-1.76^{1}	-1.76	-2.52	-2.44	-2.67	-3.00	-0.35^{2345}	-2.45^{13}	-3.78$^{1\ 2}$	-3.31^{1}	-2.83^{1}
EXP_CAR	4.79	4.73	4.86	-1.29	4.88	4.64	4.91	4.97	4.71	4.25^{345}	4.69^{45}	4.91^{1}	5.22$^{1\ 2}$	5.30$^{1\ 2}$	4.78	5.04	4.84	4.81	4.61
EXP_BUS	4.93	4.84	5.07	-2.42*	4.35$^{2\ 345}$	5.07^{1}	4.94^{1}	5.08^{1}	5.01^{1}	5.24^{45}	5.22^{45}	5.09^{5}	4.67$^{1\ 2}$	4.37^{123}	4.70^{4}	4.91	4.94	5.17^{1}	4.99
EXP_BIK	2.79	3.37	2.10	9.98***	2.38	2.87	2.78	2.86	2.90	2.78	2.89	2.86	2.70	2.58	3.17^{23}	2.50^{1}	2.57^{1}	2.71	2.79
EXP_MOT	1.24	1.38	1.06	2.62**	0.89^{5}	0.98^{5}	1.04^{5}	1.58	1.99^{123}	1.41^{5}	1.72^{45}	1.26	0.93^{2}	0.74$^{1\ 2}$	1.11^{5}	1.14	1.02^{5}	1.13	1.65^{13}
EXP_WAL	4.15	4.32	3.98	2.57**	3.77	4.36	4.27	3.92	4.03	4.48^{5}	4.21	4.17	3.90	3.56^{1}	4.83^{2345}	4.20^{1}	3.99^{1}	3.77^{1}	3.88^{1}
SNORM_CAR	4.11	3.85	4.42	-3.30**	4.10	4.12	4.29	4.29	3.74	3.66^{5}	4.07^{5}	4.20	4.37	4.88$^{1\ 2}$	3.67	4.18	4.28	4.31	4.22
SNORM_BUS	2.97	2.70	3.32	-2.97**	3.40^{5}	3.35^{5}	2.87	2.64	2.35$^{1\ 2}$	3.67^{5}	3.02	2.86	2.85	2.49^{1}	2.71^{3}	3.40	3.55^{1}	2.83	2.71
SNORM_BIK	-0.61	0.19	-1.60	6.81***	-1.20	-0.71	-0.54	-0.79	-0.01	-0.55	-0.60	-0.26	-0.38	-1.10	1.01^{2345}	-0.57^{1}	-0.94^{1}	-1.18^{1}	-1.57^{1}
SNORM_MOT	-3.84	-3.36	-4.41	4.92***	-3.68	-3.94	-4.15	-3.82	-3.38	-3.43	-3.17^{4}	-3.94	-4.47^{2}	-4.26	-4.09	-4.11	-3.92	-3.91	-3.34
SNORM_WAL	-1.84	-1.48	-2.27	2.71**	-2.18	-2.13	-1.68	-2.21	-1.07	-1.19	-1.89	-1.60	-2.34	-2.19	0.65^{2345}	-2.10^{1}	-2.56^{1}	-3.07^{1}	-2.82^{1}
PNORM_CARS	-1.04	-1.25	-0.82	-1.67	-1.37	-1.23	-1.32	-0.36	-0.48	-0.45^{5}	-0.65	-0.87	-1.45	-1.78^{1}	-0.57	-0.43	-1.47	-1.32	-1.27
AWC_CARS	6.20	5.40	7.23	-7.77***	6.25	6.33	6.17	6.13	6.01	6.03	6.50	6.19	6.34	6.18	6.38	6.34	5.82	6.10	6.29
RESP_CARS	2.08	1.81	2.40	-6.50***	2.02	2.02	2.16	2.00	2.15	2.01	2.20	2.01	2.21	1.98	2.10	2.14	2.13	1.81	2.18
ABIRED_CARS	1.26	1.03	1.54	-4.21***	1.24	1.18	1.32	1.28	1.32	1.26	1.32	1.30	1.34	1.13	1.40	1.41	1.27	1.22	1.07
INT_CAR	2.21	2.25	2.16	0.62	2.11	2.16	2.45	2.30	2.03	1.18^{2345}	1.97^{145}	2.05^{145}	3.08^{123}	3.52^{123}	1.76^{34}	2.39	2.52^{1}	2.42^{1}	2.17

