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Understanding Travel Behaviour:

A Cross-Sectional Study on the Symbolic Determinants of Transport Mode Choice in the Netherlands

ERASMUS UNIVERSITY ROTTERDAM
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Abstract

The rapid motorisation of transport systems has revolutionised the way people travel. Today, not only do we commute more frequently and longer distances, but a vast majority of our travels happen through private transport means. Along with the many benefits, the privatisation of transportation also poses considerable challenges such as environmental damage. Many of these challenges require policy interventions which often comes at the cost of economic development. As economic advancement is desirable, researchers call for alternative solutions like modal shift, which is stimulating public transport over unsustainable private transport modes. Promoting modal shift requires a thorough understanding of the determinants behind individuals' transport mode choice. A notable influencer of mobility decisions is its symbolic consumption, which consists of factors such as social status and prestige. Accordingly, this paper studies the influence of five symbolic variables derived from the existing literature on car use frequency. Data is collected through a cross-sectional survey and analysed with an ordinal logistic regression model. The findings suggest that the influence of symbolic factors vary depending on the variable in question. It is concluded that policymakers should not overlook the impact of symbolic motivators in their efforts to establish more sustainable transportation.

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Chapter 1: Introduction

The integration of production and consumption processes and the rapid motorisation of the transport systems have revolutionised the way people travel. Today, not only do we commute more frequently and longer distances, but a vast majority of our travels happen through private transport means (Holz-Rau & Scheiner, 2019). For instance, in 2018 in the United Kingdom, 83% of the 808 billion passenger-kilometres came from cars, vans, and taxis. (UK Department for Transport, 2019).

To ensure that supply chains are undisrupted and people can travel effortlessly, governments spend a significant amount of tax-payer money on maintaining and advancing transport infrastructure. Consequently, investments into transport infrastructure have been a central debate topic. This discussion not only stems from the necessity of transport networks to support daily lives but also the many benefits and issues that transport infrastructure brings.

To begin with, the coupling link between transport activity and economic development is widely established in the literature (Saidi & Hammami, 2017). That is, transport activities and economic growth go hand in hand. There are several reasons for this relationship. First, advancing transport infrastructure itself creates demand for goods and services (Hong et al., 2011). Second, improving existing infrastructure and new construction results in lower time and monetary costs (Gunasekera et al., 2008). Third, the improved market accessibility results in higher productivity and trade with distant markets (OECD, 2021). In return, this leads to more balanced regional economic development, increased employment, and industrial agglomeration (Hong et al., 2011). Aside from the benefits at the aggregate level, individuals also gain from investments in transport networks. For instance, increased mobility remarkably influences well-being, quality of life, and independence (Spinney et al., 2009).

Unfortunately, increases in transport activities also pose considerable societal and environmental challenges. First, transport activities have negative externalities such as congestion, air pollution, and accidents (Santos et al., 2010). Second, transport injustices exist between the different socio-economic classes of society. Accordingly, many economists and decision-makers call for policy interventions to address these negative externalities.

However, Loo & Banister (2016) argue that policy interventions that come at the cost of economic development are undesirable and should not be implemented to address these negative externalities. Instead, Loo & Banister (2016) advocate for influencing the relationship between economic growth and transport activities. Modal shift, which is stimulating public transport over unsustainable private transport modes, is the focus of this research.

An essential factor in stimulating modal shift is understanding travel behaviour. There are four elements to consider. First, we have the transport facility factors that influence the perceived usefulness of a transport mode. These are timeliness, safety, comfort, reliability, accessibility, price, and availability (Soza-Parra et al., 2019; López & Wong, 2019; Atasoy et al., 2013; Collins & Chambers, 2005). Second, land-use regulation and built-environment also influence mobility decisions (Newman & Kenworthy, 1996; Ewing & Cervero, 2001). Third, socio-demographics such as age, gender, education, and income can impact one's mode choice (Harbering & Schlüter, 2020; Hunecke et al., 2007). Lastly, attitudes, beliefs, values, lifestyles, and norms also affect transport mode choice (Steg, 2005; Hiscock et al., 2002; Murray et al., 2010; Arroyo et al., 2020).

Concerning the transport facility factors and land-use regulation and built environment, governments can directly intervene through infrastructure investments, cost reductions, and other urban policies. Besides, there has been a significant amount of research on the impact of these factors on mobility decisions and their strategic implications for policymaking. For this reason, the above elements are not the focus of this research.

On the other hand, the impact of subjective determinants is much more complicated. These attitudes and values are embedded in one's culture and lifestyle and require a deeper understanding to develop effective policy interventions. Interestingly, existing literature shows that these symbolic motives vary dramatically over different populations. Consequently, studying their influence on transport mode choice is of great importance. Specifically, this paper is interested in the impact of the symbolic consumption of cars on the frequency of car use in the Netherlands. This will help the Dutch authorities to decide whether to spend their limited tax-payer money on conventional ideas to advance the existing public transport infrastructure or to tackle the symbolic motivators behind mobility decisions. Subsequently, the following research question arises:

How do symbolic motivations influence the frequency of car use?

To answer the central research question, chapter two will introduce a literature review on the theoretical and empirical aspects of travel behaviour. This literature review will form the basis for expected relationships and hypotheses development. Chapter three will provide the research methodology and data collection and analysis method. Chapter four will present the outcome of the field study. Finally, chapter five will conclude the findings and discuss the limitations and recommendations for policymakers and future research.

Chapter 2: Literature Review

2.1. Behaviour Theories in Mobility Research

2.1.1. The Theory of Planned Behaviour

The Theory of Planned Behaviour (TBP) by Ajzen (1991) is the most applied method for explaining and predicting travel behaviour.

TBP, originating from health-related research, is derived from the Expectancy-Value Theory (EVT). EVT assumes that, from various alternatives, an individual chooses the behaviour with the highest expected value (Bohte et al., 2009). The expected value of behaviour is, in turn, determined by a cognitive assessment that an attitude object possesses a specific attribute (Bohte et al., 2009). For instance, an individual may choose to use public transport because it is environmentally friendly and being environmentally friendly is good behaviour.

