Using telematics digital traces to predict individual differences in ecological driving.

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Abstract

Engineering innovations in transport are insufficient alone to combat its effects on the climate crisis. ‘Driving style’ – the way a driver prefers to or habitually drives their vehicle – significantly impacts fuel consumption and exhaust emissions. However, changes from an ‘aggressive’ to a more refined style – *‘eco-driving’* – offers overlooked opportunities for emissions savings. In this thesis, I explore how individual differences including personality, wellbeing and aspects of demography are related to objective eco-driving behaviours in a sample of monitored drivers. By adopting an interdisciplinary approach, this thesis incorporates methods from psychology and computer science to consider both theoretical and methodological implications. Substantially, findings across the research point to an emerging and central role of emotion dysfunction as a key influence in drivers’ inefficient operational driving behaviours. Moreover, a clear intention – behaviour gap is identified between drivers’ self-report intentions to eco-drive and their objective eco-driving behaviours. Recommendations illustrate how these insights can be translated into digital behaviour change interventions (DBCI) to encourage sustained changes in drivers’ ecological driving efficiency.

USING TELEMATICS DIGITAL TRACES TO PREDICT INDIVIDUAL DIFFERENCES IN ECOLOGICAL DRIVING.

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Acknowledgements

By the end of my first week at Lancaster University in October 2019, over half a dozen researchers and departmental staff I had met had said that my MSc by Research would be like "half a PhD in a third of the time". Writing this in October 2022, it is safe to say I did not expect the length of this Masters – both in time taken and word count – to rival a PhD. The last three years have been characterised by a few big moments: a global pandemic, a change in personal circumstances and, recently, a full-time job. In navigating these strange, sometimes difficult moments while undertaking this thesis, words cannot do justice to how grateful I am for the people along the way who were constants during this time.

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Declaration

This thesis is submitted to the Lancaster Environment Centre and the Board of Examiners of Lancaster University in fulfilment of the requirement for the degree of MSc by Research. The content of this thesis is entirely my own work, carried out under normal terms of supervision and has not been submitted in substantially the same form for the award of a higher degree elsewhere. All sources of information have been fully referenced. This thesis, with formal approval from Senate (see Appendix F), exceeds the typically permitted word limit due to the unique nature of the project.

Word length: 39,201

1. Introduction

1.1 Driving as an Act of Environmentalism

1.1.1 Addressing vehicle emissions – the issue of globalisation

High emissions of carbon dioxide (CO_2) is the leading cause of global warming (Wengraf, 2012). The carbon footprint of the global car industry alone equated to 9% of annual global emissions in 2018 (Greenpeace, 2019) and over 17% of total emissions in Europe stemmed from cars and vans exclusively in this period (Council of the European Union, 2019). Vehicle ownership has drastically increased in recent decades, with estimations that over 1.32 billion cars, buses and trucks were in active use worldwide in 2016, compared to 670 million in 1996 and 342 million in 1976 (Petit, 2018). Conversely, car occupancy levels have considerably declined throughout this period. Occupancy rates (averaged by travel purpose and including the driver) across Europe have most recently been estimated to be 1.45 passengers per vehicle (European Environment Agency, 2010) compared to 2 – 2.1 passengers per vehicle in the early 1970s (IEA, 1997, as cited in European Environment Agency, 2010).

Reducing car use provides an effective method for CO_2 reductions (Unal, Steg & Gorsira, 2018), yet the rising prevalence of low occupancy vehicle use illustrates some of the significant behavioural and sociological challenges associated with addressing vehicle emissions in an increasingly individualised and globalised society. Critically, in this zeitgeist, vehicle use interventions such as car-sharing initiatives may have limited reach. As such, these challenges highlight the importance of localised approaches to CO_2 reduction that specifically focus on the increased efficiency that can be achieved directly within the car journey (i.e., driver operational practices, engine performance optimisation) as opposed to singularly focusing on broader car-use behaviours (i.e., use reduction, vehicle choice).

1.1.2 Searching for technological salvation

Drastic improvements in vehicle efficiency have been made as a result of the increasing electrification and hybridisation of vehicles, alongside increasing levels of vehicle automation. However, greenhouse gas emissions from the global transportation sector have remained relatively stable over the past decade (Olivier & Peters, 2020). Moreover, many of these concepts which reify the dream of a 'net-zero' form of transport are still far from being fully actualised. For example, consumer attitudes to automation illustrate that whilst many are receptive to the idea of automated vehicle technology in more limited applications (AAA, 2020), concerns over safety and security hinder many consumers from endorsing autonomous vehicles (AV) (Tennant, Howard & Stares, 2021, AAA, 2020; Capgemini, 2019). Nearly 70% of European participants in one study reported they distrusted autonomous vehicles, with trust lowest amongst UK respondents, where only 9% of consumers reported that they would like to be first to try AVs (OC&C, 2019). Moreover, despite contemporary policy shifts such as the UK Government's plug-in vehicle grant scheme which has provided over £800 million since 2011 to support the early market of low emissions vehicles (UK Government, 2020), the EU market for electric and plug-in hybrid vehicles is still in its infancy and is largely dependent on these support policies (Niestadt & Bjornavold, 2019). This is reflected in uptake statistics, as ultra-low emission and zero-emission vehicles currently represent just under 6% and 3% of the UK new car market respectively (UK Government, 2020).

Consequently, even with the UK Government's ban on new petrol and diesel car sales by 2030 (UK Government, 2020), the internal combustion engine is set to remain an important part of road transport over the next decades whilst current vehicles complete their life cycle (PWC, 2007). As such, until consumer attitudes and technologies advance accordingly, alternative approaches are required to address short-to-medium term emissions which go beyond the engineering paradigm of vehicle efficiency (i.e. vehicles, road structure, traffic control systems) to consider the human infrastructure of behaviours, social norms and legislation that influence emissions outcomes (Evans, 1990).

1.1.3 An overlooked initiative: 'eco-driving'

Perhaps the most overlooked action that could garner substantial CO_2 savings is the alteration of current driving styles (Barkenbus, 2010; Oxendahl, 2018; McIlroy & Stanton, 2017). This is changes from an 'aggressive' driving style to a more refined style, frequently referred to as 'eco-driving' (Barkenbus, 2010). This remains a largely overlooked avenue, despite unequivocal evidence that driving style significantly impacts fuel consumption and exhaust emissions (Rios-Torres, Liu & Khattak, 2018; Faria, Baptista & Farias, 2017; Zannikos, Tzirakis & Sournas, 2007). Significant advantages are that CO_2 savings can be immediate, altering a driving style does not cost drivers money to achieve, and benefits are amassed to both individual drivers (e.g., fuel cost savings, greater personal safety, individual carbon footprint reduction) as well as society at large (e.g., CO_2 savings, fewer accidents and fatalities, reduced petroleum imports; Barkenbus, 2010).

However, prevailing concerns about the nature of changing driver behaviour often discourage stakeholders from this behaviour change approach. Significant trepidations exist regarding the public's minimal understanding of eco-driving and the perceived low motivation of drivers to improve their vehicle efficiency. Likewise, there is also scepticism regarding the ability to genuinely change drivers' behaviour long-term at reasonable levels of cost and invasiveness (Barkenbus, 2010; Vandenbergh, Barkenbus & Gilligan, 2008). Yet, much of this scepticism is fuelled by the arguably limited understanding and application of behavioural insights in the driving domain. Consequently, this warrants interest in the development and aetiology of eco-driving behaviours. By understanding the factors which shape eco-driving propensity, interventions can be tailored to and informed by these considerations.

1.1.4 The aetiology of eco-driving

Eco-driving is a driving style that significantly reduces the environmental impact of vehicle use by reducing fuel consumption and improving vehicle efficiency (Barkenbus, 2010). Traditionally, this is considered in the narrowed context of driver actions *after* the purchase of a vehicle and *during* the driving task (McIlroy & Stanton, 2015; Sivak & Schoettle, 2012). Accordingly, a plethora of research has illustrated that smooth acceleration style, optimal gear changes, anticipation of traffic flow and signals (i.e., to avoid inefficient braking) and driving at or safely below the speed limit have the largest effect on vehicle fuel use (McIlroy & Stanton, 2015; Barkenbus, 2010; Beusen et al., 2009; Hooker, 1998).

However, eco-driving can transcend this limited scope of specific driving actions and be conceptualised through a broader lens as a range of strategic (vehicle selection and maintenance), tactical (route selection and vehicle load) and operational decisions (driver behaviour) which can increase vehicle fuel efficiency and as a consequence, reduce greenhouse gas emissions (Sivak & Schoettle, 2012). Beyond the four strategies recognised as having the largest effect on vehicle fuel use (Barkenbus, 2010), there are many other techniques drivers can deploy to reduce fuel-inefficiency. These can be divided into 'pre-trip' (e.g., maintaining tyre pressure), 'during the trip' (e.g., unnecessary engine idling) and 'post-trip' categories (e.g., reviewing trip data; Wengraf, 2012; Barkenbus, 2010). When used in combination, these strategies can bring about discernible improvements in fuel economy and emissions (Wengraf, 2012. As a result, this thesis adopts Sivak and Schoettle's broader conceptualisation of eco-driving behaviour.

Critically, the advantages of eco-driving surpass CO_2 reductions. Financial benefits include reductions in maintenance costs and fuel savings. This is a particularly salient advantage given the current global fuel crisis. Whilst surges in petrol and diesel prices has accelerated a minority of consumers towards electric vehicle ownership (The Telegraph, 2022), the fuel savings eco-driving can produce may offer an avenue for the majority of the UK's 33 million drivers for whom transitioning to electric vehicles remains unaffordable. Beyond financial benefits, eco-driving produces tangible and widely established safety benefits with fewer accidents and traffic fatalities than other driving styles (Barkenbus, 2010; Young et al., 2011). This is a by-product of the significant and widely acknowledged overlap in the operational antecedents of safe driving and eco-driving (e.g. driving at or below the speed limit is both safe as well as fuel-efficient, Young et al., 2011; Jamson, Hibberd & Jamson, 2015; Mensing et al., 2014; Haworth & Symmons, 2001; Hedges & Moss, 1996).

As a result, it is likely feasible to encourage both safe and ecological driving through promoting eco-driving behaviours (McIlroy & Stanton, 2015; Hedges & Moss, 1996; Haworth & Symmons, 2001). Hedges and Moss (1996) illustrated that following the delivery of eco-driving training program to Parcelforce UK van drivers, subsequent accident frequency reduced by 40%, whilst fuel consumption savings was found to increase by 50%. However, whilst 'safe' driving and eco-driving greatly intersect, they should be regarded as distinct actions with discrete aetiologies and behavioural consequences (Rakotonirainy, Haworth, Saint Pierre & Delhomme, 2011). Importantly, eco-driving should also be distinguished from 'hypermiling' (Chapnick, 2007, as cited in

Barkenbus, 2010). Whilst both share the same goal of reducing fuel use, hypermiling often involves extreme and illegal practices which trade off safety for fuel economy (such as coasting and drafting; Wengraf, 2012). Comparatively, eco-driving is specifically conceptualised in terms of safe and legal ways to make driving behaviour more efficient. The deduction that safe driving is often also fuel-efficient illustrates that road safety research – considering driving behaviour more broadly – likely can provide useful insights into the behavioural precursors of eco-driving as well as how intervention might instigate improvements in individual driving style. As a result, due to the relatively novel nature of psychological eco-driving research, this thesis will often refer to the literature on risky, 'aggressive' and aberrant driving behaviour as a behavioural proxy for environmentally efficient 'eco' driving.

1.1.5 Eco-driving interventions

As eco-driving strategies need to be learned by drivers before they can be implemented, considerable research has centred on developing eco-driving training and interventions and assessing their effectiveness in reducing fuel consumption (Unal, Steg & Gorsira, 2018; CIECA, 2007). Interventions are diverse and can be broadly divided into four main categories (Wengraf, 2012): information campaigns (e.g. *'drive five miles less a week*'; UK Government 'Act on CO_2 Series', 2008), driver training (e.g., Jeffreys, Graves & Roth, 2018), in-vehicle technologies (e.g., vibrotactile feedback; McIlroy & Stanton, 2015) and gamification (e.g., leaderboard of users; Magana & Munoz-Organero, 2015).

Some suggests particular intervention designs may be more effective than others (Sanguinetti, Queen, Yee & Akanesuvan, 2020). For example, in a meta-analytic review regarding the efficacy of different eco-driving feedback designs, Sanguinetti et al. (2020) found that multimodal feedback was more effective than visual feedback alone, features of gamification significantly improved eco-driving feedback effectiveness and interventions which included feedback on both instantaneous and accumulated eco-driving performance were the most effective.

However, other evidence suggest different types of interventions may not substantially differ in comparative effectiveness (Jeffreys, Graves & Roth, 2018; Andrieu & Saint

Pierre, 2012). In this study, Jeffreys et al tested the effectiveness of five interventions featuring different combinations of blended eco-driving training (including a one-hour online resource, classroom lessons, driving lessons and a half-day eco-driving course). Whilst participating in one of the interventions led to a significant reduction in fuel use when compared to the control group, there were no statistically significant differences between the individual interventions. As a result, these findings may suggest substantial and comparable eco-driving improvements can be achieved using low-intensity and lower-cost interventions as opposed to more complex and costly programs.

1.2 Theoretical Approaches to Changing Eco-Driving Behaviours

Much research illustrates positive short-to-medium term effects of eco-driving interventions (e.g. Jeffreys et al., 2018), however these effects seemingly decrease over time (af Wahlberg, 2006, 2007; Zarkadoula et al., 2007; Beusen et al., 2009). Whilst some drivers utilise what they have learned and continue to improve their eco-driving style, many others may forget training over time or relapse to less efficient driving actions (Beusen et al., 2009; Lauper et al., 2015; Stromberg, 2013). Accordingly, there may be key individual differences which may be able to explain this disparity in intervention efficacy and longevity. In this vein, Ellison, Bliemer and Greaves (2015) found that improvements in 'safe' driving style over time were disproportionately associated with drivers who were already safe at baseline. These insights could suggest that certain drivers may be predisposed towards improving the quality of their driving behaviour.

1.2.1 Eco-Driving Motivations

Explanations for the underlying mechanisms that sustainably motivate people to adopt and maintain an *ecological* driving style are sparse. Few studies have examined the psychological antecedents of eco-driving implementation (Lauper et al., 2015; Oxendahl, 2018; Boriboonsomsin, Barth & Vu, 2011; Lai, 2015). However, as the way we drive is motivated by a myriad of strivings (e.g., safety concerns, self-regulation goals; Goldenberg, Levelt & Heidstra, 2000; Lai, 2015) which may not be explicitly 'environmental', these wider motivations are still important considerations as to why a driver may be more or less likely to implement eco-driving techniques.

Some studies have considered these specific motivations. This includes fuel and monetary savings, explicit financial incentives, increased safety, and reductions in air and noise pollution (Cristea, Paran & Delhomme, 2012; Dogan, Bolderdijk & Steg, 2014; Lauper et al., 2015; Lai, 2015). Framing the advantages of eco-driving behaviour by economic benefits (e.g., savings) is widespread in the intervention literature (Barkenbus, 2010). Financial incentives received due to improved driving style and fuel savings might extrinsically motivate drivers to adopt and maintain eco-driving practices (Lai, 2015; Stigson, Hagberg, Kullgren & Krafft, 2014; Lahrmann, Agerholm, Tradisauskas, Berthelsen & Harms, 2011). However, when financial incentives are subsequently removed, participants often relapse to their previous driving behaviour (Bolderdijk, Knockaert, Steg & Verhoef, 2011; Lahrmann et al., 2011). This indicates that the behavioural effects of practitioner-led interventions are often not sustained long-term. Moreover, financial gains may not always motivate drivers to undertake 'effortful' improvements. Dogan et al. (2014) found that drivers perceived undertaking 'effortful' eco-driving behaviour to be more worthwhile when presented with small environmental benefits (i.e., reduced CO_2 emissions) rather than equivalent small financial gains (i.e., fuel savings). This demonstrates that in some contexts, normative goals – such as to protect the environment (Lindenberg & Steg, 2007) – could motivate drivers to a greater extent than 'gain' goals such as financial remuneration. As a result, Dahlinger and Wortmann (2016) advocate that in order to sustainably motivate drivers, eco-driving incentive systems should address both extrinsic and intrinsic motivations, as well as consider incentives tailored to driver characteristics such as personality traits. This suggests that an understanding of the individual differences that can be identified in objective eco-driving data may enable researchers to conceptualise interventions to sustain eco-driving behavioural changes in the longer-term.

1.2.2 Converging approaches: road safety and pro-environmentalism

Driving behaviours – as like many other daily actions – become automated through repetition (Lauper et al., 2015). As a result, drivers may be required to change their habitualised actions into intentional behaviours in order to improve their driving style by forming an intention to improve their driving practices and subsequently putting this intention into practice (Lauper et al., 2015). As such, the motivating factors which encourage drivers to adopt and maintain an 'eco' driving style are conceptualised by focusing on several different processes, including intentional (Ajzen, 1991), habitual (Goldenberg, Levelt & Heidstra, 2000), impulsive (Goldenberg et al., 2000) and normative mechanisms (Stern et al., 1999; Unal, Steg & Gorsira, 2018).

Considering that behavioural intentions are theorised to be the direct antecedent of behaviour (Ajzen, 1991; Fishbein & Ajzen, 2010), intentional and normative processes for eco-driving are of particular theoretical interest (Lauper et al., 2015; Unal, Steg & Gorsira, 2018). These processes are often explored through two respective literatures. First, traffic research which largely considers intentional processes in wider driver behaviour (e.g. Lauper, Moser, Fischer, Matthies & Kaufmann-Hayoz, 2015). Second, pro-environmentalism research which often centres on normative considerations when considering eco-driving in the remit of pro-environmental actions (e.g., Unal, Steg & Gorsira, 2018; Unal, Steg & Granskaya, 2019).

1.2.3 The Theory of Planned Behaviour (Ajzen, 1991; Fishbein & Ajzen, 2010)

The Theory of Planned Behaviour (TPB; Ajzen, 1991; Fishbein & Ajzen, 2010) posits that eco-driving is motivated by an intention to practice eco-driving and that this is informed by three types of beliefs: drivers' attitudes towards eco-driving, subjective social norms and drivers' perceived behavioural control (Lauper et al., 2015). Notably, the TPB appears to only have been directly applied to eco-driving in one study (i.e., Lauper et al., 2015), however has inspired significant research on wider aspects of driving, such as speeding (e.g., Cristea, Paran & Delhomme, 2013; Parker, Manstead, Stradling, Reason & Baxter, 1992; Rottengatter, 1994; De Ward & Rooijers, 1992).

However, there is no shortage of critique towards the TPB in driving research (e.g. Sniehotta, Presseau & Arugo-Soares, 2014). Notably, Goldenberg et al. (2000) argues that – in practice – driver behaviour is not always as rational as the TPB proposes. Instead, they contend that many aspects of the driving task reflect other cognitive and affective processes not directly acknowledged in the TPB, such as habitualised behaviours (e.g. the automaticity of changing gears) and impulsive reactions to rapidly-evolving traffic situations grounded in emotional self-regulatory responses (e.g. aggressive driving elicited by ‘road rage’ due to perceived norm-violations of other road users; Goldenberg et al., 2000).

Lauper et al.’s (2015) findings extend this critique explicitly to the eco-driving domain. In this study, the TPB was combined with mechanisms from the health action process approach (HAPA; Schwarzer, 2008) to assess psychological precursors of eco-driving adoption. Notably, the three core mechanisms of the TPB (i.e., social norm, attitude, perceived behavioural control) were found to significantly relate to eco-driving intentions, which, in turn, was somewhat related to self-reported eco-driving behaviour (R^2 = .13). However, the HAPA mechanism of ‘action control’ (i.e., relating to active self-regulation; Schwarzer, 2008) was the strongest predictor of self-reported eco-driving behaviour (R^2 = .47; Lauper et al. 2015). It is worth acknowledging that Ajzen (2011) sought to counter these critiques by arguing that ‘affect’ is accounted for within the TPB as emotions may serve as *‘background factors that* [irrationally] *influence behavioural, normative or control beliefs’* (Ajzen, 2011, p.1116). Yet, Lauper et al’s findings do not correspond with this argument, as action control – constituting a direct role of emotion self-regulation on self-report eco-driving – significantly outperformed Ajzen’s TPB.

1.2.4 The Value-Belief-Norm Theory (Stern et al., 1999)

Conversely, several studies have adopted the Value-Belief-Norm theory of environmentalism (VBN; Stern et al., 1999) to consider the motivations for eco-driving (e.g. Unal, Steg & Gorsira, 2018; Unal, Steg & Granskaya, 2019). VBN theory (Stern et al, 1999) posits that the extent to which people endorse certain personal values affects eco-driving behaviour indirectly as values influence two types of environment-specific beliefs, problem awareness (PA) and outcome efficacy (OE), which in turn influence personal norms (PN) for eco-driving – the proposed direct predictor of behaviour (Stern et al., 1999; Steg et al., 2014; Unal, Steg & Granskaya, 2019). Specifically, Stern et al.’s theory stipulates that personal norms for eco-driving will be triggered when a person is aware of adverse consequences of their actions on the environment, and when the individual perceives they have an ability to reduce these adverse consequences (Stern et al., 1999; Unal, Steg & Granskaya, 2019). This causal chain proposed by VBN theory (Stern et al., 1999) is supported empirically by self-report studies in the eco-driving domain (Unal, Steg & Granskaya, 2019; Unal, Steg & Gorsira, 2018).

1.3 Individual Differences

Taken together, the motivational frameworks considered indicate that the driving task likely involves a range of cognitive abilities (Anstey et al., 2005; Groeger, 2000; Blane, Lee, Falkmer & Willstrand, 2018) and comprises of multiple competing motivational goals (e.g. to get somewhere quickly but also efficiently; Groeger, 2000). As such, whether an individual adopts an ecological driving style is thought to be determined by measurable individual differences in psychological constructs (Unal, Steg & Gorsira, 2018). This reflects the idea that individual drivers may each have predictable patterns of behaviour for particular driving situations. This is corroborated by behavioural research illustrating that different drivers have different driving styles (Chen et al., 2013) and multiple drivers operating the same car can be distinguished using in-vehicle sensor data (Ezzini, Berrada & Ghogho, 2018; Martinez, Heucke, Wang, Gao & Cao, 2018; Sun, Deng, Wu, Li, Zhu & Wu, 2018).

Resultantly, this thesis examines several individual differences of which theory and evidence suggest may be implicated in eco-driving behaviour. This includes drivers' personal values, environmental self-identity, personality traits, locus of control, and subjective wellbeing. It also explores related demographic measures, including the experience of major life events, typical alcohol and cigarette use, age, gender and education level.

1.3.1 Personal Values

Values are widely considered to be general trans-situational goals which serve as guiding principles in a person's life (Schwartz, 1992, 1994). Various theoretical frameworks (e.g., Schwartz, 1992, 1994, see Figure 1.1) distinguish personal values as a key tenet of environmentally significant behaviours and this is well-documented in the empirical evidence (e.g., Barbarossa, Pelsmacker & Moons, 2017; Karp, 1996; Stern et al., 1999; de Groot & Steg, 2008; Stern, Dietz & Guagnano, 1998; Schultz & Zelezny, 1999; Hansla et al., 2008; Follows & Jobber, 2000).

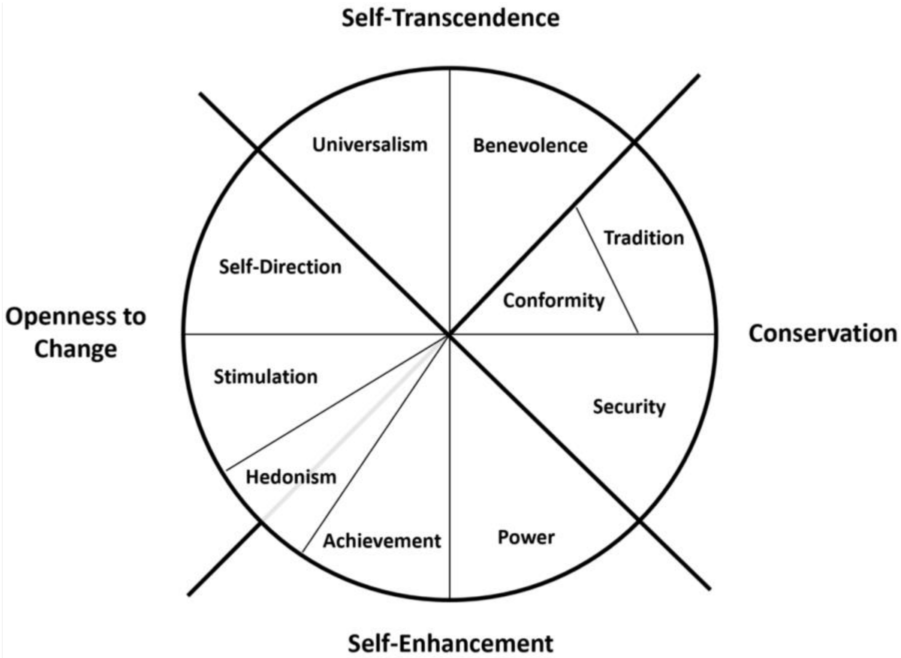

Figure 1.1. Schwartz's Theory of Basic Human Values (1992)

Notably, four values in the 'self-enhancement (SE) vs. self-transcendence (ST)' dimension of Schwartz's model (1992) are widely and consistently found particularly relevant to both pro-environmentalism and – more specifically – eco-driving behaviour (Stern, Dietz & Guagnano, 1998; Milfont & Gouveia, 2006; Steg et al., 2014). These include *biospheric values* which reflect a key concern for the environment (ST), *altruistic values* which reflect a concern for the welfare of others (ST), *egoistic values* which focus on increasing and securing personal resources (SE) and *hedonic values* which focus on improving one's feelings, doing things for the fun of it and reducing effort (SE; Steg et al, 2012; Stern, 2000).

Biospheric and Altruistic Values

Behaving in a pro-environmental way often requires individuals to give up their personal interests (i.e., comfort of own car) for the benefit of the environment or other people (i.e., public transport; Nordlund & Garvill, 2003; de Groot & Steg, 2008). In this vein, individuals' willingness to consciously drive 'ecologically' might depend on the extent individuals are concerned about the environment, and thus, willing to refrain from individual gains associated with unecological driving (Unal, Steg & Granskaya, 2019).

Accordingly, both biospheric and altruistic values have been positively associated with behavioural and attitudinal indices of eco-driving: self-reported reduced car use (Unal, Steg & Granskaya, 2019), support for vehicle use reduction policies (Unal, Steg & Granskaya, 2019), knowledge and intention to use specific eco-driving strategies (Unal, Steg & Gorsira, 2018), willingness to switch to sustainable transport (Barborossa et al., 2017), problem awareness of fuel inefficiency (Unal, Steg & Gorsira, 2018) and intentions to purchase electric vehicles (Skippon & Garwood, 2011; Barbarossa et al., 2017). Biospheric values are typically found to predict these measures more consistently and to a greater extent than altruistic values (Unal, Steg & Granskaya, 2019; Unal, Steg & Gorsira, 2018; De Groot & Steg, 2007, 2008; Nilsson et al., 2004; Steg et al., 2005), with one key study by Unal, Steg & Gorsira (2018) establishing that drivers' biospheric values were the single strongest predictor of eco-driving *intentions.*

However, findings for biospheric and altruistic values seem to vary based on the eco-driving measures adopted. For example, Steg, Perlaviciute, van der Werff and Lurvink (2014) reported that both values were unrelated to self-reported car use (measured by journey frequency and mileage), yet stronger altruistic values were associated with owning fewer vehicles. Disparities across findings indicate that these two values may influence different aspects of eco-driving behaviour differently. In the context of Steg et al. (2014), it is plausible drivers' altruistic values may motivate the perception of multiple car ownership as superfluous, whereas typical everyday car use (i.e., journey frequency and mileage findings) may be deemed indispensable and not subject to value appraisal.

Egoistic and Hedonic Values

Acting 'pro-environmentally' is often marred by associations with egoistic and hedonic costs, as eco-actions are often considered – though do not *need* to be (Venhoeven et al., 2013) – effortful, uncomfortable or costly (Bouman, Steg & Kiers, 2018). Research has largely focused on biospheric and altruistic values, yet some evidence suggests strong egoistic and hedonic values are positively related to self-reported car use (i.e., journey frequency and mileage; Steg et al., 2014) and pro-car use attitudes (i.e., defining oneself as a 'car lover'; Steg et al., 2014). Strong hedonic values alone have been positively associated with owning multiple vehicles (Steg et al., 2014).

However, in Unal, Steg & Gorsira (2018), egoistic values failed to predict both eco-driving intention and problem awareness, two conceptualised antecedents of behaviour in VBN theory (Stern, 1999). This disparity in findings for egoistic values is congruent with the broader pro-environmental literature as whilst commonly found to correlate negatively across environmental contexts (De Groot & Steg, 2008; Gatersleben, Murtagh & Abrahamse, 2014; Stern et al., 1995; Nordlund & Garvill, 2002; Steg et al., 2005, 2011; Joireman et al., 2001), other studies have found egoistic values unrelated to environmentally-significant behaviour (see Stern, 2000).

Moreover, studies considering the role of hedonism in eco-driving appear to be sparse. This is surprising given its strong theoretical basis. Speculatively, individuals may refrain from eco-driving even when it satisfies egoistic motives (e.g. financial savings) as eco-driving might threaten other types of personal benefits achieved from driving – rooted in hedonic values – such as pleasure and comfort (e.g. thrill from driving at higher speeds; Steg et al., 2012). This is corroborated by evidence that driving serves a psychosocial function beyond its fundamental utility as a form of personal transport, particularly for younger drivers (e.g., social status, self-expression; Scott-Parker, King & Watson, 2015; Laapotti et al., 2006; Christmas, 2007; Moller & Gregersen, 2008; Moller & Sigurdardottir, 2009). Crucially, these psychosocial purposes have been implicated in aberrant and risky driving practices and outcomes (e.g., tailgating, young driver crashes; Moller & Gregersen, 2008; Blows, Ameratunga, Ivers, Lo & Norton, 2005; Keall, Frith & Patterson, 2004). Taken together, these insights highlight a substantial gap, as hedonic values may be acutely relevant in contexts where improving eco-driving requires significant effort and is perceived to reduce drivers' ability to achieve these psychosocial goals.

1.3.2 Environmental Self-Identity

Environmental self-identity, which is considered an antecedent of pro-environmental behaviour (Van der Werff, Steg & Keizer, 2013b), is the extent to which you perceive yourself as a person whose actions are environmentally friendly (Van der Werff, Steg & Keizer, 2013b). Both biospheric values and environmental self-identity are highly correlated (van der Werff, Steg & Keizer, 2013b; Balunde, Perlavicuite & Steg, 2019), yet they have been distinguished as conceptually and empirically discrete (Bardi et al., 2014; Van der Werff et al., 2013b, 2014b).

Research has demonstrated that strong environmental self-identity is associated with a greater propensity for environmental preferences, intentions and behaviour across a variety of environmental contexts (Van der Werff, Steg, Keizer, 2013; Witmarsh & O'Neill, 2010, Gatersleben et al., 2012; Nigbur, Lyons & Uzzell, 2010; Fielding, McDonald & Louis, 2008). This extends to several facets of subjective eco-driving such as self-reported operational behaviour (i.e., fuel-efficient driving), eco-driving intentions, electric vehicle purchase intentions and sustainable transport preferences (Negre & Delhomme, 2017; Barbarossa, De Pelsmacker & Moons, 2017; Barbarossa et al., 2015; Van der Werff et al., 2013a; Van der Werff et al., 2013b; Skippon & Garwood, 2011). In one study of electric car adoption (Barbarossa, De Pelsmacker & Moons, 2017), it was found that biospheric values predicted 'green' self-identity, which in turn predicted participants' intention to purchase an electric car. These findings are congruent with evidence that environmental self-identity has been found to fully mediate the relationship between biospheric values and indices of environmental behaviour (Van der Werff, Steg & Kiezer, 2014b; Van der Werff, Steg & Keizer, 2014a). Together, these insights illustrate how values and environmental self-identity might function in tandem to motivate eco-driving.

However, the strength of environmental self-identity is also contingent on the regularity of a person's past environmental actions (Van der Werff, Steg & Kiezer, 2014a; Charng, Piliavin & Callero, 1988; Lee et al., 1999 as cited in Van der Werff et al., 2014a). Accordingly, it can be speculated that one can hold strong biospheric values, yet – due to poor past eco-driving actions – not perceive themselves as a 'green driver' which, in turn, can influence their prospective eco-driving actions. This dynamic is particularly pertinent to the eco-driving domain over other eco-practices. Specifically, other practices often elicit high actual behavioural control (i.e., recycling is often wholly within individual volition), whereas the driving task involves reacting to driving behaviour of other road users, whose own aberrant driving may compromise individual efforts to drive fuel-efficiently. These insights are valuable for intervention design, as it should be feasible to strengthen drivers' environmental self-identity – and thus improve eco-driving outcomes to some extent – by priming drivers' awareness of their past fuel-efficient behaviours.

1.3.3 Personality Traits

Personality is considered predictive of a variety of behaviours (Kvasova, 2015, Brick & Lewis, 2016). Broader trait-based personality approaches may not accurately predict a person's specific behaviour across diverse situations (Fishbein & Ajzen, 2010; Poskus, 2018; Mischel, 2004; Mischel, Shoda & Ayduk, 2008), however they are able to capture underlying levels of consistency in people's actions beyond the situational variability (Allport, 1962).

Whilst much trait-based research adopts the Big Five taxonomy of personality traits (Goldberg, 1993), a six-factor model – HEXACO (Ashton & Lee, 2007; Ashton, Lee & de Vries, 2014; Lee & Ashton, 2004) – has also been adopted in contemporary personality research. This constitutes of six comparable but distinct traits of 'honesty-humility', 'emotionality', 'extraversion', 'agreeableness', 'conscientiousness' and 'openness to experience'. Most notably, HEXACO reframes Big Five 'neuroticism' less pejoratively as 'emotionality', though emotionality and neuroticism are not interchangeable (Lee & Ashton, 2004). It also includes a sixth core trait, honesty-humility. This trait shares variance with the Big Five model's conceptualisations of agreeableness and conscientiousness and its inclusion contributes unique variance when predicting attitudes and behaviour (Brick & Lewis, 2016; Lee & Ashton, 2004; Lee, Ashton, Ogunfowora, Bourdage & Shin, 2010).

1.3.3.1 The 'Green' Personality: Personality traits and wider pro-environmentalism

Personality traits considered to be desirable, positive and arguably 'adaptive' (e.g., conscientiousness; Costa & McCrae, 2012) appear positively related to pro-environmental behaviours and attitudes (for review, see Poskus, 2018). Brick and Lewis (2016) illustrated that self-reported emissions-reducing behaviours were most strongly predicted by HEXACO traits of openness, conscientiousness and extraversion. This is interesting as all three traits are compounds of the 'proactive personality' (Fuller & Marler, 2009), defined as *'one who is relatively unconstrained by situational forces, and who effects environmental change'* (Bateman & Crant, 1993, p.105).

HEXACO openness illustrates the most robust link with pro-environmental behaviour: it consistently and strongly positively predicts a variety of pro-environmental measures including intentions and self-reported behaviours (Milfont & Sibley, 2012; Pavalache-Ilie & Cazan, 2018; Wuertz, 2015; Poskus & Zukauskiene, 2017; Brick & Lewis, 2016; Markowitz, Goldberg, Ashton & Lee, 2012; Hilbig, Zettler, Moshagen & Heydasch, 2012; Hirsh & Dolderman, 2007; Hirsh, 2010; Gordon-Wilson, 2015; Soliño & Farizo, 2014; Soutter, Bates & Mottus, 2019; Nisbet et al., 2009). This might reflect that individuals' higher scores in openness can be characterised by flexible, abstract thinking – this may be necessary to envisage longer-term consequences of environmental behaviours (Brick and Lewis, 2016). Moreover, openness encompasses facet 'unconventionality' where high scorers are receptive to ideas that might seem strange or radical (Ashton & Lee, 2007). Acting 'normally' in many contexts is damaging to the environment (e.g., buying a new petrol car). As such, openness may be implicated as acting pro-environmentally might mean making choices which are counter-cultural to prevailing social norms (e.g., cycling rather than driving to work; Brick & Lewis, 2016).

