Work Package 3 – Examining Smarter Travel Options to Reduce Emissions

Deliverable D3.1 – Technical report detailing the research conducted in WP3

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GREENING TRANSPORT

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Abbreviations

Akaike Information Criterion Coefficient (AICc)

Alternative-Specific Constant (ASC)

Central Statistics Office (CSO)

Choice Experiment (CE)

Department of Transport, Tourism and Sport (DTTS)

Greater Dublin Area (GDA)

Independently and Identically Distributed (IDD)

Independence from Irrelevant Alternative (IIA)

Information and Publicity Helping the Objective of Reducing Motorised Mobility (INPHORMM)

Log-Likelihood (LL)

Messenger, Incentives, Norms, Defaults, Salience, Priming, Affect, Commitments and Ego (MINDSPACE)

Mobility Management (MM)

Multinomial Logit (MNL)

National Transport Authority (NTA)

Norm-Activation Model (NAM)

Random Utility Theory (RUT)

Service Quality Index (SQI)

Single Occupancy Vehicle (SOV)

Stated Preference (SP)

Travel Demand Management (TDM)

Travel Awareness, Publicity and Education supporting Transport Strategy in Europe (TAPESTRY)

Transportation Research Board (TRB)

Utility Maximisation (UM)

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Examining Smarter Travel Options to Reduce Transport Emissions

Abstract

This deliverable explores a strategy to encourage a realistic modal shift from the private car to sustainable travel modes such as walking, cycling, bus, rail and smarter modes like carpooling and car-sharing in the Greater Dublin Area (GDA). This research is a large component of the work that has been conducted as part of the *Greening Transport* project. It examines the responsiveness of a sample to a range of policy measures aiming to incentivise sustainable commuting practices to work and education in the GDA. By means of a stated preference (SP) experiment, a selection of policies was tested in various hypothetical scenarios in order to gauge their response in terms of travel behaviour change, ultimately quantified by analysing the potential modal shift. This technical report will assess relevant literature on this subject and delineate the experimental design, survey creation process and most importantly delve into the discrete-choice modelling results and analysis of this study.

Motivation for this work was taken from comparable experiments from leading researchers in the field of SP and discrete-choice modelling. However, an approach such as this has to date not been conducted in the context of Ireland. This presents an opportunity to gain a greater understanding of the behavioural outcomes of implementing various sustainable transport policy incentives from which a modal shift can be achieved in Ireland. The aims of this research are in line with those set-out by the *Greening Transport* project that is leading this work - exploring ways of promoting smarter travel options as a means of attaining emissions savings and mitigating the associated causes of climate change such as air pollution, burning of fossil fuels and noise pollution in urban areas. However, one of the principal goals of this study is to incentivise 'car shedding' behaviour, i.e. promoting a reduction in car usage by making alternative and sustainable travel modes more practical and competitive in terms of time and cost amongst other attributes, in addition to being equally or more convenient modes than driving a car alone.

A SP survey instrument was implemented to gather responses to a range of hypothetical scenarios, in addition to other revealed preference (current travel activity), attitudinal and socio-demographic questions to generate various types of data for analysis. The main SP component of the survey was utilised to determine the variables of statistical significance that increase or decrease the utility of the modes and predict or forecast behavioural responses and implications, in the form of direct and cross elasticities and 'what if' simulations, to various policy instruments ('carrots') included in the stated choice scenario.

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1. Introduction

The external costs of single occupancy vehicles (SOV) for the purposes of commuting to work and education such as congestion and its implications the economy, in addition to the harmful effects air and noise pollution place a heavy burden on nations globally to act swiftly. To tackle this, there have been many conceptual tools created such as travel demand management (TDM) or mobility management (MM), yet much of the focus centres on internalising these costs in the form of road pricing and parking charges (Washbrook, K., et al, 2006). This report offers a new approach, termed 'car shedding', that incentivises alternative modes, but does not penalise car owners, especially where no alternative to the private car exist. *'Car-shedding'* is hereby defined as the approach of encouraging the reassessment of the need to utilise a private car for certain purposes, accordingly reducing utility and ownership through selling or forfeiting ownership of a vehicle in exchange for more sustainable means of transport (Carroll, et al., 2017). Car-shedding will be referred to throughout this report, thus, all references to this term will be in relation to the definition provided here. To encourage car owners to shed a vehicle, various travel TDM and MM tactics were reviewed to determine the best possible technique of promoting car-shedding in the GDA. Car-shedding has been the focus of this project work, which examines the behavioural response of various policy incentives or pull factors on encouraging sustainable travel practices. It similarly assesses the sociodemographic composition of those commuting to work/education in the GDA that would consider a modal shift to alternative transport modes. A stated preference survey was devised to simulate the introduction of various incentives for alternative modes. This report presents the results of the SP survey, which was conducted in March, 2017. It comprised of nine choice scenarios, and was designed to gauge the behavioural response of a sample to a range of policy incentives intended to attract commuters to active modes, public transport, and sustainable alternatives to driving alone.

This report will also draw upon relevant literature in this field of research, in addition to delineating the experimental and survey creation process conducted in the experiment. The report is organised into four sections: Section 1 has introduced the context for the report; Section 2 includes a brief literature review of comparable studies in this area; Section 3 examines the methodology and theoretical foundation for SP surveying and discrete-choice modelling; Section 4 presents the data analysis and findings from the modelling and Section 5 then offers further discussion of the wider implications of the findings from the study.

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1.2 Research Objectives

i) To test the hypothesis that a range of transport policy incentives, in the form of 'policy plans' will encourage commuters, particularly those who commute by car, to shift to another more sustainable, convenient, cost effective and practical modes of transport.

ii) To determine the most suitable policy measures that could be adopted in Ireland to increase the use of sustainable modes of transport.

iii) To quantify behavioural responses and determine potential levels of car-shedding in the GDA given significant changes being made to transport policy and estimate the behavioural output of such measures on the commuting population; and to calculate the consequential modal share of the GDA using the National Transport Authorities Eastern Regional Transport Model.

iv) This research ultimately aims to reduce the modal share of the private car, to sway attitudes in favour of sustainable modes and destabilise long standing car hegemony and driving habits in the GDA by providing the necessary testing of various policy approaches through choice modelling.

1.3 Contribution to Knowledge

The main contribution to knowledge that this research seeks to provide is through analysing the effect that various economic market-based instruments can have on travel behaviour change, particularly in respect to modal choice. This work aims to achieve this by running a SP experiment incorporating various choice scenarios that ask respondents to make a trade-off between various attributes that will be determined by the policy plan applied to that mode in question. Estimates of direct and cross elasticities and simulations produced from Multinomial Logit (MNL) modelling based on the SP results will similarly be examined. These tests will be used to determine the extent to which travel demand is sensitive to price changes in fares for example, or other changes made to services in the experiment, in addition to the amount that people would be prepared to pay for the introduction of that particular mode-specific policy package.

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Research plan set out for this study is illustrated in Figure 1.

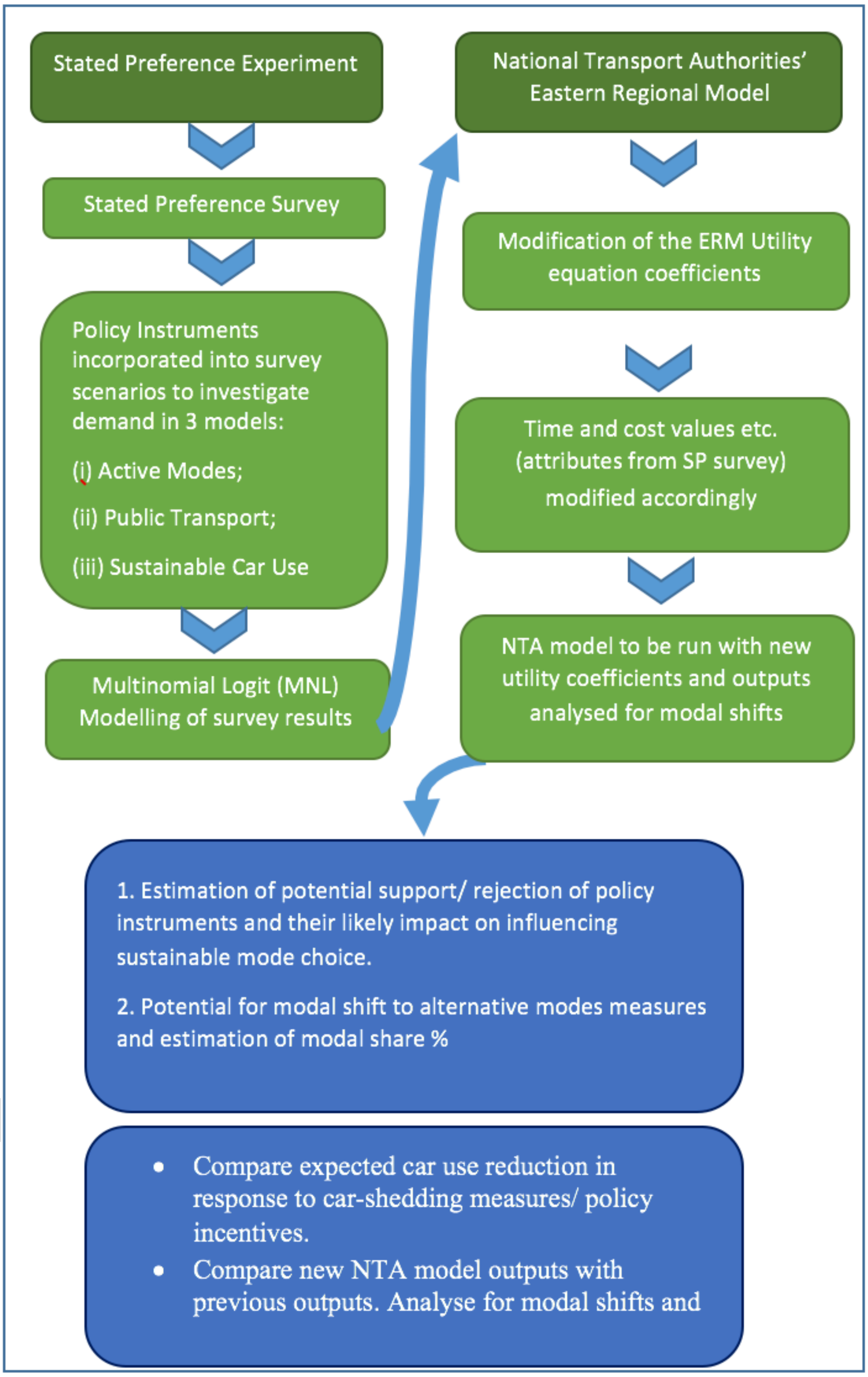

Figure 1: Research Plan

2. Literature Review

This section presents the background of the research undertaken as part of this report. It will provide an overview of the literature specific to the aims and objectives of this research, which inspired the development of the research methodology.

2.1 Theoretical and Conceptual grounds for examining travel behaviour change

Ireland has of late witnessed a surge in the numbers of commuters taking sustainable transport modes. The total number of people commuting to work in Ireland increasing from 1.7 million in 2011 to 1.88 million in 2016, representing a 10.7% rise (CSO, 2017), which is reflected by the country's strong post-recession economic performance. In 2016 an extra 9.3% (30,144 people) of commuters travelled by bus, rail and light rail services to work. Moreover, the numbers of those cycling displayed the most impressive grow across all modes, with an increase of 42.8% (CSO, 2017). Within Dublin city alone, the number of cyclists entering the city increased by 74.5% between 2010 and 2014 alone (DTTAS, 2016). Yet private cars are still pervasive as those driving to work nationally increased by 85,180 to 1,152,631 in 2016, representing the largest increase of all mode categories (CSO, 2017)). To access the potential for further accelerating this trend in commuting sustainably and likewise to reduce the incidence of SOVs, a SP study was conducted. This survey was created to test the responsiveness of a sample to a range of policy incentives applied to carpooling and car-sharing. Yet, prior to this, a review of the existing literature on SP surveying and its use in evaluating policy scenarios was conducted.

From reviewing the literature (summarised in Table 1), SP experimentation was deemed as an appropriate and established method of evaluating the impacts of a range of policy measures on mode choice behaviour (O'Fallon, et al., 2004; Baldassare, et al., 1998; Louviere, et al., 2000; Beaton, et al., 1998; Ortúzar and Willumsen, 1994). Through this, it was found that a study of this nature had to date not been conducted in Ireland, thus, it was decided that this study would significantly add to the understanding of how sustainable travel behaviour can be incentivised by applying a particular policy approach in the GDA. SP methods are extensively utilised in travel behaviour research to identify behavioural responses to choice situations that are not revealed in the market (i.e. hypothetical scenarios). O'Fallon et al. (2004); Catalano, et al. (2008); Baldassare, et al. (1998) and Malodia and Singla (2016) examined the use the of policy incentivisation as tool to stimulate a sustainable modal shift to carpooling and car-sharing, through a SP experiment. From their analysis, O'Fallon (2004) explained that policy tools are most effective when in 'packages, so policy makers can choose the tools that are suited to the constraints of the car driving population. In addition to this, they identified that improvements to alternative modes should not be overlooked in the event that car usage is discouraged through fees and charges. Catalano, et al. (2008) settled that the market share for car-

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sharing grew by up 10% given implementation of policy incentives such as reducing in-vehicle times, wait times and rising parking fees for SOVs. Younger and lower-status solo drivers were found to be more likely than others to mode shift in response to cash incentives from analysis conducted by Baldassare, et al. (1998). Interestingly, Washbrook, et al. (2006) determined that increasing road pricing and parking charges would result in more significant reductions in the demand for driving solo car journeys than reductions made to time and cost attributes of other modes such as carpooling. The empirical work revised here, established a clear foundation for the study explored in this report, as they employ discrete choice analysis to assess the responsiveness of a sample to a range of transport policy changes. It is envisaged that car-shedding behaviour will be an upshot of the introduction of such policy incentives.

The concept of car-shedding is related to the promotion of policy interventions which seek to instigate sustainable usage of the private car or reduce car ownership through making solo driving appear less convenient and time and cost efficient than other modes. Yet, in order to devise such measures, examining the factors that influence travel behaviour change is a necessary basis. There are three distinct motivational realms that must be considered when considering travel behaviour change: firstly, the *personal or individual realm* that comprises beliefs, knowledge and attitudes; secondly, the *social realm* which is influenced by interaction with other people including friends, family, the media and social norms; and, the *environmental realm* that deals largely with the geography of the area in which an individual lives (e.g. location of school, work place, local shops and facilities), as well as accessibility to public transport services and other amenities. Using these factors, effective objectives can be assigned and interventions can begin to take effect to realise a shift in behaviour through reviewing their cause-effect relationship. Failure to engage all three realms will result in the likelihood of achieving true change being significantly reduced (EUFIC, 2014). Therefore, by exploring the nature of daily-travel patterns and the potential for car-shedding in the GDA, consideration of all three of these realms is necessary to gain a full understanding of the individual thought-process that goes into mode-choice. Behaviour change is generally best attained through a mix of interferences, carried out over a considerable length of time, thus, car shedding as an approach aims to bridge the gap between hard and soft policy and to offer a holistic solution to rising car ownership and traffic congestion.

Central in the analysis of behaviour change is the formation of habits and intentions as they rely heavily on attitudes, in particular the way in which we adopt a given attitude towards an entity based on the interpretation of particular stimuli, generated from information through other sources (e.g. friends, family, the media, social norms) (Bamberg, 2011; Brög, et al., 2009). In other words, the social realm acts as a messenger or communicator, which relays information to the individual that, in turn, largely determines the outcome of the personal realm through the formation of attitudes and beliefs. These inducements can cause individuals to form positive or negative attitudes towards, for example in the context of this work, taking a given mode of transport that can have a considerable effect on future travel patterns. Once this transpires it may take significantly more effort to shift these attitudes, especially if they are built into strong intentions and potentially later everyday habits, e.g. driving to work (Petty and Cacioppo, 1986; Brög, et al., 2009). Yet, breaking habits is challenging and this comes down to the structure of controlling factors that determine the behaviour over time which can reflect previous behaviour. The social psychology Theory of Planned Behaviour (TPB) (Ajzen, 1991); an extension of the Theory of Reasoned Action (Ajzen and Fishbein, 1980), outlines how intentions to perform particular actions are formed as a result of behavioural, normative and control beliefs (Bamberg, 2011). It sets out that a positive attitude towards a given thing in addition to analogous attitudes from peers or points of contact in society and situational or behavioural control establishes the basis for intention construction. For instance, people usually don't take into account their attitude toward a bus or car mode, rather they judge it on the difficulty to use the travel option, this is known as perceived behavioural control (PBC). In the TPB model social norms are conceptualised as perceived social pressure, that is the expectations of significant reference points that encourage persons to use or not use a specific transport option (Bamberg, 2011). Social norms have been the subject of much empirical research on behaviour change. The Norm-Activation Model (NAM) (Schultz, 2007) similarly follows this line of reasoning, however it specifically accounts for pro-environmental values and attitudes. In the context of social norms and their effect on behaviour, Bamberg, et al. (2010) state with reference to the NAM that,

> 'Social norms also contribute to the development of personal norms. They inform people about what behavioural standards their social reference group views as appropriate in a particular context. When people internalise these social expectations, social norms become the content of their personal norms'.