In line with this, TBP studies behaviour in terms of three types of beliefs: attitudes, subjective norms, and perceived control (Yuzhanin & Fisher, 2016). Forward (2004) defines behaviour as a visible action. Attitudes are the set of central beliefs regarding the action in question (Ajzen, 1991). For example, one may decide not to drive a car because of its adverse effects on the environment. Subjective norms arise from perceived normative expectations of significant others and the desire to follow these expectations (Bohte et al., 2009). For instance, individuals may not use public transport because their families or friends may judge this decision. Control beliefs refer to a person's view regarding her own capacity to perform a particular act (Forward, 2004).

Altogether, Ajzen (1991) argues that attitudes, subjective norms, and perceived control do not directly influence behaviour but indirectly through intentions to perform that behaviour. In other words, TBP argues that intentions to perform a specific behaviour evolves from attitudes, subjective norms, and control beliefs.

Additionally, behaviour is also directly influenced by the extent to which an individual possesses the necessary skills and resources (Ajzen, 1991). Besides, demographic characteristics and other biological, social, and environmental factors indirectly affect travel behaviour through attitudes and subjective norms (Sniehotta et al., 2014). Lastly, TBP assumes that individuals make rational choices based on the information they are facing. Figure 2.1.1 below demonstrates the relationship between the variables of TBP.

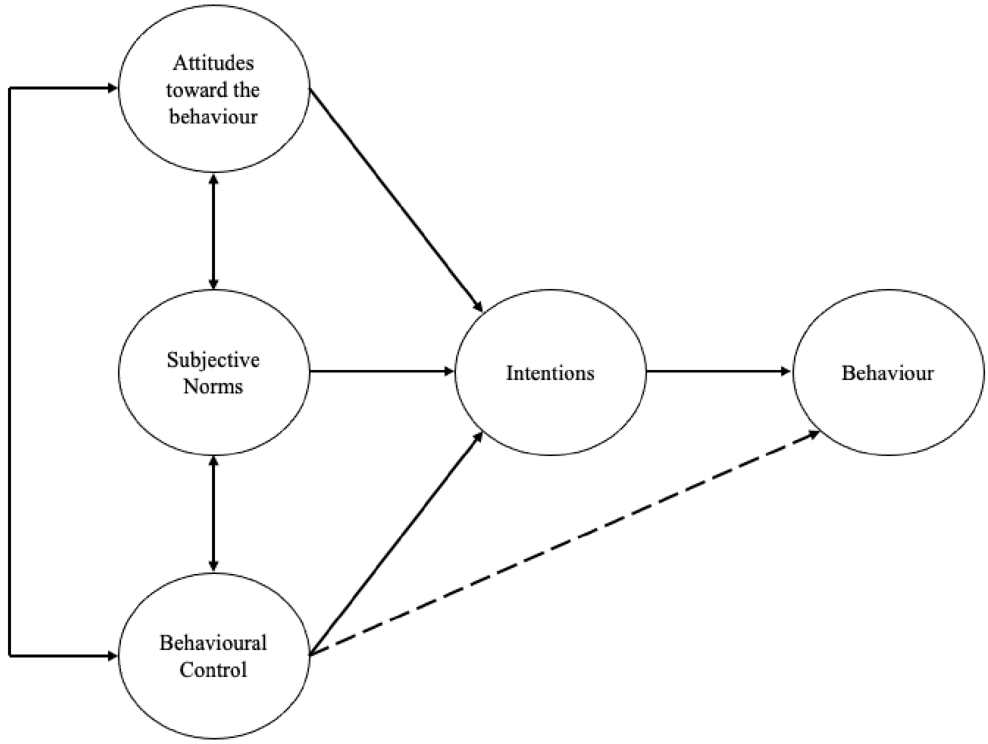

Figure 2.1.1: The Theory of Planned Behaviour
Source: Ajzen, 1991

According to Donald et al. (2014), the variables of TBP provide an empirical ground to understand how individuals decide between using public transport or private motor vehicles. Harland et al. (1999) showed evidence from the Netherlands on how attitudes, subjective norms, and control beliefs can influence personal car and public transport use. In a similar study, Bamberg et al. (2003) found that attitudes, subjective norms, and control beliefs heavily influence one's decision to use public transport in Germany. Especially, moral norms are essential in mobility decisions (Bamberg et al., 2003). Madha et al. (2016) discovered that attitude, perceived behavioural control, and subjective norms positively influence behavioural intention to use the train in Malaysia. Forward (1998) revealed that variables of TBP explains up to 69% of the variation in intention to walk, cycle, or drive a car. Forward (1998) additionally found that socioeconomic factors were indirect influences on intentions, which is in line with the theory. Besides, Hodgson & Tight (1999) argued that TBP also increases awareness towards more sustainable transport modes. Indeed, Shalender & Sharma (2021) concluded that attitudes, subjective norms, and perceived behavioural control positively affects the intention to adopt electric vehicles. All in all, literature shows that TBP is a proven model to understand modal choices in different settings.

On the other hand, economists also underline the shortcomings of TBP. First, TBP does not claim that all three factors contribute equally or simultaneously to behavioural intentions

(Yuzhanin & Fisher, 2016). For instance, Ambak et al. (2016) revealed that attitudes toward public transport are more dominant on intention to use public transport than subjective norms and control beliefs.

Second, various research argues for extended versions of TBP due to other influential variables omitted by the model. For example, Perugini & Bagozzi (2001) emphasised the role of travellers' desires and goals for modal choice. Donald et al. (2014) extended TBP with psychological factors such as moral and descriptive norms and environmental concerns. Most importantly, Bamberg et al. (2003) and Lam & Hsu (2006) revealed how crucial past travel behaviour and habits are on transport mode choice. All these additions significantly increased the explanatory power of TBP in predicting and influencing mobility decisions.

To conclude, TBP is an effective method to understand, predict, and influence travel behaviour. Despite certain shortcomings, which are minor, researchers still use this theory instead of developing new ones principally because of its simplicity and flexibility to introduce new variables.

2.1.2. Norm Activation Model

The Norm Activation Model (NAM) by Schwartz (1977) is another widely used behaviour theory in mobility research. It has been mostly applied to studies that aim to reduce car transport use by explaining pro-social behaviour and personal norms.