For traits conscientiousness and agreeableness, there is moderate support for their positive relationship with several pro-environmental indices including self-reported behaviour, environmental intentions, environmental concern and pro-environmental attitudes (Milfont & Sibley, 2012; Pavalache-Ilie & Cazan, 2018; Poskus & Zukauskiene, 2017; Brick & Lewis, 2016; Hilbig, Zettler, Moshagen & Heydasch, 2012; Markowitz, Goldberg, Ashton & Lee, 2012; Jagers & Matti, 2010; Kim, Schmocker, Bergstad, Fujii & Garling, 2013; Swami, Chamorro-Premuzic, Snelgar & Furnham, 2011; Soutter, Bates & Mottus, 2019; Nisbet & Gick, 2008; Hirsh, 2010). However, some research has failed to replicate these results (Wuertz, 2015; Hirsh & Dolderman, 2007; Hillbig, Zettler, Moshagen & Heydash, 2012; Markowitz, Goldberg, Ashton & Lee, 2012; Hillbig et al., 2013).

In one of the few studies of personality in eco-driving, Oxendahl (2018) assessed proactive personality in eco-driving improvements for light duty fleet drivers. Proactivity positively related to improvements in self-reported *occupational* eco-driving (i.e., training transfer) and this was mediated by self-reported motivation to eco-drive. Yet, a negative relationship was found between proactivity and self-reported driving *outside of work*, suggesting that work-based intervention gains did not spill over to drivers' personal driving. The rationale for this negative spillover is unclear, however illustrates the empirical value gained from measuring the influence of personality across several eco-driving behavioural contexts (i.e., strategic *and* operational). As a result, this thesis examines eco-driving across several eco-driving behavioural contexts (e.g. celeration behaviours, speeding, night-time driving).

Evidence for a relationship between pro-environmental behaviour and the remaining three HEXACO traits – emotionality, extraversion and honesty-humility – is inconsistent (Hilbig et al., 2012; Markowitz et al., 2012; Poskus & Zukaskiene, 2017; Pavalache-Ilie & Cazan, 2018; Hirsh & Dolderman, 2007; Pavalache-Ilie & Cazan, 2018).

1.3.3.2 Personality Traits and *Risky* Driving

Eco-driving is conceptually distinct from other environmental practices. Specifically, driving is predominantly perceived from a narrative of safety concerns over environmental impact (McIlroy & Stanton, 2015). This is disparate from other eco-practices (e.g. recycling) which tend to be explicit in their environmental benefits. Resultantly, evidence from road safety literature regarding the personality precursors of unsafe and dangerous driving (Young et al., 2011; Rosenbloom & Eldror, 2013; Zhang et al., 2013; Chraif et al., 2016) may be particularly useful to assess whether personality's influence in ecological driving might differ from other eco-practices, as there is a convergence in behavioural markers that characterise both safe and ecological driving (Ericsson, 2001; Young et al., 2011).

Aggressive driving styles and risky driving outcomes appear to positively relate to neuroticism, trait-level anxiety, extraversion and trait-level anger, and negatively relate to agreeableness (theoretically opposed to anger in HEXACO; Ashton & Lee, 2007) and conscientiousness (Chraif et al., 2016; Dahlen et al., 2012; Krahe & Fenske, 2002; Dahlen & White, 2006; Jovanovic et al., 2009; Smith and Kirkham, 2011; Lajunen, 2001; Benfield, Szlemko & Bell, 2007). However, findings vary by behavioural context and criterion measurement (i.e., extraversion and conscientiousness unrelated to objective driving; Akbari et al., 2019; Ehsani, Li, Simons-Morton, Tree-McGrath, Perlus, O'Brien & Klauer, 2015). Centrally, road safety evidence elucidates a clear association between trait-level conceptualisations of anxiety (e.g., trait anxiety, neuroticism) and objective measures of aggressive and aberrant driving (e.g., braking behaviour, speeding; driving lapses, traffic accidents; Chraif et al., 2016; Dahlen & White, 2006; Dahlen et al., 2012; Lucidi et al, 2010; Brandau et al, 2011; Matthews, Dorn & Glendon, 1991; Lajunen, 2001). For example, trait-level anxiety was related to greater braking behaviour specifically during the motorway period of a driving route, suggesting that anxiety-prone drivers' driving quality may vary in certain situational contexts (Stephens, Young, Logan & Lenne, 2015).

1.3.3.3 Reconciliation of approaches: implications for personality and eco-driving.

Due to limited research exploring the role of personality traits on eco-driving specifically (e.g., Oxendahl, 2018), findings have been reviewed from the pro-environmentalism and road safety literatures. Trait-level anxiety, neuroticism and emotionality appear highly relevant to unsafe driving, yet there is little supporting evidence for their role in pro-environmental actions. Studies appear to indicate extraversion to be beneficial to ecological behaviour, yet detrimental to safe driving. Whilst evidence exists for the roles of agreeableness and conscientiousness with eco-driving explicitly, these are subject to theoretical and methodological considerations. Openness is compellingly *not* related to driving safety, however its robust relationship with eco-behaviours is of interest, as any relationship identified with eco-driving would suggest highly-open drivers' motivations for eco-driving are discernible from safety motives.

1.3.4 Locus of Control

Locus of control refers to individual differences in people's perceptions of the contingency between actions and subsequent outcomes (Rotter, 1966; Rotter, 1975). This reflects individuals' tendency to perceive outcomes as either contingent on their own behaviour (i.e., 'internal' locus of control) or as determined by external and uncontrollable influences such as luck (i.e., 'external' locus of control). Locus of control is often conceptualised as a facet of personality (Rotter, 1966), however it has also been described as a coping resource for facilitating certain coping styles (Van den Brande et al., 2016; Lazarus & Folkman, 1984). Whilst it appears to be relatively stable (Rotter, 1990), research has illustrated that driving locus of control is malleable through internality training intervention (Huang & Ford, 2012).

Theoretically, locus of control integrates well within theories of driving behaviour and pro-environmentalism as it is conceptually analogous (Bamberg & Moser, 2007) to other constructs widely used in these frameworks including perceived behavioural control (Theory of Planned Behaviour; Ajzen, 1991; Fishbein & Ajzen, 2010), outcome efficacy (Value-belief-norm theory; Stern, 2000) and self-efficacy beliefs (HAPA, Schwarzer, 1992). Recent studies have begun to elucidate a direct relationship between these constructs of perceived behavioural control and eco-driving behaviour (Schießl, Fricke & Staubach, 2013; Lauper, Moser, Fischer, Mathies & Kaufman-Havoz, 2015).

In a large study, Schießl, Fricke & Staubach (2013) illustrated that one segment of drivers – characterised by self-reported high annual mileage and fast driving – were significantly more likely to report an external locus of control for eco-driving compared to the drivers with low annual mileage. Moreover, drivers who primarily used vehicle to commute to work were significantly more likely to report a higher internal locus of control as well as to report their main driving motivation as a willingness to act ecologically than those who reported primarily using their vehicle for leisure activities (Schießl, Fricke & Staubach, 2013).

In another study by Lauper et al. (2015), researchers utilised a combination of the TPB (Ajzen, 1991) and the Health Action Process Approach (HAPA; Schwarzer, 2008), featuring two conceptually-related constructs: perceived behavioural control and maintenance self-efficacy. It was found that perceived behavioural control was one of the strongest predictors of behavioural intention and implementation intention. Moreover, maintenance self-efficacy was found to significantly predict implementation intention and self-reported eco-driving behaviour. However, the association between the intention to practice eco-driving and self-reported eco-driving regularity was relatively weak, suggesting that whilst individuals who perceive it within their control to eco-driving may be more likely to hold eco-driving intentions and even plans of how to achieve these intentions, they often fail to implement these intentions through their actual behaviour.

1.3.5 Subjective Wellbeing and Major Life Events

Subjective wellbeing (SWB) refers to the personal perception and experience of positive and negative emotional responses and the global and domain-specific cognitive evaluations of satisfaction with life (Proctor, 2014; Diener, 1984). Subjective wellbeing has been implicated in driving behaviour as drivers' impulsive reactions to rapidly evolving traffic situations are thought to be grounded in their emotional responses (Jeon, 2015; Goldenberg et al., 2000). Despite this, major theories applied to driving behaviour (e.g., TPB, Ajzen, 1991; Fishbein & Ajzen, 2010) have focused largely on cognitive factors, only partially and peripherally addressing these affective aspects (Jeon, 2015).

Challenging this, several affective-based theories such as Matthews' (2001) transactional model of driver stress and personal maladjustment theory (Mayer & Treat, 1977; Lennon, Watson, Arlidge & Fraine, 2011) argue that aggressive drivers are characterised by acute or chronic stress and challenging life periods which predispose them to driver stress vulnerability (Selzer, Rogers & Kern, 1968). Driver stress appears to be associated with maladaptive, confrontative forms of coping during the driving task such as antagonising other drivers and inefficient risk-taking practices (Matthews et al., 1997; Matthews, 2001b; Ward et al., 1998; Rowden, Peter, Watson, Barry, Biggs & Herbert, 2006).

The majority of research focuses on the impact of task-derived poor wellbeing (i.e., driver stress, anger, mood) on driving. Drivers experiencing high stress during driving may adopt specific aggressive behaviours as coping strategies to self-regulate the task-derived frustration (Lonsdale, 2010; Roseborough & Wiesenthal, 2014; Wickens et al., 2013a; Hennessy & Wiesenthal, 2005; Dukes et al., 2001). 'Road rage' – aggressive driving often elicited due to perceived norm-violations of other road users (Goldenberg et al., 2000) – provides empirical evidence for the impact of negative emotions on driving *safety* (Burns and Katovich, 2003; Lonsdale, 2010; Roseborough & Wiesenthal, 2014; Wickens et al., 2013a; Hennessy & Wiesenthal, 2005; Dukes et al., 2001). For example, in one driving simulation study, when drivers experienced high stress-provoking driving situations, they reported greater frustration and anger which was followed by subsequent increases in aggressive operational driving actions (i.e., increased acceleration, throttle pressure and steering wheel use; Stephens & Groeger, 2009).

However, some research suggests that stable individual differences in drivers' wellbeing – rather than just the task-derived stress alone – may interact to shape driving actions.

Drivers' trait-level anxiety appears implicated in uneconomical driving (Goldenberg et al., 2000; Hennessy & Wiesenthal, 1997; Hennessy, Wiesenthal & Kohn, 2000; Kontogiannis, 2006; Garrity & Demick, 2001; Ge et al., 2014; Westerman & Haigney, 2000; Hill & Boyle, 2007). Trait-anxious drivers engage in various fear-related problematic driving behaviours such as exaggerated cautiousness, anxiety-based performance deficits and aggressive driving (Clapp et al., 2011a; Taylor, Deane & Podd, 2007; Matthews et al., 1998; Stephens & Groeger, 2009). Even when placed in low anger-provoking driving situations, drivers higher in trait-level anger reported greater state-level anger and acceleration profiles compared to those lower in trait anger (Stephens & Groeger, 2009). This suggests that even in typically non-provocative situations inherently anger-prone drivers are more likely to drive inefficiently. Evidence also suggests aversive driving experiences (e.g. traffic accidents) may interactionally contribute to the development of trait-level 'driving anxiety' (Clapp et al., 2011b; Mayou, Simkin & Threlfall, 1991).

Critically, measures of subjective wellbeing assess individuals' subjective experiences of their quality of life, but do not directly consider the experiences, such as life stressors, which may contribute to this self-assessment. As personal maladjustment theory stipulates that experiencing negative affect is associated with aggressive driving, it is also of interest to consider whether the *objective* experience of negative life stressors may be implicated in unecological driving. Road safety research illustrates associations between negative major life events (e.g. separation or divorce, hospitalisation; Lagarde, Chastang, Gueguen, Coeruet-Pellicer, Chiron & Lafont, 2004; Lancaster & Ward, 2002) and road traffic accidents, traffic violations and drink-driving (Lagarde et al., 2004; Lancaster & Ward, 2002). However, the impact of major life events has not yet been studied in eco-driving context. As a result, this thesis examines the influence of both subjective evaluations of wellbeing and objective experiences of negative major life events on eco-driving behavioural outcomes.

1.3.6 Demographic patterns

Demographic factors have been widely studied in the contexts of driver behaviour and pro-environmentalism (e.g., Scott-Parker, King & Watson, 2015; Sovacool et al., 2018), though research has yet to considerably establish how demographic patterns may relate to eco-driving specifically (McIlroy & Stanton, 2015). Age, gender and driving experience often permeate this literature (e.g. Scott-Parker et al., 2015), while other relevant aspects of demography such education level and recreational drug use have also been considered in these contexts (Sovacool et al., 2018).

Much of the research constructs demographic factors as ‘external’ and individual differences as ‘internal’ to the individual when considering the motivations a person may have for behaviour enactment, with this distinction referred to as the ‘internal-external gap’ (Courtenay-Hall & Rogers, 2010). This approach is limited, as it asserts that aspects of the self – such as personality and identity – are wholly separable from our social location, despite individual differences being the *“very embodiment of the host of factors listed as ‘external’ to them”* (Courtenay-Hall & Rogers, 2010, p.293). This does not recognise the intersecting complexity of group and individual differences, despite evidence that several stable psychological differences (e.g., personality) mediate the relationships identified between demographic factors (e.g., age and gender) and patterns in pro-environmental behaviour.

1.3.6.1 Age

The influence of age on driving is widely conceptualised as the *‘young driver problem’* in road traffic research (Scott-Parker et al., 2015), illustrating that younger drivers are more likely to report engaging in risky driving practices such as speeding and tailgating (Moller & Gregersen, 2008; Rhodes & Pivik, 2010; Rhodes et al., 2005; Groeger, 2006), more likely to carry peer-aged passengers than older drivers (Laapotti et al, 2016) which is related to increased speeding intentions and driver crash likelihood (Keall, Frith & Patterson, 2004; Baxter et al., 1990) and are more likely to report social driving – characterised as driving ‘for excitement’ and without a destination – which is associated with traffic offences and increased risk of injury for young drivers (Blows, Ameratunga, Ivers, Lo & Norton, 2005; Pilkington et al., 2014). Conversely, influence of age in pro-environmental behaviour is inconclusive – stereotypes commonly regard older individuals as acting more pro-environmentally (Miernik, Ones & Dilchert, 2013), yet only weak empirical support exists for this (Wiernik, Ones & Dilchert, 2013; Pinto, Nique, Añaña & Herter, 2011; Swami, Chamorro-Premuzic, Snelgar & Furnham, 2011) and some studies finding age to be unrelated to environmentally-significant behaviours including eco-driving intention (e.g. Gatersleben, Murtagh & Abrahamse, 2014; Stromberg, Karlsson & Rexfelt, 2015).

1.3.6.2 Driving Experience / Licence Length

Findings for driver experience often intersect with that of age (Scott-Parker, King & Watson, 2015). Greater driving experience has been associated with safer driving practices, such as increased hazard perception over time (Wallis & Horswill, 2007) and decreased crash likelihood (McCartt et al., 2009; Groeger, 2006). Moreover, statistics suggest risks are greatest for newly-licenced young drivers (UK House of Commons, 2021), though irrespective of age, crash risk has been found to decline steeply over the first three months of independent driving (McCartt et al., 2009). Despite the obvious intersect between age and driving experience (i.e., novice drivers are more likely to be younger; Kinnear et al., 2008), this finding suggests research which measures both length of time with a licence and driver age maximise insights which can be drawn about fuel-inefficient driving.

1.3.6.3 Gender

Across studies of safe- versus eco-driving, the literature is mixed for the influence of gender on driving quality (McIlroy & Stanton, 2015). In the context of risky, unsafe driving practices, clear gender differences have been found (Harre et al., 2000, Oltedal & Rundmo, 2006), as men have been found to be more likely to report risky driving (especially during adolescence, Vavrik, 1997), drive significantly faster than women (Harre et al., 1996) and appear to have triple the fatality rate of women (NHTSA, 2009). Yet, studies specific to eco-driving reflect paradoxical findings. Whilst women drivers were more likely to self-report eco-driving behaviour (e.g. Delhomme, Cristea & Paran, 2013) and report valuing the environmental benefits of electric vehicles than men (Vassileva & Campillo, 2017), men appear to be more knowledgeable about eco-driving strategies (McIlroy & Stanton, 2017; King, 2011) and are more likely to be ‘early adopters’ of electric vehicles than women (Vassileva & Campill, 2017). These findings may reflect well-established and pervasive gender differences in car-culture (O’Connell, 1998) which can be considered likely to influence domain-specific knowledge and car-purchasing habits. Yet, improvements in workplace gender equality in recent decades has brought about more intensified car use across all genders (Best & Lanzendorf, 2005). Consequently, it is plausible that broader changes in gender equality may function as a driving force for dynamical change in drivers' attitudes and behaviours.

1.3.6.4 Education Level

Studies suggest education can influence individuals' perceptions of sustainability and mobility (Sovacool, Kester, Noel & Zarazua de Rubens, 2018). Research has found that higher levels of education are related to higher levels of environmental knowledge, particularly for those with degree-level qualifications (Diamantopoulous, Schlegelmilch, Sinkovics & Bohlen, 2003; Sovacool, Kester, Noel & Zarazua de Rubens, 2018). As environment-specific knowledge is considered a behaviour-distal precursor to environmentally-significant behaviour (Stern et al., 1999; Diamantopoulous et al., 2003), it has been hypothesised that awareness of environmental problems (e.g. environmental knowledge) rises with high education and contributes to pro-environmental, low carbon practices (Buchs & Schnepf, 2013).

It has been argued that university-educated individuals might learn to place higher value on protecting the environment as universities often lead the 'green' movement by endorsing and implementing optimal transport technologies (Sovacool et al., 2018; Sovacool et al., 2012; Filho, 2000; Vassileya & Campillo). For example, electric vehicle drivers in a Norwegian sample were more likely to have a higher education level and reported greater environmental concern than drivers of other vehicles (Sovacool, Kester, Noel & de Rubens, 2018). However, McIlroy and Stanton (2015) found that drivers did not significantly differ in their knowledge of eco-driving strategies by their education. Moreover, highly educated drivers' ecological behaviours (i.e. electric vehicle ownerships) may be driven by socio-economic comorbidities and education might otherwise negatively impede other eco-driving decisions and increase personal emissions (Sovacool et al., 2018). This suggest that education may impact discrete eco-driving behaviours in different ways and covary with aspects of drivers' social location (i.e., socio-economic status, countries' attitudes and approach to sustainability).

1.3.6.5 Recreational Drug Use: Alcohol Consumption and Smoking Behaviour

Nicotine smoking and alcohol consumption are particularly focal lifestyle traits, as they are common and modifiable 'risk' behaviours which have been associated with subsequent engagement in multiple other risk behaviours, both during later adolescence and adulthood (DuRant, Smith & Kreiter, 1999; MacArthur, Smith, Melotti, Heron, Macleod, Hickman, Kipping, Campbell & Lewis, 2012; Chliaoutakis, Koukouli, Lajunen & Tzamalouka, 2005).

Whilst research has widely considered the role of these traits in terms of real-time behavioural consequences on driving outcomes (i.e., drunk-driving, smoking whilst driving; Stephens, Bishop, Liu & Fitzharris, 2017; Bingham, Elliott & Shope, 2007; Shyhalla, 2014), this thesis is more interested in the underlying psychosocial motivators of recreational drug use which may characterise a general proclivity towards risk-taking behaviour (Jessor, 1987). Broadly, research theorises that individuals engage in these high-risk behaviours to 'self-medicate' underlying negative affect such as chronic stress (Sinha, 2008). Evidence empirically supports this, as recreational drug use has been consistently associated with stress (Sinha, 2001, 2008), lower subjective wellbeing (Dobson, Brown, Ball, Powers & McFadden, 1999; Sinha, 2001, 2008) and coping motives (Cooper, 1994; Cooper, Russell, Skinner, Frone & Mudar, 1992; Park, Armeli, Tennen, 2004). In this vein, the 'self-medication' hypothesis is convergent with Matthews' (2001) theory of driver stress vulnerability as both propose that these risky behaviours (i.e., recreational drug use and poor driving respectively) function as maladaptive strategies for individuals to self-regulate negative affect.

Alcohol Consumption

Alcohol use frequency and intensity has been consistently associated with both self-reported and objectively-measured *sober* aberrant driving (Fergusson, Swain-Campbell & Horwood, 2003; Beirness & Simpson, 1988; Horwood & Fergusson, 2000; Begg, Langley & Williams, 1999; Simpson & Beirness, 1991). For example, Valencia-Martin, Galan and Rodriguez-Artalejo (2008) found that average alcohol intake and binge drinking were both associated with self-reported hazardous driving behaviour as well as traffic accidents, with this relationship stronger when participants reported heavy average alcohol consumption and binge drinking jointly. Moreover, Zhao, Wu, Houston & Creager (2010) found that in a driving simulator study of sober driving, participants classified by self-reported behaviour as ‘binge drinkers’ were more likely to exceed the speed limit and sped for a longer duration than non-binge drinkers.

Notably, evidence indicates that the impact of these lifestyle traits may intersect with key demographic differences. For example, middle-aged drivers report both lower average alcohol intake and less impaired driving (Alcaniz, Santolino and Ramon, 2016). This also extends to within-group differences, as for young women, riskier driving practices (e.g., speeding and tailgating) have been associated with habitual alcohol consumption and self-reported stress (Dobson, Brown, Ball, Powers & McFadden, 1999).

Smoking Behaviour

Cigarette smoking is widely considered to be a risk factor for collision involvement, traffic accident injury and accident mortality which are all behavioural proxies for driving inefficiency (Pederson et al., 1998; Leistikow, Martin & Samuels, 2000; Sacks & Nelson, 1994; Hutchens, Senserrick, Jamieson, Romer & Winston, 2008; Igarashi et al., 2017). Beyond obvious, real-time impacts of smoking during driving (i.e., driver distraction leading to inattention; Avi, Yehonatan, Alon, Alexandra & Arieh, 2001; Saadat & Karbakhsh, 2010; Hutchens et al., 2008), nicotine addiction research has elucidated that smokers are more likely to engage in ‘risky’ behaviours (MacArthur et al., 2012).

1.4 Measuring eco-driving: self-report versus objective behaviour

1.4.1 The absence of objective eco-driving behaviour

Significant eco-driving evidence has been gained by means of self-report measures of behavioural intention (e.g., Unal et al., 2018; Unal et al., 2019; Lauper et al., 2015) and behaviour (e.g. Schießl et al., 2013). Self-report measures of driving are advantageous as they are easy and cheap to administer, simple to complete and provide a standardised way of collecting data. However, there is significant dispute regarding the usefulness and validity of these measures in the context of driving (Taubman-Ben-Ari, Eherenfreund-Hager & Prato, 2016; Gunther, Rauh & Krems, 2017).

The broader limitations of self-reported behaviour are well-known (Blanchard, Myers & Porter, 2010; af Wahlberg, 2009; af Wahlberg, 2010). Responses may be affected by self-serving biases, recall biases and shared variance with other self-report measures (Taubman-Ben-Ari et al., 2016). More specifically, the use of behavioural intentions as a proxy for eco-driving behaviour may be problematic due to evidence of a weak relationship between eco-driving intentions and behaviours, even when self-reported (Lauper et al., 2015; Unal et al., 2018; Unal et al., 2019; Faries, 2016; Sheeran & Webb, 2016; Sniehotta et al., 2014). As such, the extent to which self-reported eco-driving behaviour and intentions may reflect *real driving* is in doubt (af Wahlberg, 2009; af Wahlberg & Dorn, 2015; Helman & Reed, 2015; Wolf, Oliveira & Thompson, 2003; Forrest & Pear, 2005; Stopher, Zhang & Fitzgerald, 2008; Marshall, Wilson, Molnar, Man-Song-Hing, Stiell & Porter, 2007).

Furthermore, self-reported eco-driving measures often conceptualise eco-driving as a collective 'act' which can be measured using a few broad scale items (e.g., *'I intend to drive more fuel efficiently'*; Unal et al., 2018, Unal et al, 2019; Lauper et al., 2015). While this has practical benefits, this approach fails to recognise and measure the discrete strategies involved in operational eco-driving behaviours (e.g. braking versus speeding). Moreover, it also misses the opportunity to operationalise eco-driving more broadly in the context of other strategic and tactical decisions drivers can make (e.g. trip route, length of journey). This is important, as individuals may differ in how they utilise different eco-driving strategies. As a result, self-report methodologies have limited practical utility for both our understanding of individual differences in eco-driving behaviour, as well as for shaping information-based interventions which often require granular information about drivers' specific eco-driving practices in order to feedback to target populations (Allcott & Mullainathan, 2010).

1.4.2 Digital traces from telematics – a new discipline

In recent years, emerging methods for monitoring drivers using in-vehicle sensors have been adopted in order to collect naturalistic driving data within everyday driving (Horrey & Lesch, 2008, Vaezipour et al., 2015). Data logging technologies such as GPS, accelerometers and other in-car recording devices provide novel methodologies for eco-driving research, as they have enabled researchers to objectively and accurately measure eco-driving using digital traces with little burden on study participants (Blanchard, Myers & Porter, 2010; Marshall et al., 2007; Huebner et al., 2006). Using data mining techniques, these technologies are able to derive an array of driving efficiency metrics which reflect core driving behaviours (e.g., acceleration and braking) as well as wider journey features (e.g., the type of roadways used; Marshall et al., 2007). This is a considerable strength of this methodology, as it can enable researchers to glean granular insights about the behavioural disparities across eco-driving behaviours.

Despite the promise of these novel methods, extremely few psychological studies have operationalised eco-driving behaviour through objective measures (e.g., Stephens & Groeger, 2009; Stephens, Young, Logan & Lenne, 2015; Lajunen, 2001). This is most likely due to the inaccessibility of naturalistic driving data; researchers often do not have the resources to collect data on 'everyday driving' (van Schagen & Sagberg, 2012; Helman & Reed, 2015). Additionally, companies which often monitor customers through these methods, such as telematics insurance providers and vehicle manufacturers, have often been bound by data privacy policies which constrain their ability or willingness to share customer driving data with researchers. Yet, there is promise in recent shifts by the private sector to engage collaboratively with the academic community to address sustainability issues (Riel, Tichkiewitch, Stolfa, Stolfa, Kreiner, Messnarz & Rodic, 2016). This research project in collaboration with Insurance & Mobility Solutions (IMS) serves as a clear exemplar of how industry-academia partnership can be utilised for eco-innovation within the automotive arena.

Moreover, the prevalent paradigm in psychological research adopts an *"explanation-focused"* approach to data analysis – that is, a goal to accurately describe the causal underpinnings of behaviour (p.2, Yarkoni & Westfall, 2017; Hinds & Joinson, 2019). Conversely, novel interdisciplinary research has started to adopt computer science methods in order to incorporate techniques such as machine learning (e.g. Rosenbusch, Soldner, Evans & Zeelenberg, 2021; Rafaeli, Ashtar & Altman, 2019) into psychological practice which are able to go beyond simply *explaining* behaviour in order to *predict* – with relative accuracy and reliability – future behaviour (Yarkoni & Westfall, 2017).

Critically, these advanced methods have significant implications for psychological eco-driving research, as the possible ability to forecast the behavioural, psychological and demographic characteristics of drivers who may be most susceptible to unecological driving may enable the optimal, targeted use of intervention resources as well as deliver valuable actuarial insights for ecological risk-pricing. Accordingly, this thesis assumes an interdisciplinary approach by utilising methodologies from both 'conventional' psychology and computer science to advance our understanding of how fundamental individual and demographic differences – such as personality and age – may play a role in the enactment of environmentally efficient driving.

1.5 This Thesis

1.5.1 Thesis objectives

Taken together, prior research and theory offer substance to the idea that certain individual and demographic differences might be implicated in the propensity to adopt eco-driving practices. As a result, this thesis has three main objectives. The first seeks to address whether several aspects of individual differences (including values, environmental self-identity, personality traits, locus of control and subjective wellbeing) and demography (including age, education level, recreational drug use and major life stressors) are predictive of several eco-driving behaviours measured objectively using telematics technology. To my knowledge, this has not yet been tested before in this capacity. Second, this thesis aims to combine self-report and objective measurement to develop a broader understanding of the relationship of drivers' subjective eco-driving intentions and actual eco-driving behaviours. Finally, this thesis aims to develop a series of recommendations for how psychological insights could be used in practice by our industry partner, IMS, as well as wider policy stakeholders, in the design of technology-assisted eco-driving behavioural interventions.

1.5.2 Hypotheses

In accordance with the objectives of this thesis outlined above as well as the literature review undertaken, seven hypotheses are proposed:

Hypothesis 1: Higher scores on honesty-humility, agreeableness, conscientiousness and openness to experience personality traits will predict greater eco-driving behaviours.

Hypothesis 2: A quadratic relationship (an inverted 'U' shape) is predicted between emotionality and eco-driving behaviour.

Hypothesis 3: Higher scores on extraversion personality traits will predict poorer eco-driving behaviours.

Hypothesis 4: Higher scores on biospheric and altruistic value orientation and environmental self-identity will predict greater eco-driving behaviours.

Hypothesis 5: Higher scores on egoistic and hedonic value orientation will predict poorer eco-driving behaviours.

Hypothesis 6: Overall scores on the SLW & PWI scale will not predict eco-driving behaviours.

Hypothesis 7: Higher scores on the locus of control (high = externality) will predict poorer eco-driving behaviours.

2. Methods

2.1 Participants

Participants were recruited online via an email advertisement campaign delivered by Carrot Insurance to a stratified sample of their Carrot Insurance telematics policy customers in the UK. In order to participate, customers were required to be 18 years or older at the time of policy commencement, hold a full UK Driving License and have held a telematics insurance policy with Carrot Insurance for at least the prior three months.

The customer sample selected to receive the email study invitation consisted of 1634 individuals delivered in three tranches (each tranche approx. $n = 500$, with this approach taken in order to anticipate response rate and distribute the survey proportionately. The sample was stratified by the industry partner by the participation requirements above as well as by length of policy (i.e., 3 – 6 months / 6 – 9 months / 9 – 12 months). This form of proportionate stratification was adopted with the aim of increasing the representativeness of the sample and reducing potential bias in driving quality. Notably, Carrot Insurance adopts a 'traffic light' system to distinguish the quality of customers' driving on a weekly basis, aggregating their behaviours into a collective 'score'. Accordingly, this differentiates 'Green'-averaging drivers who are driving satisfactorily, 'Yellow'-averaging customers who are driving adequately, and 'Red'-averaging drivers whose driving safety is inadequate and requires improvement otherwise risking early policy termination by Carrot Insurance. As such, this bias towards retaining 'Green' and 'Yellow' customers and dispensing of 'Red' customers creates a dynamic whereby the longer a customer has 'survived' their policy, the more probable they are a 'better' driver. In this vein, this research's requirement for a minimum policy length of three months – in order to obtain reliable driving data from customers – significantly inhibits the recruitment of 'Red'-averaging customers.

A priori power analysis was conducted using the software G*Power which showed that for linear multiple regression analyses, a sample of only 98 was enough to determine medium effect sizes of $f^2 \geq .25$ found in the literature (e.g. Lai, 2015; Oxendahl, 2018; Unal, Steg & Gorsira, 2018; Cristea, Paran & Delhomme, 2012) with a power of .95 when

α = .05 with up to six predictors. In return for their time, participants were compensated with a £5 Amazon eGift Card that was delivered via Carrot Insurance using their incentive distribution partner, GiftCloud.

2.2 Measures

2.2.1 Self-report survey measures

2.2.1.1 *Demographic questions*

Several demographic questions measured participants' age, gender identity, ethnicity, licence length, current UK region residency, education level, smoking frequency, alcohol consumption frequency and major life events. See table below for measurement approach (Table 2.1).

Table 2.1. Measurement of Demographic Variables

Demographic Variable	**Measurement Approach**
Age	Text entry
Gender identity	Multiple-choice question with five options: *'Male', 'Female', 'Non-binary', 'Prefer to self-describe* [text box]*'* and *'Prefer not to say'.*
Ethnicity	Multiple-choice question with six options: six options: *'White', 'Black', 'Asian', Mixed or multiple ethnic groups', 'Other ethnicity* [text box]*'* and *'Prefer not to say'.*
Licence Length	Separate text entry boxes for *'Years'* and '*Months*'.
Current UK region	Interactive clickable map, requiring participants to select one of twelve UK regions: *'Scotland'*, *'North East', 'North West', 'Yorkshire and the Humber', 'East Midlands', 'West Midlands', 'Wales', 'East of England', 'London', 'South East', 'South West'* and *'Northern Ireland'* (CIHT, 2020)

Education level	Multiple-choice question consisting of four generalised UK levels of qualifications as options: *'GCSE (or equivalent', 'A Level (or equivalent)', 'University undergraduate programme'* and *'University postgraduate programme'*.
Smoking frequency	Multiple-choice question worded as *'How frequently do you smoke?'*, with four options: *'Often', 'Sometimes', 'Rarely'* and *'Never.*
Alcohol Consumption Frequency	Multiple-choice question worded as *'How frequently do you drink alcohol?'* with four options: *'Often', 'Sometimes', 'Rarely'* and *'Never'*.
Major Life Events	Multiple-choice question worded as *'Have you experienced any of the following major life events in the last year? Select all that apply.'*. Nine options were derived by the research team: *'Childbirth or adoption', 'Separation from a relationship or divorce', 'Personal illness', 'Illness of a close other', 'Injury or medical emergency involving you', 'Injury or medical emergency involving a close other', 'Moving to a new home (including University'),'Bereavement of a close other (e.g. partner, family, friend)'* and *'Change of job circumstances'*.

2.2.1.2 *Scales and measures*

When examining Alpha, α >.50 was accepted as adequate internal reliability in line with recommendations from Hinton, Brownlow, McMurray & Cozens (2004), with an Alpha score of α >.75 taken to indicate high reliability (Hinton et al., 2004). This was selected, as Kline (1999) and Cortina (1993) both acknowledge that more diverse psychological constructs and scales featuring few items commonly incur smaller Cronbach Alpha values.

The Perceived Accessibility Scale (PAC) measured perceived ease of engaging in preferred activities using different transport modes (Lattman, Olsson & Friman, 2016). The scale consisted of four items such as *"It is possible to do the activities I prefer with public transport"* and participants responded on a seven-point Likert-scale ranging from *"I don't agree"* (1) to *"I completely agree"* (7) as to what extent they agreed or disagreed with the statement. Total scores could range from 1 – 7, whereby higher scores indicated greater perceived accessibility using public transport modes. This scale had very good internal consistency (α = .81).

Personality was measured using the 60-item short measure of the HEXACO PI-R (Ashton & Lee, 2008). The measure consisted of six domain scales, featuring 10 items per scale presented as statements such as *"I sometimes can't help worrying about little things"*. Participants responded on a five-point likert-type scale ranging from *"strongly disagree"* (1) to *"strongly agree"* (5) as to what extent they agreed or disagreed with each statement. Scores for each domain scale could range from 1 – 5. Each of the six domain scales showed good reliability: Honesty/Humility (α = .69), Emotionality (α = .75), Extraversion (α = .74), Agreeableness (α = .68), Conscientiousness (α = .71), and Openness to experience (α = .73).

The Environmental Portrait Value Questionnaire (E-PVQ) consisted of 17 items which measured human value orientations considered to underlie environmental beliefs and behaviours; biospheric (i.e. concern for environment), altruistic (i.e. concern for others), egoistic (i.e. concern for personal resources) and hedonic values (i.e. concern for pleasure and comfort; Bouman, Steg & Kiers, 2018). The measure consisted of four domain scales, featuring between 3 to 5 items per scale. Items consisted of descriptions of what another individual (matched to self-reported gender identity; he, she, they) thought was very important in life, such as *"It is important to* ***them*** *to protect the environment".* Participants responded on a seven-point Likert-scale ranging from *"not like me at all"* (1) to *"very much like me"* (7) as to what extent the person described was similar to themselves. Scores from each domain scale could range from between 1 – 7. The egoistic biospheric domain scale illustrated low but acceptable internal reliability (α = .64), whilst the remaining three showed very high internal reliability: altruistic (α = .87), biospheric (α = .90), and hedonic (α = .91).