Research has given weight to the argument that social norms and normative messages can encourage a change in behaviour. Schultz et al. (2007) conducted an experiment to test the effectiveness of social norms through normative messaging and they found that people reduced energy consumption when other people in the area were used as 'anchors' or 'reference points' to enhance relativity. Rather than 'rationally' reducing their costs as a result of saving energy, people were observed to respond more strongly when viewing that others where in fact reducing their consumption. Leading to those who were above the average consumption to reduce their consumption and those below to increased their consumption to meet the average (Schultz, 2007; Metcalfe and Dolan, 2012). Such empirical work has shown how social norms act as powerful incentives that are difficult to overcome once they have been accepted into habitual behaviour, but with the aid of techniques such as 'reference points' and 'anchors' change can be achieved as they act as incentives. Car-shedding measures strive to create sustainable travel norms and destabilise current unsustainable car dependent norms.

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In addition to the theories and concepts just defined, there is no shortage of mechanisms and conceptual frameworks that have been developed to tackle changes in attitudes and behaviour towards motorised transport. For instance, INPHORMM (Information and Publicity Helping the Objective of Reducing Motorised Mobility) and its successor TAPESTRY (Travel Awareness, Publicity and Education supporting a Sustainable Transport Strategy in Europe), were funded by the European Commission to focus efforts in promoting sustainable travel. Furthermore, the MINDSPACE (Messenger, Incentives, Norms, Defaults, Salience, Priming, Affect, Commitments and Ego) initiative is an example of a strategy aimed at influencing behaviour for use in public policy development, which was introduced by the UK Cabinet Office (2010). It is a mnemonic of influences on behaviour that can be used when devising policy and summarises the main effects of context on behaviour. *Messenger, Incentives and Norm*s have already been dealt with; *Defaults* are the options that are pre-selected if an individual does not make an active choice; through *Salience* our attention is drawn to what is novel seems relevant to us; *Priming* shows that people's subsequent behaviour may be altered if they are first exposed to certain rights, words or sensations; *Affect* deals with how our emotional associations can powerfully shape our actions; through *Commitments* we seek to be consistent with our public promises and reciprocate acts; and finally how *Ego* makes us behave in ways that support the impression of a positive and consistent self-image (UK Cabinet Office, 2010; Metcalfe and Dolan, 2012). By considering these behavioural effects it becomes apparent that what people intend to do is crucial in the context of habit formation. Conceptual frameworks such as these are invaluable in creating soft policy and market-based interventions as they set the foundations for policies or measures to ultimately break habits that are unsustainable and that have negative connotations for economic performance i.e. by means of congestion and pollution.

The microeconomic concept of 'utility maximisation' (UM) has historically been applied to situations where decisions or choices take place rationally by rational beings (i.e *homo economicus* or the economic man) in the evaluation of costs and benefits (Thaler and Sunstein, 2008), however, this does not necessarily provide for the fact that humans can also act irrationally and impulsively in certain situations where there are market inefficiencies. Travel choices under this principle are based on an assessment of individual preferences for a travel mode and the relative costs of taking that mode (Bamberg, et al., 2010). The principle of utility maximisation will be explored in greater depth later in relation to the discrete choice methodology in Section 3.3. Behavioural economics conversely, provides a counterargument to the rational man model, as it concentrates on how individuals act in reality, as opposed to how they rationally should (Thaler and Sunstein, 2008). Mode choices are generally rationed decisions; however, such decisions can be effected by certain interventions aimed at shifted attitudes, norms and perceived behavioural control (Waygood and Avineri, 2010b). In this way, a distinction is made between planned and impulsive or spontaneous behaviour (as a result of the *priming* of information), as the latter occurs with no prior planning being made. Work conducted by

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Thaler and Sustein (2008) centres on the presentation of information and how specific information can influence the probability of behavioural changes taking place. Techniques like this come under the umbrella of 'choice architecture', and these methods can help 'nudge' individuals to make more sustainable travel decisions and engender sustainable habit formation. 'Nudges can help individuals to overcome biases they may have, and they can be used to highlight certain choices for them, increasing the effect of behavioural change' (Metcalfe and Dolan, 2012).

Like the Schultz et al. (2007) experiment, the use of reference points through the contextualisation of information can allow an individual to make informed choices and make better judgment as well as influencing the perceptions of choices by means of 'anchoring' (Brög, 2002). Van Acker et al. (2010) propose combining theories from microeconomics (UM) with theories from social psychology (TPB and NAM) to provide for a comprehensive framework for analysing travel behaviour. This would provide for a more all-inclusive view of travel behaviour and a merging of social sciences. In relation to perceptions and intention construction, plans may not always convert into actual practice, as an intention takes place at the deliberation stage versus the decision-making or execution stage, under volitional control. Habits and intentions are interlinked, in that one effects the other in a sort of reciprocal relationship, as an intention is the precursor of actual behaviour. Triandis (1977; Garling and Axhausen, 2003) defines that 'the stronger determinant habit is, the weaker determinant intention is, and vice versa'. Intentions are generally created with a particular goal in mind, only when this goal is perceived to be attainable does the intention trigger the behaviour to take place. Habit or habitual choice has in this way been defined as choosing to perform an act without deliberation (Van Acker, et al., 2010; Van Acker and Witlox, 2010) versus intentions which are normally formed with a self-determined amount of forethought. In this research, policy incentives will be utilized as the main tools to encourage changes to currently held intentions and thus, engender more sustainable habit formation.

2.1.1 The role of policy incentives in delivering sustainable modal choice behaviour

The topic of policy intervention in influencing sustainable travel, particularly with regards to reducing car usage, has been well versed in the literature. Travel demand management (TDM) measures and mobility management (MM) have been the main practical tools applied to bring about changes to travel behaviour. TDM include structural policies like laws and regulations, economic market-based instruments or changes to the physical environment (Eriksson, et al., 2010). Travel Plans, in particular, are a mechanism for delivering mobility management or a package of TDM measures 'targeted at a specific site by an agent with a strong relationship with the local transport users to deliver transport and wider goals to the organisation and society as a whole' (Enoch, 2012). Market-based instruments used as 'carrots' or incentives to reduce car usage or switch from driving alone to other more sustainable transport modes are the focus of this research. Mode-specific policy plans are

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introduced in the SP survey scenarios incorporating measures such as: a reduction in street clutter, pedestrian priority, increasing the incidence of fully segregated cycle lanes, bus and rail fare reductions, scheduling improvements to ensure reliability and increase service frequencies, as well as exemptions of tolls and cost subsidies for carpoolers and car-sharers. This is in line with O'Fallon, et al. (2004) view that 'government policy proposals are best developed in 'packages'. This is also supported by Farrell, et al. (2010), who determine that a mix of measures are optimal in achieving a modal shift and can result in significant environmental benefits. The European Union project entitled 'Travel Plan Plus' is an example of a TDM put into practice, where in the County of Bages, Catalonia, measures included conducting mobility audits for organisations, promoting travel alternatives to the car through public transport fare subsidies and setting up a joint car and vanpooling programme, resulting in a 3 per cent reduction in single occupancy car use. Plans akin to this in other European cities have also resulted in a fall in single occupancy car use, for instance: 6 per cent in Cambridge (UK) and 3 per cent in Gyor (Hungary) (Enoch, 2012).

As discussed in Section 2.1, the stimulus for the research in this report was taken from an extensive literature review of approaches to rouse travel behaviour change through policy provision that is not forceful or that inhibits the private car as a mode, but makes alternative modes convenient, time and cost effective to use and more practical than the driving solo in a private car. Table 1 summarises some of the work that has been done in this area.

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Table 1: Review of the literature regarding policy interventions for behaviour change

Author(s)	Year	Title	Main findings
Ahern and Tapley	2008	The use of stated preference techniques to model modal choices on interurban trips in Ireland.	The passengers in this study chose their modes based predominantly on the times and costs associated with travelling. Frequency and reliability appeared to be less important to travellers.
Baldassare, Ryan and Katz	1998	Suburban attitudes toward policies aimed at reducing solo driving.	Younger and lower-status solo drivers are more likely than others to say they would change in response to any fees or cash incentives.
Brazil, Caulfield	2010	Examining the factors that impact upon mode choice for frequent short trips.	Good weather was shown to encourage individuals to walk or cycle, whereas poor weather attracted more to driving. The amount of CO2 emitted during a short trip was not a concern for drivers.
Eriksson, Nordlund and Garvill	2010	Expected car use reduction in response to structural travel demand management measures.	The combined pull and push measure led to larger expected car use reduction compared to the measures evaluated individually and the reduction was mainly by means of trip chaining and changing travel mode. Personal norm or general intention, and the perceived impact of the measure, were found to be important for the expected car use reduction in response to the TDM measures.
Farrell, McNamara, and Caulfield	2010	Estimating the potential success of sustainable transport measures for a small town.	No one soft measure promoted in isolation is the silver bullet; rather, a mix of these options would be optimal for achieving a modal shift.
Habibian and Kermanshah	2011	Exploring the role of transportation demand management policies.	Synergy is function of policies' levels, and the integration of increasing parking cost with either cordon pricing or increasing fuel cost has greater synergy at higher levels of the two policies. In contrast, the integration of other two policies (i.e. cordon pricing and increasing fuel cost) had no synergy in the examined ranges.
Loukopolulos, et al.	2004	Car-user responses to travel demand management measures: goal setting and choice of adaptation alternatives.	Both Study 1 and Study 2 revealed that very little change was required by car-users in order to adapt. Inconveniences arising from a TDM measure tended to be resolved wherever possible by changing travel pattern. This resulted in the most common reduction in frequency of car use.
Mackett	2001	Policies to attract drivers out of their cars for short trips.	The action that would do most to attract drivers away from their cars is to improve bus services; 21% of short car driver trips could be attracted to bus. The main actions that are required are improvements to the route pattern (10%) and improvements to frequency (6%), another 1% would like them to operate all night.
Meloni, et al.	2013	Propensity for voluntary travel behaviour changes: an experimental analysis.	Most of the car drivers are in fact not aware of their alternatives and most of the times they are not able to quantify possible benefits deriving from behaviour changes. This study also highlighted that there are individual habits, such as pro-environmental efforts, that characterise a higher probability to change also travel mode behaviour.
Meyer	1999	Demand management as an element of transportation policy: using carrots and sticks influence travel behaviour.	This paper suggests that there are strategies that can be used to begin the process of gaining public support for more controversial actions. These strategies attempt to link the general public sense of fairness to public policies aimed at negatively effecting someone's ability or cost to travel by single occupant vehicle. The basic ingredient to successful future adoption of area-wide TDM actions is to link it to broader goals that the public can support.
O'Fallon, Sullivan and	2008	Constraints affecting mode choices by morning car commuters.	The variation in the effects of the policy tools on car driver behaviour across the three main urban centres means that there is no single policy mechanism that will address congestion issues across urban areas in New Zealand. Government policy proposals will be best developed in 'packages', such that implementers can choose the tools appropriate to

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Hensher			the constraints their car driving population faces.
Ogilvie, et al.	2008	Interventions to promote walking: systematic review.	Interventions such as individualised marketing and information provision could increase walking among targeted participants by up to 30-60 minutes a week on average, in the short-term.
Pooley, et al.	2011	Household decision-making for everyday travel: a case study of walking and cycling in Lancaster (UK).	Attempts to increase rates of walking and cycling in urban areas are unlikely to succeed unless the convenience of the car is countered by restrictions on car use and the complexities of everyday travel are addressed.
Pooley, et al.	2013	Policies for promoting walking and cycling in England: a view from the street.	It is argued that there needs to be a more integrated approach to transport policy that combines interventions to make walking and (especially) cycling as risk-free as possible with restrictions on car use and attitudinal shifts in the way in which motorists view other road users.
Sottile, Cherchi, Meloni	2015	Measuring soft measures within a stated preference survey: the effect of pollution and traffic stress on mode choice.	Utility to Park and Ride increases with the level of awareness, aspects associated with stress have a greater influence on travel choice than environmental aspects.
Taylor, and Ampt	2003	Travelling smarter down under: policies for voluntary travel behaviour change in Australia.	Whilst voluntary behaviour change programs are not yet for the whole community, the trials around Australia have shown firstly that a sizeable minority of households and individuals can be attracted to the programs, and secondly that the participants can achieve ongoing, substantial reductions in their usage of private motor vehicles.

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2.2 Current State of the Transport Sector and sustainable mobility provision within the GDA.

The study area in question for this study is the GDA, which includes the counties of Dublin, Meath, Kildare and Wicklow, as shown in Figure 2. The GDA was selected as the most appropriate area for this research due to there being a greater selection of alternate transport options available in this region compared to the rest of Ireland (i.e. more alternatives to the private car to offer viable options in the choice scenarios). In recent years, the GDA has seen the introduction of several alternative travel options to the private car and various projects seeking to extend, improve and connect existing public transport routes such as the Luas Cross City project. Moreover, there currently exist two car-sharing/car-club providers in operation; 'GoCar' and Toyota's 'Yuko' car club.

Figure 2: Map of the GDA (National Transport Authority, 2016)

GoCar, in partnership with the German car-sharing company 'Cambio' launched in 2008 and has grown substantially in Dublin and continues to be the largest car-sharing provider in Ireland. Yuko (Japanese for 'Let's Go') is Ireland's newest car-sharing provider, which, was launched in Dublin in June, 2016. Yuko is a noteworthy addition to the car-sharing scene of Dublin as the fleet of vehicles available to share are all plug-in hybrids. In further support of shared mobility, a range of city bike sharing providers are also in operation in Cork, Galway, Limerick as well as the largest operation in Dublin which have grown substantially since launching in 2009. In Dublin network, there are at present 1,500 bicycles at 101 stations with further 15 stations, and an addition 100 bikes planned in the summer of 2017. 18.4 million journeys have been made on the Dublin bikes scheme since its launch, with a long-term subscription base of over 67,000 people and an average journey duration of 14 minutes (Dublinbikes, 2017). A carpool networking website (www.carsharing.ie), (not to be confused with the type of service that GoCar and Yuko provide) similarly exists, which is supported by the National Transport Authority of Ireland (NTA) and acts as an online community for carpoolers that connects travellers with matching travel destinations.

Mobility services such as car and bike sharing, carpooling and on-demand taxi services like Mytaxi etc., offer further sustainable alternatives to commuters, that can help the process of reducing the need to own a car, thus, simplifying the car-shedding process.

2.3 Benefits of and Barriers to car-shedding

Benefits:

- Space usually used for car parking could be reallocated to bicycle parking, much needed residential space, or areas for the enjoyment of society as a whole and not just an amenity for car drivers.
- Reduction in traffic congestion, leading to less traffic delays, accidents and greater economic efficiency of the road network.
- Abatement in emissions produced by road transport, increasing air quality in urban areas and having many health benefits such as a reduction in respiratory problems caused by air pollution.

Barriers:

- Lack of vision and leadership and political will by government and local authorities to devote time to the development and adoption of 'car-shedding' style measures to reduce car use.
- Shortage of financial and staff resources to create, enforce, monitor such schemes or policy tools.
- Lack of belief and trust in TDM and mobility management approaches due to the novelty of the concept and due to there being relatively few comparable cases in the Irish context to provide evidence on the success or results of similar project/ schemes. Which leads to the approach seeming unconvincing to government officials and local authority councillors.

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3. Research

The following section outlines the theoretical underpinnings of SP surveying and discrete choice modelling. The results of the SP experiment will be presented and using the framework of discrete choice statistical modelling the findings from the survey will be discussed to determine the extent to which policy incentives influence a sustainable travel behaviour change and a shift in modal choice. The first part of this chapter will elaborate on the design and structure of the experiment, the experimental design process and the theoretical background of multinomial logit modelling will then be examined before the application of this approach in the context of this study is presented. Finally, the results and findings from the modelling will then be investigated.