NAM argues that feelings of moral obligation to act on personal norms has a causal impact on altruistic behaviour (Schwartz, 1977). Park & Ha (2014) define these norms as self-expectations for a particular behaviour originating from values associated with that behaviour. In other words, a person's intention to act pro-socially is determined through his perceived responsibility for that act (Liu et al., 2017). Accordingly, the development of attitudes such as pride and guilt depends on how consistently one's behaviour is in line with his norms (Liu et al., 2017).

In this context, the norm activation is driven by two elements. Firstly, individuals must be aware of the consequences of their behaviour. For example, car users must understand the environmental damage that they cause (Møller et al., 2018). Second, individuals must feel personally responsible for the consequences of acting anti-socially. In other words, people should be aware of their moral obligations toward the welfare of others (Setiawan et al., 2014). This is called the ascription of responsibility. Accordingly, NAM argues that individuals who understand the consequences of their behaviour and feel responsible for their actions will form personal norms which underlie their moral obligations to society, ultimately leading to pro-social behaviour. In this view, if a person is aware of the consequences of the problems he is causing, this awareness will stimulate him to consider his own contribution to solving these problems (Liu et al., 2017). Figure 2.1.1 below demonstrates the central aspects of NAM.

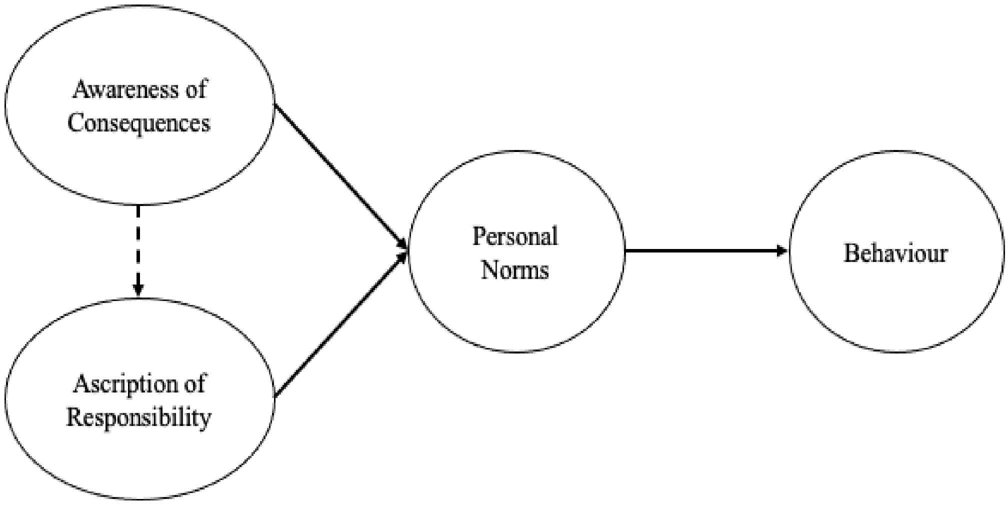

Figure 2.1.2: The Norm Activation Model
Source: Schwartz, 1977

Much research has shown that NAM provides an empirical ground on understanding and influencing travel behaviour. He & Zhan (2018) studied the influence of altruism and pro-social behaviour on intention to use electric vehicles in China. Accordingly, they found a significantly positive relationship between personal norms and intention to adopt electric cars. Møller et al. (2018) found that pro-environmental awareness, personal norms, and feeling responsible for your actions drive Danish adolescents' transport mode choice. Bamberg & Schmidt (2003) derived a structural model from NAM to study the travel behaviour of university students. They found that personal norms significantly affect car use for university routes. Nordfjærn & Rundmo (2019) also found that altruistic values influence modal choice and are associated with the ascription of responsibility. Interestingly, Nordfjærn & Rundmo (2019) showed that females are more aware of the consequences of their actions than males in their study.

Transport economists also underlie certain shortcomings of NAM. Firstly, literature still debates whether NAM is a mediator or a moderator model. On the one hand, researchers who use NAM as a mediator model claim that the ascription of responsibility and awareness of consequences only indirectly influence behaviour mediated through social norms (He & Zhan, 2018). On the other hand, the supporters of the moderator argument argue that the ascription of responsibility and awareness of consequences moderate the relationship between norms and behaviour (He & Zhan, 2018).

Second, NAM is hardly ever applied to mobility research by itself. Researchers often combine it with other variables or theories. For instance, Setiawan et al. (2014) integrated NAM with TBP and revealed that travel behaviour is influenced more by perceived control than personal norms. Studies by Klöckner & Matthies (2009), He & Zhan (2018), and Hunecke et al. (2001) underlined the importance of antecedents of personal norms, external costs, and environmental awareness in addition to the awareness of consequences and ascription of responsibilities. All these additions significantly increased the explanatory power of NAM.

To conclude, NAM is a commonly used method to understand how personal norms can eventually lead to pro-social behaviour in the context of transport choices. Despite certain shortcomings, NAM is still effective at understanding mobility decisions, particularly when it is jointly used with other models such as TBP.

2.1.3. Value-Belief-Norm Theory

The Value-Belief-Norm Theory (VBN) is a conceptual model that analyses pro-environmental cognitions and behaviour from values and norms (Stern et al., 1999). In the context of transport, VBN argues that choosing environmentally friendly modes can be stimulated through moral obligations to act sustainably (Lind et al., 2015). In other words, VBN is a framework that advocates for normative factors to encourage socially desirable behaviour and attitudes.

VBN originated from the Norm-Activation Model described in the previous section. The theory furthers NAM by the Value Theory (VT) of Schwartz (1992) and the New Environmental Paradigm (NEP) of Dunlap et al. (2000). Accordingly, VBN consists of three elements derived from NAM, VT, and NEP: values, beliefs, and norms (Stern et al., 1999).

The value component proposes a universal set of motivational values that define standards for behaviour (Nordfjærn & Rundmo, 2019). In this context, VBN suggests three types of values. First, altruistic values refer to individual values over the well-being of other humans (Nordfjærn & Zavareh, 2017). Examples include equality, social justice, a world at peace, and helpfulness (Jakovcevic & Steg, 2013). Second, biospheric values refer to individual values for environmental well-being (Kiatkawsin & Han, 2017). Examples are respecting the earth, preventing pollution, and unity with nature (Jakovcevic & Steg, 2013). Both altruistic and biospheric values positively affect the intention to act pro-socially. Third, egoistic and hedonistic values indicate a stronger emphasis on one's needs and well-being over the interests of the society (Kiatkawsin & Han, 2017). Consequently, these values negatively influence the intention to act pro-socially. Hedonic value items include pleasure, self-gratification, and egoistic values are social power, authority, and wealth (Jakovcevic & Steg, 2013).