The Locus of Control Scale (LOC; Rotter, 1966) consisted of 29 items which measured an individual's perception of whether themselves or external factors control their life outcomes. Each item consisted of a pair of statements such as *"Becoming a success is a matter of hard work, luck has little or nothing to do with it"* versus *"Getting a good job depends mainly on being in the right place at the right time"*, whereby participants selected the statement that they most identified with. Scores for the scale could range between 0 – 23, whereby higher scores indicate externality and lower scores indicate internality of locus of control. Although the scale had low internal consistency (α = .50), this was to be expected as Rotter (1989) himself acknowledges that items within the scale were designed to sample behaviour across a wide variety of situations to reflect locus of control as a broad construct, at the expense of high internal reliability as correlations among behaviours in different situations were expected to be positive but low.

The Environmental Self-Identity Scale (Environmental Self-Identity) consists of three items which measured the extent to which individuals perceive themselves as a type of person who acts environmentally friendly (Van der Werff, Steg & Keizer, 2013b). Participants responded to items such as *"I am the type of person who acts environmentally friendly"* on a seven-point scale ranging from *"totally disagree"* (1) to *"totally agree"* (7). Total scores could range from 1 – 7, whereby higher scores indicate greater self-perception as an environmentally-conscious individual. This scale had high internal reliability (α = .90).

General subjective wellbeing was measured using the Satisfaction with Life as a Whole & Personal Wellbeing Index Scale (SLW&PWI; The International Wellbeing Group, 2013) which contained nine items. Participants were asked *"How satisfied are you with…?"* and responded to items such as *"feeling part of your community?"* on an 11-point scale ranging from *"no satisfaction at all"* (1) to *"completely satisfied"* (11). Total scores could range from 1 to 11, whereby higher scores indicated greater subjective wellbeing. This scale had high internal reliability (α = .88).

Behavioural intention to eco-drive was measured using a three-item scale developed by Unal, Steg and Gorsira (2018). Participants were asked *"To what extent do you intend to* *perform the following driving behaviours?"* and responded to items such as *"I intend to switch to a higher gear as soon as possible"* on a 7-point scale ranging from *"I do not intend to do this"* (1) to *"I fully intend to do this"* (7). Total scores could range from 1 to 7, with higher scores indicating greater behavioural intention to perform eco-driving behaviours. The scale had low – though adequate – internal reliability (α = .61).

2.2.2 *Measures of objective eco-driving*

The driving data provided by my industry partner IMS Data Science consists of ten objective eco-driving measures sourced from customer journeys throughout their policy (minimum 3 months, maximum 12 months). This includes seven operational behaviours derived from the accelerometer data consisting of acceleration, braking, speeding, cornering, duration over an hour, volume of journeys and time of day. Moreover, it comprises of three tactical behaviours including; number of journeys, average duration of journeys, and average number of miles. Each of the seven operational measures reflect the 'point' counts customers received during each journey as a result of undesirably performing the respective inefficient action (e.g. braking too sharply). Table 2.2 explains how each objective eco-driving variable is derived by the industry partner (e.g. a speeding 'point' received for travelling at a speed 10mph above the average speed limit).

Table 2.2. Objective Eco-Driving Variable Descriptors

Variable Name	**Variable Description**
Number of Journeys	The total number of journeys undertaken by each participant over the duration of their policy so far (min. 3 months, max. 12 months).
Av. Duration of Journeys	The average duration in minutes of all journeys undertaken by each participant over the duration of their policy so far. The duration data provided by IMS was rounded to the nearest whole minute.
Av. Number of Miles	The average number of miles of all journeys undertaken by each participant for the policy period so far. The

	mileage data provided by IMS was rounded to two decimal places.
Acceleration	Participants received acceleration ‘points’ due to inefficient acceleration per journey made. Points were derived [REDACTED] and were given in any instance where the acceleration over the previous second was above a given threshold (approximately [REDACTED] G).
Braking	Participants received braking ‘points’ due to inefficient deceleration per journey. Points were derived once per second and were given in any instance where the deceleration over the previous second was above a given threshold (approximately [REDACTED] G).
Speeding	Participants received (average) speeding ‘points’ due to travelling at an inefficient speed per journey. Average speed points were accumulated when the vehicle travels at a speed of more than [REDACTED] mph over the average speed for that road, with [REDACTED] point/s given per minute.
Cornering	Participant received cornering ‘points’ due to inefficient turning behaviour per journey. Points were derived [REDACTED] and were given in any instance where the vehicle changes direction by [REDACTED] degrees at a given speed of more than [REDACTED] mph.
Duration	Participant received duration ‘points’ due to inefficient journey durations per journey. Points were derived [REDACTED] every [REDACTED] for every message received from the device driven for over [REDACTED] hour/s of continual driving.
Volume of Journeys	Participants received volume of journey ‘points’ due to an inefficient volume of journeys. Points were accumulated [REDACTED] in the instance where there

	have been more than [REDACTED] journeys in a rolling [REDACTED] time window.
Night-Time Driving (IMS define this as ‘Time of Day’)	Participant received night-time driving ‘points’ due to driving during the night (per journey). This is implicated due to poorer driving quality observed during this period as a result of the impact of darkness on driving conditions. Points were accumulated [REDACTED] for every [REDACTED] for every message received from the device driven between the hours of [REDACTED] and [REDACTED].

2.3 Procedure

All participants were recruited through an email advertisement campaign delivered by Carrot Insurance to a stratified sample of Carrot Insurance telematics policy customers. The email advert briefly informed prospective participants about the broad purpose of the research, the £5 Amazon eGift Card incentive, details of the study and how to take part (See Appendix B).

Prospective participants were encouraged to click the “Take Part” link if they wanted to learn more about the research and participate. This featured an embedded link to the online survey hosted on the platform Qualtrics that was personalised for each customer. This was performed using anonymised, hashed data provided by Carrot Insurance which served as a proxy for customer policy reference numbers (See Appendix D). This eliminated the need for participants to provide any personal data, as it enabled the research team to anonymously tie participant survey responses to their historic driving data during data analysis.

Upon clicking, participants were first presented with a detailed information page, followed by a consent page, before commencing the survey. Following provision of consent, the survey listed a series of four initial demographic questions (age, gender identity, ethnicity, license length). Then, participants were presented the Environmental-VQ; HEXACO-60, Environmental Self-Identity, Locus of Control scale, Behavioural Intention to Eco-Drive Scale, Perceived Accessibility of Public Transport Scale and the

Satisfaction with Life as a Whole & PWI Scale. Lastly, participants were presented with a five closing demographic questions (current UK region, educational attainment level, smoking frequency, alcohol consumption frequency, recent major life events). Following completion of the survey questions, participants were presented with a debrief page. After survey data collection, the list of customers (anonymously identified through their hashes) that had completed the survey were sent to Carrot Insurance. Carrot Insurance used the hashes to query participants' historic driving journey data and return the dataset. Carrot Insurance also used the hashes to identify participating customers and distribute the £5 Amazon eGift Card incentive via their incentive distribution partner, GiftCloud.

2.4 Ethics

Prior to any data being collected, the study received full ethical approval from the Faculty of Science and Technology Ethics Committee based at Lancaster University (Reference: FST19123, see Appendix A). The study procedure also complied with British Psychological Society ethical guidelines and guidelines for internet-mediated research (British Psychological Society, 2014; Hewson et al., 2013).

On the first page of the online survey, participants were presented with a participant information page. This page detailed the purpose of the research, specified what taking part comprised of and communicated the potential benefits and disadvantages of participating in the study (See Appendix C). No deception took place as the full aims of the study were described. This page also clarified details regarding participant anonymity and data handling in line with Lancaster University and GDPR guidelines. Participants were advised that they did not have to take part in the study if they did not wish to and could withdraw participation at any time up to two weeks following completion of the survey, without any adverse consequences in terms of their car insurance policy with Carrot Insurance. On this page, participants were additionally provided information about ethical approval by the Faculty of Science and Technology (FST) Research Ethics Committee and contact details for both the Principal Investigator as well as the Head of the Lancaster Environment Centre, in case participants had any queries about the research or concerns or complaints regarding their experience. The consent page summarised information pertaining to participation in several statements and requested consenting participants to click a box in order digitally sign their consent to the statements (See Appendix D).

For ethical purposes, all questions within the Qualtrics survey were programmed to request responses to unanswered questions in lieu of forced response, whereby participants were notified of unanswered questions and asked if they would like to answer the question or continue without answering.

After completing the survey, participants were presented with a debrief page. This elaborated on the purpose and background of the research, provided resources about eco-driving, reiterated information regarding rights to withdraw from the study and listed contact details if participants wished to voice concern or complain about their experience. Moreover, the debrief page provided several sources of support, advice and information if participants felt they were affected by any of the topics discussed during the survey, including a link to Carrot Insurance's Customer Support service and links to the following charities and support services: Mind (https://www.mind.org.uk/information-support/types-of-mental-health-problems/stress/what-is-stress/), Samaritans (https://www.samaritans.org), Brake (http://www.brake.org.uk/) and THINK! (https://www.think.gov.uk).

3. Results

Following data collection using the procedure outlined in the previous section, data analysis was conducted to address the thesis objectives and hypotheses as outlined (see Section 1.5.). The project industry partner IMS are the data controllers of the telematics journey datasets. Therefore, requests to view and access the data should be made to IMS.

3.1 Analysis Plan

First, the analysis provides a description of how the survey and driving data were processed, including how scores for the survey measures were calculated, how the driving data was formulated into variables and the rationale for data removal. Next, demographics and variable descriptive statistics were reported for the final sample. Tests of normality were conducted to establish whether the variables met the assumptions of parametric testing. Then, relationships between all variables were assessed. This was to inform the confirmatory analyses and explore the relationships between variables of interest, including the relationships between outcome eco-driving variables, and the relationship between self-reported behavioural intentions to eco-drive and (objective) eco-driving variables. Afterwards, confirmatory analyses were conducted to assess whether any of the relevant variables were predictive of eco-driving behaviour variables (both objective and self-reported) in line with the hypotheses. Following confirmatory analyses, additional exploratory analysis was undertaken to assess the predictive relationship between demographic variables and eco-driving behaviour variables (both objective and self-reported). Then, predictive modelling using conditional inference trees was conducted to explore non-linear relationships between study variables, focusing on predicting eco-driving behaviours and driver gender.

3.2 Data processing and scoring

The data was downloaded from Qualtrics and processed using R. Data for licence length was transformed from two columns ‘Years’ and ‘Months’ into one column reflecting total licence length in months. To consider the cumulative impact of multiple major life events (e.g. moving home), responses to the eight questions were summed to create a total score

(‘Major Life Event Frequency’). Scores for the Perceived Accessibility of Public Transport scale, Environmental Self-Identity scale, Satisfaction with Life as a Whole and Personal Wellbeing Index scale and behavioural intention for eco-driving scale were created by averaging the items of each respective scale to create a mean score. For the Locus of Control scale, some items required reverse coding; items were then summed to create a total score. For each of the four value domain scales in the Environmental-Portrait Value Questionnaire, the responses to the corresponding items for each value domain were averaged to create a mean score for that value. This generated four overall value scores per participant which were used in the analysis; one for biospheric values, altruistic values, hedonic values and egoistic values. For each of the six personality domain scales in the HEXACO Personality Inventory, the responses to each of the ten corresponding items for each trait domain were averaged to create a mean score for that trait.

I analysed pre-processed metrics devised by IMS, whereby for each journey undertaken, the customer received ‘point’ counts for each of the seven main driving quality measures (i.e. acceleration) each time they operated the car inefficiently (See Table 2.2). If a participant received greater than 0 points for a journey, then that journey was coded as 1 (indicating that driving inefficiency occurred for that driving measure during the journey). If a driver did not incur any points during a journey, then that journey was coded as 0 (indicating they drove efficiently). Then each participant was ascribed a percentage score for each driving metric that reflected the proportion of their journeys in which they received ‘points’. This approach was selected as we identified a large volume of journeys across participants whereby no ‘points’ were collected. Critically, if a measure of central tendency was conducted across all journeys instead, the resulting values would have been equal or very close to zero. As such, using the percentage statistic provided greater variability, which was able to illustrate differences between drivers more effectively. The number of journeys, average duration of all journeys and average miles of all journeys were also calculated. This resulted in a total of ten data points per participant. Finally, the processed survey and driving datasets were column-merged together using the participant hashes assigned.

3.3 Data Removal

Following the email advertisement campaign, the online survey received 145 completed responses, providing a response rate of 8.87% from the initial 1634 contacted. However, following removal of those who had missing values (*n* = 12) and those who wished to withdraw from the study (*n* = 1), the final sample consisted of 132 participants.

3.4 Final Sample Demographics

Considering the anticipated ‘survivor bias’ noted previously (see Section 2.1.), the final sample was distributed by average driving quality as expected (as per Carrot Insurance’s traffic light metrics; Green’ = [REDACTED]%, ‘Yellow’ = [REDACTED]%, ‘Red’ = [REDACTED]%). Participants were aged between 18 and 72 years (*M* = 20.57; *SD* = 4.86) with 71 participants identifying as women (53.79%) and 61 identifying as men (46.21%). The sample was predominantly white (*n* = 105; 79.54%), with 6 people identifying as black (4.54%), 16 as Asian (12.12%), 1 as being from a mixed or multiple ethnic background (0.76%), 2 as being from another ethnic background not listed (1.5%) and 2 preferring not to disclose their ethnicity (1.5%). A large proportion of participants reported living within the North and Midland regions of England (62.12%), with the remaining reasonably distributed across the rest of the UK. Approximately a third of participants had completed or were in the process of completing an undergraduate (30.30%) or a postgraduate degree programme (4.5%), with the remaining participants educated to A Level or equivalent (46.21%) and GCSE or equivalent (18.94%). The length of time that participant had held their Full UK Driving License ranged from 4 to 649 months (*M* = 25.18; *SD* = 56.03).

3.5 Descriptive Statistics of Study Variables

Table 3.1. Descriptive statistics of all study variables (*n* = 132)

Variable	*M*	*SD*	*Median*	*Min*	*Max*
Age (Years)	20.57	4.86	20.00	18.00	72.00
Licence Length (Months)	25.18	56.03	19.00	4.00	649.00
Smoking Frequency	3.42	1.03	1.00	1.00	4.00
Alcohol Consumption Frequency	2.65	0.96	2.00	1.00	4.00

Major Life Events Frequency	1.90	1.60	1.00	0.00	9.00
Biospheric Values	5.34	1.32	5.50	1.00	7.00
Altruistic Values	6.17	0.91	6.40	3.00	7.00
Hedonic Values	6.14	1.00	6.33	3.00	7.00
Egoistic Values	4.39	0.99	4.20	2.40	7.00
Honesty-Humility (HEXACO)	3.43	0.57	3.40	2.00	4.80
Emotionality (HEXACO)	3.14	0.61	3.10	1.40	4.90
Extraversion (HEXACO)	3.08	0.58	3.10	1.30	4.30
Agreeableness (HEXACO)	3.20	0.54	3.20	1.10	4.80
Conscientiousness (HEXACO)	3.60	0.53	3.60	1.70	4.90
Openness to Experience (HEXACO)	3.13	0.60	3.05	1.20	4.40
Environmental Self-Identity	4.92	1.29	5.00	1.00	7.00
Locus of Control	11.74	2.13	12.00	6.00	18.00
Behavioural Intention for Eco-Driving	5.36	1.15	5.33	1.67	7.00
Perceived Accessibility of Public Transport (PAC)	3.35	1.46	3.38	1.00	7.00
Satisfaction with Life as a Whole & Personal Wellbeing Index (SLW&PWI)	7.54	1.73	8.00	3.00	11.00
Number of Journeys	1244.27	1026.88	903.50	80.00	5248.00
Average Duration of Journeys	17.54	4.32	16.59	10.12	40.83
Average Miles of Journey	4.96	2.55	4.47	1.53	20.65
Acceleration Points Frequency (Percentage)	24.18	10.88	25.38	1.22	53.14
Braking Points Frequency (Percentage)	7.67	6.04	6.22	0.00	29.13
Speeding Points Frequency (Percentage)	6.77	9.46	2.95	0.00	43.52
Sharp Cornering Points Frequency (Percentage)	7.70	6.21	6.21	0.00	28.45
Duration Points Frequency (Percentage)	1.90	2.73	1.12	0.00	25.65

Volume of Journeys Points Frequency (Percentage)	15.41	15.62	9.70	0.00	91.26
Time of Day Points Frequency (Percentage)	3.03	3.32	1.71	0.00	14.48

3.6 Normality Tests

Scores from seven variables including acceleration points frequency [W = 0.99, p = .55], egoistic values [W = 0.98, p = .07], Honesty-Humility [W = 0.99, p = .55], Emotionality [W = 0.99, p = .25], Extraversion [W = 0.98, p = .09], Conscientiousness [W = 0.99, p = .19] and Openness to Experience [W = 0.98, p = .14] were found to be normally distributed when conducting Shapiro-Wilks tests. However, the remaining 23 variables listed in Table 3.1. had distributions which were significantly different from a normal distribution (p <.05).

3.7 Exploratory Analyses

Exploratory analyses were conducted initially in order to inform confirmatory analyses and explore relationships across the variables. This included assessing relationships between the ten objective eco-driving outcome variables, the associations across the wider study variables and the associations between self-reported eco-driving intentions and the objective eco-driving behaviours. To assess this, Spearman’s correlations across all 31 key study variables were conducted (see Table 3.2) in line with Bishara and Hittner (2017) recommendations as these are robust against non-normality.

3.7.1 *Correlations Between Eco-Driving Outcome Variables*

Relationships between the ten eco-driving outcome variables were explored (see Table 3.2). Moderate-to-strong positive correlations were illustrated across the eco-driving behaviours, though most consistently across more ‘operational’ driving metrics (e.g., acceleration, braking). These relationships suggest that when drivers receive ‘points’ for one driving behaviour (e.g. speeding), similar rates of other inefficient driving actions may be likely to co-occur (e.g., braking; R^2 = .56, p < .001). This was unsurprising considering several of the eco-driving measures are derived simultaneously using the same accelerometer data sources (e.g., measures of g-force). Among the ten eco-driving variables, ‘volume of journeys’ – which represents points received for excessive vehicle use over a rolling 24-hour period – and ‘number of journeys’ demonstrated the weakest associations with the other eco-driving metrics. These findings suggest that increases in vehicle use may not necessarily correlate with the exhibition of other inefficient driving actions.

3.7.2 *Correlations Between Wider Study Variables*

It was of interest to explore correlations across all study variables to understand the underlying variable relationships with eco-driving and wider measures and to inform confirmatory analyses (see Table 3.2). Some weak-to-moderate relationships were identified between eco-driving variables and demographic traits (e.g., alcohol consumption frequency was positively associated with braking; $R^2 = .40$, $p < .001$). Comparatively, correlations between eco-driving variables and psychological measures were predominantly non-significant, though weak negative relationships were found between biospheric values and braking ($R^2 =$ —.23, $p < .001$) and between Openness to Experience and volume of journeys ($R^2 =$ —.22, $p < .05$). Moreover, Openness to Experience was positively associated with ‘points’ received for duration over an hour ($R^2 =$ —.22, $p < .05$). Self-reported intentions to eco-drive was positively associated with seven psychological variables within the study: biospheric values, altruistic values, hedonic values, environmental self-identity, trait honesty-humility, agreeableness and conscientiousness (R^2 range between —.14 to —.42).

Table 3.2. [Page 59 and 60] Correlations matrix showing Spearman’s r for all study variables.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1. Number of Journeys	–																															
2. Av. Duration of Journeys	.01	–																														
3. Av. Number of Miles	.03	.79***	–																													
4. Acceleration (Percentage)	.32**	.29**	.33**	–																												
5. Braking (Percentage)	.27	.41***	.64***	.40***	–																											
6. Speeding (Percentage)	.22	.38***	.42***	.34**	.56***	–																										
7. Cornering (Percentage)	.22	.35**	.60***	.49***	.60***	.32*	–																									
8. Duration over an hour (Percentage)	.17	.70***	.71***	.30*	.46***	.45***	.34*	–																								
9. Vol of Journeys (Percentage)	.55***	–.06	.02	.24*	.25	.25	.32*	.12	–																							
10. Time of Day (Percentage)	.30	.32**	.31**	.14	.36*	.31*	.33***	.29	.35***	–																						
11. Age (Years)	.14	.07	.01	.13	.04	.18	–.12**	.01	–.04	.04**	–																					
12.Licence Length (Months)	.42*	.01	.09	.15	.23	.20	.01**	.15	.03	.11**	.36***	–																				
13. Education	–.17	–.01	.00	–.18	–.00	–.01	–.15	.08	–.24**	.06	.13	.05	–																			
14. Smoking Frequency	.01	–.05	.01	.01	.21*	.03	.01	–.06	.21*	.13	.00	–.06	–.12	–																		
15. Alcohol Consumption	.05	.18*	.35*	.18*	.40***	.17	.24*	.25*	.10	.14	–.15	.04	–.04	–.25	–																	
16. Biospheric Values	–.03	–.05	–.10	.00	–.23**	–.16	.04	–.12	–.01	.05	.10*	.02	.06	–.07	–.09	–																
17. Altruistic Values	.05	.05	–.06	.06	–.12	.02	–.05	–.04	.00	.05	.24	.11	–.01	–.05	–.05	.59***	–															

18. Hedonic Values	.10	.03	.01	.06	.02	.02	.04	–.01	.06	.04	.14	.07	–.01	–.01	.15	.39***	.61***	–														
19. Egoistic Values	.04	.02	–.08	–.07	–.09	–.07	–.04	–.04	.05	–.03	–.20	–.05	–.10	.06	.03	.19*	.11	.26*	–													
20. Environmental Self-Identity	–.05	.05	–.03	–.05	–.12	–.11	.14	–.03	.04	.02	.04	–.03*	.11	–.20	.04	.67***	.47***	.35***	.15	–												
21. Honesty-Humility	–.15	–.05	–.06	.12	–.14	–.08	.01	–.14	–.09	–.05	.10	–.06	.06	–.12	–.15	.39***	.32***	.13*	–.19*	.19**	–											
22. Emotionality	–.17	.03	–.05	–.16	–.13	–.14	–.16	–.04	–.22	–.08	.05	–.03	.10	–.01	–.00	.09	.08*	.04	.05	.01	–.09	–										
23. Extraversion	.05	.01	.06	–.07	.08	.02	.07	.03	.02	.07	–.12	–.00	–.08	–.03	.01	.02	.13	.19	.20	.10	.08	–.28***	–									
24. Agreeableness	.01	.10	.08	.13	.00	–.01	.02	.00	.04	–.01	.04	–.01*	.09	–.18*	–.04	.26**	.21**	.11	.04	.30*	.40***	–.04	.16	–								
25. Conscientiousness	–.01	.03	.06	.07	–.06	.02	.07	.05	–.07	.12	.23	–.01	.15	–.27*	–.04	.24***	.27***	.27***	–.09	.30***	.40	–.04	.19*	.28***	–							
26. Openness to Experience	–.13	.22*	.05	.10	–.10	–.01	–.02	.12	–.22*	.09	.15	.01	.18	–.10	–.01	.33*	.15*	.10	–.07	.23*	.12	.14	–.13	.18*	.23**	–						
27. Locus of Control	.05	.06	.03	–.06	–.02	.10	.08	.06	.17	.02	–.17	–.08	–.08	–.03	–.02	.05	.01	–.05	.03	.13	.00	.05	–.08	.15	–.14	–.06	–					
28. Behavioural Intention for Eco-Driving	.02	–.01	–.05	.02	–.04	–.13*	.05	–.04	.01	.00	–.11	–.09	.17	–.24*	.06	.27***	.14**	.22**	.08	.42***	.36***	.02	.07	.33***	.40***	.12	.02	–				
29. Perceived Accessibility Scale	–.04	.19*	.11	.02	–.07	.02	.01	.03	–.11	–.06	.02	.02	–.08	–.11	–.11	.04	–.07	–.12	.07	.05	–.13	–.09	.08	.08**	–.14	.09	.09	–.01	–			
30. Satisfaction with Life as a Whole & Personal Wellbeing Index	–.05	.00	.00	–.02	–.04	.04	.04	.09	.00	–.03	–.07	–.07	–.01	–.18*	.15	.12	.11	.31**	.04	.16	.15*	.01	.35***	.03	.24**	–.11	–.03	.27***	–.06	–		
31. Major Life Events Frequency	–.00	.10	.11	.00	.06	.10*	.00	.10	.05	.07	.13	.01	.05	.12*	.16*	.06	.11	.14	.07	.12	.02	–.03	–.00	.10	.10	.10	.12	.07	.10	–.10	–	
32. Gender	–.16	–.02	–.08	–.02	–.18	–.08	–.16*	–.01	–.14	–.14*	.07	.00	.09	–.06	.03	.09	.17*	.11	.09	.07	.00	.51***	–.17*	.05	.04	.08	.05	–.09	–.04	.07	.13	–

†$p < .07$. *$p<.05$. **$p<.01$ ***$p<.001$

3.7.3 *Eco-driving behavioural intentions versus objective eco-driving behaviours*

As discussed earlier in this thesis (see Section 1.4.1), driving behaviour research has often relied heavily on measuring intentions as a proxy for behaviour (e.g. Unal, Steg & Gorsira, 2018) despite widespread evidence of an intention – behaviour gap (Lauper et al., 2015; Faries, 2016, Manski, 1990). Therefore, it was of interest to explore whether self-reported behavioural intention to eco-drive was related to objective measures of eco-driving behaviour, as it would suggest that eco-driving intention could be considered an antecedent to eco-driving behaviour. To assess this, Spearman's correlations between objective eco-driving variables and behavioural intention to eco-drive were conducted. These are reported in both Table 3.2 and Table 3.3 below, with the latter provided for improved interpretability and detail.

Self-reported eco-driving intention was found to be significantly weakly negatively related to inefficient speeding frequency [R^2 = –.11, p = .04, 95% CI = –0.28, 0.06], however no other statistically significant relationships were found between eco-driving intention with the remaining objective measures of eco-driving behaviour (all p >.05).

Table 3.3. Spearman's correlations between objective eco-driving variables and behavioural intention to eco-drive, with 95% confidence intervals (n = 132).

	Spearman's Correlations			
	R^2	p	95% *C.I.* for R^2	
			Lower	Upper
Acceleration *[Percentage]*	.01	.93	–0.16	0.18
Braking *[Percentage]*	–.06	.78	–0.23	0.11
Speeding *[Percentage]*	–.11*	.04	–0.28	0.06
Cornering *[Percentage]*	.04	.78	–0.13	0.21
Duration over an hour *[Percentage]*	.05	.95	–0.12	0.22
Volume of Journeys *[Percentage]*	.02	.79	–0.15	0.19
Time of Day *[Percentage]*	–.02	.96	–0.19	0.15
Total number of journeys	.02	.90	–0.15	0.19
Average duration *[minutes]*	–.03	.82	–0.20	0.14
Average distance *[miles]*	–.08	.65	–0.25	0.09

*Significant to $p < .05$

3.8 Confirmatory Analyses

To assess my seven hypotheses (see Section 1.5.2), regression analyses were conducted.

3.8.1 *Regression Models*

3.8.1.1 *Assumptions*

Linear regression modelling was adopted to assess linear relationships. Scatterplots of standardised predicted values versus standardised residuals illustrated that the data met the assumptions of homogeneity of variance and linearity, and the residuals were approximately normally distributed in all models (Andy Field, 2012). Moreover, tests to see if the data met the assumption of collinearity indicated that multicollinearity was not a concern across the models (all VIF < 5).

3.8.1.2 *Linear Regression Analysis*

For each of the criterion variables including both objective eco-driving behaviours and self-reported eco-driving intentions (see Table 3.1.), four models were built: 1) a model comprising of the six HEXACO trait variables as predictors, 2) a model of the four value orientations and environmental self-identity as predictors, 3) a model featuring only subjective wellbeing as a predictor (SLW&PWI), and 4) a model featuring only the measure of locus of control as a predictor. Model specification was largely theory-driven. For example, environmental self-identity is conceptually related to biospheric values and pro-environmental behaviour and thus included in the same models (Van der Werff, Steg & Keizer, 2013b). As the four models specified were fitted to each of the ten eco-driving criterion variables, this created a total of 40 regression models. Notably, separate linear regression models for each criterion variable was chosen instead of a multivariate regression approach. This was selected in agreement with the industry partner to aid interpretability and applied value, as they were interested in the discrete predictors of each individual driving behaviour and past evidence (see Section 1.3) led us to expect that the predictors would differ across eco-driving outcome variables due to context dependency of driving behaviour. Using separate regression models per criterion variable was deemed more appropriate for the applications of this work by providing a more detailed view of how each predictor influences each outcome.

As Hypothesis 2 did not predict a linear relationship, this analysis also conducted quadratic models to assess the relationship between HEXACO emotionality and eco-driving behaviours. Quadratic functions were calculated by conducting general linear modelling and including a third variable which represented the square of the predictor variable, HEXACO trait emotionality.

3.8.2 *Results by Hypothesis*

Hypothesis 1: Higher scores on honesty-humility, agreeableness, conscientiousness and openness to experience personality traits will predict greater eco-driving behaviours.

Linear regression models illustrated that honesty-humility was not a significant predictor of any of the ten eco-driving variables, including eco-driving intention (all p >.05). Linear regression models illustrated that agreeableness and conscientiousness significantly predicted eco-driving intention (see Table 3.13.), however was not a significant predictor for any objective eco-driving variables. Openness to experience significantly predicted average duration of journeys (see Table 3.10.), however did not significantly predict the remaining nine eco-driving variables. As no consistent linear relationships was illustrated between the four personality traits and the battery objective measures of eco-driving, the hypothesis was rejected.

Hypothesis 2: A quadratic relationship is predicted between emotionality and eco-driving behaviour.

Quadratic functions were calculated by conducting general linear modelling with the addition of a third variable; the square of the emotionality trait variable. No significant quadratic relationships were found between emotionality and eco-driving behaviour variables (all p >. 05). However, general linear models conducted illustrated that emotionality significantly predicted both acceleration and volume of journeys (see Table 3.4. and Table 3.9.). As no curvilinear relationships were observed, hypothesis two was rejected.

Hypothesis 3: Higher scores on extraversion personality trait will predict poorer eco-driving behaviours.

Linear models illustrated that extraversion did not significantly predict any of the eco-driving variables (all p >.05; see Table 3.4. – Table 3.13.). As no linear relationship was found between extraversion and eco-driving quality, hypothesis three was rejected.

Table 3.4. Linear model of personality traits predicting acceleration [$R^2 = .07$, $R^2_{Adjusted} = .03$, $F(6, 125) = 1.65$, $p = .14$]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	27.90	11.67	0.00	2.39	.02*	4.81	51.00
Honesty-Humility	0.67	1.97	0.03	0.34	.73	-3.22	4.56
Emotionality	-3.96	1.68	-0.22	-2.36	.02*	-7.30	-0.63
Extraversion	-2.48	1.81	-0.13	-1.37	.17	-6.06	1.11
Agreeableness	2.37	2.02	0.12	1.17	.24	-1.62	6.36
Conscientiousness	0.45	2.05	0.02	0.22	.83	-3.61	4.52
Openness to Experience	1.56	1.70	0.09	0.92	.36	-1.81	4.93

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.5. Linear model of personality traits predicting braking [R^2 = .03, $R^2_{Adjusted}$ = -.01, F (6, 125) = 0.73, *p* = .62]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	12.79	6.60	0.00	1.94	.06	-0.29	25.87
Honesty-Humility	-1.32	1.11	-0.12	-1.19	.24	-3.53	0.88
Emotionality	-0.77	0.95	-0.08	-0.81	.42	-2.66	1.12
Extraversion	-0.08	1.03	-0.01	-0.08	.94	-2.11	1.95
Agreeableness	1.83	1.14	0.16	1.60	.11	-0.43	4.09
Conscientiousness	-0.53	1.16	-0.05	-0.46	.65	-2.83	1.77
Openness to Experience	-0.60	0.96	-0.06	-0.62	.53	-2.51	1.31

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.6. Linear model of personality traits predicting average speed [R^2 = .01, $R^2_{Adjusted}$ = -.04, F (6, 125) = 0.24, *p* = .96]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	0.64	10.48	0.00	0.06	.95	-20.11	21.39
Honesty-Humility	-0.22	1.77	-0.01	-0.13	.90	-3.72	3.28
Emotionality	-0.04	1.52	-0.00	-0.03	.98	-3.03	2.95
Extraversion	-0.36	1.63	-0.00	-0.22	.83	-3.58	2.87
Agreeableness	0.22	1.81	-0.01	0.12	.91	-3.37	3.80
Conscientiousness	1.16	1.84	0.07	0.63	.53	-2.49	4.81
Openness to Experience	1.04	1.53	0.07	0.68	.50	-1.99	4.06

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

Table 3.7. Linear model of personality traits predicting cornering [R^2 = .04, $R^2_{Adjusted}$ = -.01, F (2, 125) = 0.79, *p* = .58]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	12.57	6.79	0.00	1.85	.07	-0.86	26.00
Honesty-Humility	-0.39	1.14	-0.04	-0.34	.74	-2.65	1.88
Emotionality	-1.78	0.98	-0.18	-1.82	.07	-3.71	0.16
Extraversion	-0.36	1.05	-0.03	-0.34	.73	-2.45	1.73
Agreeableness	-0.82	1.17	-0.07	-0.70	.48	-3.14	1.50
Conscientiousness	1.03	1.19	0.09	0.87	.39	-1.33	3.40
Openness to Experience	0.66	0.99	0.06	0.67	.50	-1.30	2.62

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.8. Linear model of personality traits predicting how many journeys had a duration above an hour [R^2 = .05, $R^2_{Adjusted}$ = .00, F (2, 125) = 1.09, *p* = .37]

Variables	*B*	*SE B*	β	*t*	p	95% *C.I.* for *B*	
						Lower	Upper
Intercept	0.08	2.97	0.00	0.03	.98	-5.79	5.96
Honesty-Humility	-0.70	0.50	-0.14	-1.40	.16	-1.69	0.29
Emotionality	0.12	0.43	0.03	0.28	.78	-0.73	0.97
Extraversion	0.33	0.46	0.07	0.72	.47	-0.58	1.24
Agreeableness	0.03	0.51	0.01	0.07	.95	-0.98	1.05
Conscientiousness	0.05	0.52	0.01	0.09	.93	-0.99	1.08
Openness to Experience	0.81	0.43	0.18	1.87	.06	-0.05	1.67

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

Table 3.9. Linear model of personality traits predicting volume of journeys [$R^2 = .09$, $R^2_{Adjusted} = .05$, F (6, 125) = 2.18, $p = .049$*]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	69.05	16.56	0.00	4.17	<.001***	38.28	101.82
Honesty-Humility	-4.05	2.79	-0.15	-1.45	.15	-9.58	1.47
Emotionality	-5.50	2.39	-0.22	-2.30	.02*	-10.23	-0.77
Extraversion	-5.08	2.57	-0.19	-1.98	.05	-10.18	0.01
Agreeableness	1.52	2.86	0.05	0.53	.59	-4.14	7.19
Conscientiousness	0.70	2.91	0.02	0.24	.81	-5.07	6.46
Openness to Experience	-4.52	2.42	-0.17	-1.87	.06	-9.30	0.26

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.10. Linear model of personality traits predicting average duration of journeys [R^2 = .07, $R^2_{Adjusted}$ = .02, F (6, 125) = 1.46, *p* = .20]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	10.51	4.65	0.00	2.26	.03*	1.31	19.71
Honesty-Humility	-0.91	0.78	-0.12	-1.16	.25	-2.46	0.64
Emotionality	0.27	0.67	0.04	0.41	.68	-1.05	1.60
Extraversion	0.42	0.72	0.06	0.58	.56	-1.01	1.85
Agreeableness	0.90	0.80	0.11	1.12	.27	-0.69	2.49
Conscientiousness	0.20	0.82	0.02	0.25	.81	-1.42	1.82
Openness to Experience	1.40	0.68	0.20	2.07	.04*	-0.06	2.74

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

Table 3.11. Linear model of personality traits predicting average distance of journeys in miles [R^2 = .04, $R^2_{Adjusted}$ = -.01, F (6, 125) = 0.81, *p* = .56]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	1.50	2.79	0.00	0.54	.59	-4.03	7.02
Honesty-Humility	-0.55	0047	-0.12	-1.17	.24	-1.48	0.38
Emotionality	0.14	0.40	0.03	0.34	.74	-0.66	0.93
Extraversion	0.22	0.43	0.05	0.51	.61	-0.64	1.08
Agreeableness	0.59	0.48	0.12	1.22	.23	-0.37	1.54
Conscientiousness	0.45	0.49	0.09	0.91	.36	-0.52	1.42
Openness to Experience	0.24	0.41	0.06	0.59	.59	-0.57	1.04

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

Table 3.12. Linear model of personality traits predicting number of night-time journeys [$R^2 = .04$, $R^2_{Adjusted} = -.01$, F (2, 125) = 0.87, $p = .51$]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	3.40	3.63	0.00	0.94	.35	-3.78	10.58
Honesty-Humility	-0.46	0.61	-0.08	-0.75	.46	-1.67	0.75
Emotionality	-0.80	0.52	-0.15	-1.53	.13	-1.83	0.24
Extraversion	-0.15	0.56	-0.03	-0.26	.79	-1.26	0.97
Agreeableness	-0.15	0.63	-0.02	-0.24	.81	-1.39	1.09
Conscientiousness	0.87	0.64	0.14	1.36	.18	-0.40	2.13
Openness to Experience	0.49	0.53	0.09	0.93	.36	-0.56	1.54

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.13. Linear model of personality traits predicting eco-driving behavioural intention [R^2 = .26, $R^2_{Adjusted}$ = .22, F (2, 125) = 7.14, p < .001***]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	0.36	1.11	0.00	0.33	.74	-1.83	2.56
Honesty-Humility	0.29	0.19	0.14	1.57	.12	-0.08	0.66
Emotionality	0.07	0.16	0.04	0.42	.68	-0.25	0.38
Extraversion	0.03	0.17	0.02	0.18	.86	-0.31	0.37
Agreeableness	0.49	0.19	0.23	2.57	.01*	0.11	0.87
Conscientiousness	0.60	0.20	0.28	3.09	.002**	0.22	0.99
Openness to Experience	-0.02	0.16	-0.01	-0.14	.89	-0.34	0.30

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to p < .05, **Significant to p <.01, ***Significant to p < .001.