Variables[4]	All	Gender			Age[1]					Income[2]					Distance to campus[3]				
		M	F	t[5]	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
INT_BUS	2.05	1.86	2.27	-2.73**	2.94$^{2\,3\,4\,5}$	2.11$^{1\,3}$	1.83^{1}	1.87^{1}	1.61^{1}	2.65$^{4\,5}$	2.19	2.00	1.72^{1}	1.47^{1}	1.59$^{4\,5}$	2.02	2.12	2.25^{1}	2.29^{1}
INT_BIK	0.44	0.57	0.27	3.62***	0.20	0.51	0.44	0.57	0.45	0.49	0.57	0.29	0.47	0.27	0.70^{5}	0.33	0.44	0.41	0.29^{1}
INT_MOT	0.25	0.32	0.17	2.26*	0.07^{5}	0.19^{5}	0.17^{5}	0.30	0.61$^{1\,2\,3}$	0.21	0.37	0.39	0.18	0.14	0.14	0.28	0.22	0.28	0.34
INT_WAL	0.70	0.76	0.63	1.23	0.74	0.73	0.71	0.63	0.67	1.31$^{2\,3\,4\,5}$	0.67$^{1\,5}$	0.47^{1}	0.44^{1}	0.19$^{1\,2}$	1.86$^{2\,3\,4\,5}$	0.42^{1}	0.29^{1}	0.24^{1}	0.40^{1}
HAB_CAR	3.42	3.36	3.48	-1.18	3.60	3.38	3.41	3.41	3.39	2.72$^{2\,3\,4\,5}$	3.33$^{1\,4\,5}$	3.61^{1}	3.89$^{1\,2}$	4.06$^{1\,2}$	3.10$^{3\,5}$	3.50	3.64^{1}	3.48	3.50^{1}
HAB_BUS	0.55	0.45	0.67	-3.59***	0.60	0.58	0.58	0.56	0.42	0.84$^{3\,4\,5}$	0.62$^{4\,5}$	0.44^{1}	0.30$^{1\,2}$	0.28$^{1\,2}$	0.68	0.46	0.46	0.55	0.53
HAB_BIK	0.58	0.75	0.38	6.08***	0.54	0.63	0.53	0.63	0.55	0.65	0.60	0.44	0.56	0.66	0.52	0.41^{4}	0.51	0.80^{2}	0.61
HAB_MOT	1.33	1.27	1.41	-1.78	1.24	1.33	1.38	1.30	1.35	1.65$^{2\,4\,5}$	1.26^{1}	1.34	1.19^{1}	0.97^{1}	1.65$^{3\,4\,5}$	1.54$^{4\,5}$	1.29^{1}	1.07$^{1\,2}$	1.14$^{1\,2}$
HAB_WAL	0.12	0.17	0.06	2.65*	0.01^{5}	0.08	0.10	0.10	0.29^{1}	0.13	0.19	0.18	0.06	0.03	0.05	0.09	0.11	0.09	0.22
CAPAC_CAR	0.72	0.73	0.73	-0.01	0.53	0.58	0.91	0.71	0.85	-0.38$^{2\,3\,4\,5}$	0.47$^{1\,4\,5}$	0.94$^{1\,5}$	1.52$^{1\,2}$	2.16$^{1\,2\,3}$	0.39^{3}	1.17	1.13^{1}	0.81	0.43
CAPAC_BUS	1.80	1.74	1.90	-1.18	2.08^{5}	2.07^{5}	1.71	1.60	1.31$^{1\,2}$	2.02	1.81	1.87	1.59	1.80	1.47	2.15	2.02	1.99	1.61
CAPAC_BIK	-1.41	-0.92	-2.01	8.03***	-1.91	-1.42	-1.35	-1.11	-1.28	-1.26	-1.45	-1.35	-1.64	-1.16	-0.67$^{2\,4\,5}$	-1.40$^{1\,5}$	-1.31^{5}	-1.59^{1}	-2.09$^{1\,2\,3}$
CAPAC_MOT	-2.35	-2.19	-2.54	3.20**	-2.54^{5}	-2.46^{5}	-2.47^{5}	-2.47^{5}	-1.78$^{1\,2\,3\,4}$	-2.28	-2.09^{5}	-2.38	-2.53	-2.66^{2}	-2.56^{5}	-2.44	-2.38	-2.40	-2.05^{1}
CAPAC_WAL	-1.53	-1.20	-1.92	4.67***	-1.65	-1.66	-1.33	-1.48	-1.49	-1.06$^{4\,5}$	-1.61	-1.59	-1.88^{1}	-1.94^{1}	0.37$^{2\,3\,4\,5}$	-1.79$^{1\,4}$	-1.93^{1}	-2.43$^{1\,2}$	-2.31^{1}
AUTO_CAR	-0.29	-0.15	-0.48	1.94	-0.67	-0.51	-0.10	-0.22	0.06	-0.98$^{3\,4\,5}$	-0.38^{5}	-0.12^{1}	0.18^{1}	0.71$^{1\,2}$	-0.27^{5}	0.04^{5}	0.15^{5}	-0.15^{5}	-0.94$^{1\,3\,4}$
AUTO_BUS	0.98	1.21	0.72	2.99**	0.64	0.96	1.08	1.06	1.09	1.14	0.74	1.30	1.25	0.90	1.25^{5}	1.41^{5}	0.98	1.11^{5}	0.39$^{1\,2\,4}$
AUTO_BIK	-0.78	-0.37	-1.29	5.63***	-1.10	-0.87	-0.67	-0.66	-0.63	-0.37	-0.88	-0.81	-1.07	-0.80	-0.28^{5}	-0.72	-0.74	-0.89	-1.29^{1}
AUTO_MOT	-2.00	-1.96	-2.06	0.72	-2.17^{5}	-2.34^{5}	-2.10^{5}	-1.85	-1.20$^{1\,2\,3}$	-1.78	-1.82	-1.95	-2.15	-2.28	-2.12	-1.79	-2.24	-2.13	-1.70
AUTO_WAL	-0.68	-0.45	-0.96	2.88**	-0.90	-0.72	-0.62	-0.68^{5}	-0.56^{4}	-0.23^{5}	-0.67	-0.67	-1.03	-1.27^{1}	0.96$^{2\,3\,4\,5}$	-0.85^{1}	-1.06^{1}	-1.42^{1}	-1.41^{1}