3.1 Stated Preference Survey Design and Structure

Revealed preference (RP) assesses actual or current market occurrences to existing market forces. Census mode share data is an example of revealed preference data, as it is collected based on the actual population's preferences and not on attributes in hypothetical scenarios. SP data on the other hand is hypothetical, but built upon a solid experimental design. SP approaches are extensively utilised in travel behaviour research to identify behavioural responses to choice situations, which are not revealed in the market (i.e. hypothetical or projected scenarios). Kroes, et al. (1988) define that, 'stated preference methods refer to a family of techniques which use individual respondents' statements about their preferences in a set of transport options to estimate utility functions'. Stated choice experimentation has become a common process of assessing behaviour in the context of transportation and it is 'growing in popularity in other areas such as marketing, geography, regional science and tourism' (Hensher, 1993). However, SP data is often most beneficial if collected in conjunction with RP data and *vice versa*, as current and hypothetical data complement each other and in such a way, improve the validity of the research. Though, it is recognised that collecting SP data is more economical and cost effective, while collecting RP data is very time consuming and expensive (Sanko, 2001). Another common issue with RP data is 'the high degree of collinearity among attributes in market data, making it difficult to predict the effect of independent variation in an attribute (Kroes and Sheldon, 1988).

Accordingly, SP experimentation was deemed as an appropriate and established method of evaluating the impacts of a range of policy measures on mode choice behaviour (O'Fallon, et al., 2004; Baldassare, et al., 1998; Louviere, et al., 2000; Beaton, et al., 1998). In addition, a study such as this has (to date) not been conducted in Ireland, thus, it was estimated that this study would significantly add to the understanding of how sustainable travel behaviour may be incentivised by applying a particular incentivised policy approach. The 'attraction of choice experiments (CEs) is their ability to

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place respondents into situations in which they must make trade-offs among multiple attributes of alternatives' (Boxall, et al., 2009).

In the experiment in this study, respondents will be asked to rank in order their preferences from a choice set of three alternatives or modes (e.g. walk, cycle, drive). Each one of these choice tasks will be framed as a choice scenario with differing levels of attribute intensity associated with the alternative in question. Attributes are essentially the variants in the experiment, in which case they differ depending on the choice alternatives in each model. Figure 3 illustrates that in this study there are three defined models, one examining active modes (walking and cycling), the second concerning public transport (bus and rail), and the third will consider sustainable usage of the private car, which consists of carpooling and car-sharing. Each of the 3 models will be analysed independently to examine the influence of a number alternative-specific attributes or policy tools on modal choice behaviour. The models will be represented in separate choice sub-sections within the SP survey in order to effectively isolate the choice scenarios. As shown in Figure 3, a private car (drive alone) option is present in each model, which will be considered as a constant or 'no choice' / 'status quo' option that will have no attributes applied to it. This decision was made for a number of reasons: firstly, there was reluctance to dis-incentivise car owners by, for example, raising the costs of owning a car as these costs generally grow year-on-year, which would perhaps bother or anger potential respondents. Secondly, it is held in the literature that including a base alternative or 'current choice' option, in fact brands decisions more realistic and leads to better predictions of market penetrations, as well as better mimicking consumer choices and increasing experimental efficiency (Louviere and Woodworth, 1983; Haaijer, et al., 2001; Brazell, et al., 2006;). This leads to better model parameter estimates and in this way more accurately predicts modal choice changes in the population. Dhar (1997) states that forcing a respondent to choose amongst a limited number of options might lead to biased parameters when modelling such survey results. Thus, in the context of this study, we assume that the respondents determine the utility for each mode choice and only choose the car option if none of the other modes are appealing enough to them based on improvements being made to frequency, time, cost, infrastructure, convenience factors, or in other words, if the other alternatives offer sufficient utility to the respondent (Vermeulen, et al., 2008).

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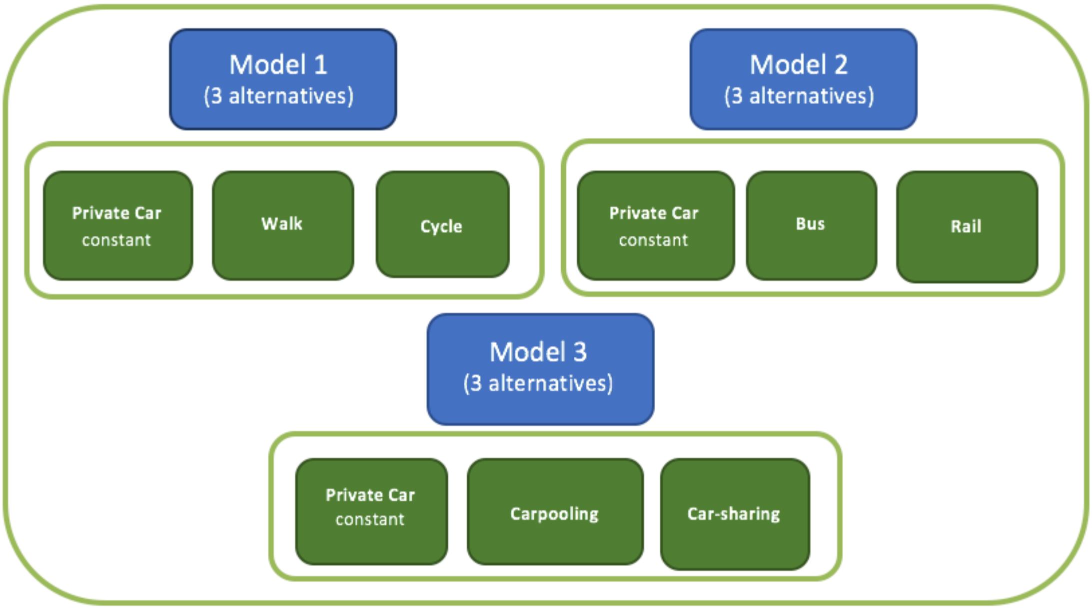

Figure 3: Stated Preference experiment design structure

In the next section, the theoretical underpinnings of discrete choice modelling will be outlined, special attention will be given the Multinomial Logit (MNL) model as it is the statistical model of choice in this study. In addition to this, the experimental design process will be outlined and discussed.

3.2 Discrete Choice Modelling

Discrete choice modelling is an econometric method of predicting the behaviour of a user based on individual choice behaviour theory (Ben-Akiva and Lerman, 1985). In this way, it is the term used to define the manner in which SP data is analysed. As previously alluded to, in a CE the collection of options or alternatives that an individual survey respondent is asked to choose from is termed a *choice set.* As the choice set is central to the structure of the experiment, it must follow the discrete choice framework, that holds the following three characteristics (Train, 2003):

- The alternatives must be *mutually exclusive* from the decision maker's perspective. Meaning that the decision-maker can only choose one of the alternatives in the choice set. For example, if bus, train and car are the three alternatives in Model 2, the respondents may only choose one modes per scenario.
- The choice set must be *exhaustive*, in that all possible alternatives are included. The car option is included in each of three models in the event that the decision-maker is not attracted to the alternatives effected by the policy plans i.e. the sustainable modes. In this way, the car option acts as a status quo option.
- The number of alternatives must be finite. Meaning that the 'researcher can count the alternatives and eventually be finished counting' (Train, 2003)

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In reference to the first of the three characteristics, Long and Freese (2006) quote McFadden in stating that 'Multinomial and Conditional logit models should only be used in cases where the alternatives 'can plausibly be assumed to be distinct and weighted independently in the eyes of the decision maker', as such the alternatives should be distinct from one another. The foundation of discrete choice modelling is derived from the traditional economic theory of consumer behaviour (Louviere, et al., 2000) and is examined under the Random Utility Theory (RUT). RUT revolves around the concept of 'utility' or the benefit that an individual assumes from a certain good or service (e.g. a mode of transport). Humans are said to be rational beings and like this they seek to maximise the utility they derive from a good or service, which is defined as the *theory of utility maximisation*. Train (2003) identifies the difference between regular regression models and discrete choice models by stating that 'regressions examine choices of 'how much' and discrete choice models examine choices of 'which''. Equation 1 illustrates that an individual will only choose alternative *i* if the utility of this alternative is greater than the utility derived from all other alternatives in the same choice set.

$$U_{in} > U_{ij} \forall j \neq i \qquad \textbf{(1)}$$

There are two distinct components of utility, the deterministic or 'representative' component V_i and a stochastic error term ε_i, which refers to the unobserved influences that are 'independently and identically distributed' (IDD) across the population (Hensher, et al., 2005). In the context of this study the deterministic element is represented by the attributes being applied to each of the alternatives, and the error term is calculated with the use of an alternative-specific constant, that takes account of all the things which either can't be quantified (in the model or generally), or unknown factors which influence behaviour/decision-making. As the utility of an individual cannot always be observed by the researcher, the researcher examines the attributes associated with each of the alternatives in addition to the various characteristics of the decision maker (Train, 2003). These alternative specific and socio-demographics attributes together are what is termed as 'representative utility'. The utility expression for random utility models can be written as:

$$U_i = V_i + \varepsilon_i \qquad \textbf{(2)}$$

To recap, the deterministic component is calculated based on an equation of attributes assigned to each alternative in the choice set, the attribute coefficients and an alternative-specific constant (ASC). This can be defined as a linear expression whereby each attribute is weighted by a parameter to 'account for the attribute's marginal utility input' (Hensher, et al., 2005):

$$V_i = \beta_{0i} + \beta_{1i} f(X_{1i}) + \beta_{2i} f(X_{2i}) + \beta_{3i} f(X_{3i}) + \ldots + \beta_{Ki} f(X_{Ki}) \qquad \textbf{(3)}$$

where:

β_{1i} is the weight (or parameter) associated with attribute X_i and alternative *i,*

β_{0i} is the alternative-specific constant (ASC), which represents the role of all unobserved, sources of utility.

To explain this further, the beta parameter accounting for the alternative in question, e.g. Bus, is estimated the with the associated attributes, which, in this are frequency, time and cost. This equation is discussed in Section 4.2

As the random error component in Equation 2 cannot be modelled, the probability of an individual choosing an alternative *i* from a choice set is the probability that this utility is greater than the utility of any other alternative in a choice set, which is represented as:

$$P_i = Prob\left(U_i > U_j\right) \forall j \neq i \qquad \textbf{(4)}$$

Before progressing to the multinomial logit model, i.e. the process of estimating individual choice behaviour, the Independence from Irrelevant Alternative (IIA) axiom must first be considered. IIA holds that the ratio of the probability of one alternative over the probability of choosing the other is not affected by the presence or absence of other alternatives (Ben-Akiva and Lerman, 1985). In other words, the random components (ε) of the utility expressions are independent and are identically distributed (IID), which relates back to the three characteristics of discrete choice listed.

3.3.1 The Multinomial logit (MNL) model

Multinomial Logit (MNL) models are the most commonly used of discrete choice model, frequently labelled 'the workhorse'. The MNL is a logistic regression model used with a nominal (unordered) dependent variable, when more than two alternatives exist. It is utilised to explain the relationship between the dependent variable and one or more continuous independent variables. The MNL form requires that the unobserved effects are independently and identically distributed (IID) across the alternatives in the choice set, according to the extreme value type I (EV1) distribution (Hensher, et al., 2005; Ben-Akiva and Lerman, 1985). The error term from Equation 3 is identically and independently distributed (IDD) or Gumbel distributed, and it is under this principle that the MNL model is derived from. Therefore, the probability of an individual choosing an alternative (e.g. bus or rail) in an MNL model is written as:

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} \qquad \textbf{(5)}$$

where:

P_i is the probability that an individual will choose alternative *i,*

V_i is the deterministic component of the utility expression in Equation 3.2,

j is the number of alternatives in the choice set.

Section 4: Interpretation of MNL Outputs

When the models have been estimated using the choice values and attributes levels from the survey experiment, there are a number of indicators that measure the performance of discrete choice models, that vary depending on what modelling software is utilised. The responses collected from the SP survey are modelled from the equations in Section 3.3 using NLOGIT discrete choice modelling software, which provides programs for estimation, simulation and analysis of multinomial choice data. It is the only statistical program available that supports mixing stated and revealed choice data sets (Econometric Software Inc., 2017). NLOGIT produces various significant outputs that require interpretation, these are: the log likelihood function, pseudo-Rho^2, the Akaike Information Criterion Coefficient (AICc), the sign of the coefficient, the statistical significance or p-value, in addition to other supplementary behavioural tests such as elasticities.

The Log-Likelihood Function

The log-likelihood function highlights an important difference that exists between regular linear regression and logistic regression, 'in linear regression the model parameters are estimated using the method of least squares, whereas in logistic regression maximum likelihood estimation is used, which selects coefficients that make the observed values most likely to have occurred' (Field, 2013). As a result of this, a typical MNL model produces two Log-Likelihood (LL) values, one is given for the observed or actual outcome from the data collected and the other is based on the predicted values or outcome. To determine whether the overall model is statistically significant, the difference between the LL function of the observed outcome (constants only/ base model) is compared with the LL of the predicted outcome, which is otherwise known as a *Log-likelihood ratio-test,* illustrated in Equation 6. The likelihood ratio has a chi-square distribution with degrees of freedom equal to the number of parameters in the new model minus the number in the base model (Field, 2013).

$$-2(LL_{base\ model} - LL_{estimated\ model}) \qquad \textbf{(6)}$$

This value specifies that the lower the LL function value is the better the model fits the data, in other words if the LL of the estimated model 'can be shown to be a statistical improvement over the LL function of the base model (i.e. statistically closer to zero), then the model may be thought of as being statistically significant overall' (Hensher, et al., 2005).

Pseudo R-squared

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The R^2 statistic provides a measurement of the quality of the estimated model. Yet, the R^2 in logistic regression in choice models should not be treated the same as R^2 in linear regression as multinomial logit (MNL) is non-linear. For this reason, the R-squared statistic in logit modelling is termed *pseudo R-squared*, and it is calculated using the following equation (Hensher, et al., 2005):

$$R^2 = 1 - \frac{LL_{Estimated\ model}}{LL_{Base\ model}} \quad \textbf{(7)}$$

The R-statistic is the partial correlation between outcome variable and each of the predictor variables and it can vary between -1 and 1 (Field, 2013). The closer the R^2 value is to 1 the better the result, so a value of close to one indicates that the model estimated fits perfectly to the sample dataset. However, even if a low R^2 value is produced, it should be interpreted with caution for it is not equivalent to ordinary least squares (OLS) or linear regression. Thus, regardless of the R-squared, 'the significant coefficients produced in the model still represent the mean change in the response for one unit of change in the predictor while holding other predictors in the model constant' (Minitab, 2013).

Akaike Information Criterion Coefficient (AICc)

The Akaike Information Criterion Coefficient (AICc) is a goodness-of-fit measure of the relative quality of the model for the dataset used in the analysis. Much like the log-likelihood function, it is used as a means of comparison of estimation between models of the same datasets (e.g. comparing the base model with the extended model). The better the model fits to the data, the lower AICc for that model will be. However, the AICc is limited in the sense of providing a test of the overall quality of the model as it is separate to the hypothesis testing, discussed in Section 4.2.

The Sign of the Coefficient

When analysing the main output of an MNL model the first element that will come to the attention of the analyst will be the sign of the parameter estimate, which should seem logical in the context of the experiment. In this study, a number of policy incentives that act as the main attributes in the model are expected to increase the probability of choosing the sustainable modes as the incentives are applied to them in the SP scenarios. In other words the coefficient signs for these sustainable modes (i.e. walk, cycle, bus, rail, carpool and car-share) should appear positive if people respond positively to the attributes. In this way, as these trips become cheaper, quicker and more convenient the respondents are understandably more likely to choose those modes of transport, signifying increased utility of the mode. As a result of this, the signs of the coefficient should make intuitive sense to the researcher.

Statistical Significance

The statistical significance or p-value (probability value) of the parameter estimates and of the model as a whole (i.e. the prob [chi squared > value]) are similarly features of the model output that are of

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high importance to the analyst. It is the most important indicator of the model's performance as the p-value of a parameter accounts for the level of truth or probability of the model results being replicated in the market or within the population of a certain area. The analyst compares the p-value of the model and the parameter estimates with a level of acceptance, known as alpha, *a*. The standard levels of acceptance are most commonly, alpha values of 10%, 5% and 1%, which are represented in the analysis as significance at 90%, 95% and 99% confidence. 'Usually the level of acceptance is taken as 0.05. If the p-value is less than the level of alpha, then the analyst rejects the null hypothesis that the estimates model is no better than the base comparison model. If the p-value exceeds alpha, then the analyst cannot reject the null hypothesis' (Hensher, et al., 2005). NLOGIT likes most other software packages will determine in the model output at which of the three levels of acceptance the coefficient meets.

The z statistic similarly indicates the given significance level at the alpha values mentioned (10%, 5% and 1%), which correspond to z-stat values of ±1.50, ±1.96, and ±2.56 respectively. It is calculated by dividing the regression coefficient by the standard error. Z-statistics will be included in the model output tables in this report.