Hypothesis 4: Higher scores on biospheric and altruistic value orientation and environmental self-identity will predict greater eco-driving behaviours.

Linear regression modelling illustrated that Environmental Self-Identity alone significantly positively predicted eco-driving intention (see Table 3.23.). However, linear models found that biospheric and altruistic values and environmental self-identity did not significantly predict any of the remaining eco-driving variables (all p >.05; see Table 3.14. – 3.23.). As no linear relationships were found, hypothesis four was rejected.

Hypothesis 5: Higher scores on egoistic and hedonic values will predict poorer eco-driving behaviours.

Linear regression models showed that egoistic and hedonic values did not significantly predict any of the eco-driving variables (all p >.05, see Table 3.14. – Table 3.23.). As no linear relationship was identified, hypothesis five was rejected.

Table 3.14. Linear model of values predicting acceleration [R^2 = .02, $R^2_{Adjusted}$ = -.01, F (5, 126) = 0.52, p = .76]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	17.99	7.56	0.00	2.37	.02*	2.99	32.98
Biospheric values	0.13	1.10	0.02	0.11	.91	-2.04	2.29
Altruistic values	0.95	1.72	0.08	0.56	.58	-2.45	4.35
Hedonic values	0.89	1.44	0.08	0.62	.54	-1.96	3.73
Egoistic values	-0.70	1.02	-0.06	-0.69	.49	-2.71	1.31
Environmental Self-Identity	-0.55	1.02	-0.07	-0.54	.59	-2.57	1.46

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.15. Linear model of values predicting braking [$R^2 = .04$, $R^2_{Adjusted} = .004$, $F (5, 126) = 1.12$, $p = .36$]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	12.66	4.16	0.00	3.05	<.01**	4.44	20.88
Biospheric values	-0.91	0.60	-0.20	-1.52	.13	-2.10	0.28
Altruistic values	-0.59	0.94	-0.09	-0.63	.53	-2.46	1.27
Hedonic values	0.61	0.79	0.10	0.77	.44	-0.95	2.17
Egoistic values	-0.25	0.56	-0.04	-0.45	.65	-1.35	0.85
Environmental Self-Identity	0.18	0.56	0.04	0.32	.75	-0.92	1.28

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.16. Linear model of values predicting average speed [R^2 = .04, $R^2_{Adjusted}$ = -0.00, F (5, 126) = 0.98, p = .44]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	12.09	6.53	0.00	1.85	.07	-0.84	25.02
Biospheric values	-0.37	0.94	-0.05	-0.39	.70	-2.24	1.50
Altruistic values	1.52	1.48	0.15	1.03	.31	-1.41	4.46
Hedonic values	-0.73	1.24	-0.08	-0.59	.56	-3.18	1.72
Egoistic values	-0.79	0.88	-0.08	-0.90	.37	-2.52	0.95
Environmental Self-Identity	-0.98	0.88	-0.13	-1.12	.27	-2.71	0.76

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to p < .05, **Significant to p <.01, ***Significant to p < .001.

Table 3.17. Linear model of values predicting cornering [R^2 = .03, $R^2_{Adjusted}$ = -.01, F (5, 126) = 0.78, p = .57]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	10.59	4.30	0.00	2.46	.02*	2.09	19.10
Biospheric values	-0.74	0.62	-0.16	-1.18	.24	-1.97	0.49
Altruistic values	-0.12	0.98	-0.02	-0.12	.90	-2.05	1.81
Hedonic values	-0.04	0.82	-0.01	-0.05	.96	-1.65	1.57
Egoistic values	-0.56	0.58	-0.09	-0.98	.33	-1.70	0.58
Environmental Self-Identity	0.91	0.58	0.19	1.59	.12	-0.23	2.06

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to p < .05, **Significant to p <.01, ***Significant to p < .001.

Table 3.18. Linear model of values predicting the number of journeys with a duration over one hour [$R^2 = .01$, $R^2_{Adjusted} = -.03$, $F(5, 126) = 0.22$, $p = .95$]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	3.22	1.91	0.00	1.68	.10	-0.57	7.01
Biospheric values	0.03	0.28	0.02	0.12	.90	-0.51	0.58
Altruistic values	-0.32	0.43	-0.11	-0.74	.46	-1.18	0.54
Hedonic values	0.24	0.36	0.09	0.65	.52	-0.48	0.95
Egoistic values	-0.11	0.26	-0.04	-0.44	.66	-0.62	0.40
Environmental Self-Identity	-0.10	0.26	-0.05	-0.38	.70	-061	0.41

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.19. Linear model of values predicting volume of journeys [R^2 = .03, $R^2_{Adjusted}$ = -.01, F (5, 126) = 0.71, *p* = .62]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	6.67	10.84	0.00	0.62	.54	-14.78	28.12
Biospheric values	-2.51	1.57	-0.21	-1.60	.11	-5.61	0.59
Altruistic values	1.67	2.46	0.10	0.68	.50	-3.20	6.54
Hedonic values	0.59	2.05	0.04	0.29	.77	-3.47	4.66
Egoistic values	-0.21	1.45	-0.01	-0.15	.88	-3.09	2.66
Environmental Self-Identity	1.85	1.45	0.15	1.28	.21	-1.02	4.73

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

Table 3.20. Linear model of values predicting number of night-time journeys [$R^2 = .01$, $R^2_{Adjusted} = -.03$, $F(5, 126) = 0.29$, $p = .92$]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	4.32	2.32	0.00	1.86	.07	-0.28	8.92
Biospheric values	-0.22	0.34	-0.09	-0.67	.51	-0.89	0.44
Altruistic values	0.23	0.53	0.06	0.44	.66	-0.81	1.27
Hedonic values	-0.19	0.44	-0.06	-0.43	.67	-1.06	0.68
Egoistic values	-0.22	0.31	-0.07	-0.71	.48	-0.84	0.39
Environmental Self-Identity	0.13	0.31	0.05	0.41	.69	-0.49	0.74

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.21. Linear model of values predicting average duration of journeys [R^2 = .01, $R^2_{Adjusted}$ = -.03, F (5, 126) = 0.29, *p* = .92]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	16.42	3.02	0.00	5.44	*p* < .001***	10.45	22.39
Biospheric values	-0.48	0.44	-0.15	-1.11	.27	-1.35	0.38
Altruistic values	0.46	0.68	0.10	0.68	.50	-0.89	1.82
Hedonic values	-0.05	0.57	-0.01	-0.08	.93	-1.18	1.09
Egoistic values	-0.05	0.40	-0.01	-0.13	.90	-0.85	0.75
Environmental Self-Identity	0.28	0.41	0.08	0.69	.49	-0.52	1.08

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

Table 3.22. Linear model of values predicting average distance of journeys in miles [$R^2 = .02$, $R^2_{Adjusted} = -.01$, $F(5, 126) = 0.61$, $p = .69$]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	5.79	1.78	0.00	3.26	$p < .01$**	2.27	9.30
Biospheric values	-0.33	0.26	-0.17	-1.29	.20	-0.84	0.18
Altruistic values	0.03	0.40	0.01	0.07	.94	-0.77	0.83
Hedonic values	0.02	0.34	0.01	0.06	.95	-0.65	0.69
Egoistic values	-0.20	0.24	-0.08	-0.85	.40	-0.67	0.29
Environmental Self-Identity	0.31	0.24	0.16	1.30	.19	-0.16	0.78

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.23. Linear model of values predicting eco-driving behavioural intention [R^2 = .20, $R^2_{Adjusted}$ = .17, F (5, 126) = 6.32, p < .001***]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	3.01	0.73	0.00	4.15	<.001***	1.58	4.45
Biospheric values	-0.00	0.10	-0.01	-0.04	.96	-0.21	0.20
Altruistic values	-0.09	0.16	-0.07	-0.52	.60	-0.41	0.24
Hedonic values	0.23	0.14	0.20	1.68	.10	-0.04	0.50
Egoistic values	-0.06	0.10	-0.05	-0.57	.57	-0.25	0.14
Environmental Self-Identity	0.35	0.10	0.39	3.59	<.001***	0.16	0.54

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to p < .05, **Significant to p <.01, ***Significant to p < .001.

Hypothesis 6: Overall scores on the SLW & PWI scale (subjective wellbeing) will not predict eco-driving behaviours.

Linear regression models illustrated that subjective wellbeing significantly predicted intentions to eco-drive (see Table 3.34.), however did not significantly predict any of the nine objective eco-driving variables (all $p > .05$; see Table 3.34.). This provides support for hypothesis six, as these findings illustrate no linear relationship between subjective wellbeing and objective measures of eco-driving quality.

Hypothesis 7: Higher scores on the locus of control (high = externality) will predict poorer eco-driving behaviours.

Linear models were conducted which illustrated that locus of control scores did not significantly predict any of the ten eco-driving variables (all $p > .05$; see Table 3.25.). As no linear relationships were found between locus of control and eco-driving measures, hypothesis seven was rejected.

Table 3.24. Table displaying several linear models of subjective wellbeing predicting eco-driving variables.

Model	R^2	$R^2_{Adjusted}$	Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
									Lower	Upper
Acceleration [F (1, 130) = 0.01, *p* =.91]	.00	-0.01	Intercept	24.64	4.27	0.00	5.77	<.001***	16.19	33.10
			SLW&PWI	-0.06	0.55	-0.01	-0.11	.91	-1.15	1.03
Braking [F (1, 130) = 3.07, *p* =.08]	.02	.02	Intercept	11.66	2.34	0.00	4.98	*p*<.001***	7.03	16.30
			SLW&PWI	-0.53	0.30	-0.15	-1.75	.08	-1.13	0.07
Speeding [F (1, 130) = 0.50, *p* =.48]	.00	-.00	Intercept	9.33	3.71	0.00	2.52	.01*	1.99	16.67
			SLW&PWI	-0.34	0.48	-0.06	-0.71	.48	-1.29	0.61
Cornering [F (1, 130) = 0.14, *p* =.71]	.00	-.00	Intercept	8.58	2.44	0.00	3.52	*p*<.001***	3.76	13.39
			SLW&PWI	-0.12	0.31	-0.03	-0.37	.71	-0.74	0.51

Table 3.24 Continued. Table displaying several linear models of subjective wellbeing predicting eco-driving variables.

Model	R^2	$R^2_{Adjusted}$	Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
									Lower	Upper
Number of Journeys with Duration over an hour [F (1, 130) = 0.41, *p* =.53]	.00	0.00	Intercept	1.23	1.07	0.00	1.15	.25	-0.89	3.35
			SLW&PWI	0.09	0.14	0.06	0.64	.53	-0.19	0.36
Volume of Journeys [F (1, 130) = 0.00, *p* =.95]	.00	-.01	Intercept	15.81	6.13	0.00	2.58	.01*	3.67	27.94
			SLW&PWI	-0.05	0.79	-0.01	-0.07	.95	-1.62	1.52
Night-Time Driving [(1, 130) = 0.19, *p* =.66]	.00	-.01	Intercept	2.58	1.30	0.00	2.75	.01**	1.00	6.16
			SLW&PWI	-0.07	0.17	-0.04	-0.44	.66	-0.41	0.26

Table 3.24 Continued. Table displaying several linear models of subjective wellbeing predicting eco-driving variables.

Model	R^2	$R^2_{Adjusted}$	Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
									Lower	Upper
Average Duration [F (1, 130) = 0.01, *p* =.92]	.00	-0.01	Intercept	17.71	1.69	0.00	10.46	*p*<.001***	14.36	21.07
			SLW&PWI	-0.02	0.22	-0.01	-0.10	.92	-0.46	0.41
Average Distance (Miles) [F (1, 130) = 0.01, *p* =.92]	.00	-0.01	Intercept	5.06	1.00	0.00	5.04	*p*<.001***	3.07	7.04
			SLW&PWI	-0.01	0.13	-0.01	-0.10	.92	-0.27	0.24
Eco-Driving Intention [F (1, 130) = 11.02, *p* =.001**]	.08	.07	Intercept	3.95	0.44	0.00	9.08	*p*<.001***	3.09	4.81
			SLW&PWI	0.19	0.06	0.28	3.32	.001**	0.08	0.30

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

Table 3.25. Table displaying several linear models of locus of control predicting eco-driving variables.

Model	R^2	$R^2_{Adjusted}$	Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
									Lower	Upper
Acceleration [F (1, 130) = 0.17, *p* =.69]	.00	-.01	Intercept	26.32	5.35	0.00	4.92	<.001***	15.74	36.90
			LOC	-0.18	0.45	-0.04	-0.41	.69	-1.06	0.70
Braking [F (1, 130) = 0.01, *p* =.08]	.00	-.01	Intercept	7.36	2.97	0.00	2.48	.01*	1.49	13.23
			LOC	0.03	0.25	0.01	0.10	.08	-0.47	0.52
Speeding [F (1, 130) = 0.56, *p* =.46]	.00	-.00	Intercept	3.36	4.64	0.00	0.72	.47	-5.83	12.55
			LOC	0.29	0.39	0.07	0.75	.46	-0.48	1.06
Cornering [F (1, 130) = 0.36, *p* =.55]	.00	-.00	Intercept	5.90	3.05	0.00	1.94	.06	-0.13	11.93
			LOC	0.15	0.26	0.05	0.60	.55	-0.35	0.66

Table 3.25 Continued. Table displaying several linear models of locus of control predicting eco-driving variables.

Model	R^2	$R^2_{Adjusted}$	Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
									Lower	Upper
Number of Journeys with Duration Over an Hour [R^2 = .01 $R^2_{Adjusted}$ = 0.00, F (1, 130) = 1.08, *p* =.30]	.01	.00	Intercept	0.53	1.34	0.00	0.39	.69	-2.12	3.18
			LOC	0.12	0.11	0.09	1.04	.30	-0.11	0.34
Volume of Journeys [R^2 = .02 $R^2_{Adjusted}$ = 0.02, F (1, 130) = 3.11, *p* =.08]	.02	.02	Intercept	2.23	7.59	0.00	0.29	.77	-12.79	17.25
			LOC	1.12	0.64	0.15	1.76	.08	-0.14	2.38
Night-Time Driving [R^2 = .00 $R^2_{Adjusted}$ = -0.01, F (1, 130) = 0.07, *p* =.80]	.00	-.01	Intercept	3.44	1.63	0.00	2.10	.04*	0.21	6.67
			LOC	-0.04	0.14	-0.02	-0.26	.80	-0.31	0.24

Table 3.25 Continued. Table displaying several linear models of locus of control predicting eco-driving variables.

Model	R^2	$R^2_{Adjusted}$	Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
									Lower	Upper
Average Duration [F (1, 130) = 0.14, *p* =.71]	.00	-.01	Intercept	16.77	2.12	0.00	7.90	*p*<.001***	12.57	20.96
			LOC	0.07	0.18	0.03	0.38	.71	-0.28	0.42
Average Distance (Miles) [F (1, 130) = 0.09, *p* =.77]	.00	-.01	Intercept	4.59	1.26	0.00	3.66	*p*<.001***	2.11	7.08
			LOC	0.03	0.11	0.03	0.30	.77	-0.18	0.24
Eco-Driving Intention [F (1, 130) = 0.29, *p* =.59]	.00	-.01	Intercept	5.06	0.57	0.00	8.92	*p*<.001***	3.94	6.18
			LOC	0.03	0.05	0.05	0.54	.59	-0.07	0.12

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

3.9 Additional Exploratory Analysis

Following confirmatory analyses, it was of interest to understand the predictive relationships between key demographic variables and eco-driving behaviours to assess whether this aligned with evidence of demographic differences identified in previous driving behaviour research (see Section 1.3.6).

3.9.1 *Regression Models*

To explore the predictive relationships between demographic variables and driving inefficiency, ten linear regression models were built, one per eco-driving variable as the criterion variable. Six demographic variables were included as predictor variables; age, licence length, education level, smoking frequency, alcohol consumption frequency and major life event frequency. The findings for each of these variables are considered in turn below. Notably, the role of gender has been analysed independently to the remaining aspects of demography (see Section 3.10.2). This was largely a practical consideration, as our industry partner are unable to use direct inferences from gender in their modelling due to European Union gender equality legislation (Edmonds, 2015).

3.9.1.1 *Assumptions*

Linear regression modelling was adopted to assess linear relationships between two variables. Scatterplots of standardised predicted values versus standardised residuals illustrated that the data met the assumptions of homogeneity of variance and linearity, and the residuals were approximately normally distributed in all models (Andy Field, 2012). Moreover, tests to see if the data met the assumption of collinearity indicated that multicollinearity was not a concern across the models (all VIF < 5).

3.9.1.2 *Alcohol consumption frequency*

Linear regression models demonstrated that alcohol consumption frequency significantly positively predicted six of the nine objective eco-driving variables; acceleration, baking, cornering, duration over an hour, average duration and average miles (see Table 3.26. – 3.35.).

3.9.1.3 *Smoking frequency*

Linear models illustrated that smoking frequency was a significant positive predictor of volume of journeys (see Table 3.31.) and average duration of journeys (see Table 3.32.), and a negative predictor of eco-driving intention (see Table 3.35.). Smoking frequency was unrelated to the remaining seven eco-driving measures (all p >.05).

3.9.1.4 *Education Level*

Linear regression models illustrated that education level negatively predicted volume of journeys (see Table 3.31.), whereby the more educated an individual was, the fewer journeys they undertook in a 24-hour rolling period. Education level was unrelated to the remaining nine eco-driving measures (all p >.05).

3.9.1.5 *Major Life Event Frequency*

Linear regression models revealed that major life event frequency significantly positively predicted speeding behaviour (see Table 3.28.). Major life event frequency was unrelated to the remaining nine eco-driving measures (all p >.05).

3.9.1.6 *Licence Length*

Linear regression models found that licence length did not significantly predict any of the eco-driving measures (all p >.05; see Table 3.26. – Table 3.35.).

3.9.1.7 *Age*

Linear regression models found that age did not significantly predict any of the eco-driving variables (all p >.05; see Table 3.26. – 3.35.).

Table 3.26. Linear model of demographics predicting acceleration [$R^2 = .07$, $R^2_{Adjusted} = .03$, $F(6, 125) = 1.66$, $p = .14$]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	28.77	10.79	0.00	2.67	.01**	7.42	50.12
Age	0.21	0.54	0.10	0.39	.70	-0.86	1.28
Licence	-0.00	0.05	-0.03	-0.10	.92	-0.10	0.09
Education	-2.29	1.19	-0.17	-1.92	.06	-4.65	0.07
Smoking Frequency	-0.68	0.96	-0.06	-0.71	.48	-2.58	1.22
Alcohol Frequency	2.34	1.03	0.21	2.28	.02*	0.31	4.37
Major Life Event Frequency	0.06	0.61	0.01	0.09	.93	-1.14	1.25

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.27. Linear model of demographics predicting braking [$R^2 = .17$, $R^2_{Adjusted} = .13$, F (6, 125) = 4.17, $p < .001$***]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	4.79	5.59	0.00	0.86	.39	6.26	15.85
Age	-0.23	0.28	-0.19	-0.82	.41	-0.79	0.33
Licence	0.03	0.02	0.26	1.14	.26	-0.02	0.08
Education	0.21	0.63	0.03	0.33	.74	-1.04	1.45
Smoking Frequency	0.72	0.51	0.13	-1.43	.15	-0.28	1.72
Alcohol Frequency	2.01	0.54	0.32	-3.72	<.001***	0.94	3.08
Major Life Event Frequency	0.34	0.32	0.09	1.08	.28	-0.29	0.97

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.28. Linear model of key demographics predicting average speed [R^2 = .07, $R^2_{Adjusted}$ = .03, F (5, 126) = 1.64, p = .14]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	-2.02	9.39	0.00	0.14	.88	-20.31	16.27
Age	0.20	0.47	0.11	0.44	.66	-0.72	1.13
Licence	0.00	0.04	0.01	0.04	.97	-0.08	0.08
Education	0.08	1.04	0.01	0.08	.94	-1.97	2.14
Smoking Frequency	-0.50	0.84	-0.05	-0.60	.55	-2.15	1.15
Alcohol Frequency	1.17	0.89	0.12	1.32	.19	-0.59	2.94
Major Life Event Frequency	1.25	0.53	0.21	2.38	.02*	0.21	2.30

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to p < .05, **Significant to p <.01, ***Significant to p < .001.

Table 3.29. Linear model of demographics predicting cornering [R^2 = .12, $R^2_{Adjusted}$ = .08, F (5, 126) = 2.79, p = .013*]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	7.14	5.91	0.00	1.21	.23	-4.56	18.83
Age	-0.08	0.30	-0.06	-0.27	.78	-0.68	0.51
Licence	0.04	0.03	0.32	1.35	.18	-0.02	0.09
Education	-0.71	0.66	-0.09	-1.07	.29	-2.03	0.60
Smoking Frequency	-0.04	0.53	-0.01	-0.07	.95	-1.09	1.02
Alcohol Frequency	1.26	0.57	0.19	2.20	.03*	0.13	2.39
Major Life Event Frequency	0.02	0.34	0.01	0.06	.95	-0.65	0.69

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.30. Linear model of demographics predicting the number of journeys with a duration over one hour [R^2 = .06, $R^2_{Adjusted}$ = .02, F (6, 125) = 1.36, *p* = .24]

Variables	*B*	*SE B*	*β*	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	1.15	2.69	0.00	0.43	.67	-4.17	6.46
Age	-0.03	0.14	-0.05	-0.19	.85	-0.30	0.24
Licence	0.00	0.01	0.08	0.33	.74	-.02	0.03
Education	0.01	0.30	0.00	0.05	.96	-.58	0.61
Smoking Frequency	-0.35	0.24	-0.13	1.44	.15	-0.83	0.13
Alcohol Frequency	0.59	0.26	0.21	-2.29	.02*	0.08	1.11
Major Life Event Frequency	0.16	0.15	0.09	1.03	.31	-0.15	0.46

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001.

Table 3.31. Linear model of demographics predicting volume of journeys [R^2 = .11, $R^2_{Adjusted}$ = .07, F (6, 125) = 2.53, p = .02*]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	19.51	14.96	0.00	1.30	.19	-10.10	49.12
Age	0.02	0.76	0.01	0.03	.98	-1.48	1.52
Licence	0.03	0.07	0.12	0.51	.61	-0.10	0.16
Education	-4.29	1.68	-0.22	-2.55	.01*	-7.61	-0.95
Smoking Frequency	2.77	1.35	0.18	-2.05	.04*	0.09	5.45
Alcohol Frequency	0.01	1.44	-0.00	-0.01	.99	-2.85	2.87
Major Life Event Frequency	-0.16	0.85	-0.02	-0.19	.85	-1.85	1.52

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to $p < .05$, **Significant to $p <.01$, ***Significant to $p < .001$.

Table 3.32. Linear model of demographics predicting average duration of journeys [$R^2 = .09$, $R^2_{Adjusted} = .04$, $F(6, 125) = 1.99$, $p = .07$]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	12.05	4.18	0.00	2.88	$p < .01$**	3.78	20.33
Age	0.26	0.21	0.30	1.25	.22	-0.16	0.68
Licence	-0.02	0.02	-0.28	-1.15	.25	-0.06	0.02
Education	-0.37	0.47	-0.07	-0.80	.43	-1.31	0.56
Smoking Frequency	-0.89	0.38	-0.21	-2.35	.02*	-1.64	-0.14
Alcohol Frequency	0.94	0.40	0.21	2.32	.02*	0.14	1.74
Major Life Event Frequency	0.33	0.24	0.12	1.37	.17	-0.15	0.80

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.33. Linear model of demographics predicting average distance of journey in miles [$R^2 = .11$, $R^2_{Adjusted} = .07$, $F(6, 125) = 2.53$, $p = .02$*].

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	2.56	2.45	0.00	1.05	.30	-2.29	7.40
Age	0.06	0.12	0.11	0.46	.65	-0.19	0.30
Licence	-0.00	0.01	-0.03	-0.14	.89	-0.02	0.02
Education	-0.11	0.27	-0.03	-0.39	.70	-0.65	0.44
Smoking Frequency	-0.41	0.22	-0.16	-1.85	.07	-0.85	0.03
Alcohol Frequency	0.78	0.24	0.29	3.31	p<.01**	0.32	1.25s
Major Life Event Frequency	0.16	0.14	0.10	1.14	.26	-0.12	0.44

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates. *Significant to $p < .05$, **Significant to $p < .01$, ***Significant to $p < .001$.

Table 3.34. Linear model of demographics predicting night-time driving [R^2 = .10, $R^2_{Adjusted}$ = .06, F (6, 125) = 2.2, p = .04*]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	-1.65	3.20	0.00	-0.52	.61	-7.98	4.68
Age	0.17	0.16	0.25	1.05	.30	-0.15	0.49
Licence	0.00	0.01	0.02	0.08	.94	-0.03	0.03
Education	0.14	0.36	0.03	0.38	.71	-0.58	0.85
Smoking Frequency	0.30	0.29	0.09	1.03	.31	-0.28	0.87
Alcohol Frequency	0.39	0.31	0.11	1.25	.21	-0.22	1.00
Major Life Event Frequency	-0.27	0.18	-0.13	-1.50	.14	-0.64	0.09

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to p < .05, **Significant to p <.01, ***Significant to p < .001.

Table 3.35. Linear model of demographics predicting eco-driving behavioural intention [R^2 = .08, $R^2_{Adjusted}$ = .04, F (6, 125) = 1.87, *p* = .09]

Variables	*B*	*SE B*	β	*t*	*p*	95% *C.I.* for *B*	
						Lower	Upper
Intercept	5.02	1.12	0.00	4.48	<.001***	2.80	7.24
Age	-0.01	0.06	-0.02	-0.13	.90	-0.12	0.11
Licence	0.00	0.00	-0.01	0.02	.98	0.01	0.01
Education	0.21	0.13	0.15	1.70	.09	-0.04	0.46
Smoking Frequency	-0.25	0.10	-0.23	-2.50	.01*	-0.45	-0.05
Alcohol Frequency	0.14	0.11	0.13	1.34	.18	-0.07	0.36
Major Life Event Frequency	0.04	0.06	0.05	0.60	.55	-0.09	0.17

Notes: B = beta estimates, SE B = Standard error of beta estimates, β = Standardised beta estimates.

*Significant to *p* < .05, **Significant to *p* <.01, ***Significant to *p* < .001

3.10 Predictive Modelling using Conditional Inference Trees (CTrees)

Following confirmatory and exploratory analyses, machine learning models were conducted to complement inferential statistics and explore two themes of analysis: the predictive modelling of eco-driving actions and classification modelling of drivers' gender. To conduct these analyses, conditional inference trees were used (CTrees; Hothorn, Hornik & Zeileis, 2006). This is a non-parametric tree-based classification algorithm which demonstrate how predictor variables can be used to classify people into defined subgroups of an outcome variable.

This algorithm uses a process called recursive partitioning whereby *p* values from statistical hypothesis tests between predictor and outcome variables in each node are used to determine how to partition the observations into smaller and smaller clusters (i.e., differences in braking behaviour between clusters of drivers who report either 'Rarely'/'Never' drinking compared with 'Sometimes'/'Often'; see Figure 3.2.) (King & Resick, 2014; Hothorn, Hornik & Zeileis, 2006). The use of *p* values is a distinguished feature of CTrees, as unlike other tree-based methods which require models to be 'pruned' to enhance generalisability (e.g., CART trees; Breiman, Friedman, Olshen & Stone, 1984), the size of CTree models are instead controlled by significance testing (see Hothorn et al., 2006). The trees are built by partitioning significant predictor variables whereby observations with similar response values are grouped, with the split point of the predictor with the greatest reduction in residual sum of squares selected. Then, predictions are obtained by fitting a simpler model within each subgroup to provide an estimate of the outcome variable.

As CTrees are not dependent on assumptions of linearity, this algorithm was largely chosen to explore non-linear relationships between the independent variables and eco-driving practices. Moreover, due to the majority of the independent variables being non-normally distributed, this analysis was appropriate as conditional inference trees are also not dependent on assumptions of normal distribution. Unlike inferential regression models, conditional inference trees are insensitive to multicollinearity (Hothorn et al., 2006; Gries, 2021).

3.10.1 *Conditional Inference Trees to Predict Eco-Driving Behaviours*

It was of interest to explore whether the discrete eco-driving behaviours could be modelled from the study variables. To assess this, ten conditional inference tree models were built, one per eco-driving outcome variable – this includes a model focused on eco-driving intentions. For each model, all survey variables were entered, including scale items, as predictors. For all but the model of eco-driving intentions, the remaining objective eco-driving variables were not entered. This was because all objective driving measures are derived simultaneously using the same accelerometer data sources, and as such, the ability to predict scores on one objective driving measure using the other could be expected but arguably of little practical use. This resulted in each model initially containing 173 predictor variables. To reduce the dimensionality of the 173 predictor variables, Recursive Feature Elimination (RFE) in R's caret package was implemented as a backwards feature selection method to determine the optimal features to include in the models. This method uses model accuracy to identify which predictors contribute the most to predict the target variable. Using the selected variables for each CTree model, data was split into train (70%) and test (30%) sets, with the model being trained and then its predictions tested against the 'unseen' test dataset.

To evaluate the predictive performance of the constructed models, I have reported the root mean square error (RMSE), mean absolute error (MAE) and the proportional reduction in error (PRE) which I have interpreted as a coefficient of determination (R^2). Each performance metric provides a specific measure of how dispersed the spread of residuals are. The RMSE is a quadratic scoring measure which assesses the average magnitude of the error by squaring the difference between the predicted and observed values, finding the average of this squared difference across the sample and taking the square root of the average. The MAE is a linear score which measures the average magnitude of the error in a set of predictions without considering the direction of the errors and by assigning equal weighting to all individual differences. Both the RMSE and MAE are negatively oriented scores whereby lower values are better and are defined in the same unit of measurement as the target variable. They can be used together to assess the variation in the errors of the predictions, as the greater the difference between them, the greater the variance in the individual errors in the sample. The PRE (R^2) provides a single measure of how well the predicted values match the observed values. Modelling for each eco-driving variable is considered in turn, with a summary of all models' performance in Table 3.36.

Table 3.36 Performance metrics for ten CTree models predicting eco-driving outcomes[1]

Model Outcome Variable	RMSE	MAE	PRE (R^2)
Acceleration	10.87	8.91	0.04
Braking	4.66	3.80	0.07
Speeding	9.77	6.70	0.001
Cornering	6.14	4.91	NA
Duration Over an Hour	1.98	1.57	NA
Volume of Journeys	13.24	10.64	0.09
Time of Day	3.31	2.63	NA
Average Miles	2.11	1.71	NA
Average Duration	5.24	3.29	NA
Intentions to Eco-Drive	1.11	0.95	NA

3.10.1.1 *Regression Tree 1: Acceleration*

Out of 173 variables, RFE selected five variables to include in the model: Item 21 of the HEXACO ('People think of me as someone who has a quick temper'; a scale item of Patience which is a facet of trait Agreeableness), item 4 of the HEXACO ('I feel reasonably satisfied with myself overall'; a scale item of Social Self Esteem which is a facet of Extraversion), item 36 of the HEXACO ('I would never accept a bribe, even if it were large'; a scale item of Fairness which is a facet of trait Honesty-Humility), item 6

[1] Six of the 10 Ctree models returned NA (Not Available) for the R-squared performance metric. Through examination of the data, it was determined that this issue was not attributed to common factors such as missing values, convergence problems, low variability in the outcome variables, data type inconsistencies, non-linear relationships or as a result of smaller sample sizes by splitting the data into train and test sets. As a result, to evaluate these models' performance, it was deemed more appropriate to use the two alternative performance metrics: RMSE and MAE.

on the SLW&PWI Scale (‘How satisfied are you with how safe you feel?’) and Dependence (a facet of trait Emotionality).

Item 4 of the HEXACO (‘I feel reasonably satisfied with myself overall’) was selected for splits. The resultant model explained 3.86% of the variance in inefficient acceleration [R^2 = .04, *RMSE* = 10.87, *MAE* = 8.91] and was one decision deep (see Fig. 3.1.). The tree (see Fig. 3.1.) illustrates that if a participant’s HEXACO 4 score (‘I feel reasonably satisfied with myself overall) was equal to or less than 1.0 (‘strongly disagree’), the model predicted they would accelerate inefficiently during 36.88% of journeys, whereas if the participant’s HEXACO 4 score was above 1.0, the model predicted they would accelerate inefficiently during only 23.31% of journeys.

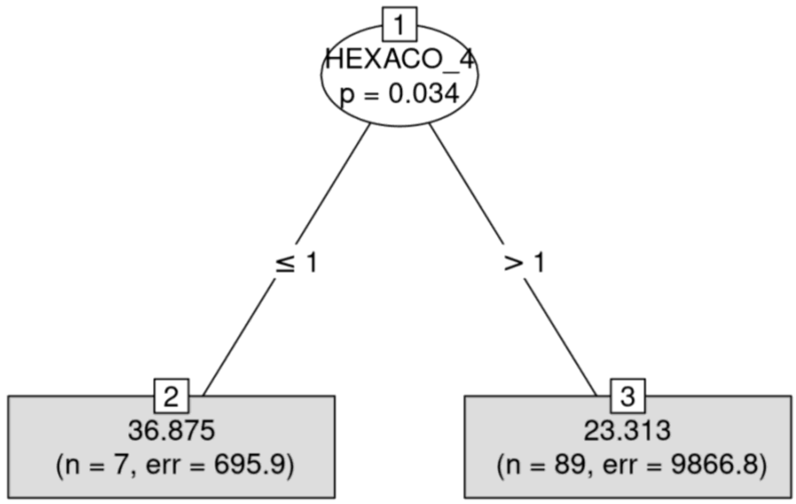

Figure 3.1. A Conditional Inference Tree predicting acceleration inefficiency. One variable, HEXACO 4 (‘I feel reasonably satisfied with myself overall’), was selected for splits. When splitting node one, ≤ 1 *refers to scores ‘Strongly disagree’ [1] and* > 1 *indicates scores ‘Disagree’ [2], ‘Neutral (neither agree nor disagree)’ [3], ‘Agree’ [4] and ‘Strongly Agree’ [5].*

3.10.1.2 *Regression Tree 2: Braking*

Out of 173 variables, RFE selected one variable to be included in the model: alcohol consumption frequency. Alcohol consumption frequency was selected for splits. The resultant model explained 7.09% of the variance in inefficient braking frequency [R^2 = .07, *RMSE* = 4.66, *MAE* = 3.80] and was one decision deep (see Fig. 3.2.). The tree (see

Fig. 3.2.) illustrates that if a participant's alcohol consumption frequency score was greater than 2.0, the model predicted they would break inefficiently during 10.41% of journeys, whereas if a participant's alcohol consumption frequency score was equal to or less than 2.0, the model predicted they would break inefficiently during only 5.13% of journeys.