Notes: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.
Items in superscript indicate which means are significantly different ($p < 0.05$) from each other using analysis of variance (ANOVA) post hoc analysis (Tukey's test if homogeneous variance, Tamhane's test otherwise).

[1] 1: less than or equal to 18 years old; 2: between 19 and 20 years old; 3: between 21 and 22 years old; 4: between 23 and 24 years old; 5: 25 or more years old.

[2] 1: less than or equal to 3 minimum wages (MWs); 2: between 4 and 6 MWs; 3: between 7 and 9 MWs; 4: between 10 and 15 MWs; 5: more than 15 MWs.

[3] 1: less than or equal to 5 kilometres (km); 2: between 5km and 7.5km; 3: between 7.5km and 10km; 4: between 10km and 15km; 5: more than 15km.

[4] The description of variables can be consulted in Appendix H.

Appendix J - Mean comparison of incentives acceptance between sociodemographic profiles

Variables[4]	All	Gender			Age[1]					Income[2]					Distance[3]				
		M	F	t	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
ATT_MAP	6.18	6.09	6.30	-2.47*	6.35[5]	6.39[5]	6.08	6.13	5.83[1,2]	6.21	6.21	5.95	6.27	6.29	6.30	6.21	6.17	6.15	6.07
INT_MAP	5.71	5.60	5.87	-2.55*	5.92	5.88	5.51	5.73	5.52	5.92	5.82	5.56	5.77	5.54	5.88	5.85	5.64	5.64	5.60
SWI_MAP	4.28	4.10	4.50	-3.51***	4.19	4.21	4.24	4.36	4.49	4.73[3,5]	4.47[3,5]	3.95[1,2]	4.44[5]	3.62[1,2,4]	4.57[3]	4.35	4.04[1]	4.12	4.27
ATT_MONE	6.53	6.53	6.53	0.00	6.70[5]	6.59[5]	6.58[5]	6.64[5]	6.17[1,2,3,4]	6.61	6.52	6.47	6.54	6.47	6.54	6.61	6.59	6.58	6.40
INT_MONE	6.27	6.25	6.28	-0.35	6.41	6.39	6.23	6.18	6.04	6.46[5]	6.29	6.19	6.21	5.84[1]	6.42	6.38	6.28	6.17	6.13
SWI_MONE	5.74	5.63	5.88	-2.45*	5.86	5.75	5.74	5.91	5.56	6.05[3,5]	5.88[5]	5.52[1]	5.70	5.18[1,2]	5.83	5.75	5.72	5.69	5.70
ATT_POIN	4.60	4.59	4.61	-0.16	4.87	4.64	4.39	4.88	4.43	5.01[3]	4.68	4.43[1]	4.52	4.43	4.78	4.43	4.43	4.60	4.63
INT_POIN	3.96	4.00	3.91	0.65	3.95	3.89	3.81	4.20	4.15	4.46[3,4,5]	4.21[5]	3.71[1]	3.77[1]	3.37[1,2]	4.24[2]	3.49[1]	3.77	3.94	4.08