NEP stresses the importance of balancing economic development with ecological protection (Dunlap et al., 2000). The paradigm refers to ecological attitudes set by individual beliefs regarding the human ability to affect the balance in nature, limitations about technological advancement, and individuals' right to rule over the external environment (Lind et., 2015). NEP leads individuals to comprehend the adverse consequences of their actions (awareness of consequences) and to make a personal effort to solve these negative consequences (ascription of responsibilities) (Nordfjærn & Zavareh, 2017). Thus, NEP also implicitly refers to the norm-activation part of VBN.

Altogether, VBN consists of a chain of variables that relate to values, ecological concerns, and the extent to which individuals are aware of the consequences of their egoistic behaviour and their willingness to take responsibility for these negative consequences (Lind et al., 2015). In the context of modal choice, the literature argues that these values, beliefs, and norms will disincentivise driving and stimulate intention to use public transport. Figure 2.1.3 below depicts the central aspects of VBN.

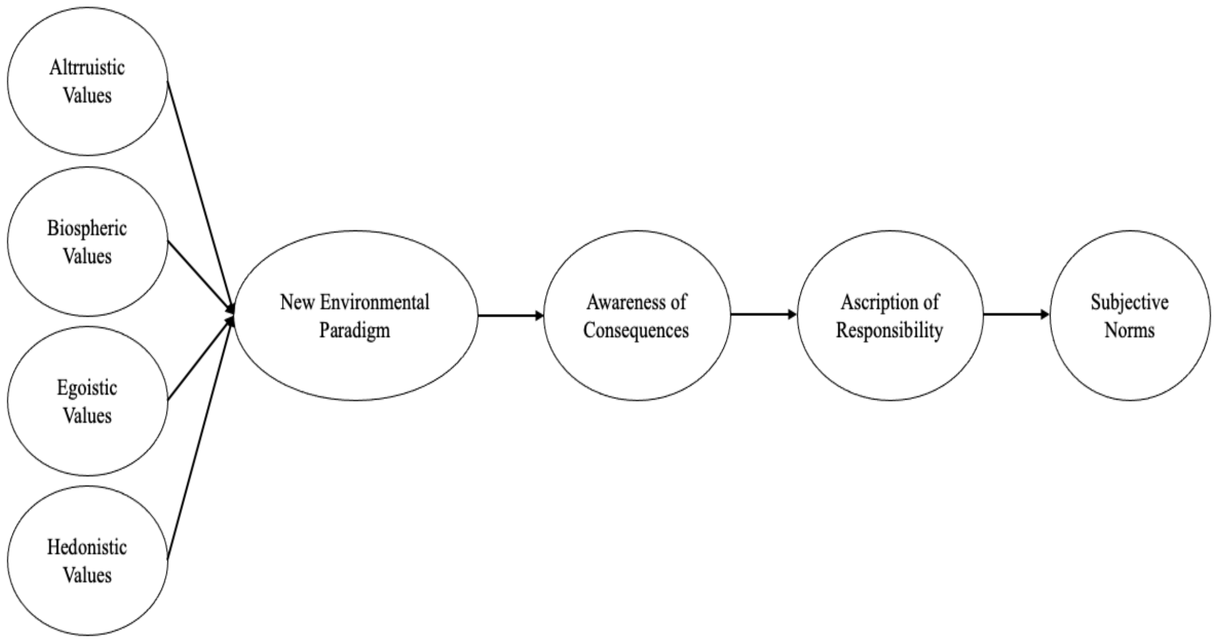

Figure 2.1.3: Value-Belief-Norm Theory
Source: Stern et al., 1999

Several studies used this framework to predict transport mode choice. Nordfjærn & Rundmo (2019) showed that values, environmental beliefs, and norms can explain the acceptance of disincentives to use cars. Lind et al. (2015) applied VBN to the Norwegian urban population and revealed that values and beliefs explain 58% of the variance in personal norms, which, in turn, is a significant predictor of mobility decisions. Jakovcevic & Steg (2013) discovered that normative considerations that are stimulated by values positively influence the intention to reduce car use in Argentina. The findings of Jakovcevic & Steg (2013) are particularly crucial for countries where high structural barriers remain for alternative transport options, and there is little public discussion on reducing car usage.

2.2. Symbolic Motives

Behaviour theories in the previous section showed that subjective determinants such as attitudes, beliefs, and norms influence transport mode choice. These models mainly focus on altruistic values and intention to act pro-socially. Other variables such as self-expression, pride, and status may also alter mobility decisions.

Pojani et al. (2018) studied the influence of symbolic determinants of mobility intentions of youth in Tirana. They found that a materialistic ideological orientation, for instance, a strong emphasis on social status, positively and significantly impacts the intention to drive. Additionally, Pojani et al. (2018) showed that social influences from friends and family are significant determinants of transport mode choice. Their study thus underlines that symbolic motives arising from personality and expectations of others matter for travel behaviour.

Hiscock et al. (2002) conducted in-depth interviews on the psycho-social benefits individuals derive from driving. They suggested that car ownership reflects prestige and other high-status attributes like skill, having a thrilling life, high income, and masculinity. Solomon (1992) similarly argued that car ownership reflects cultural values such as power, materialism, individualism, and freedom. Additionally, Hiscock et al. (2002) found that men indicate higher self-esteem, and certain types of motor vehicles yield even higher prestige. For instance, an interviewee mentioned: *"society respects money, power, and goodness in that hierarchy, so someone with a flash car, people might say, lots of money, if he had a Rolls Royce or something, they might give him more esteem, more prestige, accorded to him than the person who had a motorcycle"*. Hiscock et al. (2002) also reported that, unlike cars, public transport is perceived as a sign of inferiority and is often associated with the margins of society. Şimşekoğlu et al. (2015) similarly concluded that power and prestige acquired by vehicle ownership and perception of public transport users as of *lower social status* significantly influence mobility decisions.