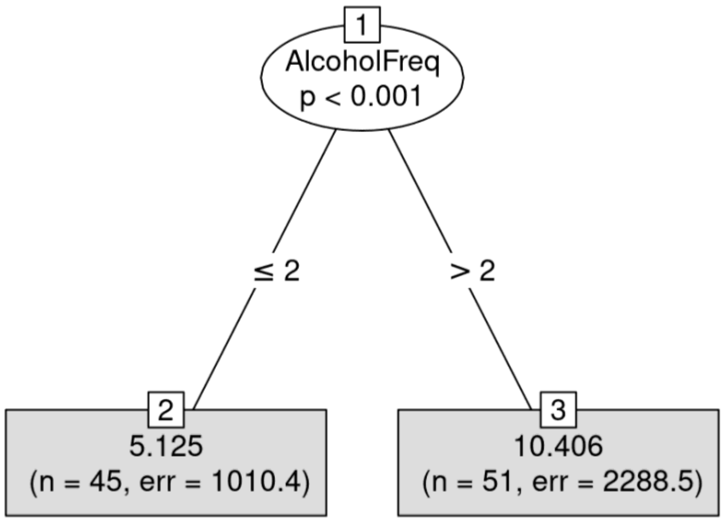

Figure 3.2. A Conditional Inference Tree predicting braking inefficiency. One variable, Alcohol Consumption Frequency, was selected for splits. When splitting node one, ≤ 2 *refers to scores 'Never' [1] and 'Rarely' [2] and* > 2 *indicates scores 'Sometimes' [3] and 'Often' [4].*

3.10.1.3 *Regression Tree 3: Speeding*

Out of 173 variables, RFE selected 10 to be included in the model: item 1 of the eco-driving intentions scale ('I intend to follow the maximum speed limit as much as possible'), Greed Avoidance (a facet of trait Honesty-Humility), item 29 of the HEXACO ('When it comes to physical danger, I am very fearful') related to facet-level Fearfulness (a facet of trait Emotionality), Behavioural Intentions to Eco-Drive Scale, item 2 of the Biospheric Values scale ('It is important to them to protect the environment'), item 4 of the Biospheric Values scale ('It is important to them to be in unity with nature'), trait Openness to Experience, Unconventionality (a facet of trait Openness to Experience), item 55 of the HEXACO ('I find it boring to discuss philosophy') related to facet-level Unconventionality (a facet of trait Openness to Experience) and item 13 from the

HEXACO related to facet-level Creativity (part of trait Openness to Experience; 'I would enjoy creating a work of art, such as a novel, a song, or a painting').

Item 1 of the eco-driving intentions scale ('I intend to follow the maximum speed limit as much as possible') was selected for splits. The resultant model explained 0.11% of the variance in inefficient speeding [R^2 = 0.001, *RMSE* = 9.77, *MAE* = 6.70] and was one decision deep (see Fig. 3.3.). The tree (see Fig. 3.3.) illustrates that if a participant's self-reported score on Item 1 of the eco-driving intentions scale was equal to or below 3, the model predicted they would speed inefficiently during 17.57% of journeys, whereas if a participants' score on Item 1 of the eco-driving intentions scale was above 3, the model predicted they would speed inefficiently during only 5.3% of journeys.

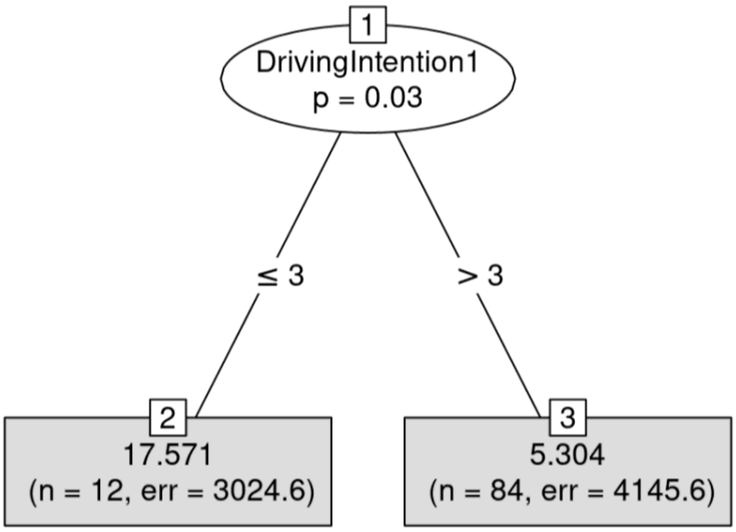

Figure 3.3. A Conditional Inference Tree predicting speeding inefficiency. Item 1 of the Eco-Driving Intention Scale was selected for splits. When splitting node one, ≤ 3 *refers to scores 'I don't agree' [1], whilst* > 3 *indicates scores 'Neutral' [4] and 'I completely agree' [7].*

3.10.1.4 *Regression Tree 4: Cornering*

Out of 173 variables, RFE selected three variables to include in the model: Hedonic Values, Fairness (a facet of trait Honesty-Humility) and Unconventionality (a facet of trait Openness to Experience). None were chosen for splits. The resultant model provided a prediction based on the average value of all observations for the criterion variable cornering [R^2 = NA, *RMSE* = 6.14, *MAE* = 4.91] (see Fig. 3.4.).

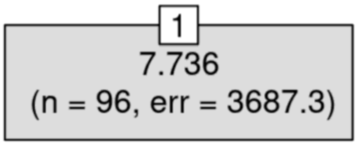

Figure 3.4. A Conditional Inference Tree predicting cornering inefficiency. No variables selected for splits, only one terminal node.

3.10.1.5 *Regression Tree 5: Duration Over an Hour*

Out of 173 variables, RFE selected 5 variables to include in the model: Unconventionality (a facet of trait Openness to Experience), item 1 of the Altruism E-PVQ scale ('It is important to them that every person has equal opportunities'), Greed Avoidance (a facet of trait Honesty-Humility), trait Openness to Experience and trait Emotionality. No variables were chosen for splits. The resultant model provided a prediction based on the average value of all observations for the criterion variable of duration over an hour frequency [R^2 = NA, *RMSE* = 1.98, *MAE* = 1.57] (see Fig. 3.5.).

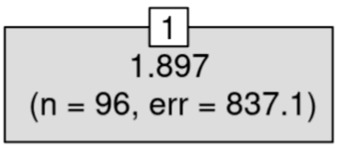

Figure 3.5. A Conditional Inference Tree predicting duration of journey being over an hour. No variables selected for splits, only one terminal node.

3.10.1.6 *Regression Tree 6: Volume of Journeys*

Out of 173 variables, RFE selected seven variables to include in the model: Perfectionism (a facet of trait Conscientiousness), Fearfulness (a facet of trait Emotionality), Sentimentality (a facet of trait Emotionality), Gentleness (a facet of trait Agreeableness), Fairness (a facet of trait Honesty-Humility), Creativity (a facet of trait Openness to Experience) and Hedonic Values.

Creativity (a facet of trait Openness to Experience from the HEXACO) was selected for splits. The resultant model explained 8.78% of the variance in excessive volume of journeys [R^2 = 0.09, *RMSE* = 13.24, *MAE* = 10.64] and was one decision deep (see Fig. 3.6.). The tree (see Fig. 3.6.) illustrates that if a participant's scale score on Creativity was equal to or below 3, the model predicted they would receive volume of journey points for 22.40% of their journeys, whereas if their scale score was above 3, the model predicted they would receive volume of journey points for only 10.66% of their journeys.

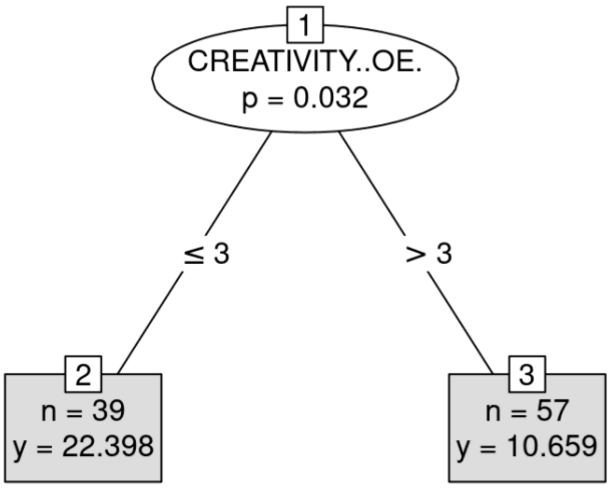

Figure 3.6. A Conditional Inference Tree predicting volume of journey inefficiency. One variable, Creativity (a facet of trait Openness to Experience), was selected for splits. When splitting node one, ≤ 3 *refers to scores 'strongly disagree' [1], 'disagree' [2] and 'neutral (neither agree nor disagree) [3] whilst* > 3 *indicates scores 'neutral' [4] and 'strongly agree' [5].*

3.10.1.7 *Regression Tree 7: Time of Day*

Out of 173 variables, RFE selected one variable to include in the model: Perfectionism (a facet of Conscientiousness). Perfectionism was not selected for splits. The resultant model provided a prediction based on the average value of all observations for the criterion variable of time of day (night driving) frequency [R^2 = NA, *RMSE* = 3.31, *MAE* = 2.63] (see Fig. 3.7.).

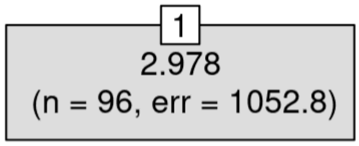

Figure 3.7. A Conditional Inference Tree predicting time of day inefficiency. No variables selected for splits, only one terminal node.

3.10.1.8 *Regression Tree 8: Average Duration*

Out of 173 variables included in the model, RFE selected five to be included within the model: trait Openness to Experience, Inquisitiveness (a facet of Openness to Experience), item 1 of the Altruism E-PVQ scale (‘It is important to them that every person has equal opportunities’), Unconventionality (a facet of trait Openness to Experience) and scores on the Perceived Accessibility Scale. None were chosen for splits. The resultant model provided a prediction based on the average value of all observations for the criterion variable of average duration of journeys [R^2 = NA, *RMSE* = 5.24, *MAE* = 3.29]. (see Fig. 3.8.).

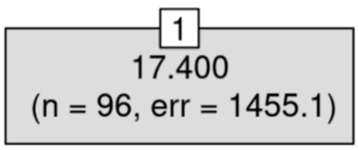

Figure 3.8. A Conditional Inference Tree predicting average duration of journeys. No variables selected for splits, only one terminal node.

3.10.1.9 *Regression Tree 9: Average Distance (Miles)*

Out of 173 variables included originally in the model, RFE selected one to be in the model: Fairness (a facet of trait Honesty-Humility). Fairness was not selected for splits. The resultant model provided a prediction based on the average value of all observations for the criterion variable of average distance of journeys [R^2 = NA, *RMSE* = 2.11, *MAE* = 1.71] (see Fig. 3.9.).

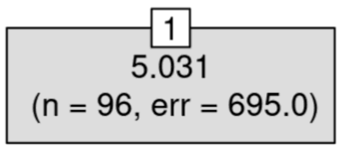

Figure 3.9. A Conditional Inference Tree predicting average distance of journeys (in miles). No variables selected for splits, only one terminal node.

3.10.1.10 *Regression Tree 10: Eco-Driving Behavioural Intention*

Out of 173 variables included in the model, RFE selected two to include in the model: Perceived Accessibility Scale score and item 1 of the Perceived Accessibility Scale ('It is easy to do daily activities with public transport'). Neither were selected for splits. The resultant model provided a prediction based on the average value of all observations for the criterion variable of intentions to eco-drive [R^2 = NA, *RMSE* = 1.11, *MAE* = 0.95] (see Fig. 3.10.).

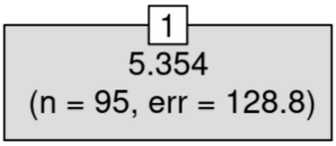

Figure 3.10. A Conditional Inference Tree predicting behavioural intention to eco-drive. No variables selected for splits, only one terminal node.

3.10.2 *Conditional Inference Trees to Classify Gender*

It was of interest to explore the prospective use of gender segmentation in eco-driving interventions. To assess this, I decided to build a conditional inference classification tree (CTree; Hothorn, Hornik & Zeileis, 2006), using binary gender as the criterion variable and entering all remaining variables, including individual scale items, as predictors (see Figure 3.11.). This resulted in a model with 183 predictor variables. To reduce the dimensionality of these predictors, Recursive Feature Elimination (RFE) was implemented as a feature selection method. This method uses model accuracy to identify which predictors contribute the most to predict the target variable. Out of 183 predictor variables, RFE selected three to include within the model: trait Emotionality, Fearfulness (a facet of trait Emotionality) and Sentimentality (a facet of trait Emotionality). Using the selected variables for each CTree model, data was split into train (70%) and test (30%) sets, with the model being trained and then tested against the test dataset. The predictive performance of the constructed model was evaluated using several cost metrics: accuracy, Cohen's Kappa, precision, recall and specificity (see Table 3.38.). Accuracy is the most intuitive and direct performance metric and denotes the ratio of correctly predicted observations to the total observations: the tree had a classification accuracy of 69% (see Table 3.37.). Cohen's Kappa is a performance metric that compares an observed accuracy with an expected accuracy (i.e., random chance). Precision refers to the ratio of correctly predicted positive observations to the total predicted positive observations. Recall pertains to the ratio of correctly predicted positive observations to all the observations in the sample. Specificity measures the ratio of correctly predicted negative observations to all the observations in the sample. The F1 score is the weighted average of the precision and recall measures: this measure accounts for both false positives and false negatives.

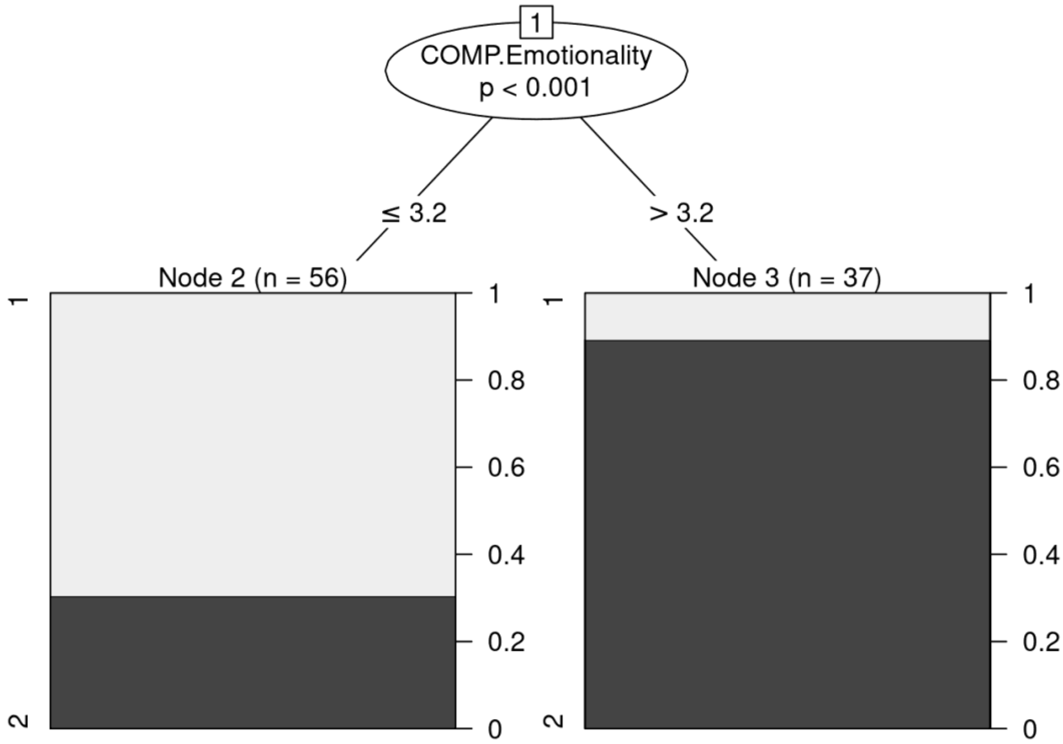

Figure 3.11. A Conditional Inference Tree predicting male and female gender. Out of 3 variables, one variable, HEXACO Emotionality, was selected for splits. Due to variable coding, light grey (1) refers to male gender and dark grey (2) indicates female gender. The proportion of male and female participants are displayed in each terminal node, with the predominant class being the model's prediction for that given pathway.

Table 3.37. Classification accuracy of conditional inference tree for variable 'gender'.

Gender of Participant	Model's Predicted Classification		Percentage Correct (%)
	Male	Female	
Male	15	9	83.33%
Female	3	12	57.14%
Overall %			69.23%

Table 3.38. Cost metrics for conditional inference classification tree for variable ‘gender’.

Metric Name	Metric Estimate
Accuracy	69.23
Precision	.63
Recall	.83
Specificity	.57
F1	.71

4. Discussion

4.1 Thesis Objectives

Modifying an 'aggressive' driving style to a more refined 'eco-driving' style affords opportunities for substantial fuel and carbon emission savings as well as tangible safety benefits (Barkenbus, 2010; Vaezipour et al., 2015; Haworth & Symmonds, 2001). Despite unilateral benefits accrued from eco-driving (e.g. Barkenbus, 2010), the efficacy of existing interventions dissipates in the long-term as many drivers often relapse to previous – less efficient – driving behaviours (Beusen et al., 2009; Lauper et al., 2015; Stromberg, 2013). As such, exploring the ways in which driver characteristics, including psychological and demographic factors, predict eco-driving practices is of considerable value. These insights will inform and advance eco-driving intervention design, as individual differences identified in eco-driving enactment may be contributing to the differentiated success of current behavioural interventions already in practice.

Prior to this study, the influence of numerous 'core' individual differences on eco-driving behaviours had not yet been widely studied. Moreover, existing studies often rely on limited self-report measures of eco-driving behaviour, while use of objective methodologies such vehicle accelerometer data is largely absent (e.g., Unal et al., 2018). The present study addresses these gaps, seeking to identify several psychological and demographic factors which may contribute to explaining why some individuals may perform certain eco-driving behaviours more than others. Moreover, in recognition of self-report research that illustrates an eco-driving 'intention-behaviour gap' (Lauper et al., 2015), the present study also aimed to elucidate the relationship between drivers' subjective eco-driving intentions and *actual objective* eco-driving behaviours, as this may have implications for the design and effectiveness of interventions pivoted on intention-formation processes to achieve eco-driving behavioural improvements.

4.2 Approach

This thesis' collaboration with industry partner IMS provided the novel opportunity to access large-scale naturalistic driving data through the recruitment of customers of their telematics insurance subsidiary, Carrot Insurance, as participants in our research. The decision to recruit Carrot telematic customers was not only a practical consideration rooted in the availability of customers' naturalistic driving data held by Carrot, but also chosen as this segment of drivers are distinct from mainstream car insurance policyholders in several ways.

First, telematics customers typically tend to be younger and tend to have less driving experience. As driving behaviour is widely regarded as habitual (Goldenbeld, Levelt & Heidstra, 2000; Lauper et al., 2015), this may suggest that early drivers' driving style may be more malleable to change than those with more driving experience who typically opt for non-telematics policies. Second, telematics drivers' choice of insurance policy is often guided by affordability; risk of early policy termination provides a reliable extrinsic incentive for short-term driving behaviour improvements sustained by behavioural interventions. Third, Carrot – much like other telematics insurers within the market – regularly interact with a subset of customers by providing feedback messaging through their smartphone application, 'Better Driver'. This affords unique opportunities to both deliver personalised behavioural interventions and measure the subsequent impact ripples from these interventions using customer driving data which is not plausible with traditional car insurance products.

4.2.1 **Theoretical Considerations**

4.2.1.1 *Inefficient Driving: High-Risk Behaviours for Maladaptive Coping*

Alcohol Use and Smoking Behaviour

Providing the most cogent and pertinent findings of the study, participants' alcohol use behaviours positively predicted a vast profile of inefficient driving measures, including inefficient acceleration, braking, cornering, driving continually for over one hour and both the average duration and distance of participants' aggregated journeys (see Table 3.26 – 3.35). Moreover, exploratory data analysis using conditional inference trees demonstrated that alcohol use frequency was one of the few study variable which could be modelled to predict an objective eco-driving measure. In this case, alcohol use frequency predicted braking inefficiency (see Figure 3.2.). Specifically, drivers who reported drinking 'sometimes' or 'often' were predicted to brake inefficiently significantly more often (i.e., predicted braking 'points' during 10.41% of journeys) than drivers who reported drink 'rarely' or 'never' (braking points during 5.13% of journeys).

Together, these findings directly implicate self-reported *habitualised* alcohol use behaviours as a coherent predictor of inefficiency across several driving contexts. This corroborates existing evidence that typical alcohol is implicated in a battery of aberrant and risky driving behaviours (Stephens, Bishop & Fitzharris, 2017; Chliaoutakis, Koukouli, Lajunen & Tzamalouka, 2005; Macdonald & Pederson, 1988) and extends this to an eco-driving behavioural context. Critically, these findings do not imply a proclivity to 'drink-driving' (Zhao et al., 2014; Fillmore, Blackburn & Harrison, 2008; Charlton & Starkey, 2014; Terry-McElrath, O'Malley & Johnston, 2014; Stephens, Bishop, Liu & Fitzharris, 2017; Zhao, Zhang & Rong, 2014) as self-reported alcohol use was unrelated to night-time driving (see Table 3.34.) and evidence indicates this is the period of time in which the majority of alcohol-impaired driving occurs (Ursachi, Owen, Fosdick & Horodnic, 2018).

Cigarette smoking – another high-risk lifestyle behaviour – positively predicted drivers' excessive vehicle use (i.e., volume of journeys) and negatively predicted eco-driving intentions (see Table 3.31 and Table 3.35). Notably, smoking was the only demographic measure to predict both an objective (i.e., excessive vehicle use) and subjective eco-driving measure (i.e., weaker intentions to eco-drive). To an extent, these findings corroborate evidence that smoking is associated with poorer outcomes in particular driving contexts (MacArthur et al., 2012; Pederson et al., 2019; Igarashi et al., 2017).

Notably, some research speculates that individuals' smoking and alcohol consumption are both high-risk behaviours adopted as behavioural strategies for 'sensation-seeking' – a temperamental predisposition towards risk-taking (Smorti, 2014; Patil, Shope, Raghunahthan & Bingham, 2006; Conrod, Castellanos & Mackie, 2008; Jonah, 1997; Zuckerman, 2007; Dahlen & White, 2006; Lee, Mehler, Reimer & Coughlin, 2016). Sensation-seeking has four distinct components: experience seeking, thrill and adventure seeking, disinhibition and boredom susceptibility (Zuckerman, 2007), with stronger associations between risk-taking behaviours and the thrill and adventure seeking and disinhibition components of sensation seeking (Newcomb and McGee, 1991; Zuckerman, 2007). While alcohol and cigarette use reflect behavioural disinhibition, several inefficient driving behaviours have been implicated as ‘thrill and adventure-seeking’ behavioural strategies for trait sensation-seeking (Zhang, Qu, Tao & Xue, 2019; Jonah, Thiessen & Au-Yueng, 2001; Louw, Hajiseyedjavadi, Jamson, Romano & Boer, 2019). This arguably suggests that a behavioural proclivity for alcohol consumption or cigarette smoking may not be a direct precursor to inefficient driving but reflect the idea that these behaviours – alcohol use, smoking and inefficient driving – may instead each function as covarying behavioural opportunities for sensation-seeking. This perspective hints at a plausible ‘third variable’ role centrally played by sensation-seeking. Whilst it was beyond the remits of this study to measure trait sensation-seeking or allied constructs (e.g. risk-taking), future research would be well placed to consider the plausible influence of trait sensation-seeking on driving inefficiency.

In this sensation-seeking context, it is interesting that, despite predicting a battery of other driving behaviours, drivers’ alcohol use frequency did not predict speeding behaviour. As speeding is an overt and highly monitored driving behaviour in the UK context, it is feasible that participants may have been averse to speeding due to perceived risks of detection and punishment – both in terms of legal sanctions (Livingstone, 2011) and from their telematics insurer Carrot Insurance who monitors them – and instead opt to pursue these goals using the other driving actions implicated by alcohol use (i.e. acceleration, braking).

Moreover, it is important to speculate that whilst drivers’ alcohol use was able to predict braking inefficiency using conditional inference tree modelling, this was not emulated with any of the other *five* facets of driving efficiency predicted by alcohol use using inferential regression models. Given this battery of – albeit subtler – relationships, it was surprising that these relationships did not extend to ctree models. As such, this disparity across analysis methods suggests that drivers’ alcohol use habits may be extremely useful for theory-led intervention design but has limited utility for eco-driving risk stratification beyond the forecasting of braking inefficiency.

Subjective Wellbeing and Major Life Events

Some evidence suggests a proclivity to sensation-seeking is associated with immature and maladaptive self-regulation of negative affect (Taylor & Hamilton, 1996; Steinberg et al., 2018), with evidence that sensation-seeking is mediated by self-regulation (Wang, Yang & Zhang, 2020). Both poor wellbeing and maladaptive coping motives have been directly implicated in aberrant and unsafe driving practices (Jeon, 2015; Goldenberg et al., 2000; Burns & Katovich, 2003; Lancaster & Ward, 2002). Matthews' (2001) transactional model of driver stress argues that experiencing stressful life events may predispose individuals to driver stress vulnerability (Matthews, 2001). This is associated with maladaptive, confrontative forms of coping during the driving task such as antagonising other drivers and inefficient risk-taking practices (Matthews et al., 1997; Matthews, 2001b; Ward et al., 1998; Rowden, Peter, Watson, Barry, Biggs & Herbert, 2006). Coping motives have been associated with worse vehicle control (Matthews et al., 1998), reduced attention (Matthews & Wells, 1996), lower perceptual sensitivity in detecting hazardous stimuli (Matthews et al., 1998) and driving fatigue (Matthews & Desmond, 2009). Despite this evidence, poorer wellbeing and maladaptive emotion regulation are yet to be linked explicitly to unecological driving outcomes.

Resultantly, this study considered the role of drivers' wellbeing on ecological driving outcomes. This consisted of two measurement approaches. First, drivers' wellbeing was considered in terms of their subjective *evaluations* of their general wellbeing (using the SLW & PWI Scale; The International Wellbeing Group, 2013)**.** Second, drivers' wellbeing was considered in terms of the objective, cumulative *experience* of negative major life events recently. This dual approach was adopted for a few reasons. First, individuals differ in their subjective sensitivity and reactions to stressful events (Peeters, Buunk, Schaufeli, 1995; Shamoa-Nir & Koslowsky, 2010; Luhmann, Hofmann, Eid & Lucas, 2012). This might suggest that subjective appraisals of wellbeing – rather than objective experience of stressful events – could more proximally influence driving outcomes (Matthews, 2001). Conversely, the available literature implicates *subjective* wellbeing in *subjective* self-reported measures of driving behaviour and intentions (e.g. Jeon, 2015; Goldenberg et al., 2000; Stephens & Groeger, 2009; Clapp et al., 2011a). As a result, the opportunity to measure both *objective* driving as well as a more *objective* measure of wellbeing (i.e., major life events) can help us understand whether *evaluations* versus *experiences* of poor wellbeing might influence eco-driving outcomes disparately and resultantly shape the design of eco-driving behavioural interventions targeting poor wellbeing.

Accordingly, the study findings for the impact of wellbeing on eco-driving outcomes are mixed, with two key disparities identified in how drivers' wellbeing evaluations versus their experiences influences eco-driving intentions versus objective driving behaviour. First, the disparity between drivers' evaluations of their wellbeing versus their objective experiences of major life events on objective eco-driving measures. Drivers' cumulative experience of major life events significantly predicted objectively-measured inefficient speeding, whereas subjective wellbeing was unrelated to objective eco-driving. This suggests that, in the context of inefficient speeding, drivers' evaluations of their own wellbeing may not accurately mirror the underlying behavioural impact that cumulative major life events may have on driver speeding outcomes. However, beyond the speeding context, major life events were unrelated to the remaining eco-driving measures. This could reflect evidence that speeding in particular is a highly hedonistic and sensation-inducing driving behaviour compared to other, less *gratifying* driving actions (Lheureux, Auzoult, Charlois, Hardy-Massard & Minary, 2015; Manning, 2009; Hirschman & Holbrook, 1986; Kidwell & Jewell, 2003).

Moreover, the second disparity lies in how subjective wellbeing impacts on drivers' eco-driving *intentions* versus their objective eco-driving *behaviours*. Namely, subjective evaluations of wellbeing positively predicted eco-driving intentions but was wholly unrelated to objective eco-driving *behaviours*. Interestingly, there is a visible congruence between *objective* experiences of poor wellbeing and *objective* driving, compared with subjective evaluations of wellbeing and subjective eco-driving intentions. Some researchers have speculated on why we may have observed this 'gap' between intention and behaviour for subjective wellbeing.

Providing a theoretical perspective, some research suggests that the relationship between subjective wellbeing and pro-environmental *intentions* (*not* behaviour) may be bidirectional (Netuveli & Watts, 2020; Verhofstadt et al., 2016; Martin, White, Hunt, Richardson, Pahl & Burt, 2020; Schmitt et al., 2018). Specifically, this proposes that just having 'moral' pro-environmental *attitudes and intentions* can lead to increases in eudaimonic wellbeing (i.e., feelings of virtue; Boskovic & Jengic, 2008) irrespective of whether those intentions actually materialise into subsequent behavioural actions (Verhofstaft et al, 2016). This suggests that increases in subjective wellbeing are unreliant on objective eco-driving improvements to bolster feelings of virtue, as 'good intentions' to drive efficiently may be enough alone to increase drivers' subjective feelings of virtue.

Comparatively, a methodological perspective argues that the disparity between eco-driving intentions and behaviour in terms of subjective wellbeing may be driven by the 'bandwidth-fidelity dilemma' (Cronbach & Gleser, 1957; Salgado, 2017). This suggests that measures of similar scope or 'bandwidth' – in this case, the broad scales used to measure subjective wellbeing (SLW & PWI Scale) and eco-driving intentions – are more likely to be found to relate to each other than those with different bandwidths, such as the very narrow breadth of the individual objective eco-driving behaviours (i.e., speeding). Considering evidence which implicates more granular measures of driver wellbeing in objectively poor driving outcomes (e.g., driver stress; Trogolo, Melchior & Medrano, 2014), future research would do well to explore whether narrower bandwidth measures – such as perceived stress or state-level emotion-regulation motives prior to the driving task – may instead yield significant relationships with objective eco-driving measures.

HEXACO Trait Emotionality

Where this study's conceptualisations of wellbeing reflect individuals' appraisals of their overall wellbeing and their objective experience of negative life events, HEXACO trait emotionality is related but conceptually distinct in that it specifically relates to a stable combination of habitual behaviours, cognitions and emotional patterns in how and whether individuals experience anxiety in response to life's stresses, experience fear of physical dangers, feel a need for emotional support from others and feel empathy and sentimental attachment with others (Lee, & Ashton, 2007; Abdullahi, Orjj, Rabiu & Kawu, 2020).

Whilst there are mixed findings across the study for the role of wellbeing on eco-driving outcomes, the findings for *emotionality* (Ashton & Lee, 2007; Watson, 2021) provides important nuance. This study hypothesised a quadratic relationship between emotionality and eco-driving. Conversely, results instead elucidated linear relationships whereby higher trait emotionality predicted fewer volume of journey ‘points’ (i.e. less excessive use) and fewer inefficient acceleration ‘points’.

One interpretation of these findings – compared with those which hint to a role of self-regulatory motives in eco-driving – is that trait emotionality may express itself on driver behaviour disparately depending on the anxiety-provoking situational context of the eco-driving practice (i.e., provoking vs. non-provoking, operational vs. strategic). Notably, individuals high in emotionality *“fear physical dangers and experience anxiety in response to life’s stresses”*, whilst low-emotionality individuals are *“not deterred by the prospect of physical harm, feel little anxiety even in stressful situations… feel self-assured… and feel little emotion in reaction to the concerns of others”* (Lee & Ashton, 2016). It is plausible that high-emotionality drivers may avoid using their car extensively due to the subjective anxiety and negative affect derived from driving which may not be experienced by low-emotionality drivers. This is consistent with evidence that fear and travel avoidance amongst anxious drivers is well-documented (Clapp, Olsen, Danoff-Burg, Hagewood, Hickling, Hwang & Beck, 2011). Moreover, high-emotionality drivers – when they *do* operate their car – may be characterised by a less assured and more cautious driving style (Stephens et al., 2015). This could explain disparities in acceleration profiles, as these drivers may be less likely to accelerate brashly when compared with the unwarranted acceleration patterns of excessively ‘self-assured’ low-emotionality drivers.

Critically, an important consideration is that findings regarding the influence of trait emotionality and allied trait-level conceptualisations (i.e., trait-anxiety, Big Five neuroticism; Costa & McCrae, 1992) on naturalistic driving appear to vary significantly by study methodology and scope. Whilst this study novelly implicated *high* trait emotionality as seemingly *beneficial* for ecological vehicle use frequency and acceleration, Stephens et al. (2015) illustrated in a naturalistic driving study that drivers high in trait-anxiety – an allied personality measure – were more likely to brake aggressively during *stress-evoking* driving situations. Moreover, previous studies largely measure only a few operational driving behaviours of highly trait-anxious drivers (e.g., speeding and braking; Chraif et al., 2016; Stephens et al., 2015; Dahlen et al., 2012). As such, whether ‘high’ or ‘low’ emotionality is regarded as problematic, beneficial or wholly unrelated to eco-driving will significantly vary by the measures that researchers adopt to conceptualise and contextualise driving. These methodological considerations make clear the empirical value that analysing distinct eco-driving behaviours – as opposed to generic self-reports or collective 'eco-driving' scores – offers, as this can provide a more holistic view of how individual differences (e.g., trait-emotionality) may interact with or impact on different driving contexts (e.g., provoking vs. non-provoking driving contexts).

4.3 Methodological Contributions

Many of the findings in this study provide key methodological considerations which can contribute to efforts to understand eco-driving behaviour. This includes nuances in the measurement of eco-driving specifically (e.g. objective behaviours versus subjective cognitions, implicit versus explicit driving actions) as well as the types of measures used to operationalise psychological and behavioural predictors (e.g. abstract versus domain-specific).

4.3.1 *The Intention – Behaviour Gap*

Largely due to the difficulty of accessing objective naturalistic driving data, a significant amount of evidence in the eco-driving domain relies on self-reported measures of either drivers' (perceptions of their) behaviour or their precursory intentions to perform actions associated with eco-driving (e.g., Unal et al., 2018; Unal et al., 2019; Lauper et al., 2015; Schießl et al., 2013). The latter use of intentions as a proxy measure for behaviour has its foundation in theory and research which considers behavioural intentions as a proximal variable to behavioural enactment (i.e., Theory of Planned Behaviour by Ajzen, 1991; Fishbein & Ajzen, 2010; Value-Belief-Norm Model by Stern et al., 1999).

However, the limitations of this self-report approach for eco-driving research are well-established (see Section 1.4.1). Most critically, there are prevalent discrepancies across findings for the self-reported versus objective measures in eco-driving behaviours (Wolf, Oliveira & Thompson, 2003; Ogle, 2005; Forrest & Pear, 2005; Stopher & Fitzgerald, 2007; Marshall, Wilson, Molnar, Man-Song-Hing, Stiell & Porter, 2007). Lauper et al. (2015) even establishes this 'intention-behaviour gap' explicitly, as it was found that the relationship between drivers' eco-driving intentions and their *self-reported* eco-driving behaviour was very small. Accordingly, this study measured eco-driving intentions to establish whether findings identifying relationships between individual differences and subjective appraisals of eco-driving did *in fact* extend to a battery of drivers' *objective* eco-driving actions.

Values and Environmental Self-Identity

Personal values and related environmentally-relevant beliefs are often implicated in pro-environmental behaviour (Steg et al., 2014; Unal et al., 2018; Bolderdijk et al., 2013), yet evidence extending this to eco-driving has only measured drivers' generalised intentions to eco-drive (Unal et al., 2019; Unal et al., 2018). Evidence indicates that individuals may perceive the driving act to be less explicitly environmental than other 'eco-practices' (e.g., recycling; McIlroy & Stanton, 2015). This is important for intervention design, as motivating value-based ecological behaviour is deemed to be contingent on a person's awareness of adverse outcomes to their actions (i.e. inefficient driving) on the environment (i.e. pollutant emissions; Stern et al., 1999).