SWI_POIN	3.35	3.28	3.42	-1.05	3.31	3.21	3.20	3.64	3.65	3.90[3,4,5]	3.59[3,5]	3.03[1,2]	3.19[1]	2.66[1,2]	3.58[3]	3.16	3.03[1]	3.40	3.42
ATT_RANK	4.83	4.80	4.86	-0.50	5.15[3]	5.02	4.58[1]	4.90	4.56	5.11	4.81	4.70	4.90	4.73	4.86	4.75	4.77	4.78	4.93
INT_RANK	4.03	3.97	4.08	-0.87	3.98	4.05	3.84	4.16	4.18	4.62[2,3,4,5]	4.06[1]	3.81[1]	3.95[1]	3.53[1]	4.14	3.85	3.84	3.90	4.23
SWI_RANK	3.42	3.32	3.53	-1.7	3.28	3.41	3.25	3.55	3.70	4.08[2,3,4,5]	3.53[1,5]	3.14[1]	3.46[1,5]	2.67[1,2,4]	3.51	3.22	3.31	3.41	3.54
ATT_VOUC	6.50	6.41	6.60	-2.65**	6.68[5]	6.61[5]	6.50	6.54[5]	6.15[1,2,4]	6.55	6.54	6.41	6.42	6.45	6.54	6.60	6.43	6.52	6.45
INT_VOUC	6.26	6.11	6.44	-3.77***	6.40[5]	6.46[5]	6.24	6.22	5.87[1,2]	6.45	6.36	6.07	6.16	6.05	6.34	6.37	6.14	6.30	6.19
SWI_VOUC	5.60	5.38	5.87	-4.89***	5.67	5.73	5.54	5.65	5.38	5.97[3,5]	5.69[5]	5.28[1]	5.62	5.13[1,2]	5.75	5.72	5.47	5.60	5.49
ATT_JOUR	5.97	5.82	6.14	-3.5***	6.19	6.01	5.88	6.05	5.79	6.00	5.95	5.96	6.05	5.92	6.04	6.07	5.76	6.00	5.97
INT_JOUR	5.54	5.34	5.77	-4.04***	5.59	5.54	5.43	5.60	5.64	5.72	5.60	5.52	5.48	5.46	5.61	5.71	5.22	5.59	5.59
SWI_JOUR	4.53	4.29	4.81	-4.48***	4.40	4.46	4.44	4.65	4.81	4.94[5]	4.56	4.49	4.56	4.00[1]	4.56	4.66	4.25	4.54	4.64
ATT_INFO	6.26	6.17	6.39	-2.67**	6.42[5]	6.35[5]	6.27	6.43[5]	5.89[1,2,4]	6.24	6.36	6.21	6.32	6.27	6.42	6.23	6.22	6.17	6.22
INT_INFO	5.92	5.79	6.07	-2.99**	5.95	6.04	5.91	5.91	5.68	6.07	6.00	5.78	5.86	5.81	6.11	5.95	5.85	5.73	5.90
SWI_INFO	4.95	4.72	5.22	-4.4***	4.76	4.94	4.95	5.05	5.02	5.25[5]	5.16[5]	4.86	4.90	4.45[1,2]	5.09	5.17	4.87	4.87	4.82
ATT_FEED	5.63	5.50	5.79	-2.72**	5.88[5]	5.64	5.71	5.58	5.37[1]	5.67	5.71	5.64	5.77	5.41	5.70	5.56	5.65	5.52	5.67
INT_FEED	5.14	4.94	5.38	-3.61***	5.18	5.15	5.24	4.98	5.09	5.37	5.25	5.17	5.21	4.82	5.20	5.15	5.14	5.01	5.19
SWI_FEED	4.23	3.96	4.55	-4.75***	4.10	4.07	4.33	4.21	4.50	4.61[5]	4.25	4.34	4.27	3.72[1]	4.26	4.16	4.24	4.18	4.29