Heffner et al. (2006) studied automobile semiotics. They argued that cars are merely symbols with which consumers construct and maintain a self-identity. In other words, individuals who drive communicate and express who they are, indicating their social status, beliefs, interests, and values (Heffner et al., 2007). For example, owning a sports car make people believe that they are a part of the nobility. Indeed, CNW Marketing Research (2006) showed that according to 31% of hybrid electric vehicle users, their car expresses who they are to society. The results of Heffner et al. (2007) on users of hybrid vehicles in Northern California are also similar to the findings of the CNW Marketing Research (2006). For instance, owners claimed that their electric vehicles reflect their personalities and provide them prestige because, for example, they own the newest technology.

Grimmer (2011) studied the effect of symbolic consumption on motor vehicle ownership through a qualitative study with new car owners and car dealers. Their findings suggest that car ownership is a process of social identity construction for self-esteem and establishing a status within society. For example, an interviewee mentioned that people who own a similar car to his car are generally accepted as adventurous and rich in society (Grimmer, 2011). Another respondent claimed that car brands express social identity and associated high-end brands like Mercedes and BMW with professionals, whereas brands like Subaru are affiliated with farmers (Grimmer, 2011). Besides, all car dealers in the study also mentioned that buyers categorise brands and car types as a sign that shows where you belong in society. Hence, Grimmer (2011) demonstrated that cars are consumed conspicuously to highlight status, self-identity, and image.

Steg et al. (2001) performed the first empirical study on the influence of symbolic-affective factors on transport mode choice. They identified feelings of superiority, power and sensation, and status as essential symbolic-affective factors and analysed their impact on intention to drive. Accordingly, Steg et al. (2001) found that symbolic values such as social status, prestige, and pleasure are significant determinants of the attractiveness of car use. However, Steg et al. (2001) also noted that transport facility factors, which they refer to as instrumental variables, are more influential than symbolic motives.

Steg (2005) conducted arguably the most important study on the symbolic-affective drivers of car use. Steg (2005) criticised existing literature due to their negligence of symbolic determinants. She argued that a car is much more than just a transport mode and advocated for image arousal, status, feelings of superiority and power, and sensation. Additionally, Steg (2005) indicated that cars are a way to express personality and are often associated with having a thrilling life. Steg (2005) also underlined that car advertisements target people's sensitivities to power, self-esteem, social status, and control. To test the relationship between the symbolic and affective variables and car use, Steg (2005) used Dittmar's (1992) theoretical model. Dittmar (1992) argued that material possessions have three functions: instrumental, affective, and symbolic. Instrumental functions refer to the fulfilment of certain activities. For instance, one may desire a car to travel faster or with more comfort. Affective function relates to non-instrumental desires and needs (Steg, 2005). Symbolic function is about expressing self-identity or social status (Dittmar, 1992). Accordingly, Steg (2005) concluded that affective and symbolic variables are responsible for most of the variation in commute related travel. This result is compelling given that commute related travel, which is, strictly speaking, assumed to be driven by instrumental factors such as comfort and timeliness, is strongly affiliated with non-instrumental factors. Figure 2.4.1 below depicts these symbolic variables. Note that altruistic values defined in section 2.1. are also included in symbolic factors as literature argues that they stem from personal characteristics and social environment.

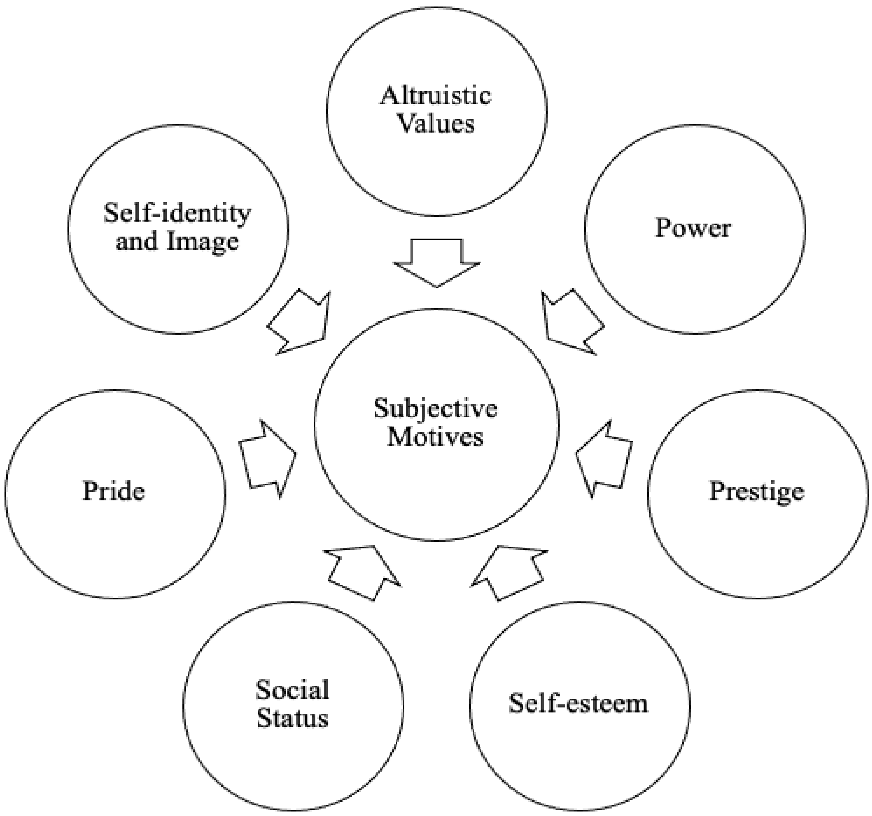

Figure 2.4.1: Symbolic determinants of travel behaviour

All in all, this review shows that both academicians and transport planners should not overlook the influence of symbolic consumption of transport modes. Although the literature agrees that transport facility factors are the principal driver of car use, recent research showed that car ownership is increasingly associated with symbolic variables. These elements are particularly challenging since they can vary dramatically over different groups of society. For this reason, authorities should first try to understand why people perceive cars as a symbol of status, prestige, and power. Concerning the identity construction with cars, authorities must establish educational and motivational measures to create a more pro-environmental culture. This will ultimately promote environmentally friendly transport modes.