Biospheric values presented the strongest case for the function of values in eco-driving intentions and enactment, as individuals' *willingness* to engage in these behaviours may significantly differ by the extent to which they genuinely concerned about the environment (Unal et al., 2019; Stern et al., 1999). Yet, this study found that neither biospheric values, the remaining three value orientations (i.e., altruistic, hedonic and egoistic) or drivers' environmental self-identity predicted *any* objective eco-driving behaviours. Given the evidence outlined and explanations for the intention-behaviour 'gap', it was expected that values and Environmental Self-Identity beliefs may *at least* systematically motivate eco-driving intentions – if not drivers' *actual behaviours.* Paradoxically, only Environmental Self-Identity predicted drivers' intentions to eco-drive (see Table 3.23.). Moreover, during conditional inference tree modelling, no study variables were selected to predict drivers' eco-driving intentions (see Fig 3.10).

These findings were surprising for a few reasons. First, biospheric and altruistic values were not even implicated in drivers' self-reported eco-driving *intentions,* despite compelling previous evidence for their role in environmental cognitions and the explicit 'ecological' valence of the intentions measure (e.g., Unal et al., 2018; Stern et al., 1999).

Relatedly, there are valuable theoretical and methodological considerations for the fact that Environmental Self-Identity – but not biospheric values – predicted drivers' intentions, as VBN theory (Stern et al., 1999) posits biospheric values as a precursor to environmentally-significant beliefs. This study's exploratory correlational analyses demonstrated that biospheric values were strongly associated with Environmental Self-Identity scores (r (131) = .67, p = .001; see Table 3.2.). One prospect is that Environmental Self-Identity may be a more proximal predictor compared with more distal values, and that, though subject to prospective mediation analyses, could mediate a relationship between biospheric values and eco-driving intentions. This would be consistent with evidence that biospheric values are associated with wider pro-environmental intentions via Environmental Self-Identity (e.g., van der Werff, Steg & Keizer, 2013). As many interventions pivot on environmental and 'safety' (i.e., altruistic) value appeals, these methodological insights are useful as they suggest biospheric values may need to be explicitly linked to a drivers' self-concept (i.e., priming Environmental Self-Identity beliefs) within interventions to be influential in motivating *intentional* eco-driving.

Moreover, the fact that hedonic values *positively* predicted eco-driving intentions is wildly incongruent with contemporary theory that hedonic pursuits (i.e., pleasure, comfort) may dissuade ecological driving due to a focus on experiencing transient, immediate positive emotions and instant rewards from driving 'riskily' (Harvey, Thorpe & Fairchild, 2013; Schueller & Seligman, 2010; Isler & Newland, 2017). Yet, this alludes to the prospect that hedonism can be repurposed. Specifically, 'alternative hedonism' (Soper, 2007, 2008, 2016, 2017) proposes reconciling 'moral' behaviours and hedonism by legitimising the pursuit of pleasure and, thus, harnessing aspects of hedonic value orientation to motivate ethical consumption behaviours (Caruana, Glozer & Eckhardt, 2019). This 'reframing' approach is relatively novel to eco-driving, yet some research has already explored this prospect in terms of drivers' battery electric and hybrid vehicle preferences (Tchetchik, Zvi, Kaplan & Blass, 2020), car ownership and use reduction campaigns (Kandt, Rode, Hoffmann, Graff & Smith, 2015) and fleet vehicles selection (Wilbers & Wardenaar, 2007).

Personality Traits

Personality research has also been thwarted by the focus on self-reported eco-driving behaviours, as few studies which have adopted objective measures appear to suggest that findings implicating personality traits within drivers' intentions rarely extend to naturalistic driving (e.g., Akbari et al., 2019; Ehsani et al., 2015). Whilst this study's findings provide evidence for roles of HEXACO emotionality and openness in specific objective eco-driving behaviours (see Section 1.2.1. and 1.3.3. for discussion), the remaining four traits – honesty-humility, extraversion, agreeableness and conscientiousness – were unrelated to objective eco-driving practices. However, three of these – honesty-humility, agreeableness and conscientiousness – predicted drivers' eco-driving behavioural intentions. Critically, these findings demonstrate significant disparities between intention and behaviour, whereby the traits actually related to drivers' objective eco-driving (i.e., emotionality, openness) are unrelated to their intentions, whereas the traits implicated in intentions are unrelated to behaviours. Methodologically, these insights illustrate nuance gained from adopting the HEXACO taxonomy of personality (Ashton & Lee, 2009) over the pervasively used Five Factor Model (i.e., the Big 5; Goldberg, 1993; Costa & McCrae, 1992), as insights regarding the distinct relationship between honesty-humility and drivers' eco-driving intentions versus *behaviour* would not have been identified (i.e., Five Factor Model does not distinguish trait honesty-humility in its dimensions).

The discrepancy between findings characterises a clear intention-behaviour 'gap' (Faries, 2016; Sheeran & Webb, 2016) as they suggest that drivers higher in these three traits (i.e., conscientiousness, agreeableness and honesty-humility) may form stronger eco-driving intentions – and thus, are arguably motivated to improve their driving behaviour – yet *consistently* fail to implement these intentions into their actual eco-driving practices. This is more broadly corroborated by correlational analyses which demonstrated that drivers' eco-driving intentions were unrelated to nine of the ten objective eco-driving measures, with the only significant correlate – speeding – being weak (see Table 3.3.).

Taken together, these findings across measures of values, personality and eco-driving intentions suggests measuring intentions alone as a proxy or inference for eco-driving behaviour (e.g. Unal et al., 2018; Cristea et al., 2012; Unal et al., 2019) is a very limited approach, as whilst individual differences evidentially motivate intentions, intentions are seemingly not (or poorly) associated with actual eco-driving behaviour. In the context of interventions, this casts some doubt as to whether widely adopted theoretical frameworks which concentrate on changing drivers' behavioural intentions (e.g., TPB; Ajzen, 1991) provide an adequate foundation for designing methods which can successfully improve eco-driving *behaviour* (Bamberg, 2013).

However, these critiques do not render intentional approaches to intervention wholly redundant. Evidence suggests that the intention-behaviour 'gap' likely occurs as a result of unforeseen barriers or temptations, or simply due to forgetting the intention, disrupting the intention-behaviour relation (Lewin, Dembo, Festinger & Sears, 1944; Dahlstrand & Biel, 1997; De Vries, Mesters, Van der Steeg & Honing, 2005). Accordingly, stage model approaches (e.g., HAPA by Schwarzer, 2008; Dahlstrand and Biel, 1997) suggest there are there are other intermediary processes which may 'close' the intention-behaviour gap and mediate their relationship. For example, Lauper et al. (2015) found that implementation intention (i.e. *"a plan when, where, and how to practice eco-driving*"; Lauper et al., 2015, p.34) partially mediated the effect of eco-driving intentions on self-reported eco-driving behaviour. Accordingly, it may be efficacious for interventions to not merely focus on enhancing eco-driving intentions, but also directly address the transition to eco-driving behaviour realisation by enhancing other intermediary cognitions such as drivers' planning of how to implement eco-driving strategies (Lauper et al., 2015; Sniehotta et al., 2005).

4.3.2 *The Abstraction Issue*

The 'abstraction issue' (Alison, Bennell, Mokros, & Ormerod, 2002; Shaw, 2021) – also known as the bandwidth-fidelity dilemma (Cronbach & Gleser, 1957; Salgado, 2017) – is another methodological consideration which traverses several findings of this study. This posits that psychological measures of more abstract personality traits tend to be less precise at predicting behaviour than domain-specific beliefs as they are conceptually more distal from the measured behaviour. Despite this, there are significant benefits to broader measurement (e.g., explanatory power and predictive utility for broad criteria) which create a trade-off between the bandwidth of a measure (i.e., breadth) and its fidelity (i.e., depth; Cronbach & Gleser, 1957; Salgado, 2017).

In the findings for HEXACO personality traits (Ashton & Lee, 2007), it was surprising that trait agreeableness was only related to eco-driving intentions, and unrelated to the objective measures of eco-driving. Specifically, the HEXACO (Ashton & Lee, 2007) posits agreeableness against 'anger' and both lower agreeableness and greater trait anger have been widely implicated within both self-reported *and* objective studies of aberrant driving (e.g. Chraif et al., 2016; Akbari et al., 2019; Deffenbacher et al., 2001). Accordingly, it is feasible that the absence of findings may reflect the reality that anger only forms a small part of the broader construct that is agreeableness. Speculatively, this substantiates that research should look to more focal measures of driving anger, as well as glimpses to the benefits of research methods such as ecological momentary assessment (EMA) which could enable us to understand how drivers' real-time responses in the driving environment are governed by the intersect between trait-level anger and state-level transitory feelings of anger (Deffenbacher, Oetting, Thwaites, Lynch, Baker, Stark, Thacker & Eiswerth-Cox, 1996).

Comparatively, this study also measured drivers' locus of control as whilst externality of control had been somewhat implicated in self-reported unecological driving (e.g., high mileage, faster driving; commuting choices; Schießl et al., 2013), other research found this association only extended to drivers' eco-driving intentions (Lauper et al., 2015). Paradoxically, this study's findings illustrated locus of control as unrelated to both *objective* eco-driving as well as drivers' intentions to eco-drive. Notably, this study adopts the well-validated Locus of Control Scale by Rotter (1966) as it was considered more valuable to measure individuals' broader self-efficacy beliefs which surpass driving-specific cognitions and consider eco-driving within its remit as an environmental act. Yet, Rotter (1975) highlighted that narrower, more specific beliefs should predict corresponding behaviours within a domain more accurately than broader expectancies. This is consistent with studies which have utilised narrower driving-specific measures (e.g., Driving Internality & Driving Externality Scales; Montag & Comrey, 1987; Multidimensional Traffic Locus of Control Scale; Ozkan & Lajunen, 2005) and illustrated a relationship between external driving LOC and indices of risky and aggressive self-reported driving (e.g. Lajunen & Summala, 1995; Totkova, 2020; Jones & Foreman, 1984) as well as benefits from driving-specific internality training (Huang & Ford, 2012; Stanton, Walker, Young, Kazi & Salmon, 2007). Arguably, these insights suggest that locus of control could best be considered as a domain-specific construct

(Huang & Ford, 2012). Notably, the complete absence of findings for LOC – including for eco-driving intentions – does lead to speculation about what association, if any, a more focal measure might provide.

However, this absence of findings for LOC could also allude to wider methodological considerations about the study's design and data analysis. Critically, participants' locus of control was only measured once, whilst their driving journey data – captured over three to twelve months – was aggregated. Consequently, these findings do not account for plausible within-person fluctuations in locus of control beliefs which could have differentially shaped the quality of drivers' eco-driving practices. Instead of a fixed trait, Rotter (1990, p.490) regarded locus of control as a *"relatively stable"* variable which can show situational specificity. Moreover, evidence indicates driving-specific locus of control may be variably shaped by prior driving experiences (Kouabenan, 2002; Stanton et al., 2005, 2007) and suggests it is malleable through internality-based interventions (Huang & Ford, 2012; Stanton et al., 2005, 2007). Taken together, these insights indicate that future studies could incorporate longitudinal methods (e.g., EMA) to evaluate the malleability of drivers' eco-driving-specific LOC in response to driving stressors (i.e., car incidents, 'near misses') as well as explore whether fluctuations might in turn influence drivers' subsequent eco-driving behaviours.

4.3.3 *Conceptualising Eco-Driving: Implicit and Explicit Actions*

One theme which permeates this study's findings is that eco-driving practices can be conceptualised – using the practice's context, immediacy of decision-making and speculated underlying psychological mechanisms – into two major, observable tranches of motivated eco-driving: 'explicit' and 'implicit' actions. This concept broadly aligns with Sivak and Schoettle's (2012, p.96) breakdown of eco-driving as "strategic… tactical… and operational decisions that improve vehicle fuel economy". In this thesis' considerations, 'strategic' and 'tactical' driver choices reflect seemingly more explicit ecological driver actions arguably governed by more rational, intentional and volitional processes (e.g., vehicle use frequency, duration). Conversely, 'operational' eco-driving appears to reflect implicitly ecological and more transitory vehicle use practices, arguably subject to emotional self-regulation motives (e.g., braking, acceleration) and subsequent habituation. This conceptual distinction is vital for intervention design, as drivers' perceptions of how *ecological* a driving action *is* could have key implications for the nature of approaches used to influence their behaviour in those contexts.

Amongst other study findings coherent with this argument (e.g., acceleration and braking profiles for drivers with poor wellbeing; see Section 1.3.1.), this study's results for HEXACO trait openness provides a clear case in point for this conceptual distinction. The results illustrated that higher levels of openness positively predicted the average duration of participants' journeys. This is a valuable and well-established 'strategic' eco-practice, as shorter journeys emit a disproportionate amount of emissions due to 'cold starts' (Sloman, Cairns, Newson, Anable, Pridmore & Goodwin, 2010). One interpretation is that drivers 'higher' and 'lower' in openness may meaningfully differ in the *purposes* for using their vehicle, with the formers' patterns reflecting more indispensable longer journeys (i.e., commuting) compared with the normalised 'quick errands' of less 'open' drivers (Neves & Brand, 2019). Future studies could explicitly investigate and measure drivers' self-reported journey purpose using ecological momentary assessment (EMA), however in isolation this finding presents a firm case for interventions to 'prime' individuals towards 'openness' to altering *the context of when* they use their cars (i.e., strategic car use).

However, what these considerations more broadly speak to is the prevailing narrative that drivers' normative motives for hedonism and safety regularly overshadow ecological (or economic) concerns *during* the driving task (McIlroy & Stanton, 2015; Pampel et al., 2015, 2017). Notably, openness was not implicated in any of the remaining eco-driving practices which could suggest that this 'open' tendency may not 'spill-over' to those practices which are perceived by driver as less clearly 'environmental'. This parallels the milieu of public information campaigns which provide disproportionate attention to vehicle use reduction strategies (i.e., sustainable and active travel initiatives; Burns & Cracknell, 2019) to the detriment of building awareness for wider, more operational and less explicitly 'green' modifications (e.g., sustainable braking distances). Given that many drivers have little awareness of wider eco-driving strategies (McIlroy & Stanton, 2017), these considerations suggest that drivers' poor awareness is likely to impact whether they perceive they can improve their driving efficiency. It also suggests that, when drivers have awareness of explicit eco-driving strategies (e.g. '*avoid short journeys'),* individual differences (such as trait openness) may shape drivers' responsiveness to interventions focused on targeting these ecological motivations for driving efficiency.

4.4 Using Demography: Implications for Telematics Driver Populations

The cornerstone of risk-based car insurance is collecting data about particular driver characteristics to identify sophisticated 'rating factors'; these are used to tailor drivers' premiums competitively by accurately predicting and pricing for the risk they pose. Though not publicly accessible due to commercial sensitivity, rating factors used by insurers to model drivers' risk seem to be derived predominantly from demographic questioning (ABI, 2008). This includes overt risk factors such as drivers' age, the length of time holding a driver's licence, occupation, certain lifestyle habits (e.g., smoking) and – until relatively recent legislative changes prohibiting the practice in 2012 – drivers' gender (Edmonds, 2015). Yet, whilst several of the study's findings partially support this approach by suggesting that specific demographic questions (i.e., drivers' alcohol use and smoking frequency) can surpass what psychological measurement can ascertain about eco-driving, the remaining findings are more complex and allude to wide nuances in the behaviour of 'monitored' drivers.

Driver Age and Licence Length

Driver age and licence length are two well-established risk factors for capturing drivers' risk of unsafe and 'risky' driving (Kelly & Nielson, 2006; Box & Wengraf, 2013; Groupe Consultatif Actuariel Europeen, 2011). Prior evidence largely supports the posited 'young driver problem' (i.e. Scott-Parker et al., 2015; Rhodes & Pivik, 2010; see Section 1.3.6.1.), including explicit differences in fuel consumption and emissions performance (Huang, Ng, Zhou, Surawski, Lu, Du, Forehead, Perez & Chan, 2021). Paradoxically, this study found drivers' age and licence length to be wholly unrelated to objective eco-driving quality and drivers' eco-driving intentions. This proposes a conceptual 'blind spot': when drivers are 'monitored', getting older or gaining more experience may not (*linearly)* correspond to increasingly optimised eco-driving. Considering evidence for the efficacy of monitoring as a behaviour change technique in road safety contexts (see Warren, Meads, Whittaker, Dobson & Ameratunga, 2018), it is feasible that age and driving experience do not influence monitored insureds' driving efficiency due to a heightened awareness of monitoring technology and its associated feedback and disincentives.

Notably, the sampling approach only captured ‘Yellow’ and ‘Green’-averaging drivers. This reflects the unique nature – and bias – of the telematics insurance industry as it often renders out *‘bad’* novice and young drivers. This is likely psychological, by dissuading this subset of volitionally-bad drivers from purchasing a telematics policy at the outset, as well as behavioural, as a consequence of these drivers failing their ‘probationary’ policy period (i.e., Carrot’s ‘Red’ drivers). These considerations highlight the empirical value offered by studying individual differences of drivers across the spectrum of driving quality, as monitored drivers could illustrate less variability in their driving efficiency compared with non-monitored.

An additional methodological consideration is that this study’s method solely captures the variability in eco-driving for a narrow range of relatively ‘novice’ and young drivers during what is likely a relatively early period of their driving career. This offers the prospect that younger, monitored insureds (satisfactory) driving may fluctuate *after* this early period of monitoring. It would be interesting for future studies to longitudinally measure within-person differences in how these eco-driving behavioural patterns may evolve as ‘monitored’ customers transition from ‘novice’ to significantly more ‘experienced’ drivers, and subsequently move to unmonitored insurance policies.

Education

Occupational data – a correlate of education (Galobardes, Shaw, Lawlor, Lynch & Davey-Smith, 2006; Piha, Laaksonen, Marikainen, Rahkonen & Lahelma, 2010) – already appears as a key classifier for risk. As noted (see Section 1.3.6.4), some evidence infers more highly educated drivers may be more likely to illustrate behavioural precursors to eco-driving (i.e., greater environmental knowledge, greater environmental concern; Sovacool et al., 2018; Diamantopoulous et al., 2003) as well as to enact specific eco-driving practices (Vassileva & Campillo, 2017; Sovacool et al., 2018). The findings of this study illustrate that lower level of education predicted vehicle overuse (i.e., volume of journey ‘points’; see Table 3.31.), though this strong relationship was not emulated in conditional inference tree analyses. Resultantly, this finding is likely limited to informing the design of ‘strategic’ vehicle use interventions as opposed to being used as a factor within models to predict driver inefficiency.

This finding appears driven by participants’ transition to and completion of university, yet education was otherwise unrelated to eco-driving in this study and evidence illustrates knowledge of eco-driving strategies does not differ by education level (McIlroy & Stanton, 2017). Education may proxy for disparities in social location such as improved occupational outcomes (Galobardes et al., 2006) which may systematically shape the ways – and frequency – that drivers use their cars (e.g. on-site versus remote working; Haas & Hamann, 2008; Try, 2004; Haslam, 2012; Senthanar, Varatharajan & Bigelow, 2021).

Gender

Amendments to the Equality Act 2010 (Amendment Regulations 2012) now restrict insurers from using drivers’ gender as a factor to price their risk (Edmonds, 2015). This received significant industry backlash, as the Association of British Insurers (ABI) claimed the industry’s use of gender where relevant and based on “objective, reliable and relevant data” was the “cornerstone of pooling risk” (Edmonds, 2015, p.5.).

This legislation was despite evidence of robust gender differences in ‘risky’ driving for unmonitored drivers (Vavrik, 1997; Harre et al., 2005; NHTSA, 2009). Paradoxically, this governing narrative was not fully supported by this study’s findings. While male gender predicted inefficient cornering and night-driving, it was unrelated to the remaining eco-driving practices including those most ‘risk-adjacent’ (e.g., speeding, acceleration, braking). Moreover, subsequent exploratory ctree modelling illustrated that none of the eco-driving variables were used to predict drivers’ gender. Instead, only HEXACO emotionality was able to predict driver gender (accuracy of 69.23%; see Fig. 3.11 and Tables 3.37 – 3.38.).

This study’s chosen sample and the unique contexts of both implicated driving actions can account for the gender disparity between monitored and unmonitored drivers. First, this participant sample meaningfully differ from the ‘average’ mainstream policyholder: their driving quality is overtly monitored by their telematics insurer and often widely influenced using incentives (i.e., vouchers) and disincentives (i.e., early policy termination). Second, the two driving behaviours that *were* implicated – inefficient cornering and night-time driving – add nuance to this argument. Conjecturally, inefficient cornering is likely to be a less salient metric to customers and thus may be reflecting gender differences akin to non-telematics populations. Moreover, night driving is a more 'strategic' aspect of vehicle use, often subject to broader social influences governed by gender: men have greater night-driving confidence (RAC Foundation, 2018), are more likely to engage in late-night social driving and 'cruising' (Bengry-Howell, 2005) and work night-shifts (Presser, 2003; Trades Union Congress, 2016). These considerations have key implications for the context-driven personalisation of interventions, as well as adds nuance it could suggest that eco-driving benefits accrued by monitoring drivers may dissipate when they are no longer (or no longer perceive to be) monitored (i.e., transition to non-monitored insurance policies).

Beyond these explicit findings, the exploratory finding that male gender can – in 83.33% of cases – be accurately modelled by lower HEXACO emotionality scores has significant conceptual and ethical implications. As an arguably positive implication, eco-driving interventions could utilise gender data as a proxy for difficult-to-obtain emotionality scores to target male drivers with interventions which directly seek to address the negative impact of lower trait emotionality on drivers' inefficient acceleration and vehicle overuse (see Section 1.2.1 for discussion).

However, in the realm of risk pricing, this novel approach could also be contentiously exploited by insurers. Focus has shifted to Big Data and machine learning methods to identify novel metrics which can proxy the predictive utility afforded by gender disparities. Importantly, HEXACO emotionality serves as a valuable and direct predictor of driving inefficiency in its own right. However, it is feasible that brief measures of HEXACO emotionality could be given to customers, with their scores used in models of drivers' risk *intentionally* – though indirectly – to proxy for customer gender (see Wachter & Mittelstadt, 2019). This practice may also be problematic where – based on this study's modelling – in 30.77% of cases the drivers' gender was incorrectly predicted. This feasible legislative 'side-step' alludes to wider ethical obstacles faced by the insurance industry as it endeavours to incorporate new forms of personalised data (e.g., psychological insights) to predict risks drivers pose. Many disparities in these 'individual differences' are entwined with and inseparable from aspects of drivers' social location and demography, including several *'protected characteristics'* (e.g., race, religious beliefs; Courtenay-Hall & Rogers, 2010). Beyond the prospect of indirect (but legal) discrimination, transparency concerns also arise as insureds, in the absence of adequate disclosure from insurers about their practices, are unlikely to be aware of the impact these forms of psychological questioning may have or the longevity of their actuarial influence, as many individual differences (e.g., HEXACO personality) are widely regarded as relatively stable traits (Eysenck & Eysenck, 1985; Rotter, 1990).

4.5 Applied Issues and Future Directions

4.5.1 *The use of telematics data*

Beyond the difficulty of obtaining 'everyday' driving data, the lack of objective measures in driving research lies also in that the use of telematics 'digital traces' presents novel challenges for psychological researchers. Specifically, due to the size and nature of the "Big Data" derived from these monitoring technologies, as well as the desired research outcomes, classic psychological methods for data wrangling and analysis are limited in their ability to fully utilise these large and complex datasets (Montag, Duke & Markowitz, 2016).

The data generated by vehicle telematics devices reflect raw, unstructured and large-scale 'digital traces' of driving behaviour captured through accelerometer sensors (Verbelen, Antonio & Claeskens, 2018; Yarkoni, 2012). To derive insights from this information, extensive data wrangling methods are required which are able to develop specific metric aggregates of driving features (e.g. sudden deceleration, speeding over limit) which can then be used to conduct statistical tests. This has largely not been achievable using statistical software such as SPSS which has been widely used in psychological research. Consequently, this has historically functioned as a barrier to accessing these large-scale and 'noisy' datasets (Yarkoni, 2012). Yet, in recent years many researchers have begun to transcend 'orthodox' practice in order to ascertain the skills to make use of advanced software (e.g., R, Python or MATLAB) which are more commonly allied to computational science. Critically, these metrics make use of contextual data sources (e.g.

telematics metadata, GPS) which can offer meaningful context and nuance about the nature of drivers' journeys.

Due to this project's collaborative and applied nature, this study utilises participant journey data pre-processed using journey metrics developed by IMS (See Table 2.2). With consideration to the implications of the findings for the industry partner, this was a practical decision as it enables the project's findings and recommendations to be directly aligned with how IMS currently evaluate drivers. In spite of this, it is important to acknowledge that these metrics are designed by IMS largely to gauge driver *safety* rather than *ecological efficiency.* The legitimacy of this approach is rooted in the significant overlap in the operational antecedents of safe and eco-driving (e.g. Young et al., 2011; Mensing et al., 2014; Vaezipour et al., 2015). However, there are more precise, ecologically-sensitive and direct approaches – unreliant on safety as a proxy – which can be developed to quantify environmental driving quality. Despite early research which pursues these prospective approaches (e.g., Tanvir, Chase & Roupahil, 2019; Allessandri, Cattivera, Filippi & Ortenzi, 2012; Barth & Boriboonsomsin, 2009; LeBlanc, Sivak & Bogard, 2010; Ishiguro, 1997), a systematic methodology for quantifying the influence of discrete driving actions on eco-driving – while controlling for wider factors that affect fuel economy and emissions (e.g., congestion, route choice) – still does not exist (Tanvir, Chase & Roupahil, 2019).

Relatedly, measures of vehicle fuel economy are often adopted in studies as a solution to the overreliance on evidence from driving safety research. Yet, this use as an autonomous evaluative benchmark for ecological driving efficiency fails to address that even therein lies trade-offs between economic (fuel-optimal) and ecological (emissions-reducing) vehicle operation (Mensing, Bideaux, Trigui, Ribet & Jeanneret, 2014; Johansson, Gustafsson, Henke & Rosengren, 2003). Namely, modelling has illustrated that purely fuel-saving driving is associated with increased carbon monoxide (CO) and hydrocarbon (HC) pollutant emissions (Mensing et al., 2014). Aptly, akin to the nature of our partnership with IMS, recent shifts towards innovative industry-academia collaboration highlights opportunities to pursue more comprehensive, emissions-based eco-driving metrics using the data-rich resources afforded by industry. Beyond providing objective eco-driving measurement to behavioural research, this approach would provide stakeholders (i.e., usage-based insurers and fleet managers) with value-added insights fundamental for ecological risk management and customer feedback optimisation.

Furthermore, the telematics data utilised was obtained from a sample of relatively proficient ‘Green’- or ‘Yellow’-averaging customers (no ‘Red’ customers; see Section 3.4.). Resultantly, the findings of the study suggest individual differences may have a limited scope for eco-driving improvements for a large proportion of (telematics) drivers. Specifically, there is evidence that individuals find it difficult to reduce their consumption behaviours beyond a certain point – likely as doing so would “disturb socially necessary consumption practices” (e.g. daily commutes; p. 1041, Knowles, 2014). Corroborating this, as illustrated in Table 3.1., the mean frequency by which participants received ‘points’ for each inefficient action was – in actuality – quite low. Consequently, it is feasible that for this segment of ‘good’ drivers, priming or targeting these psychological constructs through behavioural intervention may be ineffective if they cannot reduce their consumption further. However, future research could establish whether patterns in individual differences differ for ‘Red’-averaging customers, as this may provide novel ways to target problematic drivers who are ‘at-risk’ of early policy termination due to poor driving quality.

4.5.2 *Data processing approaches*

Due to the format of the data provided by my industry partner (i.e. ‘points’ per inefficient actions within each journey; see Table 2.2), there was some aspect of choice regarding how variables could be created and analysed. As outlined previously (See Section 3.2.), I chose to create percentage scores which reflected the proportion of participants’ journeys whereby they had received ‘points’ for each respective metric. Yet, several other avenues for data processing and its analysis are available to researchers to address wider questions about not only eco-driving *adoption*, but maintenance and improvement. For example, scores could be aggregated temporally into ‘bins’ in order to analyse aspects such as changes in daily or monthly eco-driving quality. In this study, drivers’ journey scores were aggregated and, as such, the processing approach does not account for the likely prospect that drivers’ ecological driving style may naturally improve (or materially worsen) over time as some early research suggests (Day, Thompson, Poulter, Stride & Rowe, 2018, McCartt et al., 2009). As such, it is of considerable value for future projects to explore whether pertinent individual differences (e.g. trait openness) may underpin any naturalistic changes in drivers' ecological driving style over time as this could have significant implications for the personalisation of eco-driving interventions.

Moreover, this temporal approach to data processing could even focus on drivers' behaviour during more granular and specified 'at-risk' daytime periods and journey functions (e.g. stressful 'rush hour' commutes, longer journeys) to explore the role of situational specificity in different driving contexts and outcomes (i.e., stress-evoking, congestion-free, unknown routes). Aptly, studies illustrate that traffic congestion and travel time have a meaningful impact not only the emissions of a journey (Zhang, Batterman & Dion, 2011) but also driver mood, stress and life satisfaction (Morris & Hirsch, 2017; Choi, Coughlin & D'Ambrosio, 2013; Wener & Evans, 2011; Evans, Wener & Phillips, 2002; Hennessy & Wiesenthal, 1999; Redmond & Mokhtarian, 2001; Sposato, Roderer & Cervinka, 2012). In light of this study's findings and the case presented for the roles of driver stress and maladaptive coping during the driving task, the negative and cyclical impact that drivers' journey experience (e.g., poor wellbeing exacerbated due to traffic) may have is a really and nuanced avenue for future studies and interventions.

Furthermore, it is important to be cognisant that despite the rationale, the study's selected sample – Carrot Insurance customers who had held their current insurance policy for at least three months – has notable drawbacks. First, our sample did not include insights from any 'Red' customers (See Section 3.4.) who typically face early policy termination by Carrot Insurance due to unsafe and aberrant driving recorded. As a result, our findings reflect a 'survivor bias' as they limitedly only reflect the qualities of drivers who have managed to 'survive' their policy for at least three months. This unfortunately provides little empirical insight into the qualities of the subset of drivers who enact the most problematic driving practices – and thus – would benefit most from behavioural interventions. Second, this sampling choice also misses an opportunity to capture the experiences of newly qualified drivers in the early months of independent driving before their driving behaviour might stabilise (Day et al., 2018). This early period of driving is a significant avenue for future research, as behavioural intervention may be most optimal for novel drivers as evidence suggests their driving style may be more malleable for long-term change when compared to more experienced drivers (Castellucci, Bravo, Arezes &

Lavalliere, 2020; Kinnear, Lloyd, Helman, Husband, Scoons, Jones, Stradling, McKenna & Broughton, 2013).

4.5.3 *Computational Methods for Psychological Eco-Driving Research: Conditional Inference Trees*

As acknowledged by Yarkoni and Westfall (2017) in their seminal paper, psychological science has been largely dominated by a hypothesis-driven and confirmatory paradigm. However, in the age of 'Big Data', we are beginning to see the early incorporation of computational methods in the analysis of psychological and behavioural research (e.g., Shaw, Taylor, Ellis & Conchie, 2021; Orru, Monaro, Conversano, Gemignani & Sartori, 2020). This approach – centred on prediction and classification algorithms that can learn from large datasets – not only complements traditional inferential statistics, but also glimpses to a future of exploratory data analysis whereby discipline researchers identify novel relationships in purely data-driven ways.

In view of this paradigm shift, this thesis adopted a similarly interdisciplinary approach (see Approaches and Methods, Section 1.5.2) through the use of conditional inference trees ('ctrees'; Hothorn et al., 2006). This algorithm was used to explore non-linear relationships between the study's independent variables and eco-driving inefficiency (see Section 3.10.) in order to complement confirmatory analyses as well as with the hope of generating novel insights due to its capacity to identify new, unforeseen risk patterns for eco-driving inefficiency. Considering the plethora of findings implicating several demographic and individual differences in confirmatory and exploratory analyses (see Sections 3.8. and 3.9), it was anticipated that some of these associations would likely extrapolate to predictive modelling (see Section 3.10.). Paradoxically, as considered in this discussion, across the ten regression ctree models that were built, only four – acceleration, braking inefficiency, speeding inefficiency and volume of journeys – were able to be predicted by independent variables, with large error rates. Critically, the disparity between these two methods does not render inferential findings unimportant as these differences reflect the competing goals of these methods to explain (i.e., inferential statistics) versus predict (i.e. computational methods) drivers' eco-driving behaviour. Yet, what these differences do signify is a limitation on industry from using some of these inferentially-derived risk patterns for preventative interventions (i.e., pricing of eco-driving risk) as – based on this study’s findings alone – these factors appear at this moment unable to robustly forecast customers’ risk of unecological driving.

5. Recommendations

5.1 Overview

Improving eco-driving behaviours – particularly in the long-term and across contexts – is difficult (Sovacool, Bergman, Hopkins & Jenkins, 2020; Sovacool & Griffiths, 2020; Barkenbus, 2010). There is currently insufficient evidence of 'what works' to improve this behavioural challenge (Barkenbus, 2010; Oxendahl, 2018). In response to this, this study's findings – many of which novel to the academic literature – offer recommendations for the direction of eco-driving theory and research, behaviourally-informed driving interventions and public policy. These opportunities are discussed in turn.

5.2 Recommendations for Theory

The majority of the empirical research fails to acknowledge and distinguish eco-driving behaviour and its unique motivations as discrete from the remits of conscious pro-environmentalism and proxy of driving safety. Moreover, current theories largely conceptualise eco-driving as a singular 'act' driven by motivated, value-based and conscious processes with limited scope for a central role of drivers' emotions and habit. Instead, this thesis argues that eco-driving is a collection of nuanced, complex and interacting driving actions. These are proposed to be performed by drivers through *both motivated* and *habitual* decision-making processes and differ meaningfully by how heavily they are shaped by situational and emotional cues. A working conceptual model is visualised in Figure 5.1, illustrating how these determinants may interact to influence ecological driving behaviours.

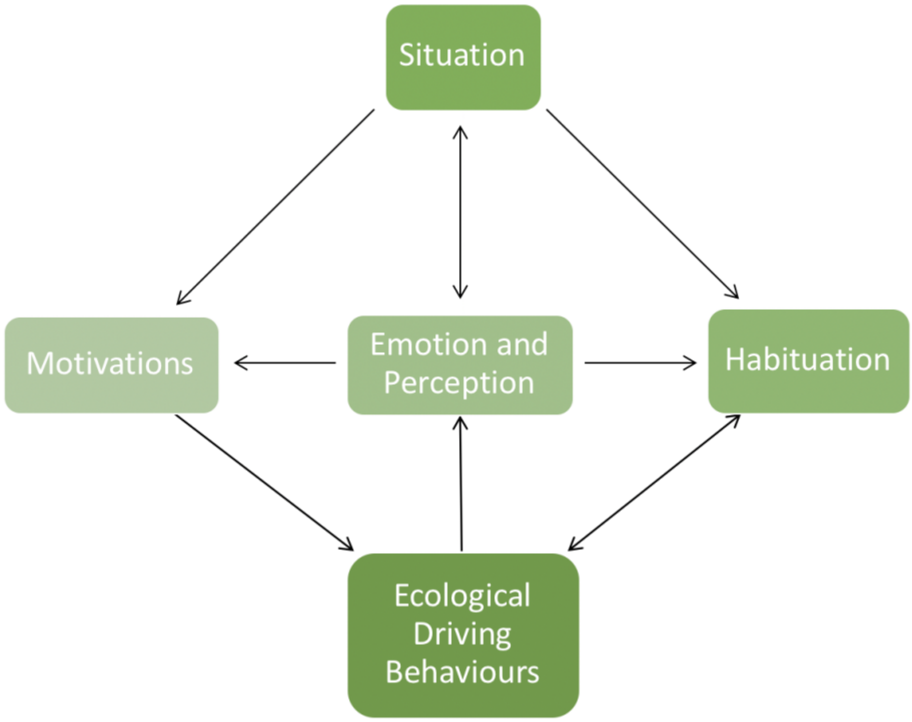

Figure 5.1. Conceptual working model of eco-driving behaviour.