Variables	All	Gender			Age[1]					Income[2]					Distance[3]				
		M	F	t	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
ATT_SOCM	3.67	3.67	3.70	-0.21	4.00	3.79	3.57	3.62	3.35	4.04	3.82	3.63	3.65	3.53	3.67	3.44	3.53	3.59	3.94
INT_SOCM	2.94	2.90	3.01	-0.9	3.01	2.98	2.78	2.89	3.07	3.31	3.21	2.93	2.82	2.71	2.92	2.65^{3}	2.69^{2}	2.94	3.30
SWI_SOCM	2.54	2.45	2.64	-1.62	2.65	2.43	2.42	2.64	2.75	$3.04^{3\,5}$	2.71^{5}	2.43^{1}	2.48	$2.04^{1\,2}$	2.52	2.22^{5}	2.46	2.52	2.79^{2}
ATT_CHAL	4.70	4.60	4.85	-1.96*	5.12^{5}	4.86^{5}	4.67	4.72	$4.17^{1\,2}$	4.89	4.90	4.50	4.70	4.59	4.77	4.56	4.70	4.55	4.83
INT_CHAL	3.97	3.85	4.12	-2.11*	4.29	3.97	3.93	3.90	3.85	4.37^{3}	4.13	3.73^{1}	3.88	3.81	4.01	3.83	3.94	3.82	4.13
SWI_CHAL	3.35	3.16	3.58	-3.35***	3.51	3.34	3.15	3.53	3.44	$3.85^{3\,5}$	3.42	3.07^{1}	3.52	2.90^{1}	3.43	3.28	3.39	3.20	3.41
ATT_BUDD	5.60	5.40	5.86	-3.24***	5.93^{5}	5.78^{5}	5.55	5.49	$5.19^{1\,2}$	5.71	5.62	5.75	5.27	5.72	5.54	5.46	5.63	5.63	5.70
INT_BUDD	5.07	4.88	5.29	-3.3***	5.34	5.25	4.90	4.73	4.99	$5.38^{3\,4}$	5.19	4.81^{1}	4.66^{1}	5.19	5.05	5.01	5.12	5.07	5.09
SWI_BUDD	4.34	4.09	4.62	-4.1***	4.61	4.32	4.27	4.17	4.34	$4.75^{3\,4}$	4.47	4.07^{1}	4.02^{1}	4.22	4.37	4.34	4.29	4.25	4.39
ATT_SOCIALINC	4.69	4.63	4.76	-1.35	$5.01^{3\,5}$	4.79^{5}	4.59^{1}	4.74	$4.37^{1\,2}$	4.95	4.78	4.57	4.71	4.54	4.76	4.55	4.62	4.60	4.80
INT_SOCIALINC	4.19	4.08	4.30	-1.07	4.28	4.21	4.08	4.15	4.23	$4.58^{3\,4\,5}$	4.34	4.03^{1}	4.05^{1}	3.91^{1}	4.26	3.99	4.09	4.11	4.34
SWI_SOCIALINC	3.53	3.37	3.72	-3.58***	3.57	3.47	3.44	3.58	3.71	$4.02^{3\,4\,5}$	3.64^{5}	3.36^{1}	3.49^{1}	$3.04^{1\,2}$	3.61	3.39	3.47	3.47	3.62
ATT_VALMAXINC	6.30	6.22	6.40	-3.06**	6.48^{5}	6.39^{5}	6.26	6.36^{5}	$6.00^{1\,2\,4}$	6.35	6.31	6.20	6.32	6.27	6.38	6.34	6.24	6.28	6.24
INT_VALMAXINC	5.95	5.82	6.09	-3.8***	6.07	6.06	5.87	5.92	5.76	6.14	6.02	5.82	5.91	5.74	6.08	6.05	5.84	5.89	5.89
SWI_VALMAXINC	5.21	5.05	5.42	-4.33***	5.24	5.23	5.17	5.32	5.15	$5.60^{3\,5}$	$5.35^{3\,5}$	$4.92^{1\,2}$	5.25^{5}	$4.65^{1\,2\,4}$	5.38	5.27	5.08	5.14	5.17
ATT_ALLINC	5.50	5.43	5.60	-2.6**	$5.76^{3\,5}$	5.61^{5}	5.44^{1}	5.55	$5.18^{1\,2}$	5.66	5.55	5.42	5.49	5.43	5.57	5.44	5.45	5.45	5.54
INT_ALLINC	4.98	4.88	5.12	-3.2***	5.09	5.05	4.90	4.95	4.92	$5.28^{3\,4\,5}$	5.11	4.83^{1}	4.90^{1}	4.74^{1}	5.08	4.93	4.89	4.91	5.04
SWI_ALLINC	4.21	4.03	4.41	-4.51***	4.20	4.18	4.14	4.27	4.32	$4.64^{3\,4\,5}$	4.33^{5}	4.03^{1}	$4.21^{1\,5}$	$3.68^{1\,2\,4}$	4.32	4.19	4.11	4.14	4.23

Notes: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

Items in superscript indicate which means are significantly different ($p < 0.05$) from each other using analysis of variance (ANOVA) post hoc analysis (Tukey's test if homogeneous variance, Tamhane's test otherwise).

[1] 1: less than or equal to 18 years old; 2: between 19 and 20 years old; 3: between 21 and 22 years old; 4: between 23 and 24 years old; 5: 25 or more years old.