2.3. Summary of the Findings of the Existing Literature

The review of the behaviour theories in section 2.1. shows that values, attitudes, and beliefs can significantly influence transport mode choice. First, the Theory of Planned Behaviour (TBP) argues that transport mode choice is driven by three types of beliefs: attitudes, subjective norms, and perceived control. Accordingly, these beliefs construct one's intention to perform a particular behaviour. Second, the Norm Activation Model (NAM) advocates that feelings of moral obligation to act on personal norms has a causal impact on altruistic behaviour. In this context, the norm activation consists of two elements: awareness of the consequences of your actions and a feeling of responsibility for these actions. Finally, the Value-Belief-Norm Theory (VBN) proposes a universal set of motivational values that define standards for behaviour and stresses the importance of balancing economic development with ecological protection. Accordingly, VBN consists of a chain of variables that relate to values, ecological concerns, and the extent to which individuals are aware of the consequences of their egoistic behaviour and willingness to take responsibility for their actions.

Section 2.2 points out that altruistic values are not the only element influencing travel behaviour. Variables like self-expression, pride, prestige, and social status may also alter mobility decisions. Indeed, the literature showed that symbolic consumption is a determinant of car ownership and frequency of car use. Some studies even found dramatic results like the perception of public transport as a sign of inferiority in society. Out of all the identified symbolic values, social status, self-identity, pride, and prestige seemed to be the most frequently mentioned motivators of car ownership and use.

The findings of this chapter form the foundation of hypotheses development and the expected relationships between predictor variables and the dependent variable. Based on the behaviour theories of section 2.1, a variable on altruistic values is constructed to capture the relationship between these values and car use frequency. The findings of section 2.2 are used to form the variables on social status, pride, prestige, and identity construction with car ownership. A detailed overview of these variables is provided in the next chapter.

Chapter 3: Data & Methodology

3.1. Data Collection Method

Quantitative research can either be experimental or non-experimental. In experimental studies, the researcher tests hypotheses under a controlled environment in which he manipulates control variables to investigate their impact on the dependent variable (Watson, 2015).

Non-experimental methods are generally based on surveys or existing data sets. Though less robust to bias than experimental studies, they are less time consuming and highly effective in acquiring large amounts of data. Besides, although the lack of randomisation does not allow for causal conclusions, the researcher can still obtain strong correlational results (Muijs, 2010).

In transport behaviour literature, non-experimental studies emerge as the dominant method. These methods let the researcher capture the travel habits of different groups on a large scale and construct variables specific to his needs in a relatively straightforward way. Given its wide use in transport behaviour literature, efficiency to collect large amounts of data, and ability to create questions that can capture symbolic motives such as prestige and pride, self-administered survey research is deemed the most appropriate for this paper. Specifically, a cross-sectional study, meaning that the respondents will complete the survey once.

The questionnaire is distributed through social media channels. These platforms provide mass reach to the target audience at no cost. Besides, they ensure to a certain extent that different groups of the population are adequately sampled. Despite their mass reach, the researcher's network is still not extensive enough for consistent results. For this reason, each recipient is asked to distribute the survey further to their network. This sampling method is called snowball sampling. The survey questions are provided in Appendix A.

3.2. Hypotheses Development and Expected Relationships

Social status is the level of social value an individual is considered to have by society. Literature showed that individuals tend to see transport mode choice as a reflection of one’s place in society. For instance, travelling by public transport is seen as a sign of inferiority (Hiscock et al., 2002). In accordance, the following relationship is formed:

Hypothesis 1: Perceiving public transport as a sign of inferiority in society positively influences car use frequency.

Pride is another notable variable influencing car use. Several studies showed that people take pride in their car and sense a form of pleasure in its ownership (Bergstad et al., 2011). In this paper, pride is defined as a feeling of pleasure people derive from driving a car because it reflects an achievement. Therefore, the following relationship is developed:

Hypothesis 2: Deriving a sense of pride from owning a car positively influences car use frequency.

People also tend to see their cars as a source of prestige. For example, Steg (2005) revealed that prestige is a significant determinant of the attractiveness of car use. In this study, prestige is defined as the belief that having a car will make others respect or admire the car owner. Subsequently, the following relationship is expected:

Hypothesis 3: Perceiving car ownership as a source of prestige positively influences car use frequency.

Self-identity is an interesting variable altering transport behaviour. Previous studies showed that cars are merely symbols with which consumers construct and express their identity (Heffner et al., 2007). In other words, individuals who drive communicate who they are to others. Accordingly, the following relationship is developed:

Hypothesis 4: Perceiving car ownership as a reflection of one's personality and lifestyle positively influences car use frequency.

Finally, behaviour theories like TBP, NAM, and VBN proved that altruistic values significantly impact mobility decisions. That is, an individual’s motivation to contribute to the welfare of others and society influences their transport mode choice (Schwartz, 1972). Subsequently, the following relationship is derived:

Hypothesis 5: Holding altruistic values negatively influences car use frequency.

These five hypotheses provide the relationships between symbolic values and travel behaviour. Table 3.2.1. summarised the expected impact of each variable.

Table 3.2.1
Expected impact of symbolic factors on frequency of car use frequency

Variable	Expected Impact on Car Use Frequency
Social Status	Positive
Pride	Positive
Prestige	Positive
Self-identity	Positive
Altruistic Values	Negative

Notes: This table provides the expected relationship between each symbolic motivator behind transport mode choice on the frequency of car use.

3.3. Data Analysis Method

Regression analysis is a mathematical process for demonstrating, predicting, and forecasting the relationships between an outcome variable and one or multiple explanatory variables. In this study, logistic regression is applied for hypothesis testing.

Logistic regression models are extensions of the linear regression methods. The fundamental difference between the two forms of regression lies in their outcome variables (Hosmer et al., 2013). In logistic models, the dependent variable is discrete, taking two or more possible values in contrast to the continuous outcome variable of linear models (Hosmer et al., 2013). Besides this difference, methods used in a logistic regression analysis follow, on average, the same principles of linear regression (Hosmer et al., 2013).