As illustrated within this model, the findings from this study point to an emerging and substantive role of emotions in eco-driving behaviour which – as yet – is still to be fully acknowledged in eco-driving theory. Specifically, a clear case is outlined for the maladaptive use of unecological driving as a route for emotion self-regulation of negative affect (see discussion in Section 4.2.1). This challenges core theories disproportionately adopted to explain (broad) driving behaviour (e.g., Theory of Planned Behaviour; Ajzen, 1991; Fishbein & Ajzen, 2010) as it illustrates these frameworks – which assume drivers use vehicles in *rational* ways – do not realistically model how difficult emotions and mood states are likely to be 'managed' within the complex driving environment (e.g., 'road rage'; Goldenberg et al., 2000; Redshaw, 2004). Evidence also suggests that driving may not only be a route for self-regulation, but also a *cause* of self-regulation motives (Matthews, 2001). Theoretical perspectives appropriated from the safe driving and pro-environmentalism literatures are unable to address these complexities and highlight a need for nuanced eco-driving theory.

Moreover, the proposed model (Fig. 5.1) identifies processes for *motivated* driving actions. Prominent pro-environmental theories pedestal individuals' personal values as a primary motive for *broader* pro-environmental behaviour (e.g., VBN theory by Stern et al., 1999). However, this study's findings for personal values (i.e., unrelated to both objective and subjective measures) suggest we cannot rely on values in this way as a central tenet of eco-driving enactment. This provides valuable steer for outdated theory which indiscriminately views eco-driving through the broader lens of pro-environmentalism (e.g., Unal et al., 2018; Steg et al., 2014; Unal et al., 2019) as it indicates that interventions which target values may not be an effective route to eco-driving behavioural changes. Accordingly, theory needs to consider the nuances of eco-driving which may limit any distal influence of 'eco-values' commonly ascribed to other eco-behaviours. For example, drivers operate in environments where driving 'safely' is a more salient, value-driven motive, than the risks of ecological impact (i.e. emissions). Second, unlike wider 'eco-behaviours' (e.g. recycling), the ability to drive ecologically is heavily shaped by situational factors beyond drivers' control (e.g. behaviour of other road users, the traffic environment) which influence emotional constraints (i.e. driver stress). These situational and emotional forces could diminish any distal influence of personal values on motivated eco-driving. This study found biospheric values to be strongly associated with Environmental Self-Identity, and Environmental Self-Identity predicted drivers' eco-driving *intentions*. This offers food for thought, as path or cluster analyses could elucidate whether a relationship between personal values and eco-driving *intentions* may be mediated by more proximal determinants such as Environmental Self-Identity.

5.3 Recommendations for Research

This thesis adopted both an interdisciplinary and mixed methods approach. To *measure* eco-driving behaviour, we utilised rare objective metrics of multiple naturalistic eco-driving behaviours as well as obtained a more conventional self-report measure (i.e., eco-driving intentions). To *analyse* this data, we used 'orthodox' inferential statistics for hypothesis testing, as well as employed predictive modelling techniques for exploratory data analysis which are more closely allied to computational science than psychological and behavioural science. Whilst the constraints of conducting behavioural research in this area are clear (e.g. inaccessibility of naturalistic driving data versus self-report, upskill required for interdisciplinary data analysis), this study's research approach – and the accompanying findings – provides several key recommendations for how eco-driving research must evolve given the opportunities afforded by the era of 'Big Data' and novel psychological and behavioural measures of interest.

5.3.1 Eco-driving research in the era of 'Big Data'

First, the use of naturalistic driving data in this research clearly demonstrates that objective data collection should, where possible, become the default measurement approach for eco-driving in research. Despite increasing opportunities for naturalistic data collection which have been driven by private sector forces (e.g., in-lab virtual reality, telematics devices, smartphone accelerometers), current research remains comparatively over-reliant on drivers' subjective self-reports as measures of eco-driving *behaviour* (e.g., Lauper et al., 2015; Unal et al., 2018; Unal et al., 2019). This includes measures of eco-driving behavioural *intentions:* this is often adopted as a *proxy* for behaviour instead of its theory-proposed function as a *precursor to* eco-driving enactment (Ajzen, 1991, Stern et al., 1999). This is in spite of evidence of an intention – behaviour gap between drivers' intentions to drive in an ecological way in both subjective reports of eco-driving behaviour (Lauper et al., 2015) and objective driving behaviours as demonstrated in the present study. This approach is inadequate as subjective measures are unable to identify the genuine determinants of *actual* driving inefficiency. This can misinform policy and erode the efficacy of behavioural interventions designed to improve driving efficiency. Resources should be focused on improving access to naturalistic driving measurement: this requires incentivising academia-industry partnerships. This thesis – an example of industry-academia collaboration spearheaded by Lancaster University's Centre for Global Eco-Innovation – is clear evidence that this approach is both feasible and mutually beneficial.

Second, through the naturalistic driving data provided by IMS, this study measures several discrete driving efficiency metrics. Contrastingly, there is a tendency for research and industry to focus attention on either 'explicit' actions such as speeding or to attempt to unify several driving efficiency metrics into overall eco-driving 'scores'. This is appealing in many ways. For academia, this provides the prospect of an objective eco-driving domain 'scale' which might address the abstraction issue. For industry, this could offer vehicle manufacturers a novel 'feature' for consumers, and more focally give vehicle insurers a packaged 'metric' to benchmark customers' driving efficiency. Yet, this study illustrates this approach is inadequate as drivers differed in efficiency across the spectrum of driving behaviours, suggesting that drivers are unable to be defined as characteristically ‘good’ or ‘bad’ eco-drivers overall. Unifying these metrics – or only focusing research on particular behaviours – means we are unable to understand more about the behavioural disparities *across* actions. This has value beyond theory by offering a more comprehensive picture of how drivers behave ecologically within the complex driving environment. For example, we can analyse how efficiency differs within-participants depending on how explicit (e.g. speeding) or implicit (e.g. harsh cornering) perceptions of the actions’ effects on the environment are. We can also identify the risks for negative spillover in behavioural interventions, whereby drivers might bolster their efficiency in one driving behaviour (e.g. infrequent car use) to the detriment of other environmental driving actions (e.g. peak-time journeys). Clear evidence exists for negative spillover of pro-environmental behaviour (Truelove, Carrico, Weber, Toner, Vandenbergh, 2014; Thogersen & Crompton, 2009), however we require eco-driving-specific evidence of spillover to manage these risks.

Third, whilst existing research has often sought to identify generalised trends in eco-driving propensity (e.g. Unal et al., 2018, Lauper et al., 2015), the present study’s findings point to the need for research to become more focal on the psychological, behavioural and environmental drivers of specific inefficient ‘events’ (i.e., the contexts in which a driver receives a ‘point’ for an inefficient action; e.g. disproportionate braking on busy multi-lane roundabouts in big cities). Notably, participants’ propensity for inefficient driving *throughout a journey* is relatively low (see Table 3.1), suggesting that a participants’ driving during a journey may be fairly efficient except for a few – consistent – *‘bad moments’*. Accordingly, further research to understand how certain determinants – such as drivers’ emotion state, habits and the event context (e.g., other drivers’ behaviours, the traffic environment, driver familiarity with the road, route choice, journey purpose) – may be influencing these events. This research would be invaluable in the design of context-specific eco-driving behavioural interventions. This can be achieved using research methods novel to the eco-driving domain such as ecological momentary assessment (EMA), the predictive modelling of ‘events’ and the integration of greater data sources (e.g. vehicle metadata, location data, approximated trip purpose). These ideas speak to the promise of interdisciplinary eco-driving research as a means for bolstering behaviour change initiatives and public policy.

5.3.2 Prospective measures of interest

Accepting the benefits and limitations of study design choices is an unavoidable facet of research. Due either to survey length concerns or as a product of hindsight following data analysis and iterative literature review, there are several theoretically-relevant variables not included within this study, but which warrant future research as they are, largely, yet to be explicitly considered in the context of drivers' ecological driving.

First, future studies could measure both wider trait (i.e., anxiety, stress) and state-level (mood or emotions) wellbeing constructs. Specifically, theories of driver stress (e.g. Matthews, 2001; Rowden et al., 2006) and the demonstrated use of recreational drugs to 'self-medicate' chronic stress (Sinha, 2008, 2001; Park et al., 2004; Mayer & Treat, 1977) provides a reliable case for researchers to holistically consider the independent relationships established in the literature between indices of poorer wellbeing (e.g., coping motives, stressors), lifestyle traits (i.e., problematic alcohol use, smoking), sensation-seeking or 'risk-taking' proclivity and measures of ecological driving quality.

Second, this study pivots on the measurement of objective driving behaviour and, as a consequence, does not intend to meaningfully explore participants' subjective perceptions of their own eco-driving behaviour beyond the brief measure of eco-driving intentions. Notably, theories of pro-environmental behaviour (i.e. VBN theory; Stern et al., 1999) often stipulate problem awareness (PA) – an awareness of the adverse consequences of our actions on the environment – as an integral part of motivating 'eco' actions (e.g. energy conservation, recycling). Yet, it is important to consider that driving is noticeably distinct from other environmental practices: the prevailing narrative of bad driving is that it is unsafe, rather than uneconomical or unecological (McIlroy & Stanton, 2015). Fundamentally, if drivers do not cognitively evaluate driving as an explicitly environmental act akin to other, more discernible, eco-practices (e.g., energy conservation), this might be negating the efforts of existing interventions which are designed to motivate drivers through environmental appeals. As a result, it would be theoretically valuable for future studies to consider both self-reported and objective eco-driving, as well as compare these cognitions with drivers' wider eco-attitudes (e.g. recycling intentions). This could establish whether cognitions held for driving might sit comfortably within the remits of pro-environmentalism. If not, this requires stakeholders to rewrite the narrative of driving as an ‘eco’ act (i.e., public initiatives, information campaigns, legislation changes) in order to motivate drivers to *intentionally* adopt ecological driving.

5.4 Recommendations for Behavioural Intervention

Evidence from psychological and behavioural research is being increasingly used to inform the design and iterative trialling of ‘behaviourally-informed’ interventions for environmental challenges (Moore & Boldero, 2017; Nielsen, van der Linden & Stern, 2020). In this applied field, ‘behavioural interventions’ are a “class of initiatives that may, either by themselves or in conjunction with more typical policy tools (e.g. infrastructure, incentives), achieve greater greenhouse gas (GHG) reductions than have been achieved by the typical tools alone” (p.1613, Nielsen et al., 2020). Despite recent surges in environmental behavioural change initiatives (OECD, 2017), unecological driving has received little attention from the applied behavioural science community explicitly. This may be for a plethora of reasons. Significant hopes rest on engineering innovations to reify the hope of ‘net zero’ transport (e.g. widespread electrification, autonomous vehicles), yet these approaches remain far from being fully actualised. Whilst improving eco-driving behaviour is difficult (Sovacool et al., 2020), modifying drivers’ driving style through behavioural intervention offers the prospect of disproportionate, immediate and low-cost pollutant emissions savings (Barkenbus, 2010; Vaezipour et al., 2015, Rios-Torres et al., 2018).

Both the available eco-driving-specific intervention evidence (e.g., Barkenbus, 2010; Oxendahl, 2018; McIlroy & Stanton, 2017) and insights from road safety interventions highlight several strategic opportunities to improve ecological driving – particularly within IMS’s monitored-driver context. First, key considerations lie in the choice of specific eco-driving target behaviours (e.g. speeding versus vehicle use frequency) and decision-making processes (i.e. ‘reflective’ versus ‘automatic’ decisions). Specifically, most practitioner-led eco-driving initiatives focus on ‘reflective’ driving decisions (i.e., strategic behaviours such as car sharing initiatives) made in advance, to the detriment of addressing ‘automatic’ operational choices (e.g. harsh braking) which often – though not always – take place during a journey. Given opportunities for data-driven smartphone-based digital interventions, this is limited as operational driving decisions during journeys can now feasibly be targeted (e.g., ‘BackPocketDriver’ app; Warren et al., 2018). As such, improving the efficiency of *both* strategic and operational vehicle use behaviours offers opportunities for emissions savings which surpass the benefits to addressing strategic practices alone (e.g., peak-time journeys) which may be constrained by factors beyond individual control (e.g., on-site and shift-based jobs). Moreover, evidence of what works to improve the efficiency of both strategic and operational driving behaviours will remain relevant as – post-electrification – drivers will still need to be *‘energy efficient’* in their practices to optimise their vehicle’s battery supply. Second, smartphone-based digital eco-driving interventions – delivered through IMS’s smartphone application ‘Better Driver’ – offers prospect of data-driven, segmented, personalised and *live* interventions. This offers core opportunities to deliver data-driven, ‘timely’ intervention – these can utilise customers’ vehicle use data (e.g. inefficient ‘events’) to deliver live prompts, ‘nudges’ and feedback preceding, during and immediately after a drivers’ journey when they may be most receptive to behavioural influence. Whilst these intervention approaches appear to vastly surpass the efficacy of ‘blanket’ interventions, they are still for now largely unrealised (Felsen & Reiner, 2015; Barton & Grune-Yanoff, 2015).

As illustrated, insights from the behavioural intervention literature point to the increased efficacy of personalised interventions (Felsen & Reiner, 2015). Accordingly, the present research sought to identify ‘individual differences’ – psychological, behavioural and demographic factors – which, in predicting objective eco-driving behaviour, could evidence certain psychological barriers or enablers for efficient driving and form the basis for novel behavioural interventions. Resultantly, the findings of this research – combined with behavioural evidence and theory – identify four fundamental areas of opportunity for novel eco-driving behavioural interventions. These are conceptualised as behavioural ‘design strategies’ (see Table 5.1).

Table 5.1 Design Strategies for Eco-Driving Behaviour Change

Design Strategy 1	Design interventions which facilitate emotion self-regulation.

Design Strategy 2	Facilitate drivers' openness to eco-driving using behavioural design.
Design Strategy 3	Enhance eco-driving self-efficacy through identity and literacy.
Design Strategy 4	Deliver behaviourally-informed eco-driving feedback.

Insights are delivered by adopting a template which identifies the target behavioural 'barrier' or 'enabler' scoped from the present study or wider research (*'Behavioural Conditions'*) synthesises the relevant behavioural evidence and theory ('*Behavioural Evidence')* and provides high-level recommendations for the design of digital eco-driving interventions to address that antecedent of inefficient behaviour (*'Intervention Design Recommendations')*. These proposed principles apply explicitly to the behavioural and situational context of monitored drivers and focus on the central use of digital behaviour change interventions (DBCI) delivered through mobile smartphone applications.

5.4.1 **Design Strategy 1: Design for Emotion Self-Regulation**

Psychological Conditions: Evidence from this research (see Section 4.1) offers a consistent pattern of findings which – alongside wider research (e.g. Matthews, 2001) – indicates that poorer wellbeing and maladaptive emotion-management detrimentally influence drivers' ecological efficiency across several driving actions. This suggests that drivers may 'manage' difficult emotions and mood states (e.g. 'road rage') *within* the driving environment by performing certain *operational* actions inefficiently (e.g., speeding) as an approach to cope with negative affect (e.g. driver stress; Matthews, 2001; Goldenberg et al., 2000; Redshaw, 2004).

Behavioural Evidence: Emotion dysregulation involves using nonadaptive strategies to regulate negative emotions (Gross, 1998, 2015a; Colombo, Diaz-Garcia, Fernandez-Alvaro & Botella, 2021Aldao et al., 2010; Urzua et al., 2016). Evidence from randomised controlled trials (RCT) illustrates efficacy of digital technologies to deliver interventions which target emotion dysregulation (Colombo, Fernandez-Alvarez, Garcia Palacios, Cipresso, Botella & Riva, 2019). These interventions use methods such as Ecological Momentary Interventions (EMIs) (Heron and Smyth, 2010) to deliver personalised and just-in-time emotion regulation strategies, based on the behaviour and affective state of individuals (Colombo et al., 2019; Perna, Grassi, Cadirola & Nemeroff, 2017). In the context of eco-driving specifically, substantial evidence supports emotion regulation strategies to address 'aggressive' driving behaviour (e.g. Li, Zhang, Wang, Sun, Zeng, Tang, Guo & Cao, 2021; Braun, Weber & Alt, 2021).

Whilst some of these strategies are delivered outside of the vehicle (e.g., visual-attribute-based signage, Li et al., 2021), others delivered within the vehicle environment include the use of emotion-adaptive music (Eyben et al., 2010; Hernandez et al., 2014), adaptive user interfaces (Braun et al., 2019), empathic speech (Braun et al., 2019b) and emotion-aware navigation (Pfleging, Rang & Broy., 2016). Yet, these implicit affective features – currently being applied by premium manufacturers including BMW, Audi and Mercedez-Benz (Braun et al., 2021) – rely on emotion-adaptive technologies which may be less feasible for insurer-moderated interventions. Instead, active behavioural change strategies offer effective and more feasible routes for drivers' emotion regulation. This includes facilitating reappraisals (strategies which deflate frustrating situations; Braun et al., 2019; Zhang et al., 2016) and relaxation techniques (e.g., breathing exercises; Nasoz et al., 2010; Oehl et al., 2019). Both strategies can be delivered to drivers either pre-, during and post-journey to facilitate regulation in response to both prior stress and negative emotions derived from the journey itself (e.g. 'road rage'; Braun et al., 2021).

Intervention Design Recommendations: Testing different data-driven emotion regulation interventions based on reappraisal and relaxation strategies using randomised controlled trialling is recommended to determine 'what works' when supporting insureds to regulate emotions in advance of or in response to the eco-driving task. An illustrative example of reappraisals are self-monitoring messages (e.g., "How are you currently feeling?") which can encourage individuals to evaluate the impact of negative emotions on their wellbeing and whether they have the resources to cope ("What could you do to feel calmer before you drive?"). Relaxation strategies in this context might take the form of directed guidance (e.g., "Are you feeling stressed? Take a few deep breaths before you continue your journey"; Nasoz, Lisetti, Athanasios & Vaslakos, 2010). Deploying strategies *during* a journey has low feasible due to technological constraints and ethical considerations for driver distraction and safety. However, designing opportunities for emotion regulation intervention both pre- and post-journey are recommended.

For pre-journey interventions, data-driven approaches could use predictive models to ascertain whether customers illustrate predictable patterns of vehicle use (e.g., timing, frequency, inefficient ‘episodes’). If this is feasible, pre-journey interventions could be delivered using proactive ‘prompts’ (e.g., app notifications) to offer customers adaptive strategies for self-regulation ‘just-in-time’ *in advance* of vehicle use. In contrast, post-journey prompts could integrate post-trip feedback with emotion regulation strategies to support customers to self-regulate their driving stress (Matthews, 2001) and heighten their ability to self-monitor (i.e., increase customer awareness that their emotion dysregulation influenced particular aspects of their driving).

5.4.2 **Design Strategy 2: Facilitate Openness Through Behavioural Design**

Psychological Conditions: Evidence in this study suggests that greater ‘openness’ – a personality trait characterised by being more receptive to new and unusual ideas and experiences (Ashton & Lee, 2007) – facilitates a reliable habit of drivers using vehicles for characteristically *longer* journeys over shorter ones (see Section 4.3.3. for discussion). This strategic eco-driving habit is desirable: shorter journeys emit a disproportionate amount of emissions (Sloman et al., 2010) and characterise ‘quick errands’ which may be feasible to undertake using sustainable forms of transport instead (e.g., walking, cycling, e-scooters; Neves & Brand, 2019). Strategic vehicle use decisions such as journey length are clear examples of driving actions which are ‘explicit’ in their environmental impact (Sivak & Schoettle, 2012) and use reduction strategies have received considerable – and arguably disproportionate – focus within public policy over the more ‘implicit’ (largely operational) actions drivers can take to minimise the environmental impact of their driving (Burns & Cracknell, 2019). This could suggest patterns in trait openness could facilitate wider eco-driving behaviours if drivers become aware of the benefits of more implicit eco-driving strategies.

Behavioural Evidence: Research insights surrounding the role of openness can be used to bolster interventions to enable customers to be more receptive to adopting new or ‘unconventional’ strategic eco-driving behaviours (e.g., frugal vehicle use). Whilst driving-specific evidence is sparse, wider randomised controlled trial evidence suggests this can be achieved using two approaches: enhancing drivers’ ‘openness’ directly using personality change interventions (see Stieger, Wepfer, Ruegger, Kowatsch, Roberts & Allemand, 2020) or by subtly redesigning how drivers make strategic eco-driving decisions using ‘choice architecture’ (Thaler & Sunstein, 2008). These approaches differ largely by the decision-making processes – ‘reflective’ versus ‘automatic’ – they target.

Personality change interventions focus on intentional ‘reflective’ processes to achieve self-regulated personality change by encouraging individuals to identify why trait change is necessary or desirable, perceive associated behavioural changes as feasible and provide reinforcing opportunities to habitualised any changes to behaviour (Hennecke, Bleidorn, Denissen & Wood, 2014). Despite debate to whether personality change should be the focus of interventions (English & Carstensen, 2014), evidence suggests commonly used interventions which target *specific* behaviours (e.g., trip purpose, journey length) may be successful for changes in openness as the accumulation of context-specific behavioural changes can lead to trait-level changes to how personality is expressed in those contexts (Stieger, et al., 2020; Alleman & Fluckiger, 2017).

Conversely, randomised controlled trials which use ‘choice architecture’ focus on influencing ‘automatic’ decisions predominantly (Thaler & Sunstein, 2008). These interventions use behavioural frameworks (e.g., ‘EAST’; BIT, 2012) and behaviour change techniques (BCTs – evidenced design strategies including incentives, defaults options and ‘social norms’; Michie, Richardson, Johnston, Abraham, Francis, Hardeman, Eccles, Cane & Wood, 2013) to influence how choices are presented, perceived and selected by individuals (Michie et al., 2013; Thaler & Sunstein, 2008). Some evidence suggests integrated intervention approaches which target a combination of ‘automatic’ processes (e.g., behavioural changes and habit formation strategies) and ‘reflective’ processes (e.g., motivated, intention-based strategies) may translate short-term outcomes into long-term sustained behaviour change (Wrzus & Roberts, 2017; Stieger, et al., 2020; Alleman & Fluckiger, 2017)

Intervention Design Recommendations: To enable drivers to make novel and potentially ‘countercultural’ strategic eco-driving decisions (e.g., frugal vehicle use habits, carsharing initiatives), it is recommended that digital behaviour change interventions integrate both opportunities for customers to initiate motivated changes in their strategic vehicle use behaviours (e.g., commitments, goal setting exercises) as well as embed communications-focused design features which – using behaviour change techniques (BCTs) – can make choosing ecological strategic actions easier for customers.

These design features could embed in the mobile application's stable user interface (e.g. 'incentive' messages for eco-driving within customers' rewards portal) as well as be incorporated as digital prompts (e.g., in-app notifications). As this design strategy specifically concerns *strategic* eco-driving, these interventions would be most optimally delivered both pre- and post-journey. This digital and behavioural context offers opportunities test competing BCTs through A / B testing and randomised controlled trialling to learn what design features and messages work most effectively in encouraging strategic eco-driving behaviours (e.g. measurable reductions in shorter journeys or vehicle use frequency) across different elements of the smartphone application (i.e., feedback, rewards pages, app notifications) as well as at different times (i.e., optimal timing schedule pre- and post-journey).

Post-journey messaging is already commonplace (e.g., feedback), however it is feasible that predictive modelling methods could identify reliable patterns in customers' vehicle use habits (e.g., timing of journeys, route frequency, trip purpose, vehicle use frequency) and enable the delivery of low-risk, personalised *pre-journey* 'nudges' in advance of predicted vehicle use. These could use BCTs such as adding 'friction costs' and communicating consequences to potential vehicle use (i.e., social norms messages indicating implicit boundaries for vehicle use; "About to make a short trip? Why not walk instead?"). Conversely, post-journey 'openness' nudges could be used as digital prompts or in journey feedback to disincentivise when customers reach a particular threshold for strategic inefficiency (e.g., when a customer receives 'points' for vehicle overuse). These could use pertinent BCTs such as making consequences and material losses salient (e.g., the environmental impact or fuel costs of using a car excessively), social comparisons and norms (e.g., messages comparing a customers' vehicle use frequency with other customers in their area; "Our customers in your area are driving less than you").

5.4.3 Design Strategy 3: Enhance Eco-Driving Self-Efficacy Through Identity and Literacy

Psychological Conditions: Evidence from this present study and wider research (Van der Werff, Steg & Keizer, 2013; McIlroy & Stanton, 2017) illustrates a pattern of insights which indicate drivers' low self-perceptions as 'eco-drivers' (i.e., environmental self-identity) and low eco-driving 'literacy' (i.e., knowledge of strategies; McIlroy & Stanton, 2017) may together hinder drivers' *intentions* to drive ecologically. However, as the present study illustrates, even strong eco-driving behavioural intentions do not automatically lead to eco-driving outcomes – this is especially pertinent for automated practices such as driving style (Lauper, Moser, Fischer, Matthies & Kaufmann-Hayoz, 2015; Webb & Sheeran, 2006). Resultantly, interventions need to not only address barriers of low environmental self-identity and eco-driving literacy but bridge the intention – behaviour gap (Lauper et al., 2015). These goals can be achieved using techniques which directly address the transition to behaviour realisation (i.e., ecological driving). For eco-driving, this has largely focused on strengthening components of task and maintenance self-efficacy (Lauper et al., 2015; Sniehotta et al. 2005, Schwarzer, 2008).

Behavioural Evidence: Behavioural evidence illustrates self-efficacy beliefs – individuals' beliefs in their ability to perform a behaviour (Bandura, 1977; LaMorte, 2016) – can be strengthened through interventions which focus on offers of encouragement and support and the development of mastery experiences (Bandura, 1978, 1997; Muretta, 2005). Within a driving context, significant experimental and trial evidence supports the use of gamification features integrated within either the design of mobile apps or in-vehicle displays to improve driving efficiency and safety both pre-, during and post-trip (Nousias, Tselios, Bitzas, Amazilatis, Montesa, Lalos, Moustakas & Chatzigiannakis, 2019; El Hafidy, Rachad, Idri & Zellou, 2021; Yen, Fu & Chiou, 2022; Bui & Veit, 2015; Fitz-Walter, Johnson, Wyeth & Tjondronegoro, 2016; Brijs, Ross, De Vos, Filtness, Talbot, Hancox, Pinkington-Cheney, Katrakazas, Michaelaraki, Yannis, Kaiser, Furian, Lourenco, Wets & Brijs, 2022). Gamification can take many forms: gamified elements, driver avatars and player types, discrete motivational features (e.g., Serious Game platforms which focus on self-improvement and making a difference in the real world; Lazarro, 2004; Stavros, Lalos, Tselios, Bitzas, Amaxilatis, Chatzigiannakis, Gerasimos & Moustakas, 2017), rewards and incentives, pointification, leaderboards (Magana & Munoz-Organero, 2015), designs for progressive difficulty and accomplishments to name a select few (Nousias et al., 2019; Kim, 2011; Chou, 2015; Bui & Veit, 2015).

Intervention Design Recommendations: The use of RCTs, online experimentation and pre-testing with customers is recommended to test, evaluate and iterate different gamification features based on their efficacy for improving eco-driving self-efficacy and objective eco-driving behaviours. Certain gamification features – delivered pre or post trip – offer fundamental opportunities to boost not only eco-driving self-efficacy, but literacy and self-identity through engaging and interactive learning. Mirroring similar game solutions (e.g., Kim, 2011), an eco-driving learning programme is recommended which incorporates distinct game phases and transitionary ‘player types’ (e.g., “Novice” vs “Master Eco-Driver”). For example, a phased approach could take the form of an onboarding phase (i.e., new customers learn and begin to apply eco-driving strategies), a habit formation phase (i.e., data-driven feedback is integrated to reinforce new efficient driving behaviours) and a maintenance phase (i.e., efficient driving behaviours are ‘mastered’ and maintained). Digital prompts (e.g. app notifications) could be used to disseminate eco-driving ‘tips’ (e.g., handling driver stress, driving style impact). Driver safety concerns aside, digital prompts (e.g. verbal) delivered *during* a journey within live feedback offers data-driven opportunities to tailor self-efficacy messages to customers when they experience significant inefficient ‘events’ which threaten drivers’ eco-driving self-efficacy.

5.4.4 **Design Strategy 4: Behaviourally-Informed Eco-Driving Feedback**

Psychological Conditions: Meta-analytic evidence demonstrates that the most common strategy used to promote eco-driving is feedback which conveys information about fuel efficiency to the driver with the goal of reducing environmental impact (Sanguinetti, Queen, Yee & Akanesuvan, 2020; Froehlich, Dillahunt, Mankoff, Consolvo, Harrison & Landay, 2009). Evidence suggests more drivers would adopt an eco-driving style if they had greater understanding of how their current driving practices impact fuel efficiency and emissions (Abrahamse, Steg, Vlek & Rothengatter, 2005). While beyond scope of this study's focus, considerations for the role of feedback in encouraging and improving eco-driving permeates the research and intervention landscape (Sanguinetti et al., 2020). In the context of this thesis' own recommendations, several implications for how feedback is designed and presented can be identified. For example, how drivers perceive and respond to feedback might be characterised by individual differences in emotion dysregulation and trait emotionality (e.g., emotional reactance to feedback). In recommendations for designing driver 'openness', feedback is clearly highlighted as an avenue to reinforce 'open' habits. Finally, recommendations for bolstering eco-driving self-efficacy pivot on opportunities to integrate feedback on performance within gamified features to promote eco-driving 'mastery' (e.g., leaderboards, incentives and rewards, phased game platforms which require increases in efficiency to transition to higher player 'ranks'). These considerations highlight how psychological research to understand how individual differences contribute to eco-driving enactment can inform how feedback is designed to optimise eco-driving outcomes.

Behavioural Evidence: The delivery of digital eco-driving feedback is by far the most considered area for behavioural interventions. This has traditionally taken the approach of feedback delivered *after* a driver journey, however relatively recent novel opportunities afforded by Big Data and advancements in digital infrastructure (i.e., smartphone apps, navigation devices, in-vehicle interfaces) offer opportunities to influence drivers' driving efficiency *during* a journey in response to their behaviours (i.e., real-time, personalised feedback; Barkenbus, 2010; Sanguinetti et al., 2020).

Across these contexts, eco-driving feedback can take many forms (Sanguinetti, 2020; Tulusan, Staake & Fleisch, 2012). Behavioural research using RCTs including online and field experimentation offers key considerations for the design of eco-driving feedback systems (Sanguinetti et al., 2020; Barkenbus, 2010). This includes personalisation (i.e., data-driven feedback; Fischer, 2008), timing (i.e., delayed versus real-time live feedback), modalities (i.e., visual, auditory, vibrotactile; McIlroy & Stanton, 2017; van der Voort, Dougherty & Maarseveen, 2001; Young, Birell & Stanton, 2009; Birell, Young, Jenkins & Stanton, 2012), feedback granularity (i.e., broader versus specific information; Rousikhah, King & Rakotonirainy, 2013), feedback framing (i.e., ecological efficiency, fuel savings, safety framing; Dogan et al., 2014; Jenness, Singer, Walrath & Lubar, 2009), visual design (i.e., symbolic versus numerical; Azzi, Reymond, Merienner

& Kemeny, 2011; Madden, Hewett & Roth, 2000), regularity (i.e., intermittent versus continuous), tone (i.e., informational versus reinforcing; e.g. praise and punishment) and use of social or own-self comparisons (i.e., leaderboards, population-level statistics, longitudinal efficiency improvements).

The use of these feedback design principles is highly context-specific (Sanguinetti, 2020). For example, the design of real-time feedback systems must not compromise driver safety due to anticipated driver distraction (Azzi et al., 2011; Recarte & Nunes, 2003; Young, Regan & Hammer, 2007; Summala, Lamble & Laakso, 1998; Kircher, Fors & Ahlstrom, 2014) – this may prioritise intermittent, directive and granular feedback designs either through auditory channels (i.e., brief event-specific directives; e.g. "Your speed is currently inefficient. Reduce it now to return to the 'eco-zone'") or through less invasive vibro-tactile feedback (e.g., McIlroy & Stanton, 2015). These approaches may best disrupt 'automatic' habits which characterise eco-driving decisions made in the operational driving context. Conversely, post-journey feedback interventions offer significant opportunities to offer more 'reflective' feedback design features which are consistent (i.e., stable feedback interface, daily performance notifications), nuanced (e.g., tailored using varying modalities, incentive framing and visual designs) and utilise inter and intrapersonal behavioural comparisons (i.e., leaderboards, social norms, skill improvements).

Intervention Design Recommendations: Monitored telematics customer mobile applications such as IMS's *'Better Driver'* should embed cross-platform strategies for the provision of eco-driving feedback alongside wider feedback already received (i.e., road safety and policy-related performance). Due to context-specific nuances in the digital feedback intervention landscape (Sanguinetti, 2020), an agile 'test – learn – adapt' approach is recommended to learn 'what works' in the delivery of eco-driving feedback both during and post-trips, for different elements of feedback (i.e., specific behaviours) and for different customer profiles (i.e., individual differences in emotion regulation, openness and feedback receptiveness).

This approach could be achieved through agile testing, as well as wider forms of behavioural evaluation such as A / B testing, experimental pre-testing and piloting with 'gold-standard' randomised controlled trials. These quantitative insights can be reinforced using qualitative methods such as qualitative user pre-testing, interviews and customer focus groups. Due to the vast number of approaches which could be trialled, preliminary trialling recommendations are offered for feedback opportunities *during* (i.e., real-time) and post-journey. First, interventions trialling real-time feedback *during* journeys are recommended to consider techniques which leverage intermittent, symbolic (e.g., visual designs such as ‘eco-trees’ which grow and shrink as a function of floating average of fuel consumption) and associative vibrotactile feedback (i.e., smartphone vibrations) in response to specific inefficient operational behaviours (e.g., speeding ‘events’). Critically, whilst real-time feedback seems to be more effective than delayed feedback for behaviour modulation, evidence suggests there are only moderate differences between these approaches when ‘delayed’ feedback immediately follows the journey (Sanguinetti, 2020, 2018).

Moreover, it is worth noting that strategic distinctions between real-time and post-journey feedback are largely artificial for the sake of simplicity. Specifically, multi-component digital feedback systems which integrate these intervention streams are more complex but might offer greater efficacy by amalgamating and communicating trends in drivers' real-time feedback events across time (e.g., inefficient braking) to influence drivers' *reflective*, motivated behavioural change strategies (e.g., goal-setting, graded tasks; Barkenbus, 2010; Sanguinetti et al., 2020).

5.4.5 Literature-Based Wish List for App-Based Eco-Driving Interventions

	Features	Description	EAST Applications
Must-haves:	Eco-driving metrics dashboard: Speed, Acceleration, Breaking, Turning, Volume of Journeys, Duration of Journey & overall eco-score	Discrete eco-driving metrics and overall score to accompany other features (e.g. safe driving metrics).	• Easy – simplification • Timely – provides proximal feedback.
	Journey summaries	After each journey, drivers can self-monitor their performance: map of route, good & bad eco-driving incidents with matched feedback.	• Easy – clear feedback • Attractive – attracts attention • Timely – provides feedback post-drive & helps plan goals
	Data-Driven Messaging	Providing instructions, feedback, prompts; including pre- & post-journey and daily messages using gamification (road map).	• Easy – clear messages • Attractive – gamification tools • Timely – time-tailored 'nudges'
	Rewards scheme	Offers material incentives (extrinsic motivation) such as accrued points in exchange for good eco-driving behaviour.	• Easy – straightforward points system • Attractive – incentives • Timely – proximal benefits
Should-haves:	Goal setting	Self-set goals which promote drivers' attachment to eco-driving task.	• Easy – breaks goals into easier actions • Timely – help plan response to events
	Live feedback interface	Simple interface with symbolic feedback (e.g. "eco-tree") and intermittent feedback.	• East – simple live feedback • Attractive – symbolic is visual • Timely – delivers timely feedback
Nice-to-haves:	Achievements	Offers intrinsically-motivated incentives such as mastery.	• Attractive – visually engaging & incentives • Timely – emphasises proximal benefits
	Leaderboard	Compare progress for social comparison, support & norms; popular gamification element, provides social incentives.	• Attractive – visually engaging & incentivises engagement • Timely – emphasises proximal benefits
	Friends	Connect with other friends who use product & share achievements/summaries.	• Social – makes use of networks & norms for eco-driving

EAST Framework ([BIT, 2012](BIT, 2012))

The EAST framework offers four simple principles for designing interventions based on behavioural insights.