Elasticities

Increases and decreases in the economic cost of using different travel modes have been found to influence travel behaviour (Bamberg & Schmidt, 2001; Heath & Gifford, 2002; Jakobsson, et al., 2003), and estimates of transport elasticities provide information of the extent to which travel demand is sensitive to changes in price and in public transport services (Litman, 2017). Transport (direct/ cross) elasticities are based on either actual (i.e. revealed) and/ or SP studies and are often expressed as the ratio of the proportional behavioural change to the proportional changes in prices, fares or services. (Eriksson, et al., 2010). Direct and cross elasticities are key behavioural outputs, as they provide a greater insight into the varying effects of changes to specific attributes in the model, and explicate the impacts in the form of probabilities of choosing the alternatives in question. 'A direct elasticity measures the percentage change in the probability of choosing a particular alternative in the choice set with respect to a given percentage change in an attribute of that same alternative' (Hensher, et al., 2015). Cross elasticities measure the percentage change in a different or competing alternative. Direct-point elasticity for the MNL model is calculated using this equation:

$$E^{P_{iq}}_{X_{ikq}} = \frac{\partial P_i}{\partial X_{ik}} \cdot \frac{X_{ikq}}{P_{iq}} = \frac{\partial V_{iq}}{\partial X_{ikq}} X_{ikq}(1 - P_{iq}) \qquad \textbf{(8)}$$

This equation is 'interpreted as the elasticity of the probability of alternative *i* for decision maker *q* with respect to a marginal change in the *k*th attribute of the *i*th alternative (i.e. X_{ikq}), as observed by decision maker *q'* (Hensher, et al., 2015). For example, if there was a 1% increase in the time attribute of a car alternative, what would be the consequence of this in terms of choice probability and the utility of this mode, i.e. would more people choose another alternative that offers faster trip times?

4.1 Applying the Discrete Choice modelling approach

Figure 4 outlines the key phases in conducting a SP study, up to this point the following have been set out: the research objective, the attributes and attributes levels to be used in the experiment (discussed further in Section 4.1.2), in addition to the modelling requirements for the study, which leaves the core statistical design of the experiment to be set-out as well as the creation of the choice scenarios format for the survey.

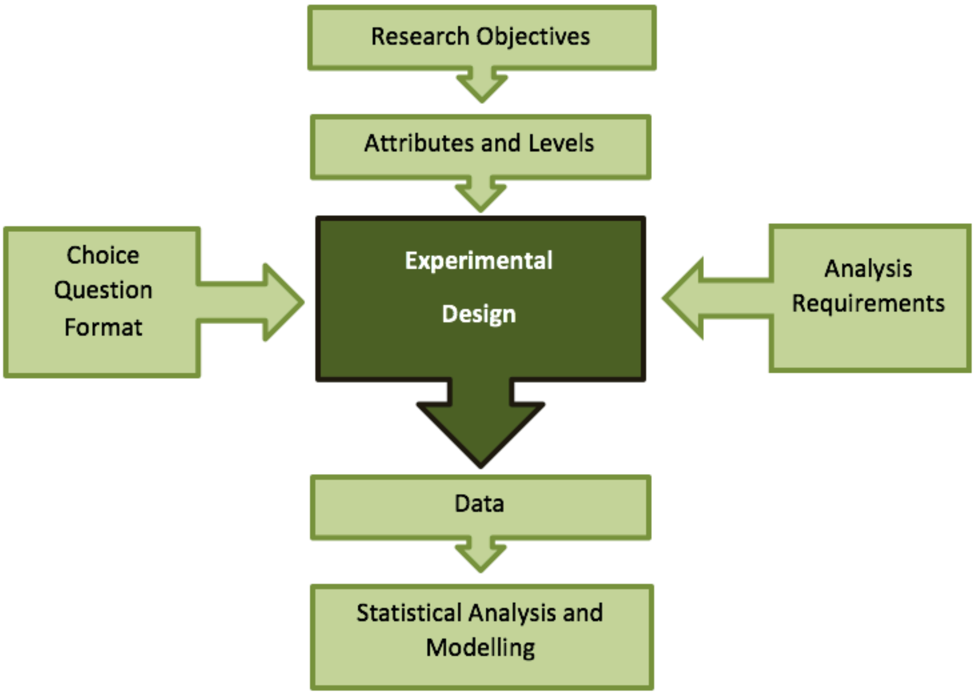

Figure 4: Key stages for developing a discrete-choice experiment (Johnson, R., F., et al., 2013).

4.1.1 Experimental design

SP surveys require crucial planning at the design stage, as this can impact on the validity and quality of modelling results produced later in the experimental process. For instance, the selection of alternatives and attributes (i.e. the features that policy instrument seeks to improve) determine the choice making behaviour of the respondent or the ability of the decision-maker to make trade-offs between the alternatives. An example of this is the carpool alternative that has the attributes convenience, time and cost applied to it. As previously stated, there were three polices or choice attributes assigned to each of the 3 models (active modes, public transport, smart car use), resulting in there being a total of 9 attributes considered in the experiment overall, which is defined as a ‘fixed choice set design'. For each of these attributes there were 3 attributes levels, that determine the extent to which the attribute varies or in other words the intensity of the policy measure and its impact on the trip characteristics. To determine the total output of the model (i.e. every possible combination of attribute levels), a full factorial design was first run, which produced 19,683 possible treatment combinations ($L^{MA} = 3^9$, where L = number of attribute levels; M = attributes; A = alternatives).

A full factorial design can be calculated using the following equation:

$$S^{ff} = \prod_{j=1}^{J} \prod_{k=1}^{K} l_{jk} \qquad \textbf{(11)}$$

where:

S^{ff} is the total number of choice situations,

J are the alternatives,

K are the attributes,

l are the levels within the attributes.

The full factorial result of 19,683 combinations were of course too many for the experiment to handle and impractical due there being many attributes and attribute levels. The most commonly used solution to reduce the size of the experiment is an *orthogonal main effects fractional factorial design,* which represents a select portion of the treatment combinations generated from the full factorial design. In this way, only the main effects of the study are to be estimated, resulting in a more efficient and practical strategy. Fractional factorial designs are supported by the rationale that usually, only some interactions are significant or of interest to the researcher. In truth, a main effects design explains the largest amount of variance in response data, often 80% or more (Sanko, 2001). Thus, by implementing a main effects design, the majority of variance can be accounted for (Hensher, et al., 2005). To generate the fractional factorial, *IBM's SPSS* software was used, which implements various statistical methods to produce the most appropriate combination of attribute levels to be used in the experimental design. SPSS generated 27 individual choice combinations to be presented in the experiment. The constraint of orthogonality ensures that 'multi-collinearity' between attributes is avoided and that the attributes are varied independently from one another (Hensher, et al., 2005; Sanko, 2001), in other words, there is zero correlation between attributes. As 27 combinations would still be excessive for one respondent to answer and would lead to low response rates from fatiguing effects, it was decided that the survey should be 'blocked' or divided into 9 versions to allow for 9 SP scenarios to be assigned in each survey version. By blocking variables, the number of scenarios each respondent was required to answer was reduced. 9 different versions of the survey were needed to evenly distribute the number of treatment combinations amongst all respondents. The 9 versions of

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survey were then randomly assigned to respondents; to minimise the influence of learning and fatigue (Beaton, et al., 1998); using the *Qualtrics'* (Qualtrics, 2017) survey flow randomiser function.

4.1.2 Defining the attributes and attribute levels

To create an effective stated preference choice scenario it is necessary to provide the respondents with a scenario in which they are prompted to make a trade-off between a number of alternatives. The attributes applied to the alternatives define the appeal of each option, thus highlighting their important in an SP survey. The alternative-specific attributes for active modes, public transport, carpooling and car-sharing in the models were carefully considered, in reference to the literature. As the attributes were determined by the resultant impacts of the mode specific policy incentives, it was necessary to first consider what elements of each mode included in the stated preference experiment could be improved in order to increase the utility of them.

Model 1 - Active Modes

For active modes, Short and Caulfield (2014), Pooley, et al. (2013), and Lawson et al. (2012) examined the challenge of ensuring safety along cycling routes and identified speed and available infrastructure as necessary attributes in the perceived risk factor of cycling. This is to ensure increase segregation between cyclists and other traffic and enhances the image of cycling as a safe and pleasant form of transport. This is supported by evidence from Caulfield et al. (2012) who concluded that segregated infrastructure was the preferred form of cycling infrastructure from the results of an SP experiment. This was followed by routes through residential streets and parks as a second preference, where lower speed limits and traffic levels are the norm. Lowering urban speeds was also found to be associated with lower serious injury rates and this was correlated with accident severity, as it increases with speed (Caulfield, et al., 2014, Nilsson, 2004). It was similarly determined here that only 5% of collisions are severe in 30km/h zones, thus adjacent traffic speed is a main policy variable to be considered with cycling and walking.

As a result of this, it was decided to include infrastructure and adjacent traffic speed as the mode specific attributes to be modelled in the study, which is shown in Table 2.

Table 2: Active Modes Model – alternatives, attributes and attribute levels

Active Modes Model		
Mode	**Attribute**	**Attribute Level**
Private Car (drive alone)	Cost	Gradual increase in the ownership costs of a car
	Infrastructure	20% of trip with even surfaced, widened paths, separated from traffic
		40% of trip with even surfaced, widened paths,

Walk		separated from traffic
		60% of trip with even surfaced, widened paths, separated from traffic
	Time	2 minutes off trip time
		4 minutes off trip time
		6 minutes off trip time
	Adj. Traffic Speed	50% of trip with 30km/h speed limit
		75% of trip with 30km/h speed limit
		100% of trip with 30km/h speed limit
Cycle	Infrastructure	20% of trip fully segregated from traffic
		40% of trip fully segregated from traffic
		60% of trip fully segregated from traffic
	Time	2 minutes off trip time
		4 minutes off trip time
		6 minutes off trip time
	Adj. Traffic Speed	50% of trip with 30km/h speed limit
		75% of trip with 30km/h speed limit
		100% of trip with 30km/h speed limit

Model 2 – Public Transport (Bus, Rail)

Bus and rail are commonly reflected upon by commuters in terms of time, cost and reliability of time, which is linked to frequency or the level of service. These factors have been widely examined SP literature. Weibin et al. (2017) for example, conducted a SP experiment to determine urban commuters valuation of travel time reliability. They found that both income level and time constraints have significant effects on utility for commuters and commuters on higher income usually prefer a modes with less travel time and higher reliability (Weibin, et al., 2017). Thus, more importance was placed travel reliability and its associated factors such as the frequency of service and headways on routes than the travel time. This is particularly critical for commuting purposes as a reliable and on-time service allows for the patron to arrive at their place of work on time, without the worry of being delayed or late. Frequency itself has been used consistently as an attribute in stated preference literature in examining modal choice. For instance, the Transportation Research Board's (TRB) 'Handbook for Measuring Customer Satisfaction and Service Quality' lists as a guideline that, frequency should be included in questionnaires concerning transport quality of service. Research conducted by Eboli and Mazzulla (2008) incorporates frequency as a main attribute in PT study and found that service frequency was a statistically significant attribute for measuring service quality in public transport in Italy, through an MNL model. Their analysis indicated that an increase in bus frequency 'from one bus every hour to one bus every 15 minutes, produced, holding all else constant, an increase of about 2.6 on the service quality index (SQI) (Hensher, et al., 2003; Eboli, Mazzulla, 2008). Bourgeat (2015) also finds that bus frequency has a strong impact on the likelihood to take the bus and it was the favored method of ‘reducing uncertainty of bus availability for both bus user and potential users. Moreover, he states that raising awareness of bus frequency is essential in generating demand among non-users (Bourgeat, 2015). The attributes and attributes of Model 2 are displayed in Table 3.

Table 3: Public Transport Model – alternatives, attributes and attribute levels

Public Transport Model		
Mode	**Attribute**	**Attribute Level**
Bus	Frequency	25% more often
		50% more often
		Twice as often
	Time	15% reduction in trip time
		25% reduction in trip time
		35% reduction in trip time
	Cost	15% reduction in trip cost
		25% reduction in trip cost
		35% reduction in trip cost
Private Car (drive alone)	Cost	Gradual increase in the ownership costs of a car
Train/ Luas	Frequency	25% more often
		50% more often
		Twice as often
	Time	15% reduction in trip time
		25% reduction in trip time
		35% reduction in trip time
	Cost	15% reduction in trip cost
		25% reduction in trip cost
		35% reduction in trip cost

Model 3 – Carpooling and car-sharing

It was identified for the literature that the convenience, time and cost were the main attributes affecting mode choice behaviour for carpool and car-share (Malodia and Singla, 2016; Horowitz and Sheth, 1976). These attributes levels determine at which level of convenience, time and cost that an individual would be willing to choose this alternative over the other two given in the hypothetical scenario.

Time and cost have a direct effect on the perceived convenience of the mode and carpool/ car-share driver, as convenience is closely linked to the time attributes through the access and wait times. For example, as the access and wait times increase as a result of pick up delays and the number of carpool members in the car, this increases the inconvenience of the trip. Horowitz and Sheth (1976) referred to convenience when stating that 'an individual has a set of evaluative beliefs about carpooling/ ridesharing and driving alone modes of travel to work with respect to cost, time saving and convenience etc.'. Malodia and Singla (2016) take inspiration from Horowitz and Sheth (1976) by incorporating a 'time-convenience' factor that discourages carpooling in their stated preference experiment. From the literature review, convenience appeared to be a significant attributes used in studies of carpooling and car-sharing, and as a result of this, it was added to as an attribute in Model 3

Time and cost were consistently used as attributes in stated preference experiments in the literature mentioned in Section 2, as they are common identifying factors and trip characteristics of commuting trips. For example in relation to carpooling Malodia and Singla (2016) stated that 'Cost and time of in-vehicle time and extra in-vehicle time significantly influenced the decision to join a carpool'. These statement is also closely comparable to public transport modes such as bus and rail as well as this time is a necessary consideration in the decision to walk or cycle. For this reason time and cost are used as attribute for Model 2 and Model 3 and time is incorporated into the active mode scenarios of Model 1.

It was decided to present all attributes in the models at three attributes levels to account low, medium and high intensities or strength of the impact of the policy incentives. This was to create an environment for the respondent to make trade-offs between the modes in the scenario based on the mode-specific characteristics. Table 4 illustrates the structure of attribute and attribute level allocation to the alternatives for Model 3.

Table 4: Smarter Car Use Model – alternatives, attributes and attribute levels

Smarter Car Use Model		
Mode	**Attribute**	**Attribute Level**
Carpooling	Convenience	10% reduction in access/ wait time
		30% reduction in access/ wait time
		50% reduction in access/ wait time
	Time	15% reduction in trip time
		25% reduction in trip time
		35% reduction in trip time
	Cost	15% reduction in trip cost
		25% reduction in trip cost
		35% reduction in trip cost
	Convenience	10% reduction in access/ wait time
		30% reduction in access/ wait time

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Car-sharing (Go Car/ Toyota Yuko)		50% reduction in access/ wait time
	Time	15% reduction in trip time
		25% reduction in trip time
		35% reduction in trip time
	Cost	15% reduction in trip cost
		25% reduction in trip cost
		35% reduction in trip cost
Private Car (drive alone)	Cost	Gradual increase in the ownership costs of a car

4.1.2 The survey instrument

The SP survey was conducted online in March 2017, and was distributed randomly to a sample of the population resident in and who similarly work or study in the area of interest for this experiment (the GDA). As a reference point, a copy of the survey is included in Appendix A of this report. The survey was organised into 4 sections:

(1) Introductory questions

(2) Perceptions of policy measures

(3) Stated preference scenarios

(4) Demographic characteristics

The introductory section set-out Census style questions to determine the mode of choice, journey length, distance, time and costs of the respondent followed by finding out if he/she possesses a driving licence, which is a defining factor in how the respondent responds to the questions in the survey. This section is essentially the revealed preference component of the survey as it collects responses from the sample on current travel practices that are revealed in the market. Section 2 explores the perception of, acceptability and impacts of various soft policy measures on the decision to travel more sustainably. Measures such as in work cycling facilities, carpool/ car-share assistance, provision of timetabling information, financial incentives and the availability of the option to telecommute were explored as ways in which people could be encouraged or motivated to change their mobility practices. This approach seeks to create an environment that makes walking, cycling and public transport more convenient than driving a private car alone and in such a way, individuals may choose their own method of changing travel rather than simply acting in response to external pressures (Taylor and Ampt, 2003). In Section 3 of the survey, the main component of the survey is featured - the SP choice scenarios, that is follow by some attitudinal questions that refer to the SP scenarios and the final section includes a number of socio-demographic questions to create explanatory variables that can be used in the modelling. The last question of the survey included an opt-in incentive that was

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alluded to on the introductory page of the survey, which entered the respondents into a draw for three chances to win €50.