[2] 1: less than or equal to 3 minimum wages (MWs); 2: between 4 and 6 MWs; 3: between 7 and 9 MWs; 4: between 10 and 15 MWs; 5: more than 15 MWs.

[3] 1: less than or equal to 5 kilometres (km); 2: between 5km and 7.5km; 3: between 7.5km and 10km; 4: between 10km and 15km; 5: more than 15km.

[4] The description of variables can be consulted in Appendix H.

Appendix K - Mean comparison of incentives acceptance between travel mode users

Variables	All	Car users			Bus users			Bike users			Motorcycle users			Walking			Most used travel mode				
		No	Yes	t	No	Yes	t	No	Yes	t	No	Yes	t	No	Yes	t	Car	Bus	Bike	Motorcycle	Walking
ATT_MAP	6.18	6.11	6.21	-1.07	6.03	6.27	-2.64**	6.16	6.31	-0.96	6.20	5.76	2.04*	6.13	6.38	-2.19*	6.13	6.23	6.47^{4}	5.13^{3}	6.21
INT_MAP	5.71	5.85	5.65	1.89	5.30	5.98	-6.27***	5.68	6.04	-1.94	5.73	5.41	1.21	5.64	6.06	-3.15**	$5.27^{2\,3\,5}$	$6.08^{1\,4}$	$6.03^{1\,4}$	$4.63^{2\,3\,5}$	$5.99^{1\,4}$
SWI_MAP	4.28	4.62	4.11	4.34***	3.92	4.52	-5.35***	4.25	4.59	-1.75	4.30	4.06	1.02	4.17	4.84	-4.56***	$3.81^{2\,3\,5}$	$4.59^{1\,4}$	$4.65^{1\,4}$	$3.29^{2\,3\,5}$	$5.01^{1\,4}$
ATT_MONE	6.53	6.53	6.53	-0.01	6.39	6.62	-2.99**	6.53	6.54	-0.11	6.55	6.15	1.96	6.49	6.72	-3.1**	6.48	6.55	6.76	5.83	6.64
INT_MONE	6.27	6.37	6.22	1.71	5.96	6.46	-5.33***	6.24	6.51	-1.93	6.30	5.78	2.16*	6.20	6.62	-4.96***	5.95 5	6.46^{1}	$6.73^{1\,4}$	$5.29^{3\,5}$	$6.62^{1\,4}$
SWI_MONE	5.74	5.91	5.66	2.53*	5.37	5.99	-5.93***	5.72	6.02	-1.79	5.79	5.04	2.78**	5.67	6.11	-3.87***	$5.36^{2\,3\,5}$	$6.00^{1\,4}$	$6.24^{1\,4}$	$4.46^{2\,3\,5}$	$6.12^{1\,4}$
ATT_POIN	4.60	4.91	4.44	3.56***	4.18	4.87	-5.37***	4.57	4.88	-1.41	4.59	4.69	-0.35	4.51	5.03	-3.19***	$4.09^{2\,3\,5}$	4.96^{1}	5.11^{1}	4.04	4.91^{1}
INT_POIN	3.96	4.36	3.76	4.29***	3.57	4.21	-4.7***	3.92	4.41	-2.15*	3.95	4.17	-0.78	3.86	4.43	-3.21***	$3.39^{2\,3\,5}$	4.42^{1}	4.68^{1}	3.54	4.44^{1}
SWI_POIN	3.35	3.85	3.10	5.76***	3.00	3.58	-4.52***	3.30	3.81	-2.32*	3.34	3.54	-0.75	3.25	3.83	-3.5***	$2.81^{2\,3\,5}$	3.73^{1}	3.81^{1}	2.96	3.90^{1}
ATT_RANK	4.83	5.03	4.73	2.32*	4.51	5.04	-4.17***	4.82	4.98	-0.73	4.84	4.69	0.6	4.78	5.09	-1.96	4.55^{2}	5.10^{1}	5.14	4.04	5.05