Logistic regression uses a logistic function to model the dichotomous dependent variable, as opposed to the linear predictor functions in linear regression models. A logistic function is an S-shaped curve that takes values from -∞ to +∞ (Menard, 2002). The standard logistic function is modelled as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3.1}$$

Naturally, the interpretation of the model is fundamentally different. With linear regression, the regression estimate is the mean value of the dependent variable given the value of the explanatory variable (Hosmer et al., 2013). This estimated quantity is referred to as the conditional mean and represented as $E(Y|X)$. On the other hand, when the outcome variable is dichotomous, the variable's mean is a function of the probability that an event will fall into a higher category, given the value of the independent variables (Menard, 2002). In accordance, the general logistic regression function, based on equation 3.1, is formulated as follows:

$$P(x) = \frac{e^{\beta_0+\beta_1 X_1+\cdots+\beta_k X_k}}{1+e^{\beta_0+\beta_1 X_1+\cdots+\beta_k X_k}} \tag{3.2}$$

In the above equation, $P(x)$ indicates the probability of the response variable equalling a specific event. β_k refers to the unknown coefficient to be estimated for each independent variable X_k, and β_0 is the intercept in the model.

An essential transformation is required to equation 3.2. As mentioned before, logistic regression follows the general principles of linear regression, which raises some concerns for its application. Specifically, in linear regression, expressed as $Y = E(Y|X) + \varepsilon$, the error term ε is assumed to follow a normal distribution with mean zero and constant variance among all levels of explanatory variables (Hosmer et al., 2013). A discrete response variable violates this assumption.

To overcome this issue, econometricians transform dichotomous variables into continuous ones that can take any real value (Menard, 2002). Accordingly, as the first step, *probabilities* are changed to *odds*, a measure of the likelihood of a specific outcome (Hosmer et al., 2013). Mathematically, Menard (2002) defines it as "*the odds that the response variable equals a value* $(Y = \theta)$ *is the ratio of the probability that the response variable equals that value* $(Y = \theta)$ *to the probability that it does not* $(Y \neq \theta)$". In other words, the odds that $(Y = \theta)$ is equal to $\mathrm{P}(Y = \theta)/[1 - P(Y = \theta)]$.

The next and last transformation is taking the natural logarithm of the odds ratio $\mathrm{P}(Y = \theta)/[1 - P(Y = 0)]$. This transformation gives us the logarithm of odds, or more commonly, the logit. In fact, the logarithm of odds is technically the inverse function of the standard logistic function. When the dependent variable is transformed into logit, the researcher no longer encounters the problem that the estimated probability exceeds the minimum and maximum values for a probability, which are one and zero (Menard, 2002). After this transformation, the conditional distribution of the response variable and the error term no longer follows a normal distribution but a binomial one (Hosmer et al., 2013). Accordingly, the logit function is formulated as follows:

$$g\big(p(x)\big) = logit.p(x) = ln\left(\frac{p(x)}{1-p(x)}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k \tag{3.3}$$

In the above equation, $g\big(p(x)\big)$ is the logit of $p(x)$. ln is short for natural logarithm. $p(x)$, which represents equation 3.2, is the probability that the response variable is equal to an event, given the linear combination of explanatory variables. After transforming into odds, $p(x)$ takes values ranging from zero to one. β_k refers to the unknown logit coefficients to be estimated for each independent variable X_k, and β_0 is the intercept in the model.

To sum up, a logistic regression first evaluates the odds of a case happening given certain explanatory variables and then takes the natural logarithm of the outcome to generate a linear version of the response variable (Hosmer et al., 2013). Mathematically speaking, probabilities, odds, and the logit are three different methods to demonstrate the same thing (Menard, 2002). The logit form is accepted as the most appropriate for working with discrete outcome variables as it corrects the non-linear relationships (Menard, 2002).

There are numerous ways to perform a logistic regression analysis. The most common methods are binary logit, multinomial logit, and ordered logit. The binary logistic regression model works with binary dependent variables which accommodate two possible values such as win and lose (Hosmer et al., 2013). The multinomial logit is a simple extension of the binary logit model. In this setting, the dependent variable can take more than two alternatives like options A, B, and C (Hosmer et al., 2013). In ordered logit models, the scale is not nominal but ordinal. There exists a rank-order relationship between different categories of the outcome variable (Hosmer et al., 2013).

In this study, the hypothesis testing will be carried out with an ordered logit model, as the dependent variable, frequency of car use, rank orders the respondents based on how frequently they travel by their car. Specifically, a proportional odds model will be applied, which calculates the odds being at or below at a specific level of the outcome variable (Liu, 2015). The proportional odds method is the default model for ordinal outcome variables with more than two ordinal categories (Liu, 2015). In this setting, for K levels of ordinal categories, the model makes $K-1$ predictions to calculate the cumulative probabilities of being below or at the K^{th} level of the response variable (Liu, 2015). Accordingly, the ordered logit model, based on the logit function 3.3, is formulated as follows:

$$logit[p(Y \leq K|X_1, X_2, \dots, X_m)] = ln\left[\frac{p(Y \leq K|X_1, X_2, \dots, X_m)}{p(Y > K|X_1, X_2, \dots, X_m)}\right] \qquad (3.4)$$

$$= \beta_0 - \beta_1 X_1 - \cdots - \beta_m X_m$$

In the above equation, $p(Y \leq K|X_1, X_2, \dots, X_m)$ indicates the probability of being at or below category K, given independent variables X_m. β_m refers to the unknown logit coefficients to be estimated for each independent variable X_m, and β_0 is the intercept in the model.