The SP experiment itself, motivated the respondent to decide on which trip characteristic / 'deal breaker' or which combination of attributes (i.e. time, cost, convenience etc.), was most important to them on their commute and then asked the respondent to rank their mode choice in order of preference, based on the three modes given. For instance, if their trip was 35% cheaper and 15% quicker by taking the bus to work/ education as a result of various policy tools being implemented, relative to trip attributes of the current service that mode of transport provides, would this spur them to switch to this mode in future or would they simply continue with their current mode of choice (i.e. no change)? This is the main research question that we are exploring in this study. For the purposes of data management and preparation of the results in the NLOGIT format, the individuals first preference was given as their choice. The reason for this was that in the data format that NLOGIT acknowledges, the dependent variable is binary with a series of zeros for the options not chosen and a single one (1) which indicates the choice that the individual made.

Figure 5 illustrates example of one of the SP scenarios included in the survey.

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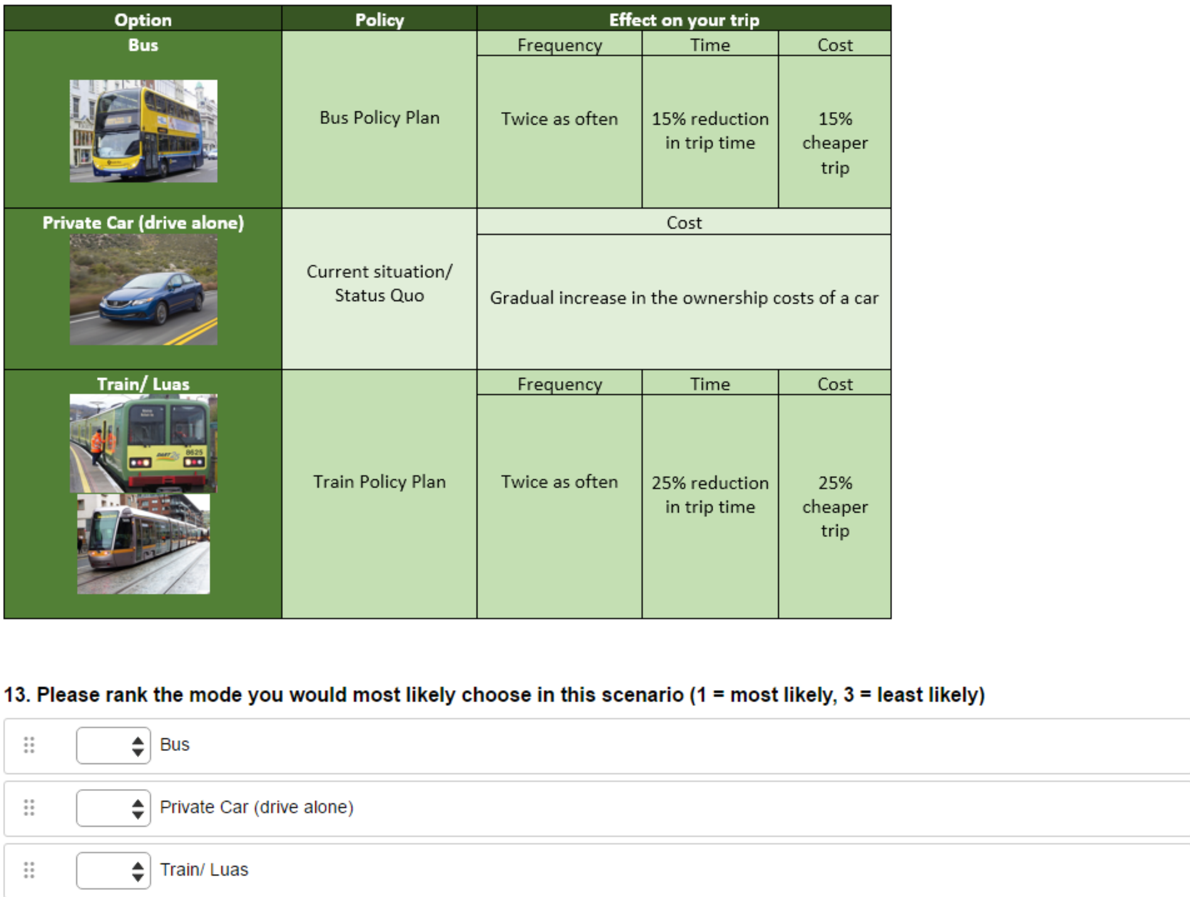

Option	Policy	Effect on your trip		
Bus	Bus Policy Plan	Frequency	Time	Cost
		Twice as often	15% reduction in trip time	15% cheaper trip
Private Car (drive alone)	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		
Train/ Luas	Train Policy Plan	Frequency	Time	Cost
		Twice as often	25% reduction in trip time	25% cheaper trip

13. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Bus
- Private Car (drive alone)
- Train/ Luas

Figure 5: Example of a stated preference showcard

The research hypothesis states that the introduction of a range of policy plans to incentivise and encourage use of alternative modes of transport ('carrot' measures) will induce a shift to more sustainable modes of transport than driving alone and make these modes more popular choices for commuters, ultimately leading to a modal shift from private car use to alternative modes, resulting in emissions savings. To reiterate this, it is hypothesised that for example, a greater prevalence of segregated cycle lanes, higher bus service frequency and high occupancy vehicle lanes will have a negative impact on the utility of driving alone to work/ education (Beaton, et al., 1998).

4.1.3 Sampling method

The sample selected for this study was the population of the GDA. The target sample was defined as those working and studying within the GDA, as the SP survey in this study concerns the commuting population specifically. To calculate the required sample size based on the population of the GDA, the following equation was used (Dillman, 2000):

$$Ns = \frac{(Npp)(pp)(1-pp)}{(Npp-1)(\frac{B}{C})^2+(pp)(1-pp)} \qquad \textbf{(12)}$$

where:

Ns is the sample size required for the desired level of precision,

Npp is the size of the population,

pp is the proportion of the population expected to choose one of the three response categories. To allow for maximum variation in the sample, a 50/50 split was utilised (i.e. 50% the respondent chooses an option, 50% they don't choose an option).

B is the acceptable amount of sample error,

C is the Z-statistic associated with the response level.

In the experiment, Equation 12 was thus written as:

$$Ns = \frac{(1{,}907{,}332)(0.5)(1-0.05)}{(1{,}907{,}332)(\frac{0.05}{1.65})^2+(0.5)(1-0.5)} = 385 \qquad \textbf{(13)}$$

From Equation 13 it can be seen that 385 respondents were found to be satisfactory for the estimation of the survey results, based on the population of the GDA (1,907,332), a 95% confidence level and 5% margin of error, and the associated z-statistic of 1.65. The sample was collected online with aid of Delve Research, an independent survey research company, who operate a panel of respondents nationally. The panel utilised by Delve in this study were firstly engaged from their own database of panellists, and later this was extended to include an external panel pool in order to meet the target sample. The panellists were awarded a number of chances to be entered into a draw for a prize incentive, in exchange for fully completing the survey provided (Delve Research, 2017). Delve Research ensured the receipt of a representative sample with a 50-50 gender split, with respondents only being accepted if they were living and working in the GDA counties, which was achieved by filtering out those residing outside of the GDA by means of a pre-survey question. In order for the sample to be finalised, only respondents that completed the socio-demographic section of the survey were considered for the modelling in this study.

4.1.4 Characteristics of the sample

A total of 552 responses were recorded, of which 432 surveys were fully completed, and therefore could be used for modelling purposes. Table 5 gives a break-down of the number of responses to each survey version as well as the gender split. The number of responses achieved for each of the 9 survey versions was very reasonable considering the number of survey scenarios in each survey. To reiterate, nine survey versions were needed to evenly distribute the 27 combinations of the attribute levels generated from SPSS and to minimise survey fatigue. Also, the gender split of 44.53% males and 55.47% attained was received by the research team as being impressive, for ensuring an equal split is a difficult task as males in the sample pool required additional reminding and attention to complete the survey then the females did.

Table 5: Number of survey responses

Survey Version	Number of Responses	Gender Split			
		Male		Female	
Version 1	65	27	55.10%	22	44.90%
Version 2	61	13	29.55%	31	70.45%
Version 3	60	18	35.29%	33	64.71%
Version 4	61	22	48.89%	23	51.11%
Version 5	60	20	43.48%	26	56.52%
Version 6	58	22	47.83%	24	52.17%
Version 7	61	28	53.85%	24	46.15%
Version 8	63	20	41.67%	28	58.33%
Version 9	63	23	45.10%	28	54.90%
Total	552	193	44.53%	239	55.47%

A summary of some the other characteristics of the sample are presented in Table 6, where they are compared with Census 2016 data. From this it can be observed that a greater percentage of the sample were aged within the 35 - 44 and 45 – 54 years old cohorts, with at least a secondary school education, married with no children, an average household income of between €24,999 to 49,999 per annum, living in the inner suburbs of Dublin and working in Dublin city centre. It must be noted that a considerably higher percentage of the sample were in employment, rather than in education, which was expected. The gender split, in addition to the age, number of children/ dependents, education, marital and economic status characteristics of the survey were found to be adequate representations of the population of the GDA when compared with the 2016 Census results for the GDA (CSO,2017).

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Table 6: Characteristics of the

	Survey		Census 2016 (GDA)	
Gender	N	%	N	%
Male	193	44.5	935,849	49
Female	239	55.5	971,483	51
Total	432	100	1,907,332	100
Age				
18 - 24 years old	38	8.8	168,686	11.7
25 -34 years old	84	19.4	304,968	21.1
35 -44 years old	114	26.4	315,207	21.8
45 - 54 years old	109	25.2	242,078	16.8
55 - 64 years old	67	15.5	186,756	12.9
65+ years old	20	4.6	226,362	15.7
Total	432	100	1,444,057	100.0
	Survey		Census 2016 (national)	
Education	N	%	N	%
No formal education/ training	3	0.7	16,711	1.5
Primary education	8	1.8	113,325	9.9
Secondary education	130	29.9	369,637	32.4
Technical or vocational	46	10.6	99,092	8.7
Advanced Certificate/ Completed Apprenticeship	26	6	63,322	5.5
Higher Certificate	49	11.3	59,886	5.2
Ordinary Bachelor Degree/ Diploma	66	15.2	99,679	8.7
Honours Bachelor Degree	55	12.6	156,350	13.7
Postgraduate Diploma/ Degree	48	11	147,700	12.9
Doctorate (Ph.D) or Higher	4	0.9	15,550	1.4
Total	435	100	1,141,252	100.0
Income				
€24,999 or less	110	25.3		
€25,000 - 49,999	129	29.7		
€50,000 - 74,999	74	17		
€75,000 - 99,999	27	6.2		
€100,000 or more	17	3.9		
I'd rather not say	78	17.9		
Total	435	100		

	Survey		Census 2016 (national)	
Marital Status	N	%	N	%
Single	179	41.5	1,055,977	55.4
Married	215	49.9	693,749	36.4
Separated	19	4.4	46,127	2.4
Divorced	15	3.5	41,373	2.2
Widowed	3	0.7	70,106	3.7
Total	431	100	1,907,332	100.0
Children/ dependents				
None	199	46	140,349	29.2
One	65	15	136,252	28.3
Two	98	22.6	124,728	25.9
Three	49	11.3	57,916	12.0
More than 3	22	5.1	21,817	4.5
Total	433	100	481,062	100.0
Economic Status				
Working for payment or profit	267	61.8	853,116	56.4
Looking for first regular job	8	1.9	12,771	0.8
Unemployed	24	5.6	99,248	6.6
Student	24	5.6	175,321	11.6
Looking after home/ family	40	9.3	115,164	7.6
Retired	36	8.3	197,761	13.1
Unable to work due to permanent sickness or disability	17	3.9	53,890	3.6
Other	16	3.7	5,350	0.4
Total	432	100	1,512,621	100.0
Living Location				
Dublin City Centre	55	12.7		
Inner Suburbs	141	32.6		
Outer Suburbs	101	23.3		
Commuter Town	78	18		
Rural Area	58	13.4		
Total	433	100		
Working location				
Dublin City Centre	135	33.8		
Inner Suburbs	116	29		
Outer Suburbs	67	16.8		
Commuter Town	53	13.3		
Rural Area	29	7.3		

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In terms of the trip attributes of the respondents, Table 7 shows that 39.5% of the sample drove to work or education, followed by 14% by bus, 11% walked, 9% took the train, DART[1] or Luas[2], 5% cycled. 4% of the respondents stated that they regularly or only telecommute (i.e. worked from home), and 2.4% carpooled to work or education. This modal split was ideal for this experiment as it presented us with a real challenge to shift many of those driving by car alone to other more sustainable modes such as walk, cycling, public transport and riding as a passenger in a car (i.e. carpool). Table 8 displays these modal share values amongst various other trip characteristics of the sample such as the trip times, distances travelled to work and education by the respondents. These attributes are also compared with data from the 2016 Census. It is observed that in the sample, 25% of the respondents' commute to work or education took 40 minutes or more closely followed by 11 to 20 minutes and 21 to 30 minutes on average. The distances travelled are linked to the time travelled, which showed that by a larger margin, 41.8% of the sample travelled over 8 kilometres to work or education. Similarly of interest is the number of cars available to each household, which 46% of the sample stated was one, followed 32% stating that two cars were available. Table 7 shows that these figures were close to the figures from the 2016 Census.

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1 Dublin Area Rapid Transit rail service
2 Luas is Dublin's light rail/ tram service

Table 7: Trip characteristics

	Survey		**Census 2016 (GDA)**				Survey		**Census 2016 (GDA)**	
Mode	N	%	N	%		**Trip time**	N	%	N	%
Not at work/education	67	12.1				10 mins or less	75	14.7	300,944	33.0
On foot	61	11.1	217,912	18.1		11 - 20 mins	112	21.9	355,748	39.0
Bicycle	27	4.9	60,454	5.0		21 - 30 mins	106	20.7		
Bus, minibus, coach	78	14.1	162,818	13.6		31 - 40 mins	88	17.2	255,094	28.0
Train, DART, Luas	51	9.2	73,005	6.1		40+ mins	130	25.4	208,463	22.9
Motorcycle or scooter	7	1.3	5,566	0.5		Total	511	100	911,786	100.0
Driving a car	218	39.5	441,147	36.7						
Passenger in a car	13	2.4	176,265	14.7		**Cost of commute**				
Van	6	1.1	35,594	3.0		€0	164	30.4		
Other, incl. taxi or truck	2	0.4	2,746	0.2		€1 - €10 per day	196	36.4		
Work mainly from home (i.e. telecommute)	22	4	25,782	2.1		€5 - €10 per day	122	22.6		
Total	552	100	1,201,289	100.0		€10 - €15 per day	39	7.2		
						€15+ per day	18	3.3		
Distance Travelled						Total	539	100		
Less than 2kms	92	17.4							**Census 2016 (GDA)**	
2 – 4kms	85	16.1				**Cars owned per household**				
4 – 6kms	74	14				One	246	46	272,687	42.5
6 – 8kms	57	10.8				Two	177	32.4	205,332	32.0
8+ kms	221	41.8				Three	26	4.8	33,760	5.3
Total	529	100				Four or more	9	1.6	10,249	1.6
						None	89	16.3	119,180	18.6
						Total	547	100	641,208	100.0

4.2 Model Results

The first stage in modelling the survey results was to construct a base model for each of the three models as part of this study, consisting only of the main attributes, attribute levels and alternative-specific constants assigned to each respective alternative/ mode (as seen in Tables 2, 3 and 4). Time should be devoted to understanding and making empirical sense of the base model output, for it acts as the main form of comparison with other more complex models produced later (Louviere, et al., 2000). In all models produced in this study, the car alternative was set as the base outcome or reference category, which serves as the main contrast point in the experiment and drives the interpretation of the results (Schofer, 2007). As shown in Tables 2, 3 and 4, the base model for the Active Modes model contained the attributes: Infrastructure, Time and Adjacent Traffic Speed, all with three levels attached to each attribute. The base model from the Public Transport model (Model 2) contained the attributes: Frequency, Time and Cost, again, all with three attribute levels. Finally, the base model for the Smart Modes model (Model 3) included the attributes: Convenience, Time and

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Cost, once again on three levels. The utility functions used in this CE for each of the three models were written as follows:

Model 1

$$
\begin{aligned}
U_{car} &= V_{car} + \varepsilon_{car} \\
U_{walk} &= V_{walk} + \varepsilon_{walk} \\
U_{cycle} &= V_{cycle} + \varepsilon_{cycle}
\end{aligned} \quad \textbf{(14)}
$$

Model 2

$$
\begin{aligned}
U_{bus} &= V_{bus} + \varepsilon_{bus} \\
U_{car} &= V_{car} + \varepsilon_{car} \\
U_{train} &= V_{train} + \varepsilon_{train}
\end{aligned} \quad \textbf{(15)}
$$

Model 3

$$
\begin{aligned}
U_{carpool} &= V_{carpool} + \varepsilon_{carpool} \\
U_{carshare} &= V_{carshare} + \varepsilon_{carshare} \\
U_{car} &= V_{car} + \varepsilon_{car}
\end{aligned} \quad \textbf{(16)}
$$

where:

U = Utility of the Mode, V is the determinist component defined below, ε = the error term

The linear expression of the representative element of the equation for the marginal utilities of the three models were then defined as:

Model 1 (Active Modes):

$V_{\mathrm{car}} = \beta_{0\mathrm{car}}$

$V_{walk} = \beta_{0\mathrm{walk}} + \beta_{1walk}$ * walkinfra + $\beta_{2\mathrm{walk}}$ * walktime + β_{3walk} * walkadjsp

$V_{cycle} =$ β_{1cycle} * cycleinfra + $\beta_{2\mathrm{cycle}}$ * cycletime + β_{3cycle} * cycleadjsp

Model 2 (Public Transport):

$V_{bus} = \beta_{0\mathrm{bus}} + \beta_{1bus}$ * busfreq + $\beta_{2\mathrm{bus}}$ * bustime + β_{3bus} * buscost

$V_{\mathrm{car}} = \beta_{0\mathrm{car}}$

$V_{train} =$ β_{1train}* trainfreq + $\beta_{2\mathrm{train}}$ * traintime + β_{3train} * traincost

Model 3 (Smart Modes – sustainable use of the private car):

$V_{carpool} = \beta_{0\mathrm{carpool}} + \beta_{1carpool}$ * carpoolconv + $\beta_{2\mathrm{carpool}}$* carpooltime + β_{3bus} * carpoolcost

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$V_{carshare} = \beta_{1carshare}$* carshareconv + $\beta_{2carshare}$* carsharetime + $\beta_{3carshare}$* carsharecost

$V_{car} = \beta_{0car}$

When these utility equations were coded in NLOGIT software and estimated, the following outputs were produced.