INT_RANK	4.03	4.40	3.83	4.06***	3.72	4.23	-3.78***	3.98	4.47	-2.09*	4.02	4.09	-0.25	3.97	4.31	-1.98*	$3.61^{2\,3\,5}$	4.38^{1}	4.62^{1}	3.38	4.34^{1}
SWI_RANK	3.42	3.87	3.20	5.04***	3.04	3.68	-5.03***	3.36	4.04	-3.06**	3.42	3.54	-0.45	3.36	3.75	-2.34*	$2.92^{2\,3\,5}$	$3.84^{1\,4}$	$4.03^{1\,4}$	$2.71^{2\,3}$	3.68^{1}
ATT_VOUC	6.50	6.53	6.48	0.65	6.30	6.63	-4.4***	6.51	6.38	0.96	6.52	6.09	2	6.47	6.66	-2.31*	6.40^{2}	6.64^{1}	6.57	5.63	6.53
INT_VOUC	6.26	6.38	6.20	1.95	5.88	6.50	-6.68***	6.25	6.37	-0.83	6.29	5.80	2.03*	6.21	6.49	-2.67**	$5.95^{2\,3}$	$6.56^{1\,4}$	$6.54^{1\,4}$	$5.08^{2\,3}$	6.28
SWI_VOUC	5.60	5.81	5.49	3.03**	5.10	5.93	-7.83***	5.57	5.90	-1.83	5.63	5.22	1.51	5.53	5.96	-3.41***	$5.10^{2\,3\,5}$	$6.01^{1\,4}$	$6.14^{1\,4}$	$4.33^{2\,3\,5}$	$5.79^{1\,4}$
ATT_JOUR	5.97	5.92	5.99	-0.74	5.91	6.00	-0.98	5.96	6.02	-0.4	5.99	5.63	1.46	5.94	6.10	-1.36	5.98	6.01	6.24	5.17	5.99
INT_JOUR	5.54	5.58	5.52	0.55	5.38	5.65	-2.41*	5.52	5.76	-1.27	5.56	5.30	1.18	5.50	5.74	-1.85	5.39^{2}	5.74^{1}	5.84	4.71	5.56
SWI_JOUR	4.53	4.87	4.37	4.16***	4.27	4.70	-3.71***	4.50	4.89	-1.95	4.54	4.48	0.23	4.46	4.89	-2.83**	$4.13^{2\,5}$	$4.84^{1\,4}$	4.86	3.88^{2}	4.82^{1}
ATT_INFO	6.26	6.26	6.27	-0.09	6.15	6.34	-2.28*	6.26	6.24	0.15	6.28	5.93	2.09*	6.25	6.33	-0.75	6.17	6.39	6.30	5.54	6.20
INT_INFO	5.92	6.02	5.87	1.54	5.62	6.11	-4.91***	5.89	6.14	-1.52	5.94	5.63	1.52	5.87	6.13	-2.29*	5.56^{2}	$6.22^{1\,4}$	6.16	5.00^{2}	6.07
SWI_INFO	4.95	5.19	4.83	3.05**	4.62	5.16	-4.66***	4.92	5.26	-1.73	4.96	4.80	0.67	4.89	5.25	-2.41*	$4.52^{2\,5}$	$5.30^{1\,4}$	5.30	$4.17^{2\,5}$	$5.24^{1\,4}$
ATT_FEED	5.63	5.59	5.65	-0.51	5.53	5.70	-1.62	5.62	5.76	-0.76	5.64	5.50	0.63	5.62	5.67	-0.31	5.63	5.62	5.78	5.04	5.72
INT_FEED	5.14	5.22	5.10	0.95	4.98	5.25	-2.15*	5.11	5.54	-2.05*	5.14	5.20	-0.25	5.12	5.27	-0.92	5.00	5.25	5.57	4.46	5.26
SWI_FEED	4.23	4.49	4.11	2.91**	4.01	4.38	-2.92**	4.19	4.64	-2.09*	4.24	4.20	0.12	4.17	4.54	-2.25*	3.97^{2}	$4.45^{1\,4}$	4.54	$3.25^{2\,5}$	4.58^{4}
ATT_SOCM	3.67	3.91	3.54	2.74**	3.42	3.83	-3.13**	3.63	4.05	-1.89	3.64	4.13	-1.82	3.61	3.96	-2.07*	3.37^{2}	3.87^{1}	4.11	3.38	3.67