Principles:

1. *Easy* – simplify messages, make an option the default, reduce hassle (or increase it)
2. *Attractive* – attract attention, design rewards and sanctions
3. *Social* – social norms, foster networks, encourage commitments to others
4. *Timely* – prompt when most receptive, design immediate costs/benefits, help to plan responses to events

5.5 Recommendations for Policy

Academic eco-driving research offers a behaviourally-informed approach for eco-driving policy, including industry innovation and government legislation. Yet, policymakers often fail to embed research evidence within policy or service design (Barkenbus, 2010). Whilst this thesis offers core recommendations for eco-driving theory, research and interventions, these are redundant without the means of stakeholders to apply them in real-world contexts to achieve emissions savings.

Current policy disproportionately relies on the increasing electrification and hybridisation of vehicles to address vehicle emissions. This is despite this transition still being in its infancy (UK Government, 2020), heavily reliant on past subsidy support policies (Neistadt & Bjornvold, 2019; Bruckmann & Bernauer, 2020), unaffordable for the working majority (Norman, 2021) and lacking sufficient large-scale charging infrastructure (Norman, 2021; Bruckmann & Bernauer, 2020). To be more holistic, vehicle emissions policies should recognise and embed behaviourally-informed strategies to address combustion engine emissions as part of the policy toolkit, as these vehicles will remain a dominant part of road transport until they complete their lifecycles (PWC, 2007).

In this regard, knowledge of eco-driving strategies amongst drivers is limited (McIlroy & Stanton, 2017) with the majority of existing awareness being around 'strategic' vehicle use decisions (e.g. vehicle use frequency, trip purpose). Accordingly, it is recommended that policy is designed to facilitate increases in eco-driving knowledge, as evidence from the present research suggests that drivers' perceptions of how 'explicit' ecological driving actions are is likely to influence the way drivers use eco-driving behaviours (e.g., speeding).

One aspect that constraints how eco-driving knowledge is disseminated to the public is the absence of established guidelines for eco-driving behaviours can be achieved (Sanguinetti, 2018). Yet, rapidly increasing uses of real-time intervention-facilitating technologies (e.g. smartphones, in-vehicle feedback interfaces) has given rise to vastly different eco-driving feedback systems which employ unique eco-driving metrics and may hamper cross-vehicle spillover effects; Sanguinetti, 2018; Kurani, Sanguinetti &

Park, 2015). To address this, policymakers should consider whether it is feasible to develop standardised eco-driving measures.

Finally, whilst the present study sought to understand the psychological precursors to inefficient driving and propose solutions to *improve* inefficiency that has been learnt and habitualised over time, public policy should be advocating for more advanced eco-driving skills development during provisional drivers' learning and firmer requirements for eco-driving in the UK standard driving test in order to establish eco-driving behaviours as the 'default' benchmark for vehicle use (Campbell-Hall & Dalziel, 2011; Jamson, Hibberd & Jamson, 2015).

6. Conclusions

This thesis aimed to explore the psychological, behavioural and demographic predictors of objective eco-driving utilising a novel interdisciplinary and mixed-method approach. This utilised methodologies from ‘conventional’ psychology and computational science to analyse large-scale naturalistic driving data obtained from a sample of monitored customers from Carrot Insurance. While several individual differences were implicated, patterns across the study’s findings point to an emerging and central role of emotion dysfunction in shaping drivers’ inefficient operational driving behaviours. This idea is consistent with wider perspectives on the antecedents of driver stress propensity (Matthews, 2001). Conceptually, the study’s findings advocate for ‘eco-driving’ as a collection of unique and complex behaviours influenced in discrete and contextual ways by certain individual differences. However, an important contribution of this thesis resides in its methodological considerations, as self-reports of drivers’ *intentions* to eco-drive were unrelated to objective eco-driving behaviours. This not only extends an eco-driving intention – behaviour gap previously identified (Lauper et al., 2015) to *objective* measures of eco-driving, but affirms that self-reports of driving cannot proxy the value of measuring objective eco-driving behaviours – as has been normalised. Using insights regarding drivers’ individual differences, this thesis presents four ‘design strategies’ for digital behavioural change interventions (DBCI) to encourage sustained changes – using ‘reflective’ or ‘automatic’ processes – in drivers’ ecological efficiency.

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Appendices

Appendix A – Ethical Approval (FSTREC1923)

Lancaster University

Applicant: Holly Marquez
Supervisor: Mike Hazas
Department: LEC
FSTREC Reference: FSTREC19123

03 July 2020

Re: FSTREC19123
Using digital traces to predict individual differences in environmental driving efficiency

Dear Holly,

Thank you for submitting your research ethics application for the above project for review by the **Faculty of Science and Technology Research Ethics Committee (FSTREC)**. The application was recommended for approval by FSTREC, and on behalf of the Chair of the Committee, I can confirm that approval has been granted for the amendment to this research project.

As principal investigator your responsibilities include:

- ensuring that (where applicable) all the necessary legal and regulatory requirements in order to conduct the research are met, and the necessary licenses and approvals have been obtained;
- reporting any ethics-related issues that occur during the course of the research or arising from the research to the Research Ethics Officer at the email address below (e.g. unforeseen ethical issues, complaints about the conduct of the research, adverse reactions such as extreme distress);
- submitting details of proposed substantive amendments to the protocol to the Research Ethics Officer for approval.

Please contact me if you have any queries or require further information.

Email:- fst-ethics@lancaster.ac.uk

Yours sincerely,

E. Suri-Payer

Dr. Elisabeth Suri-Payer,
Interim Research Ethics Officer, Secretary to FSTREC.

Appendix B – Email Advertisement to Carrot Insurance Customers (2 images)

From: **noreply (Carrot)** no-reply@carrotinsurance.com
Subject: [Test] Complete a short survey & earn a £5 Amazon eGift Card
Date: 1 July 2020 at 13:07
To: Emma Beaumont ebeaumont@ims.tech

N

Click here to open this email in a browser

You're invited to take part in a **voluntary & anonymous** research survey conducted by Lancaster University in partnership with Carrot Insurance. The research focuses on eco-driving and finding eco-friendly ways to improve the impact car emissions currently have on climate change.

By taking part in the 15 minute survey you will help to determine how eco-driving behaviours can be detected from your driving and survey data.

As a reward for completing the 15 minute survey you will receive a £5 Amazon eGift Card.*

Information on the research, how your data will be used and what's involved can be accessed via the link below. Please remember to read through the consent form and sign it before completing the survey.

Take part >

Thank you & stay safe,

the Carrot
Insurance team

www.carrotinsurance.com / Accident Line - 24 hours a day 0333 355 2990 / Customer Service - Mon - Fri 8:30-18:00 / Sat - 9:00-13:00 Talk to us on LiveChat

***Terms apply:** The reward for completing the survey will be given in the form of a £5 Amazon eGift Card. The £5 Amazon eGift Card will only be given to Carrot Insurance live policyholders who have successfully completed the full survey. Rewards should be treated like cash and kept securely. Rewards which are lost or stolen cannot be replaced. Please check the redemption instructions and terms and conditions of your chosen eGift before making your choice. Participant recruitment will end once 300 survey responses have been collected. This study has received ethical approval from the Faculty of Science and Technology Ethics Committee at Lancaster University.

Appendix C – Participant Information Sheet

Individual Differences Eco-Driving Survey

Start of Block: Participant Information Sheet

Q22 **Encouraging Eco-Friendly Driving**

You are being invited to take part in research conducted by Lancaster University in collaboration with your car insurance provider, Carrot Insurance (part of IMS). Please take the time to read the following information carefully about the research and what it will involve for you and click on to the next page if you're happy to continue.

What is the purpose of this research?

This research aims to develop a greater understanding of why people drive in eco-friendly ways (eco-driving), with a hope to develop new interventions to help drivers improve their eco-driving skills.

Why have I been invited to take part in the study?

You have been invited to take part in this study as you are a policyholder of Carrot Insurance. To be eligible to take part, you **must** meet the following criteria: Hold a **current** car insurance policy with Carrot Insurance which you have held for at least **three months**. Hold a full UK Driving License Aged 18+

What will I have to do?

If you agree to take part, you will complete a short survey with a variety of questions. Beforehand, you will be asked to provide consent for Carrot Insurance to provide Lancaster University with an anonymised version of your telematics driving data collected from your car during your policy. Lancaster University will not receive any personal information about you from Carrot Insurance. The survey should take around 15 minutes and you will receive a £5 Amazon voucher via email from Carrot Insurance for taking part. Your voucher will be sent as soon as possible but may take up to two weeks from when you complete the survey.

Please complete the survey as soon as possible from when you click the link and do not share your link to the survey as it is only designed to be used by you.

What are the possible benefits/disadvantages of taking part?

There are no perceived disadvantages of taking part in this study. Benefits include receiving a £5 Amazon voucher for successful completion, the possibility to reflect on your driving habits, as well as knowledge that research findings based on your participation may positively impact the insurance and road user industries in the future.

Do I have to take part?

No, you do not have to participate. There will be no adverse consequences in terms of your car insurance policy with Carrot Insurance. You can withdraw your participation at any time during the survey by closing the survey window/tab without having to specify a reason; if you close the window/tab, no data you have provided will be recorded or used. You can also request for your data to be withdrawn up to two weeks after you have completed the survey without giving a reason and without prejudice. After this time, your data will be included in the study.

Will my data be identifiable?

No personal information will be collected as part of this research which could identify you. An anonymised, hashed version of your insurance policy number will provided by Carrot Insurance solely for the purpose of connecting your survey responses to your driving data and for providing you with your £5 Amazon voucher incentive. This information will be stored securely in an encrypted file in line with Lancaster University guidelines.

What will happen to the data that I provide?

Data collected will be handled in accordance with the UK's General Data Protection Regulations (GDPR) and stored securely in line with Lancaster University policies. Data collected through the survey will be shared with Carrot Insurance to enable Carrot Insurance to provide the anonymised driving data and for future research purposes.

For further information about how Lancaster University processes personal data for research purposes and your data rights please visit our webpage: www.lancaster.ac.uk/research/data-protection

Who has reviewed this project?

This study has been reviewed and approved by the Faculty of Science and Technology Research Ethics Committee at Lancaster University.

What if I have a query about the research or have a concern/complaint about my experience?

Any queries about the research or concerns/complaints about any aspects of your experience taking part will be addressed. For *queries/questions* about the research, please contact the Principal Investigator, Holly Marquez at h.marquez@lancaster.ac.uk. If you'd like to speak someone at Carrot about this project, click here. For *concerns or complaints* about your experience taking part, please contact Professor Phillip Barker, Head of the Lancaster Environment Centre at Lancaster University at p.barker@lancaster.ac.uk or the Lancaster University Faculty of Science and Technology Research Ethics Committee at fst-ethics@lancaster.ac.uk.

Research Team Contact Details:

Principal Investigator: Holly Marquez
Email: h.marquez@lancaster.ac.uk

End of Block: Participant Information Sheet

Appendix D – Self-Report Survey (Including Consent Page)

Start of Block: Consent Page and Email Collection

Q23 **Participant Consent Form**

Please read the information below regarding your participation. If you have any questions or would like more information about your participation, please contact the Principal Investigator, Holly Marquez (h.marquez@lancaster.ac.uk).

Digitally signing this consent form below indicates that:
I confirm that I have read and understand the information sheet for the study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving a reason and without it affecting my policy with Carrot Insurance (IMS). If I withdraw within **two weeks** of commencement of the study my data will be removed. I consent for Carrot Insurance (IMS) to provide the researcher/s at Lancaster University with an anonymised version of my driving data, collected during the duration of my policy with Carrot Insurance. I consent for the researchers at Lancaster University to provide Carrot Insurance (IMS) with an anonymised version of the information collected in this survey for future research purposes. I understand that any information given by me may be used in future reports, academic articles, publications or presentations by the researchers, but my personal information will not be included, and I will not be identifiable. I understand that data will be kept according to University guidelines for a minimum of 10 years after the end of the study. I agree to take part in the study.

☐ **Click here to digitally sign your consent to the statements above** (box turning red indicates consent)**.** (1)

End of Block: Consent Page and Email Collection

Start of Block: Demographics

Q13 What is your age?

____

Q14 What is your gender identity?

○ Male (1)

○ Female (2)

○ Non-binary (3)

○ Prefer to self-describe (4) ____

○ Prefer not to say (5)

Q15 What is your ethnicity?

○ White (1)

○ Black (2)

○ Asian (3)

○ Mixed or multiple ethnic groups (4)

○ Other (5)

○ Prefer not to say (6)

Q21 How long have you held your Full UK Driving License for? Please answer in years and months.

○ Years (1) ____

○ Months (2) ____

End of Block: Demographics

Start of Block: E-PVQ (Values; Bouman, Steg & Kiers (2018))

Q5 (HIM) Here, we briefly describe some people. Please read each description and think about how much each person is or is not like you. Then select your response that

shows how much the person in the description is like you on the scale provided from 1 = not like me at all to 7 = very much like me.

	1 (not like me at all) (1)	(2)	(3)	(4)	(5)	(6)	7 (very much like me) (7)
It is important to him to prevent environmental pollution. (1)	○	○	○	○	○	○	○
It is important to him to protect the environment. (2)	○	○	○	○	○	○	○
It is important to him to respect nature. (3)	○	○	○	○	○	○	○
It is important to him to be in unity with nature. (4)	○	○	○	○	○	○	○
It is important to him that every person has equal opportunities. (5)	○	○	○	○	○	○	○
It is important to him to take care of those who are worse off. (6)	○	○	○	○	○	○	○
It is important to him that every person is treated justly. (7)	○	○	○	○	○	○	○
It is important to him that there is no war or conflict. (8)	○	○	○	○	○	○	○
It is important to him to be helpful to others. (9)	○	○	○	○	○	○	○

It is important to him to have fun. (10)	○	○	○	○	○	○	○
It is important to him to enjoy the life's pleasures. (11)	○	○	○	○	○	○	○
It is important to him to do things he enjoys. (12)	○	○	○	○	○	○	○
It is important to him to have control over others' actions. (13)	○	○	○	○	○	○	○
It is important to him to have authority over others. (14)	○	○	○	○	○	○	○
It is important to him to be influential. (15)	○	○	○	○	○	○	○
It is important to him to have money and possessions. (16)	○	○	○	○	○	○	○
It is important to him to work hard and be ambitious. (17)	○	○	○	○	○	○	○

Q6 (HER) Here, we briefly describe some people. Please read each description and think about how much each person is or is not like you. Then select your response that

shows how much the person in the description is like you on the scale provided from 1 = not like me at all to 7 = very much like me.

	1 (not like me at all) (1)	(2)	(3)	(4)	(5)	(6)	7 (very much like me) (7)
It is important to her to prevent environmental pollution. (1)	○	○	○	○	○	○	○
It is important to her to protect the environment. (2)	○	○	○	○	○	○	○
It is important to her to respect nature. (3)	○	○	○	○	○	○	○
It is important to her to be in unity with nature. (4)	○	○	○	○	○	○	○
It is important to her that every person has equal opportunities. (5)	○	○	○	○	○	○	○
It is important to her to take care of those who are worse off. (6)	○	○	○	○	○	○	○
It is important to her that every person is treated justly. (7)	○	○	○	○	○	○	○
It is important to her that there is no war or conflict. (8)	○	○	○	○	○	○	○
It is important to her to be helpful to others. (9)	○	○	○	○	○	○	○

It is important to her to have fun. (10)	○	○	○	○	○	○	○
It is important to her to enjoy the life's pleasures. (11)	○	○	○	○	○	○	○
It is important to her to do things she enjoys. (12)	○	○	○	○	○	○	○
It is important to her to have control over others' actions. (13)	○	○	○	○	○	○	○
It is important to her to have authority over others. (14)	○	○	○	○	○	○	○
It is important to her to be influential. (15)	○	○	○	○	○	○	○
It is important to her to have money and possessions. (16)	○	○	○	○	○	○	○
It is important to her to work hard and be ambitious. (17)	○	○	○	○	○	○	○

Q7 (THEM) Here, we briefly describe some people. Please read each description and think about how much each person is or is not like you. Then select your response that

shows how much the person in the description is like you on the scale provided from 1 = not like me at all to 7 = very much like me.

	1 (not like me at all) (1)	(2)	(3)	(4)	(5)	(6)	7 (very much like me) (7)
It is important to them to prevent environmental pollution. (1)	○	○	○	○	○	○	○
It is important to them to protect the environment. (2)	○	○	○	○	○	○	○
It is important to them to respect nature. (3)	○	○	○	○	○	○	○
It is important to them to be in unity with nature. (4)	○	○	○	○	○	○	○
It is important to them that every person has equal opportunities. (5)	○	○	○	○	○	○	○
It is important to them to take care of those who are worse off. (6)	○	○	○	○	○	○	○
It is important to them that every person is treated justly. (7)	○	○	○	○	○	○	○
It is important to them that there is no war or conflict. (8)	○	○	○	○	○	○	○
It is important to them to be helpful to others. (9)	○	○	○	○	○	○	○

It is important to them to have fun. (10)	○	○	○	○	○	○	○
It is important to them to enjoy the life's pleasures. (11)	○	○	○	○	○	○	○
It is important to them to do things they enjoys. (12)	○	○	○	○	○	○	○
It is important to them to have control over others' actions. (13)	○	○	○	○	○	○	○
It is important to them to have authority over others. (14)	○	○	○	○	○	○	○
It is important to them to be influential. (15)	○	○	○	○	○	○	○
It is important to them to have money and possessions. (16)	○	○	○	○	○	○	○
It is important to them to work hard and be ambitious. (17)	○	○	○	○	○	○	○

End of Block: E-PVQ (Values; Bouman, Steg & Kiers (2018))

Start of Block: HEXACO-60

Q2 Below, you will find a series of statements about you. Please read each statement and decide how much you agree or disagree with that statement. Then select your response on the scale provided from 1 = strongly disagree to 5 = strongly agree.

	1 (strongly disagree) (1)	2 (disagree) (2)	3 (neutral - neither agree nor disagree) (3)	4 (agree) (4)	5 (strongly agree) (5)
I would be quite bored by a visit to an art gallery. (1)	○	○	○	○	○
I plan ahead and organise things, to avoid scrambling at the last minute. (2)	○	○	○	○	○
I rarely hold a grudge, even against people who have badly wronged me. (3)	○	○	○	○	○
I feel reasonably satisfied with myself overall. (4)	○	○	○	○	○
I would feel afraid if I had to travel In bad weather conditions. (5)	○	○	○	○	○
I wouldn't use flattery to get a raise or promotion at work, even if I thought it would succeed. (6)	○	○	○	○	○
I'm interested in learning about the history and politics of other countries. (7)	○	○	○	○	○

I often push myself very hard when trying to achieve a goal. (8)	○	○	○	○	○
People sometimes tell me that I am too critical of others. (9)	○	○	○	○	○
I rarely express my opinions in group meetings. (10)	○	○	○	○	○
I sometimes can't help worrying about little things. (11)	○	○	○	○	○
If I knew that I could never get caught, I would be willing to steal a million pounds. (12)	○	○	○	○	○
I would enjoy creating a work of art, such as a novel, song, or a painting. (13)	○	○	○	○	○
When working on something, I don't pay much attention to small details. (14)	○	○	○	○	○
People sometimes tell me that I'm too stubborn. (15)	○	○	○	○	○

I prefer jobs that involve active social interaction to those that involve working alone. (16)	○	○	○	○	○
When I suffer from a painful experience, I need someone to make me feel comfortable. (17)	○	○	○	○	○
Having a lot of money is not especially important to me. (18)	○	○	○	○	○
I think that paying attention to radical ideas is a waste of time. (19)	○	○	○	○	○
I make decisions based on the feeling of the moment rather than on careful thought. (20)	○	○	○	○	○
People think of me as someone who has a quick temper. (21)	○	○	○	○	○
On most days, I feel cheerful and optimistic. (22)	○	○	○	○	○
I feel like crying when I see other people crying. (23)	○	○	○	○	○

I think that I am entitled to more respect than the average person is. (24)					
If I had the opportunity, I would like to attend a classical music concert. (25)					
When working, I sometimes have difficulties due to being disorganised. (26)					
My attitude toward people who have treated me badly is "forgive and forget". (27)					
I feel that I am an unpopular person. (28)					
When it comes to physical danger, I am very fearful. (29)					
If I want something from someone, I will laugh at that person's worst jokes. (30)					
I've never really enjoyed looking through an encyclopedia. (31)					

I do only the minimum amount of work needed to get by. (32)	○	○	○	○	○
I tend to be lenient in judging other people. (33)	○	○	○	○	○
In social situations, I'm usually the one who makes the first move. (34)	○	○	○	○	○
I worry a lot less than most people do. (35)	○	○	○	○	○
I would never accept a bribe, even if it were very large. (36)	○	○	○	○	○
People have often told me that I have a good imagination. (37)	○	○	○	○	○
I always try to be accurate in my work, even at the expense of time. (38)	○	○	○	○	○
I am usually quite flexible in my opinions when people disagree with me. (39)	○	○	○	○	○
The first thing that I always do in a new place is to make friends. (40)	○	○	○	○	○

I can handle difficult situations without needing emotional support from anyone else. (41)					
I would get a lot of pleasure from owning expensive luxury goods. (42)					
I like people who have unconventional views. (43)					
I make a lot of mistakes because I don't think before I act. (44)					
Most people tend to get angry more quickly than I do. (45)					
Most people are more upbeat and dynamic than I generally am. (46)					
I feel strong emotions when someone close to me is going away for a long time. (47)					
I want people to know that I am an important person of high status. (48)					

I don't think of myself as the artistic or creative type. (49)	○	○	○	○	○
People often call me a perfectionist. (50)	○	○	○	○	○
Even when people make a lot of mistakes, I rarely say anything negative. (51)	○	○	○	○	○
I sometimes feel that I am a worthless person. (52)	○	○	○	○	○
Even in an emergency I wouldn't feel like panicking. (53)	○	○	○	○	○
I wouldn't pretend to like someone just to get that person to do favours for me. (54)	○	○	○	○	○
I find it boring to discuss philosophy. (55)	○	○	○	○	○
I prefer to do whatever comes to mind, rather than stick to a plan. (56)	○	○	○	○	○
When people tell me that I'm wrong, my first reaction is to argue with them. (57)	○	○	○	○	○

When I'm in a group of people, I'm often the one who speaks on behalf of the group. (58)	○	○	○	○	○
I remain unemotional even in situations where most people get very sentimental. (59)	○	○	○	○	○
I'd be tempted to use counterfeit money, if I were sure I could get away with it. (60)	○	○	○	○	○

End of Block: HEXACO-60

Start of Block: Environmental Self-Identity (Van der Werff et al., 2013b)

Q24 Below, you will find a series of statements. Please read each statement and decide how much you agree or disagree with that statement. Then select your response on the scale provided from 1 = totally disagree to 7 = totally agree.

	1 (totally disagree) (1)	(2)	(3)	(4)	(5)	(6)	7 (totally agree) (7)
Acting environmentally-friendly is an important part of who I am. (1)	○	○	○	○	○	○	○
I am the type of person who acts environmentally-friendly. (2)	○	○	○	○	○	○	○
I see myself as an environmentally-friendly person. (3)	○	○	○	○	○	○	○

End of Block: Environmental Self-Identity (Van der Werff et al., 2013b)

Start of Block: Locus of Control (Rotter, 1965)

Q26 **For each pair of statements, please choose the one you agree with most. If you do not agree with either of them, choose the one that is least objectionable.**

Q27 1.

○ Getting a good job depends mainly on being in the right place at the right time. (1)

○ Becoming a success is a matter of hard work, luck has little or nothing to do with it. (2)

Q28 2.

○ Getting people to do the right thing depends upon ability. Luck has little or nothing to do with it. (1)

○ Who gets to be the boss often depends on who was lucky enough to be in the right place first. (2)

Q29 3.

○ There's not much use in trying too hard to please people, if they like you, they like you. (1)

○ People are lonely because they don't try to be friendly. (2)

Q30 4.

○ It is difficult for people to have much control over the things politicians do in office. (1)

○ With enough effort we can wipe out political corruption. (2)

Q31 5.

○ Unfortunately, an individual's worth often passes unrecognized no matter how hard he tries (1)

○ In the long run people get the respect they deserve in this world (2)

Q32 6.

○ The average citizen can have an influence in government decisions. (1)

○ This world is run by the few people in power, and there is not much the little guy can do about it. (2)

Q33 7.

○ One should always be willing to admit mistakes. (1)

○ It is usually best to cover up one's mistakes. (2)

Q34 8.

○ In the long run the people are responsible for bad government on a national as well as on a local level. (1)

○ Most of the time I can't understand why politicians behave the way they do. (2)

Q35 9.

○ No matter how hard you try some people just don't like you. (1)

○ People who can't get others to like them don't understand how to get along with others. (2)

Q36 10.

- Most misfortunes are the result of lack of ability, ignorance, laziness, or all three. (1)
- In the long run the bad things that happen to us are balanced by the good ones. (2)

Q37 11.

- I have often found that what is going to happen will happen. (1)
- Trusting to fate has never turned out as well for me as making a decision to take a definite course of action. (2)

Q38 12.

- One of the major reasons why we have wars is because people don't take enough interest in politics. (1)
- There will always be wars, no matter how hard people try to prevent them. (2)

Q39 13.

- Most students don't realize the extent to which their grades are influenced by accidental happenings. (1)
- The idea that teachers are unfair to students is nonsense. (2)

Q40 14.

- Without the right breaks one cannot be an effective leader. (1)
- Capable people who fail to become leaders have not taken advantage of their opportunities. (2)

Q41 15.

- ○ People's misfortunes result from the mistakes they make. (1)
- ○ Many of the unhappy things in people's lives are partly due to bad luck. (2)

Q42 16.

- ○ There is a direct connection between how hard one studies and the grades I get. (1)
- ○ Sometimes I can't understand how teachers arrive at the grades they give. (2)

Q43 17.

- ○ Many times I feel that I have little influence over the things that happen to me. (1)
- ○ It is impossible for me to believe that chance or luck plays an important role in my life. (2)

Q44 18.

- ○ What happens to me is my own doing. (1)
- ○ Sometimes I feel that I don't have enough control over the direction my life is taking. (2)

Q45 19.

- ○ It is not always wise to plan too far ahead because many things turn out to be a matter of good or bad fortune anyhow. (1)
- ○ When I make plans, I am almost certain that I can make them work. (2)

Q46 20.

○ Heredity plays the major role in determining one's personality (1)

○ It is one's experiences in life which determine what they're like. (2)

Q47 21.

○ A good leader expects people to decide for themselves what they should do. (1)

○ A good leader makes it clear to everybody what their jobs are. (2)

Q48 22.

○ There are certain people who are just no good. (1)

○ There is some good in everybody. (2)

Q49 23.

○ Many times we might just as well decide what to do by flipping a coin. (1)

○ In my case getting what I want has little or nothing to do with luck. (2)

Q50 24.

○ By taking an active part in political and social affairs the people can control world events. (1)

○ As far as world affairs are concerned, most of us are the victims of forces we can neither understand, nor control. (2)

Q51 25.

◯ It is hard to know whether or not a person really likes you. (1)

◯ How many friends you have depends upon how nice a person you are. (2)

Q52 26.

◯ Team sports are an excellent way to build character. (1)

◯ There is too much emphasis on athletics in high school. (2)

Q53 27.

◯ There really is no such thing as "luck." (1)

◯ Most people don't realize the extent to which their lives are controlled by accidental happenings. (2)

Q54 28.

◯ The trouble with most children nowadays is that their parents are too easy with them. (1)

◯ Children get into trouble because their parents punish them too much. (2)

Q55 29.

◯ Many times exam questions tend to be so unrelated to coursework that studying is really useless. (1)

◯ In the case of the well prepared student there is rarely if ever such a thing as an unfair test. (2)

End of Block: Locus of Control (Rotter, 1965)

Start of Block: Intention to Eco-Drive (Unal et al., 2018)

Q55 Below, there are three statements which relate to how you intend to drive your car. Please read each statement and select your response on the scale provided from 1 = I don't agree, to 7 = I agree, as to the extent you agree with the statement.

	1 (I don't agree) (1)	(2)	(3)	4 (Neutral) (4)	(5)	(6)	7 (I completely agree) (7)
I intend to follow the maximum speed limit as much as possible. (1)	○	○	○	○	○	○	○
I intend to switch to a higher gear as soon as possible. (2)	○	○	○	○	○	○	○
I intend to drive more fuel efficiently. (3)	○	○	○	○	○	○	○

End of Block: Intention to Eco-Drive (Unal et al., 2018)

Start of Block: Perceived Accessibility Scale (Lattman, Olsson & Friman, 2016)

Q23 Below, you will find a series of statements about using public transport. Please read each statement and decide how much you agree or disagree with that statement.

Then select your response on the scale provided from 1 = I don't agree to 7 = I completely agree.

	1 (I don't agree) (1)	(2)	(3)	4 (Neutral) (4)	(5)	(6)	7 (I completely agree) (7)
It is easy to do (daily) activities with public transport (1)	○	○	○	○	○	○	○
If public transport was my only mode of travel, I would be able to continue living the way I want (2)	○	○	○	○	○	○	○
It is possible to do the activities I prefer with public transport. (3)	○	○	○	○	○	○	○
Access to my preferred activities is satisfying with public transport (4)	○	○	○	○	○	○	○

End of Block: Perceived Accessibility Scale (Lattman, Olsson & Friman, 2016)

Start of Block: Satisfaction with Life as a Whole & PWI Scale

Q18 The following questions ask how satisfied you feel, on a scale from 0 to 10. **Zero** means you feel no satisfaction at all and **10** means you feel completely satisfied.

	0 (No satisfaction at all) (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	10 (Completely satisfied) (11)
Thinking about your own life and personal circumstances, how satisfied are you **with your life as a whole?** (1)	○	○	○	○	○	○	○	○	○	○	○
How satisfied are you **with your standard of living?** (2)	○	○	○	○	○	○	○	○	○	○	○
How satisfied are you **with your health?** (3)	○	○	○	○	○	○	○	○	○	○	○
How satisfied are you **with what you are achieving in life?** (4)	○	○	○	○	○	○	○	○	○	○	○
How satisfied are you **with your personal relationships?** (5)	○	○	○	○	○	○	○	○	○	○	○
How satisfied are you **with how safe you feel?** (6)	○	○	○	○	○	○	○	○	○	○	○

How satisfied are you **with feeling part of your community?** (7)	○	○	○	○	○	○	○	○	○	○	○
How satisfied are you **with your future security?** (8)	○	○	○	○	○	○	○	○	○	○	○
How satisfied are you **with your spirituality or religion?** (9)	○	○	○	○	○	○	○	○	○	○	○

End of Block: Satisfaction with Life as a Whole & PWI Scale

Start of Block: Demographics 2

Q17 In what region of the UK do you currently live?

	Off (1)	On (2)
Scotland (7)		
Yorkshire (9)		
North East (13)		
North West (14)		
East Midlands (15)		
West Midlands (16)		
East of England (17)		
London (18)		
South East (19)		
South West (21)		
Wales (22)		
Northern Ireland (23)		


Scotland
North East
North West
Northern Ireland
Yorkshire and the Humber
East Midlands
West Midlands
Wales
East of England
London
South East
South West

Q16 What is the highest level of education you have completed or are currently completing?

- GCSEs (or equivalent qualification) (1)
- A Levels (or equivalent qualification) (2)
- University undergraduate programme (3)
- University postgraduate programme (4)

Q17 How frequently do you smoke?

- Often (1)
- Sometimes (2)
- Rarely (3)
- Never (4)

Q18 How frequently do you drink alcohol?

- Often (1)
- Sometimes (2)
- Rarely (3)
- Never (4)

Q19 Have you experienced any of the following major life events in the last year? Select all that apply.

- ☐ Childbirth or adoption (1)
- ☐ Separation from a relationship or divorce (2)
- ☐ Personal illness (3)
- ☐ Illness of a close other (4)
- ☐ Injury or medical emergency involving you (5)
- ☐ Injury or medical emergency involving a close other (6)
- ☐ Moved to a new home (including University) (7)
- ☐ Bereavement of a close other (e.g. partner, family, friend) (8)
- ☐ Change of job circumstances (9)

End of Block: Demographics 2

Appendix E – Debrief Message

Thank you for participating in the present study focused on eco-driving. This research aims to explore whether key psychological factors such as personality and personal values are able to predict an individual's environmentally friendly driving ability. By understanding this to a greater extent, we hope this will aid the design of personalised driving interventions to help people become better eco-drivers for the future.

This study is based on a multidisciplinary body of research centred on understanding and improving eco-driving behaviour. Studies illustrate that behavioural interventions such as eco-feedback tools can reduce fuel use from petrol and diesel-powered vehicles by up to 16% (Fiat, 2010; Araujo et al., 2012; McIlroy, 2015; Barkenbus, 2010). As research suggests environmentally friendly behaviours (e.g. eco-driving, energy conservation, recycling) are shaped by psychological factors (e.g. personal values; Mogles et al., 2018; Knowles et al., 2014; Unal et al., 2018; Brick & Lewis, 2016; Poskus, 2018; Pavalache-Ilie & Unianu, 2012), it is important to understand the individual factors which may make individuals more likely to be better eco-drivers.

To receive a report of this research (or a summary of the findings) when it is completed, please contact Holly Marquez at h.marquez@lancaster.ac.uk. If you would like to withdraw your data from the study (which you are allowed to do any time up to two weeks from completion of the survey), please contact Holly Marquez at h.marquez@lancaster.ac.uk.

If you have any concerns/complaints about your experience taking part, please contact Professor Philip Parker, Head of the Lancaster Environment Centre at Lancaster University (p.barker@lancaster.ac.uk), the Lancaster University Faculty of Science and Technology Ethics Board (fst-ethics@lancaster.ac.uk), or alternatively if you'd like to speak to someone at Carrot Insurance about this research, click here [LINK TO CARROT CUSTOMER SUPPORT].

If you have been affected by any of the topics discussed as part of the research, please see the following sources for information, advice and support:

- Mind https://www.mind.org.uk/information-support/types-of-mental-health-problems/stress/what-is-stress/
- Samaritans https://www.samaritans.org
- Brake http://www.brake.org.uk/
- THINK! https://www.think.gov.uk

To learn more about eco-driving and tips to become a better eco-driver, the links below provide some easy-to-read insights:

- Top 10 Eco-Driving Tips - The Telegraph:https://www.telegraph.co.uk/business/sme-library/fleet-management/Top-10-eco-driving-tips/
- The effectiveness of eco-driving - RAC Foundation (2012): https://www.racfoundation.org/assets/rac_foundation/content/downloadables/easy_on_the_gas-wengraf-oct2012.pdf
- Eco-driving large-scale study report by Fiat (2010): https://www.lowcvp.org.uk/news,multinational-ecodriving-trials-show-efficiency-savings_1521.htm

Appendix F – Approval for submission of an over-length thesis

Approval for submission of an over-length thesis

Lancaster University

The Postgraduate Research Regulations permit a candidate, with the support of his or her supervisor, to apply for exceptional permission to exceed the word limit for the thesis. Candidates should complete this form and obtain the signatures of their supervisor(s)before submitting it to the Student Registry.

Student's name Holly Marquez Constantinou **Student ID number** 35372978

Department Lancaster Environment Centre **Degree** MSc by Research

Name of supervisor(s) Dr Laura-Jean Stokes (Dept. of Psychology), Dr Heather Shaw (Dept. of Psychology)

Published thesis word limit for the degree scheme: 35,000

Word length of final draft of thesis: 36,794

To support your application, please provide an explanation as to why this thesis exceeds the maximum permitted word limit (for example, has the scope or nature of the research generated an exceptional volume of material).

The word length of the final draft of this thesis is 36,794 words (excluding non-applicable content excluded as per the University's regulations). This thesis slightly exceeds the permitted word limit of 35,000 words as it includes one section ('Recommendations for Behavioural Intervention'), totalling 3,777 words, which is not conventional to a typical thesis of this nature and has been included as a unique requirement of the project's funders. Specifically, this research project is an academia-industry partnership supported by the Centre for Global Eco-Innovation and part-funded by the European Regional Development Fund. As a requirement for this project, this additional section centres on applying the research findings of the thesis in practice to the environmental challenges faced by the project's industry partner Trak Global Group, providing consultancy-style next-steps solutions for the business. This is an uncommon inclusion.

Supervisor signature(s): H Shaw L-J Stokes Date 11/10/2022

Please return this form to the Student Registry, University House or by email to recordsenquiries@lancaster.ac.uk .

Approved on behalf of the Pro-Vice-Chancellor (Education), acting on behalf of Senate

Professor Alisdair Gillespie .... Date 14.x.22

University Academic Dean

Supervisor signature(s): L-J Stokes

Date ……11/10/2022………