4.2.1 Base Model 1 (Active Modes Model)

To provide some initial context to this model, it can be seen in Table 8 details the proportions of respondents that chose each of the different modes in Model 1. The car (drive alone) option was most popular, with 35.08% of respondents choosing it, with 33.15% and 31.78% opting for the walk and cycle alternatives respectively.

Table 8: Model 1 sample proportions

Choice	Respondent Count	%
Car (drive alone)	563	35.08
Walk	532	33.15
Cycle	510	31.78
Total	1605	100

It became apparent when examining the base model results for Model 1 (Table 9) that the base attributes alone estimation did not produce the results that were anticipated, when compared to the other two models. Models 2 and 3 produced significantly better results than the first (active modes) model. The reasons for this were assumed by to be as a result of the respondents not fully making a trade -off between the three options (car, walk, cycle) presented to them in Model 1, or not fully understanding the task that was proposed. In this model, the context for the SP scenario was that respondents were offered a mode choice decision for a short distance trip (i.e. between 2 – 4kms, a distance that is generally considered suitable for these modes). Considering this distance, the respondents were then asked which of the following three modes would they most likely choose given the policy incentives assigned to the walking and cycling alternatives. Through examining the low pseudo rho-squared of 0.0013, it suggested that the base model does a poor job at fitting the MNL model to the sample data set and explaining the variances in the data. The closer to one that the rho-squared value is, the better the model result is in terms of statistical quality. This finding is mirrored through the high p-value of 0.644, which exceeds the level of alpha (0.05), meaning that we cannot reject the null hypothesis that the estimated model is no better than the constants only model. Thus, the assumption in Model 1 was that the policy scenarios provided to the respondents were not sufficient to ultimately entice those to shift from the car to more sustainable modes of transport, in this case walking and cycling, and due to this, this relationship did not exist in the base model. The *Cycletime* coefficient was positive and was the highest coefficient in the base model, signifying that reductions to a cycle trip of 2 to 6 minutes would increase the utility of the cycle mode. Simply put, as the trip became quicker the higher the likelihood of the respondent choosing this mode was. The extended model for model 1, on the other hand, produced much more significant results, indicating that socio-demographic characteristic better account of the variation found in the model.

Table 9: Base Model Output for Model 1

Observations N = 1605			
Variable		Coefficient	Z-stat
Walkinfra	Infrastructure	0.0040	1.17
Walktime	Time	-0.0143	-0.42
Walkadjs	Adj. Traffic Speed	0.00229	0.83
Cycleinfra	Infrastructure	0.0009	0.27
Cycletime	Time	0.0404	1.17
Cycleadjs	Adj. Traffic Speed	0.0020	0.74
Log Likelihood -1582.020			
Constants only log-likelihood (LL) -1584.138			
AICc 3180.0			
Pseudo Rho Squared 0.0013			
Prob. Chi-squared 0.64468			

* Significant at 90% confidence, ** Significant at 95% confidence, *** Significant at 99% confidence

4.2.2 Extended Model 1

Table 11 presents the estimated results from when a range of socio-demographic variables (coded in reference to Table 10) were added to the base model to improve the model estimation and account for the variation in the choices made in the SP scenarios. A distinct improvement was made to the model when these additional variables were estimated. As there were many predictors included in the full model output, the model was reduced to exclude the variables that were non-significant, thus the results presented here are the predictors that appeared statistically significant. From examining the output from NLOGIT, Table 11 shows that there were many significant socio-demographic variables, which improved the performance of the model, the modal fit and the quality of the model itself. Firstly, the log-likelihood value for the estimated model was -992.623, which was an improvement on the log-likelihood of the base comparison model (-1060.040), indicating that the model fits better with the data. As a result of the differences in log-likelihood, there was a notable increase in the pseudo rho-squared from the extended model (0.063) suggesting that the goodness of fit of the model rose significantly from the base model (0.0013). The AICc for the model was 2041.2, in contrast to the AICc of the base model (3180), meaning that the extended model provides a better trade-off of goodness of fit and quality of the statistical model than the base model. The p-value for the extended model (0.000) was sufficiently less than alpha, which permits the null hypothesis to be rejected as a

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greater extent of the variation in the model is explained by means of the addition of the predictor variables.

With reference to the parameter estimates in Table 11, the results indicate, unlike in the base model, that the *Walkinfra* variable is now significant at 90% confidence, and the coefficient is positive explaining that as the policy plan increases the percentage of evenly surfaced, widened footpaths, separated from traffic - the utility of the walking mode as rises. In relation to the predictors, females were more likely to walk to work or education than males, and older age groups would be more likely to walk then younger age cohorts. Furthermore, possessing a driver's licence, owning more than one car and having free parking available at your place of work or college/ university dramatically decreases the chances of that individual opting to walk to work or education, which makes intuitive sense. For the cycling alternative, this was also the case, though in addition to this, the results also suggested that those not in full time employment, i.e. the unemployed, students, the retired etc., were more likely to cycle to work or education, from previous experience, as was stated in the survey that if the respondent was not currently in employment or studying, that they should respond in accordance to how they used to travel when they were. Finally, having one child or more significantly decreased the chances of those commuting by bike.

Table 10: Socio-demographic Variable Coding

Variable	**Abbreviation**	**Coding**
Socio-demographic variables		
Gender	GEN	Male = 1, Female = -1
Age range	AGE	18 - 24 years old = 1, 25 -34 yo = 2, 35 - 44 yo = 3, 45 - 54 yo = 4, 55 - 64 = 5, 65+ yo = 6
Highest level of education	EDU	No former education/ training = 1, Primary education = 2, Secondary education = 3, Technical or vocational = 4, Advanced Certificate/ Completed Apprenticeship = 5, Higher Certificate = 6, Ordinary Bachelor Degree/ Diploma = 7, Honours Bachelor Degree = 8, Postgraduate Diploma/ Degree = 9, Doctorate (Ph.D.) or Higher = 10
Average annual household income range	INC	€24,999 or less = 1, €25,000 - €49,999 = 2, €50,000 - €74,999 = 3, €75,000 - €99,999 = 4, €100,000 or more = 5, I'd rather not say = 6
Living location	LIVE	Dublin city centre (i.e. within the canals) = 1, Inner Suburbs (i.e. within canals & M50 motorway) = 2, Outer Suburbs (i.e. outside M50 motorway = 3, Commuter Town = 4, Rural Area = 5
Working location/ Location of education	WORK	Dublin city centre (i.e. within the canals) = 1, Inner Suburbs (i.e. within canals & M50 motorway) = 2, Outer Suburbs (i.e. outside M50 motorway = 3, Commuter Town = 4, Rural Area = 5
Economic status	EMPL	Working for payment or profit = 1, Looking for first regular job = 2, Unemployed = 3, Student = 4, Looking after home/ family = 5, Retired = 6, Unable to work due to permanent sickness or disability = 7, Other = 8
Marital Status	MARIT	Single = 1, Married = 2, Separated = 3, Divorced = 4, Widowed = 5
Number of children/ dependents	CHILD	None = 1, One = 2, Two = 3, Three = 4, More than 3 = 5
Possession of a driving license	LIC	Yes = 1, No = 0

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Number of cars owned per household	OWN	None = 1, One = 2, Two = 3, Three = 4, Four or more = 5
Free parking available at workplace/ college?	PARK	Yes = 1, No = 0

Table 11: Extended Model Output for Model 1

Observations N = 1605			
Variable		Coefficient	Z-stat
Walkinfra	Infrastructure	0.0077*	1.74
Walktime	Time	-0.0124	-0.28
Walkadjs	Adj. Traffic Speed	0.0027	0.78
Walkgen	Gender	-0.2778***	-3.17
Walkage	Age	0.2374***	3.30
Walkedu	Education	0.0912**	2.19
Walklic	Licence	-1.3091***	-6.02
Walkown	Car Ownership	-0.3765***	-3.27
Walkpark	Free Parking	-0.3800**	-1.98
Cycleinfra	Infrastructure	0.0021	0.49
Cycletime	Time	0.0363	0.84
Cycleadjs	Adj. Traffic Speed	0.0028	0.83
Cycleedu	Education	0.0907**	2.22
Cycleemp	Employment Status	0.1416***	3.76
Cyclechil	No. of children	-0.1109*	-1.66
Cyclelic	Licence	-0.5030**	-2.26
Cyclepark	Free Parking	-0.5168***	-2.80
Log Likelihood -992.623			
Constants only LL -1060.040			
AICc 2041.2			
Pseudo Rho Squared 0.063			
Prob. Chi-squared 0.000			

* Significant at 90% confidence, ** Significant at 95% confidence, *** Significant at 99% confidence

4.2.3 Elasticity and simulation results from Model 1

Table 12 displays the results of direct and cross elasticities estimated in NLOGIT given changes being made to each of the three attributes present in Model 1. The results show that given a one percentage increase in the time attribute, equivalent to a 1% decrease in the time of a cycling trip, would increase the probability of choosing the cycling alternative by 0.03%. If the 1% increase in time were applied to the walking alternative it would also increase the likelihood of it being chosen by 0.03%. Yet if there was such as decrease in the time of car trip, as expected, both the cycling and walking modes would experience a decrease in the probability of each being chosen by 0.016% and 0.17% respectively. If these changes were made to the infrastructure attribute, i.e. an extra 1% increase in the incidence of fully segregated cycle tracks or the availability of well-lit, evenly surfaced and widened footpaths separated from other traffic, then the outcome of this would be a 0.066% and 0.068% increase in probability of the cycle and walking modes being opted for. Yet, the most significant elasticities from Model 1 were in relation to increases in the adjacent traffic speed attribute, which makes intuitive sense, as there is a direct linkage to the perception of safety on such

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routes given reductions of the speed of traffic and from this it is expected that the perceived level of risk in taking these modes also falls. For instance, a 0.108% and 0.111% increase in the likelihood of the cycling and walking modes being chosen would occur given an additional 1% rise in the percentage of the trip with a 30km/h or lower speed limit. In terms of the cross elasticities for adjacent traffic speed attribute, falls of 0.054% and 0.052% would ensue from the 1% rise being assigned to the car alternative only.

Thus, from analysing elasticities output, it is apparent that opportunities to encourage commuters to actives modes exist as a result of increasing the strength of attribute levels of various policy incentives, which could result in further car-shedding behaviour for daily commutes to work and education. The results indicate that if there were a further increase in the strength of the impact of the policy measures in the choice scenarios, then the probability of walking and cycling being chosen by a commuter would increase up to an additional 0.108%, hence further increasing the utility of these modes.

<u>Table 12</u>: Elasticities from a 1% changes in infrastructure, time and adjacent traffic speed attributes

Infrastructure	Car (%)	Walk (%)	Cycle (%)
Car	0	0	0
Walk	-0.0335	0.0666	-0.0335
Cycle	-0.0322	-0.0322	0.0679
Time	Car (%)	Walk (%)	Cycle (%)
Car	0	0	0
Walk	-0.0169	0.0337	-0.0169
Cycle	-0.0162	-0.0162	0.0344
Adjacent traffic speed	Car (%)	Walk (%)	Cycle (%)
Car	0	0	0
Walk	-0.0546	0.1088	-0.0546
Cycle	-0.0524	-0.0524	0.111

As a further step in the analysis of the results of Model 1, 'what if' simulations of the impacts of changing the actual attribute level values (opposed to percentage changes) were conducted using NLOGIT software. Through analysing the results of modifying the various attributes, it was found that the effect of increasing the infrastructure attribute value to 80% produced the most significant results. This scenario examines the impact of adding a further 10% (on top of the modelled 60%) of a walking or cycling route with evenly surfaced, widened paths, separated from traffic. In other words, the attribute level is increased and then modelled for its consequence on modal share and choice

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proportions. The findings from this analysis can be observed in Table 13, where the 80% value for infrastructure translated into 32 of the total 432 SP choices switching from the 'driving alone' car mode to the walk and cycle modes. These 32 choices that switched, were equivalent to 2.23% of the sample and of this 1.14% switched to cycling and walking. By simulating an increase in the time attribute to 8 minutes it led to a lesser modal shift of 1.14% of respondents shifting way from solo driving to walking and cycling. From Table 13 we can also observe from modifying the infrastructure variable, that the car goes from being the most chosen alternative in the base case to the third most preferred alternative, with walking attracting the highest modal share in the simulated scenario.

Table 13: Simulation of new value for Infrastructure attribute

Alternatives	Base Share		Scenario		Choice share changes	
***Infrastructure* - fixed at new base value of 80% reduction**						
	N	% Share	N	% Share	N	% Share
Car	506	35.06	474	32.82	-32	-2.23
Walk	478	33.12	494	34.26	16	1.14
Cycle	459	31.80	475	32.90	16	1.14
***Time* - fixed at new base value of 8 mins reduction**						
Car	506	35.06	490	33.92	-16	-1.14
Walk	478	33.12	486	33.70	8	0.58
Cycle	459	31.80	467	32.36	8	0.58

4.2.4 Base Model 2 (Public Transport Model)

Model 2, consisting of the bus and rail alternatives produced noteworthy results in the context of the aims of the experiment (i.e. encouraging a shift away from solo driving to alternative modes). This is conveyed in Table 14, which shows the proportions of respondents that chose each of the alternatives. It is observed that 42.93% of the sample opted for the Bus alternative given changes being made to the frequency, time and cost of the services, through policy intervention. The rail option was chosen by 34.58% of the sample, whereas only 22.49% chose car, which adds weight to the statement that policy incentives incorporated into the SP scenarios can modify individuals' modal choice for commuting trips.

Table 14: Model 2 sample proportions

Choice	Respondent Count	%
Bus	689	42.93
Car	361	22.49
Rail	555	34.58
Total	1605	100

Looking closer, from the base model results in Table 15, it can be seen that a number of the coefficients were statistically significant. The cost attribute in particular, was significant for both the

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bus and rail alternatives (at 95% for bus and 99% for rail), indicating that as these trips became cheaper (i.e. a 15 – 35% reduction in the fare), the utility for these modes increased. This demonstrates that the likelihood of individuals choosing to commute by bus and rail increases as the policy incentive to reduce bus/ rail fares also increases. Moreover, the most significant coefficient in this base model for Model 2 was *Traintime,* suggesting that policy incentives to reduce rail times would result in higher utility for this mode. Albeit, the pseudo rho-squared value (0.012) is not ideal, it is a large improvement over Model 1. It must also be reiterated that the R^2 used in logistic regression is not the equivalent to R^2 in linear regression, as MNL models are non-linear and the pseudo rho-squared here is not representative of the model fit. It is utilised as a means of comparison between two MNL models from the same dataset. Yet, the chi-squared p-value was 0.000 signifying that the null hypothesis can be rejected.