Variables	All	Car users			Bus users			Bike users			Motorcycle users			Walking			Most used travel mode				
		No	Yes	t	No	Yes	t	No	Yes	t	No	Yes	t	No	Yes	t	Car	Bus	Bike	Motorcycle	Walking
INT_SOCM	2.94	3.30	2.77	3.86***	2.76	3.06	-2.39*	2.89	3.46	-2.64**	2.91	3.52	-2.02*	2.89	3.20	-1.87	2.63^{2}	3.17^{1}	3.36	2.75	3.08
SWI_SOCM	2.54	2.91	2.35	4.58***	2.29	2.70	-3.65***	2.49	2.99	-2.55*	2.52	2.78	-1.09	2.47	2.88	-2.85**	2.15$^{2\,5}$	2.76^{1}	2.89	2.00	2.90^{1}
ATT_CHAL	4.70	4.82	4.65	1.27	4.53	4.82	-2.23*	4.71	4.61	0.47	4.69	4.89	-0.73	4.71	4.66	0.35	4.55	4.87	4.84	4.92	4.67
INT_CHAL	3.97	4.17	3.87	2.18*	3.85	4.05	-1.56	3.96	4.05	-0.38	3.94	4.39	-1.64	3.96	4.04	-0.48	3.76	4.15	4.16	4.25	4.05
SWI_CHAL	3.35	3.69	3.19	3.87***	3.15	3.49	-2.7**	3.32	3.72	-1.88	3.34	3.56	-0.81	3.29	3.65	-2.12*	3.03^{2}	3.53^{1}	3.84	3.21	3.60
ATT_BUDD	5.60	5.65	5.58	0.44	5.39	5.74	-2.5*	5.60	5.65	-0.23	5.60	5.61	-0.03	5.63	5.50	0.68	5.51	5.83	5.43	5.21	5.27
INT_BUDD	5.07	5.28	4.97	2.39*	4.82	5.23	-3.28***	5.06	5.21	-0.7	5.06	5.20	-0.54	5.06	5.10	-0.23	4.89^{2}	5.35^{1}	4.95	4.67	4.82
SWI_BUDD	4.34	4.72	4.14	4.22***	4.02	4.54	-4.02***	4.32	4.53	-0.95	4.32	4.50	-0.65	4.30	4.51	-1.25	3.98^{2}	4.71^{1}	4.41	3.67	4.31
ATT_SOCIALINC	4.69	4.85	4.60	2.57**	4.43	4.85	-4.41***	4.67	4.85	-1.14	4.68	4.78	-0.5	4.64	4.88	-1.96*	4.44^{2}	4.88^{1}	4.99	4.28	4.81
INT_SOCIALINC	3.72	4.45	4.05	4.54***	3.95	4.33	-3.91***	4.15	4.53	-2.21*	4.17	4.43	-1.54	4.14	4.39	-2.37*	3.88$^{2\,3}$	4.45^{1}	4.59^{1}	3.84	4.31
SWI_SOCIALINC	3.53	3.92	3.34	5.85***	3.23	3.73	-5.05***	3.49	3.93	-2.62**	3.52	3.69	-0.81	3.46	3.86	-3.09**	3.12$^{2\,3\,5}$	3.83$^{1\,4}$	3.91^{1}	2.97^{2}	3.83^{1}
ATT_VALMAXINC	6.30	6.29	6.30	-0.22	6.16	6.38	-3.47***	6.29	6.33	-0.4	6.32	5.91	2.28*	6.26	6.45	-2.6**	6.23	6.37	6.53^{4}	5.46^{3}	6.36
INT_VALMAXINC	5.95	6.05	5.89	2.15*	5.64	6.15	-6.67***	5.93	6.17	-1.97*	5.97	5.58	1.95	5.89	6.21	-3.88***	5.62$^{2\,3\,5}$	6.22$^{1\,4}$	6.26$^{1\,4}$	4.94$^{2\,3\,5}$	6.14$^{1\,4}$
SWI_VALMAXINC	5.21	5.46	5.09	4.15***	4.79	5.48	-7.82***	5.18	5.54	-2.69**	5.24	4.77	2.05*	5.12	5.64	-5.03***	4.76$^{2\,3\,5}$	5.53$^{1\,4}$	5.75$^{1\,4}$	4.03$^{2\,3\,5}$	5.64$^{1\,4}$
ATT_ALLINC	5.50	5.58	5.46	1.74	5.31	5.63	-4.66***	5.49	5.61	-0.99	5.51	5.37	0.8	5.47	5.67	-2.26*	5.34^{2}	5.65^{1}	5.75	4.90	5.58
INT_ALLINC	4.98	5.18	4.89	3.71***	4.71	5.16	-5.73***	4.96	5.27	-2.37*	4.99	4.95	0.18	4.93	5.22	-2.91**	4.67$^{2\,3\,5}$	5.25$^{1\,4}$	5.35$^{1\,4}$	4.34$^{2\,3}$	5.15^{1}
SWI_ALLINC	4.21	4.54	4.04	5.68***	3.87	4.42	-6.5***	4.17	4.58	-2.81**	4.21	4.15	0.31	4.13	4.57	-3.99***	3.79$^{2\,3\,5}$	4.52$^{1\,4}$	4.63$^{1\,4}$	3.45$^{2\,3\,5}$	4.55$^{1\,4}$

Notes: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.
Items in superscript indicate which means are significantly different ($p < 0.05$) from each other using analysis of variance (ANOVA) post hoc analysis (Tukey's test if homogeneous variance, Tamhane's test otherwise).
[1] The description of variables can be consulted in Appendix H.