Table 15: Base Model Output for Model 2

Observations N = 1605			
Variable		Coefficient	Z-stat
Busfreq	Frequency	0.0025	0.94
Bustime	Time	0.0089	1.33
Buscost	Cost	0.0228**	3.53
Trainfreq	Frequency	0.0015	0.56
Traintime	Time	0.0279***	4.00
Traincost	Cost	0.0155**	2.29
Log Likelihood -1459.354			
Constants only LL -1477.314			
AICc 2934.7			
Pseudo Rho Squared 0.012			
Prob. Chi-squared 0.000			

* Significant at 90% confidence, ** Significant at 95% confidence, *** Significant at 99% confidence

4.2.5 Extended Model 2

As in Model 1, Model 2 was similarly extended to include the various socio-demographic variables listed in Table 10, the output from which is presented in Table 16. The most noticeable indicator from these results was the log-likelihood values, LL figure for the estimated model was -872.445, much lower than the figure produced for the constants only model (-971.709), adding evidence to the assumption that the extended model is a better estimate and more accurate model than the base comparison. This is similarly reinforced by the pseudo rho-squared value of 0.102, suggesting that the model does a good job at explaining the variation in the model, and the AICc value of 1800.9, which when compared to the base model figure of 2934.7 is an improvement in the statistical quality of the estimation produced. As observed in Table 16, many of the variables were shown to be statistically significant. For example, some of the main attributes in the model displayed increased significance in the extended model, such as the *Bustime* and *Buscost* coefficients. The socio-demographic variables

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provide greater detail on the profile of the individuals who chose the alternatives. For the bus and rail options, those with a higher level of education were more likely to choose these modes than those with lower levels of education. This is also true for the economic and marital status of the individuals. Those who were not in full time employment and those were married were more likely to travel by car than bus or rail, which would perhaps be influenced by the levels of income of these individuals given their sociodemographic characteristics. The *Buschild* coefficient suggests as it is negative that individuals with one or more children individuals are much less likely to commute to work or education by bus. Older age groups showed greater chances of taking the rail to work or education, in this way increasing the utility for this mode. Akin to Model 1, by having a driving license and access to at least one car per household negatively influenced the chances of individuals commuting by bus or rail, which was expected.

Table 16: Extended Model Output for Model 2

Observations N = 1605			
Variable		Coefficient	Z-stat
Busfreq	Frequency	0.0038	1.10
Bustime	Time	0.0147*	1.71
Buscost	Cost	0.0307***	3.70
Busedu	Education	0.1116**	2.51
Busempl	Employment Status	0.1092**	2.07
Busmari	Marital Status	0.5686***	3.48
Buschil	No. of Children	-0.1116*	-1.86
Buslic	Licence	-1.6312***	-5.44
Busown	Car ownership	-0.4931***	-4.00
Trainfreq	Frequency	0.0019	0.54
Traintime	Time	0.0316***	3.52
Traincost	Cost	0.0165*	1.92
Trainage	Age	0.2264**	2.57
Trainedu	Education	0.1743***	3.70
Trainempl	Employment Status	0.1370**	2.52
Trainmari	Marital Status	0.2936*	1.75
Trainlic	Licence	-1.4228***	-4.62
Trainown	Car Ownership	-0.5399***	-4.19
Trainpark	Free parking	-1.0903***	-4.49
Log Likelihood -872.445			
Constants only LL -971.709			
AICc 1800.9			
Pseudo Rho Squared 0.102			
Prob. Chi-squared 0.000			

* Significant at 90% confidence, ** Significant at 95% confidence, *** Significant at 99% confidence

4.2.6 Elasticity and simulation results from Model 2

Table 17 displays the elasticity results from Model 2 as a consequence of a 1% change in the frequency, time and cost attributes present in this model. The most striking result from this table is in

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relation to the cost variable which resulted in the highest percentage changes in the bus and rail alternatives. Surges of 0.31% and 0.27% in the likelihood of the rail and bus modes, respectively, being chosen were produced from a 1% increase in the level of the cost attribute, which translates into a 1% decrease in bus and rail fares. However, if such cost savings were made to the car alternative, a decrease 0.21% in the probability for bus and 0.17% rail being chosen, would be experienced. Moreover, the time attribute similarly produced significant elasticity findings given a 1% decrease in trip times. For rail a 0.289% increase in the likelihood would be noticed, and a 0.25% growth for the bus alternative. The frequency variable produced less significant but still positive results as a result of such changes, increases of 0.066% for rail and 0.057% for bus.

Table 17: Elasticities from a 1% change in the frequency, time and cost attributes

Frequency	Bus (%)	Car (%)	Rail (%)
Bus	0.0575	-0.044	-0.044
Car	0	0	0
Rail	-0.0354	-0.0354	0.066
Time	Bus (%)	Car (%)	Rail (%)
Bus	0.2514	-0.1982	-0.1982
Car	0	0	0
Rail	-0.1601	-0.1601	0.2894
Cost	Bus (%)	Car (%)	Rail (%)
Bus	0.2708	-0.2145	-0.2145
Car	0	0	0
Rail	-0.1734	-0.1734	0.3119

As per in Model 1, simulations were run in NLOGIT using new attribute level values again in Model 2 (Table 18). Changing the time and costs separately, both produced significant results in terms of switching behaviour from the car to other sustainable modes. For example, for the time attribute, increasing the percentage reduction in travel time from 35% to 50% led to a direct 6.85% or 95 choice reduction in those choosing the car alternative. Likewise, for the cost attribute which was also set to 50% value, this led to a greater 7.24% of the sample opting to switch to the bus (4.06%) and to the bus (3.18). These results are encouraging, as it adds weight to the argument that by offering real incentives to commuters, and through making tangible changes of important trip attributes like trip time and cost, that those who once travelled to work and education by car may wish to take another ‘greener’ mode, owing to those modes being more practical and convenient.

Table 18: Simulation of new values for Time and Cost attributes

Alternatives	Base Share	Scenario	Choice share changes

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Time- fixed at new base value of 50% reduction						
	N	% Share	N	% Share	N	% Share
Bus	595	42.92	648	46.76	53	3.83
Car	312	22.51	217	15.65	-95	-6.85
Rail	479	34.56	521	37.57	42	3.01
Cost **- fixed at new base value of 50% reduction**						
Bus	652	48.40	651	46.98	56	4.06
Car	334	24.79	212	15.26	-100	-7.24
Rail	361	26.80	523	37.74	44	3.18

4.2.7 Base Model 3 (Smarter Car Use Model)

The final of the three models is Model 3, that includes carpooling and car-sharing as alternatives. This model is particularly important in the context of this study as it directly relates to the sustainable usage of the private car in order to encourage *car-shedding* behaviour, by means of reducing the number of people driving alone to work, rendering the car of less importance for commuting proposes. It is predicted that by attracting more people to commute by carpool or take up a car-share membership through various policy incentives, that ultimately a reduction in car use and potentially car ownership could transpire.

In this regard, Table 19 provides some appealing results. Carpool was the clear winner in terms of the choice proportions in the SP experiment with almost half of respondents (48.41) choosing this alternative. The remaining two options (Car and Car-share) were quite close with 26.79% and 24.80% of the respondents selecting these modes respectively. This provides an encouraging signal that more people can be attracted to making more efficient use of the private car by increasing the occupancy levels of cars for commuting purposes, thus reducing the modal share of those driving to work/ education alone.

Table 19: Model 3 sample proportions

Choice	Respondent Count	%
Carpool	777	48.41
Car-share	398	24.8
Car	430	26.79
Total	1605	100

The base model results for Model 3 (Table 20), are likewise strong as all the parameter coefficients are statistically significant and the chi-squared probability value is satisfactorily alpha to warrant a rejection of the null hypothesis that the policy incentives do not increase the utility of the carpool and car-share alternatives. The most significant coefficients are related to the cost attribute, suggesting that as carpooling and car-sharing become increasingly cheaper modes, the utility of these modes also increases and the likelihood of individuals choosing them rises. The same can be said for the

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convenience and time attributes in this model, which offers strong evidence that the policy plans (i.e. reducing access, wait times and trip times), included in the SP scenarios, do in fact encourage more commuters to opt for carpooling and car-sharing, consequently enhancing the chances of car-shedding behaviour in the longer term.

Table 20: Base Model Output for Model 3

Observations N = 1605			
Variable		Coefficient	Z-stat
Carpconv	Convenience	0.0109***	3.24
Carptime	Time	0.0128*	1.91
Carpcost	Cost	0.0179***	2.65
Carsconv	Convenience	0.0131***	3.33
Carstime	Time	0.0171**	2.18
Carscost	Cost	0.0192**	2.45
Log Likelihood -1393.401			
Constants only LL -1414.195			
AICc 2802.8			
Pseudo Rho Squared 0.014			
Prob. Chi-squared 0.000			

* Significant at 90% confidence, ** Significant at 95% confidence, *** Significant at 99% confidence

4.2.9 Extended Model 3

The extended Model 3 (Table 21) once again improves upon the base model results, by producing a higher pseudo rho-squared value of 0.074, in contrast to the base model value of 0.014, thus suggesting that the extended model is a much more accurate representation of the data. A comparison of the log-likelihood and AICc values supports this statement, as the extended model produced a LL figure of -856.938 and AICc of 1773.9 and the base comparison log-likelihood value of -925.384 and AICc of 2802.8 demonstrating that the extended model is of better quality and goodness of fit to the data.

Table 21 shows that all the beta coefficients are statistically significant to various confidence levels, with the exception of the *Cartime* coefficient, which exhibited a minor drop just leaving it slightly the 90% confidence level. This may suggest that individuals who chose to carpool did not place an importance on the time attribute. Various predictors in the model produced significant results with gender, age and education level being similarly significant variables for both the carpool and car-share alternatives. These coefficients indicate that females, within higher age cohorts with higher levels of education were more likely to carpool and car-share than younger males with lower levels of education. Those living in areas in the outer suburbs or peripheral locations of the GDA would have higher chances of choosing to carpool which is logical given conceivably longer commuting distances to work or education. In addition to this, single people were distinctly more likely to carpool than married individuals. Yet those working in closer proximity to Dublin city centre in full-time employment would be more likely to car-share, perhaps given the greater availability of car-sharing vehicles in the Dublin city centre. Having a driving license and the more cars owned, like in model 1 and 2 reduced the chances of those commuting by carpool and car-sharing to work or education.

Table 21: Extended Model Output for Model 3

Observations N = 1605			
Variable		Coefficient	Z-stat
Carpconv	Convenience	0.0131***	3.06
Carptime	Time	0.0126	1.47
Carpcost	Cost	0.0246***	2.86
Carpgen	Gender	-0.2023**	-2.23
Carpage	Age	0.3678***	4.68
Carpedu	Education	0.1824***	4.38
Carplive	Living location	0.1904**	2.25
Carpmari	Marital Status	-0.2210**	-2.01
Carplic	Licence	-0.9395***	-3.91
Carpown	Car Ownership	-0.3005***	-2.71
Carsconv	Convenience	0.0098**	1.97
Carstime	Time	0.0187*	1.86
Carscost	Cost	0.0209**	2.07
Carsgen	Gender	-0.3260***	-3.08
Carsage	Age	0.2589***	2.89
Carsedu	Education	0.0836*	1.65
Carswork	Working location	-0.2381**	-2.27
Carsempl	Employment Status	-0.0952*	-1.72
Carschil	No. of Children	0.1786**	2.16
Carslic	Licence	-0.5606**	-2.05
Carsown	Car Ownership	-0.3135**	-2.40
Log Likelihood -856.938			
Constants only LL -925.384			
AICc 1773.9			
Pseudo Rho Squared 0.074			
Prob. Chi-squared 0.000			

* Significant at 90% confidence, ** Significant at 95% confidence, *** Significant at 99% confidence

4.2.11 Elasticity and simulation results from Model 3

The elasticities of Model 3 are also examined, in Table 22 to analyse the impact of a 1% change to the three attributes that Model 3 incorporates (convenience, time, cost). In parallel to the attributes in the public transport model (model 2), trip cost and time are very sensitive to changes in attribute level. Trip cost is once again most significant with a 0.34% increase in the probability of car-sharing being selected and 0.23% for carpooling. However, if this change were to be applied to either carpooling or car-sharing only, then this would negatively affect the likelihood of the mode with no such change. For example, if a 1% decrease in the cost of car-sharing occurred, this would result in a fall of 0.228% in carpooling being chosen, and if the cost of carpooling was altered, car-sharing would undergo an

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0.118% reduction in the probability, thus lowering its utility overall. Comparable effects are noticed with the time and convenience attributes as boosts of 0.27% and 0.185% to the probability of car-sharing and carpooling are recorded for time and increases of 0.26% and 0.17% for these modes from changes to the convenience variable.

Table 22: Elasticities from a 1% change in the convenience, time and cost attributes

Convenience	Carpool (%)	Car-share (%)	Car (%)
Carpool	0.1739	-0.1808	-0.1808
Car-share	-0.0947	0.2601	-0.0947
Car	0	0	0
Time	Carpool (%)	Car-share (%)	Car (%)
Carpool	0.1852	-0.1805	-0.1805
Car-share	-0.0931	0.2726	-0.0931
Car	0	0	0
Cost	Carpool (%)	Car-share (%)	Car (%)
Carpool	0.2318	-0.228	-0.228
Car-share	-0.118	0.3418	-0.118
Car	0	0	0

Table 23 provides the interesting results from the analysis of Model 3, as a rather large percentage of the sample were estimated to switch from the driving alone car alternative to the smarter and more sustainable usage of the private car modes (carpooling and car-sharing). This is a substantial finding in the context of this report as it provides further evidence of the prospect if engaging with commuters in the GDA and encouraging car-shedding behaviour, without sacrificing the real benefits of owning a private vehicle, e.g. comfort, freedom, independence and status. This is particularly evident with the cost attribute, which was modified from a 35% value to 50%. The results revealed that 107 are estimated to switch to carpool and car-share given this extra cost saving. Of these 107 individuals, it is estimated that 72 could switch to carpool and 35 to car-share, which is quite significant as this translates into 5.34% and 2.61% of the sample respectively. Changes made to the time and convenience attributes also produced noteworthy findings, as 6.49% of the sample are estimated to switch to carpool (4.33) and car-share (2.15) when time is set to a 50% attribute level value, and 6.3% of respondents are predicted to move to smarter modes as a consequence of changing convenience to a 60% reduction value.

Table 23: Simulation of new values for Time and Cost attributes for Model 3

Alternatives	Base Share		Scenario		Choice share changes	
***Convenience* - fixed at new base value of 60% reduction (access + wait times)**						
	N	% Share	N	% Share	N	% Share

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Carpool	652	48.40	693	51.41	58	4.32
Car-share	334	24.79	352	26.1	27	1.97
Car	361	26.80	303	22.4	-85	-6.30
***Time* - fixed at new base value of 50% reduction**						
Carpool	652	48.40	710	52.73	58	4.33
Car-share	334	24.79	363	26.95	29	2.15
Car	361	26.80	274	20.31	-87	-6.49
***Cost* - fixed at new base value of 50% reduction**						
Carpool	652	48.40	724	53.74	72	5.34
Car-share	334	24.79	369	27.41	35	2.61
Car	361	26.80	254	18.84	-107	-7.96

4.3 Discussion of Results

This experiment was conducted with the principal aim of analysing the impact of strategically designed policy plans on the commuting population of the GDA. The tool most commonly applied to experiments in this field of research, was determined to be a SP survey that incorporated these policies into hypothetical choice scenarios. This was an approach that has, to the knowledge of the author, not been conducted in Ireland to date, which presents a valuable opportunity for further empirical research in this area as the EU directive deadlines of 2020 and 2030 approach rapidly.

In analysing the results of this survey, it became apparent that individual commuters do need a proper incentive to disrupt commuting habits that may have been in place for a considerable amount of time. Still, if such incentives can lead to tangible time and cost savings for the commuter, then this can result in extensive sustainable mode choice behaviour. The scenarios were constructed to encourage the respondents to deliberate on the attributes that were of real importance to them and from this they were prompted to make trade-off between three modes of transport in each scenario. If the respondent was not attracted by the incentives presented or if given their socio-demographic characteristics, the sustainable modes were not able to be realistically considered, then the status-quo ‘drive alone’ option was included as a no-choice alternative, for no incentives nor disincentives were applied to it. Yet, from examining the results it was found that with the exception of Model 1, the sample responded very positively to the experiment, to the extent that the car alternative was placed second or even third in order of preference. This indicated that there is robust evidence for investing more attention to providing commuters with more enticements to switch to other modes. It also suggests that operators of public transport services as well as bike sharing and car-sharing providers may benefit greatly from influencing government authorities to consider increasing their budget for measures discussed here.

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4.4 Conclusion

This report has set the context of this study with an extensive literature review of work related to modal choice behaviour and stated preference modelling, it has also defined the experiment structure and methodology of this study by outlining the theoretical background of discrete choice modelling, and delineating the investigational process required to conduct such an experiment. It finally described in detail the findings from the multinomial modelling conducted using the choices made by the survey respondents. The following conclusions can be made from these results:

- A considerable modal shift is feasible in the GDA, given resources being directed to policy packages that enhance active, public transport and smart modes of transport.
- The base model for Model 1 produced poor goodness of fit results given the attributes in the choice scenarios and as a result of respondents either not making a trade-off between the three alternatives or not comprehending the context of the scenario set-out. However, the quality and model fit to the data improved substantially in the extended model where many key socio-demographic variables such as gender, age, education and economic status reflected the variation in the choices from the sample. Modifying the adjacent traffic speed attribute led to the highest increase in the probability of the walking and cycling modes being chosen.
- The output from Models 2 and 3 resulted in much more significant results in terms of the higher choice proportions for bus, rail, carpooling and car-sharing, thus adding weight to the hypothesis that policy incentives are a valuable and effective method of encouraging a sustainable modal shift.
- Evidence supporting a modal shift to the bus and rail alternatives was apparent in Model 2, with much higher percentages of the sample opting to choose these modes, the MNL model estimates indicated that the time and cost attributes were significant determinants to increasing the utility of public transport modes and this was further strengthened in the extended model as the model fit and quality produced was the highest recorded in this experiment. Alterations to the time and cost attributes were explored in the elasticities and 'what if' simulations in NLOGIT, which found that significant losses to the utility and modal share of the car alternative would be experienced given such changes.
- Model 3 built further upon the evidence base in Model 2, as it demonstrated that car-shedding behaviour is strongest in relation to more intelligent and sustainable usage of the private car through carpooling and car-sharing owning to attractive policy incentivisation. All parameter coefficients were found to be significant from the base model which was a testament to the importance of convenience, time and cost as trip attributes. The extended model enhanced the base comparison model considerably with numerous socio-demographic characteristics explaining

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the variation in the estimates produced in the base model. However, perhaps the most appealing indicator from this analysis was present in the elasticities and simulated modal share estimates. The results indicated that up to 7.96% of the car modal share of the sample could be redistributed to carpooling and car-sharing given increases made to the attributes in the model and increases to the probability of these modes being chosen grew to up to 0.34% from a 1% increase in the time, cost and convenience variables individually.

In conclusion, an extensive amount of data from the analysis in this report suggests that car-shedding interventions (i.e. strategic policy incentives) can potentially influence a sizable reduction in car use for commuting purposes by means of modal switching from driving alone to active modes, public transport and on-demand car services like carpooling and car-sharing. The findings are a crucial element of this project as they will act as a solid base case and reference for the work carried out in the next work package (WP5), which examines modifications to the NTAs mode choice utility equations to produce more accurate forecasts of modal share up to 2030 in line with EU target deadlines, in addition to potential emission savings. SP or choice modelling approaches such as that explored in this report are valuable in the context of 'management decisions, project appraisals and policy appraisals where the decision is based on changes in the levels that attributes take' (Accent, 2010).

In comparison to similar work conducted elsewhere in the world, Catalano, et al. (2008) concluded in their analysis that, with the introduction of policies such as: increasing the availability of reserved parking areas for car-sharing and carpooling users, development of the public transport system by reducing the in-vehicle and waiting times and a rise in the parking fees for high emission vehicles, increased the model share of car-sharing from zero to 10% and carpooling seeing a moderate increase also, in Palermo, Italy. In India, Malodia and Singla (2016) also found that cost savings proved to be the most significant instrument, followed by travel time, in encouraging the up-take of carpooling. In China, Weibin, et al., (2017) determined that both income and time constraints have significant effects on utility of alternative modes of transport for commuters in Beijing. Hence, these findings from stated preference mode choice studies in other countries are relatively in line with the results produced in this paper. However, it is worth noting that as the study area of this experiment was limited to the GDA, it remains to be seen whether such outcomes could be replicated elsewhere in Ireland. As more alternatives to the private car already exist in the GDA, it would suggest that lower estimates would be recorded outside of the study area.

Overall, the results in this report show that there exists and opportunity to induce a shift from solo driving to other more sustainable modes of transport or simply by increasing the occupancy levels of private cars by means of carpooling and car-sharing. This was examined in the context of not adding disincentives to using the private car alone, which is contrary to work produced by Eriksson,

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Nordlund and Garvill (2010), who state that is it necessary to have a combination of carrot and sticks to achieve the highest modal shift. However, it was the aim of this study to isolate the car (drive alone) option as a status quo option, with no attributes associated, to act as an option for respondents who were not enticed by the policy incentives. Further examination of the potential for car-shedding behaviour will be conducted using more complex national demand forecast and regional models to establish precise modal share predictions and to produce estimates for the associated impacts on emissions levels.

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Appendix A: Copy of the Stated Preference Survey

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GREENING TRANSPORT

1. How do you usually travel to work/ education?

- ◯ Not at work/ education
- ◯ On foot
- ◯ Bicycle
- ◯ Bus, minibus or coach
- ◯ Train, DART or Luas
- ◯ Motorcycle or scooter
- ◯ Driving a car
- ◯ Passenger in a car
- ◯ Alternatively fueled car (electric etc.)
- ◯ Van
- ◯ Other, including taxi or truck
- ◯ Work mainly from home (i.e. telecommuting)

**** Please answer the following questions with reference to your current commute to work or education.**

If you are not currently in work or education please answer based on how used to travel to work or education **

2. What distance is your journey from your home to work/ education and how long does it usually take?

	Distance	Time
Select one answer from each of the drop down menus		

3. What is the approximate out-of-pocket cost of your daily commute (total = both to and from your place of work/ education)?

- ◯ It doesn't cost me anything
- ◯ €1 - €5 per day
- ◯ €5 - €10 per day
- ◯ €10 - €15 per day
- ◯ €15+ per day

4. Do you have a driving license?

- ◯ Yes
- ◯ No

5. How many cars are owned or are available for use by one or more members of your household?

- ◯ One
- ◯ Two
- ◯ Three
- ◯ Four or more
- ◯ None

6. Is free parking available at your workplace/ place of education?

- ◯ Yes
- ◯ No

GREENING TRANSPORT

7. Which of the following measures would encourage you to cycle to work if you lived close enough and owned a bicycle? (Please select one)

- Improved cycle routes
- Bicycle facilities and security in work
- Less traffic on the roads
- Loans to buy a bicycle
- Financial incentives
- N/A
- Other (please specify)

8. Which of the following measures would encourage you to use public transport to travel to/ from work? (Please select one)

- More frequent services
- Nicer vehicles
- Reliable services
- More information
- Better stop locations
- Discounted tickets
- N/A
- Other (please specify)

9. Please state the importance of the following measures in encouraging you to carpool to and from work/ education.

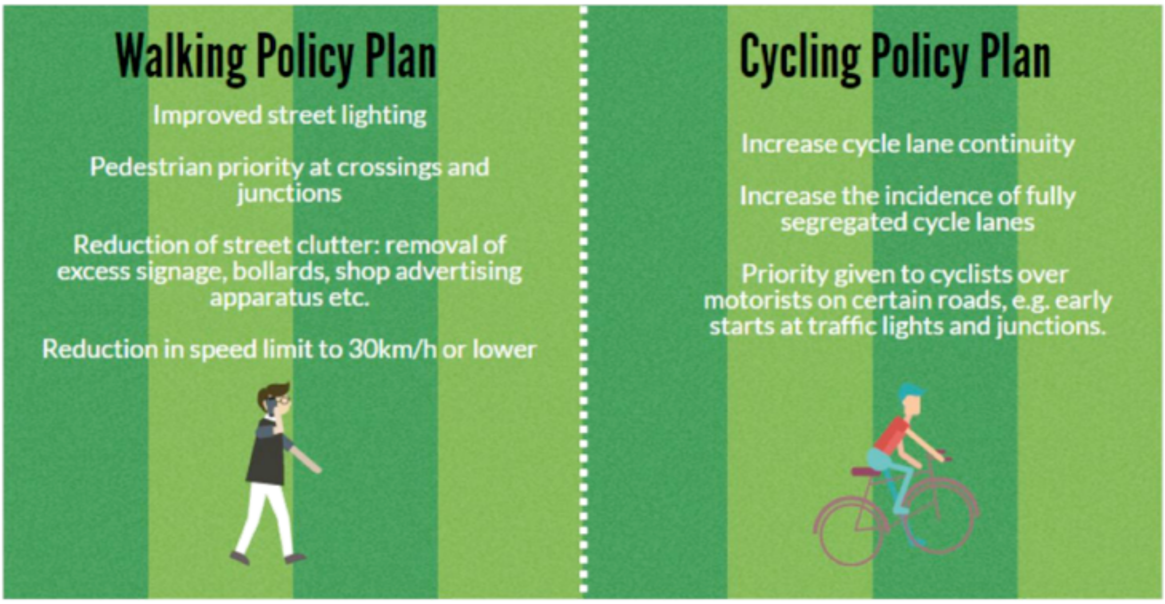
	Important	Undecided	Unimportant
Help finding a carpool/ car-share partner	◯	◯	◯
Free taxi home if let down by carpool partners/ guaranteed ride home	◯	◯	◯
Financial incentives/ rewards to carpool or car-sharing	◯	◯	◯
Free parking	◯	◯	◯
Free tolls	◯	◯	◯
Availability of carpool lanes/ high occupancy lanes	◯	◯	◯

Other (please specify)

Greening Transport

Active Modes Scenario 1

This section asks you to imagine that you have been offered a job in anew location and you are deciding how to travel to work based on the introduction of new policies.



You will be presented with choice scenarios; in which you will be asked to rank your preferred modes of transport.

Imagine how you will travel to your new work location. Taking note of the above policy plans, please consider the following scenarios and rank the modes that you would take.

Option	Policy	Effect on your trip		
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		
Walk 	Walking Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		20% of trip with widened, even paths	2 mins off trip time	50% of trip with 30km/h speed limit
Cycle 	Cycling Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		20% of trip fully segregated from traffic	2 mins off trip time	50% of trip with 30km/h speed limit

10. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Private Car (drive alone)
- Walk
- Cycle

GREENING TRANSPORT

Active Modes Scenario 2

Option	Policy	Effect on your trip		
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		
Walk 	Walking Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		40% of trip with widened, even paths	6 mins off trip time	100% of trip with 30km/h speed limit
Cycle 	Cycling Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		60% of trip fully segregated from traffic	4 mins off trip time	75% of trip with 30km/h speed limit

11. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

Private Car (drive alone)

Walk

Cycle

GREENING TRANSPORT

Active Modes Scenario 3

Option	Policy	Effect on your trip		
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		
Walk 	Walking Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		60% of trip with widened, even paths	4 mins off trip time	75% of trip with 30km/h speed limit
Cycle 	Cycling Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		40% of trip fully segregated from traffic	6 mins off trip time	100% of trip with 30km/h speed limit

12. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Private Car (drive alone)
- Walk
- Cycle

GREENING TRANSPORT

Public Transport Scenario 1

Imagine how you will travel to your new work location. Taking note of the above policy plan, please consider the following scenarios and rank the modes that you would take.

Option	Policy	Effect on your trip		
Bus		Frequency	Time	Cost
	Bus Policy Plan	25% more often	15% reduction in trip time	15% cheaper trip
Private Car (drive alone)		Cost		
	Current situation/ Status Quo	Gradual increase in the ownership costs of a car		
Train/ Luas		Frequency	Time	Cost
 	Train Policy Plan	25% more often	15% reduction in trip time	15% cheaper trip

13. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Bus
- Private Car (drive alone)
- Train/ Luas

Option	Policy	Effect on your trip		
Bus		Frequency	Time	Cost
	Bus Policy Plan	25% more often	15% reduction in trip time	15% cheaper trip
Private Car (drive alone)		Cost		
	Current situation/ Status Quo	Gradual increase in the ownership costs of a car		
Train/ Luas		Frequency	Time	Cost
 	Train Policy Plan	25% more often	15% reduction in trip time	15% cheaper trip

13. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- [ ] Bus
- [ ] Private Car (drive alone)
- [ ] Train/ Luas

GREENING TRANSPORT

Public Transport Scenario 3

Option	Policy	Effect on your trip		
Bus 		Frequency	Time	Cost
	Bus Policy Plan	Twice as often	15% reduction in trip time	15% cheaper trip
Private Car (drive alone) 		Cost		
	Current situation/ Status Quo	Gradual increase in the ownership costs of a car		
Train/ Luas  		Frequency	Time	Cost
	Train Policy Plan	50% more often	25% reduction in trip time	25% cheaper trip

15. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- [ ] Bus
- [ ] Private Car (drive alone)
- [ ] Train/ Luas

GREENING TRANSPORT

Smart Modes Scenario 1

Imagine how you will travel to your new work location. Taking note of the above policy plan, please consider the following scenarios and rank the modes that you would take.

Option	Policy	Effect on your trip		
Carpooling 	Carpooling Policy Plan	Convenience	Time	Cost
		10% reduction in access/ wait time	15% reduction in trip time	15% reduction in trip cost
Car-sharing (GoCar/ Toyota Yuko)  	Car-sharing Policy Plan	Convenience	Time	Cost
		10% reduction in access/ wait time	15% reduction in trip time	15% reduction in trip cost
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		

16. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Carpooling
- Car-sharing (GoCar/ Toyota Yuko)
- Private Car (drive alone)

GREENING TRANSPORT

Smart Modes Scenario 2

Option	Policy	Effect on your trip		
Carpooling		Convenience	Time	Cost
	Carpooling Policy Plan	30% reduction in access/ wait time	35% reduction in trip time	35% reduction in trip cost
Car-sharing (GoCar/ Toyota Yuko)		Convenience	Time	Cost
 	Car-sharing Policy Plan	50% reduction in access/ wait time	15% reduction in trip time	15% reduction in trip cost
Private Car (drive alone)		Cost		
	Current situation/ Status Quo	Gradual increase in the ownership costs of a car		

17. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Carpooling
- Car-sharing (GoCar/ Toyota Yuko)
- Private Car (drive alone)

Greening Transport

Smart Modes Scenario 3

Option	Policy	Effect on your trip		
Carpooling 	Carpooling Policy Plan	Convenience	Time	Cost
		50% reduction in access/ wait time	15% reduction in trip time	15% reduction in trip cost
Car-sharing (GoCar/ Toyota Yuko)  	Car-sharing Policy Plan	Convenience	Time	Cost
		30% reduction in access/ wait time	35% reduction in trip time	35% reduction in trip cost
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		

18. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- [ ] Carpooling
- [ ] Car-sharing (GoCar/ Toyota Yuko)
- [ ] Private Car (drive alone)

GREENING TRANSPORT

19. Which of the following features influenced your choice the most in the scenarios?

- ◯ Time
- ◯ Cost
- ◯ Frequency
- ◯ Adjacent Traffic Speed.
- ◯ Convenience
- ◯ Infrastructure

20. How difficult would it be for you to take the following modes to work/ education?

	Very Easy	Easy	Neutral	Difficult	Very Difficult
Walk	◯	◯	◯	◯	◯
Cycle	◯	◯	◯	◯	◯
Bus	◯	◯	◯	◯	◯
Train	◯	◯	◯	◯	◯
Luas	◯	◯	◯	◯	◯

21. Why do you feel that these modes would be difficult to take to work/ education?

- ◯ N/A
- ◯ Please state your reason:

22. Which of the following aspects is most important to you when commuting to and from work/ education? (Please select one)

- ◯ That the schedule is flexible
- ◯ That it is convenient to use
- ◯ That it is quick
- ◯ That I feel comfortable
- ◯ That it is cheap
- ◯ That I am protected from the weather
- ◯ That I can have control over my time
- ◯ Other (please specify)

GREENING TRANSPORT

23. Gender?

- Male
- Female

24. What is your age range?

- 18-24 years old
- 25-34 years old
- 35-44 years old
- 45-54 years old
- 55-64 years old
- 65+ years old

25. What is your highest level of education which you have completed to date?

- No former education/ training
- Primary education
- Secondary education
- Technical or vocational
- Advanced Certificate/ Completed Apprenticeship
- Higher Certificate
- Ordinary Bachelor Degree/ Diploma
- Honours Bachelor Degree
- Postgraduate Diploma/ Degree
- Doctorate (Ph.D) or Higher

26. What is your current marital status?

- Single
- Married
- Separated
- Divorced
- Widowed

27. How many children/ dependents do you have?

- None
- 1
- 2
- 3
- More than 3

28. Please answer the following:

	Dublin City Centre (i.e. within the canals)	Inner Suburbs (i.e. within canals & M50 motorway)	Outer suburbs (i.e. outside M50 motorway)	Commuter town	Rural Area
Where do you live?					
Where do you work/ study?					

29. What is your average annual household income range?

- €24,999 or less
- €25,000 - 49,999
- €50,000 - 74,999
- €75,000 - 99,999
- €100,000 or more
- I'd rather not say

30. How would you describe your present principal status?

- Working for payment or profit
- Looking for first regular job
- Unemployed
- Student
- Looking after home/ family
- Retired from employment
- Unable to work due to permanent sickness or disability
- Other (please specify)

31. To enter the prize draw for 3 chances to win €50 please enter your unique code here (this code is in your invitation email)