Ordered logistic models are also under certain assumptions. There must be no high multicollinearity between independent variables, and proportional odds should hold across all predictors (the University of St. Andrews, n.d.). The proportional odds assumption argues that the impact of explanatory variables is the same across different categories (Fullerton, 2009). In other words, the relationship between each pair of outcome groups is equal (UCLA, n.d.). Since the relationship across all groups is the same, there is a single odds ratio for the effect of each independent variable and a single set of logit coefficients (UCLA, n.d.). Accordingly, equation 3.4, where τ_m indicates a specific threshold, can be expressed as follows:

$$logit[p(Y \leq K|X_1, X_2, \dots, X_m)] = \tau_m - x\beta \qquad (3.5)$$

The dependent variable in this paper's ordered logit model is an ordinal variable that ranks the subject's car use frequency in five categories. These five categories are every day, several times a week, a few times a week, once or twice a month, and (almost) never. A respondent ought to be a frequent user of a car if he uses his car several times a week to every day. Independent variables are social status, pride, prestige, self-identity, and altruistic values. The data on these variables is collected through Likert-scale questions that examine whether respondents agree or disagree with a given statement. Accordingly, the regression model that will be used for hypothesis testing is represented as follows:

$$Car\_Use = \tau_m - \beta(SStatus + Pride + Prestige + Self\_ID + AltVal) \qquad (3.6)$$

All in all, ordered logistic regression is a robust and proven model for studies with ordinal outcome variables. Though, the assumptions proportional odds and no high correlation between predictors still have to hold for valid results. To assess multicollinearity, a bivariate correlation matrix will be applied to test the strength of the relationship between independent variables. Then, the Variance Inflation Factor will be examined to determine whether multicollinearity exists. Proportional odds assumption will be checked with a test of parallel lines to assess whether the effect of predictors is the same at each cumulative split (Fullerton, 2009). Further, a Pearson Chi-square test will be performed to determine goodness-of-fit. Finally, Pseudo R^2 values will be used to interpret the explanatory power of the model.

Chapter 4: Research Outcome

4.1. Descriptive Statistics

Descriptive statistics are summary statistics that provide essential features about the distribution of the research sample. In this paper, descriptive statistics, shown in Table 4.1.1. below, are given over a sample of 132 respondents.

In this study, male and female respondents make up 56.8% (N=75) and 43.2% (N=57) of the total sample, respectively.

The distribution of age groups seems relatively normal. Individuals aged 25 to 34 constitute the largest group with a 28.8% (N=38) share of the sample. This group is followed by subjects aged 18 to 24, 35 to 44, 45 to 54, and 55 to 64 with 27.3% (N=36), 24.2% (N=32), 16.7% (N=22), and 3.0% (N=4) shares of the sample, respectively.

Respondents' highest education levels are grouped into three categories. 62.9% (N=83) of the sample hold a bachelor's degree. 29.5% (N=39) of the subjects have a master's degree, and the remaining 7.6% (N=10) are high school graduates.

Income levels seem to have a normal distribution as well. Respondents who earn between €28,600 - €42,000 and €42,000 - €71,000 both constitute 23.5% (N=31) of the sample. 17.4% (N=23) of the individuals earn between €71,000 - €84,000. 15.2% (N=20) of the sample has an income in the €13,700 - €28,600 range. 10.6% (N=4) of the respondents earn more than €84,000. Finally, 9.8% of the subjects earn less than €13,700.

It is also imperative understand these categories. The income group €28,600 - €42,000 is the national benchmark income of the Netherlands (Hoogendoorn-Lanser et al., 2015). Income categories €13,700 - €28,600 indicates below the national benchmark income, whereas €13,700 is the national minimum (Hoogendoorn-Lanser et al., 2015). Individuals in the €42,000 - €71,000 group earn one-to-two times more than the national benchmark (Hoogendoorn-Lanser et al., 2015). Respondents in the €71,000 - €84,000 category earn twice the national benchmark income. (Hoogendoorn-Lanser et al., 2015). Finally, people in the above €84,000 group earn more than twice the national benchmark income (Hoogendoorn-Lanser et al., 2015).

Concerning the type of car respondents use, 60.6% (N=80) of the sample have a privately owned or leased car. 28.8% (N=38) owns a company lease car, and the remaining 10.6% (N=14) possess both a company car and a privately leased or purchased car.

Finally, 59.8% (N=79) of the individuals use their car every day. 27.3% (N=36) of the sample drive their vehicle several times a week. 9.1% (N=12) of the subjects use their car a few times a week, and 3% (N=4) drive their car only once or twice a month.

Table 4.1.1.
Descriptive Statistics

Variable	Category	N	%	Cumulative %
Gender				
	Male	75	56.8%	56.8%
	Female	57	43.2%	100%
Age				
	18-24	36	27.3%	27.3%
	25-34	38	28.8%	56.1%
	35-44	32	24.2%	80.3%
	45-54	22	16.7%	97.0%
	55-64	4	3.0%	100%
Education				
	High school graduate	10	7.6%	7.6%
	Bachelor's degree	83	62.9%	70.5%
	Master's degree	39	29.5%	100%
Income				
	Less than €13,700	13	9.8%	9.8%
	€13,700 - €28,600	20	15.2%	25.0%
	€28,600 - €42,000	31	23.5%	48.5%
	€42,000 - €71,000	31	23.5%	72.0%
	€71,000- €84,000	23	17.4%	89.4%
	More than €84,700	14	10.6%	100%
Car Type				
	Company lease	38	28.8%	28.8%
	Privately owned/leased	80	60.6%	89.4%
	Both	14	10.6%	100%
Car Use				
	Everyday	79	59.8%	59.8%
	Several times a week	36	27.3%	87.1%
	A few times a week	12	9.1%	96.2%
	Once or twice a month	4	3.0%	99.2%
	Almost (never)	1	0.8%	100%

Notes: This table provides the descriptive statistics of the research sample. Six variables and their categories are presented: Gender, Age, Education, Income, Car type, and Car use frequency. Given statistics are sample size (N), the respective per cent share, and cumulative per cent share of each row.

4.2. Assumption Testing and Goodness-of-Fit

4.2.1. Proportional Odds Assumption

The validity of an ordinal regression model depends on the proportional-odds assumption. The model assumes that the logit coefficients of all explanatory variables are identical throughout the different thresholds of the ordinal response variable (McCullagh, 1980). If this assumption is violated, the researcher cannot adopt an ordered logit model. In this case, researchers can run a multinomial logit regression. However, multinomial logit regressions do not account for the ordinal nature of the dependent variable, limiting the explanatory power of the model. Other alternatives include generalised ordered or partial proportional odds models, which relax the proportionality assumption across predictors (Fullerton & Xu, 2012).

The Test of Parallel Lines is the most common method to check the proportional-odds assumption. The test compares the estimated model with a single set of coefficients to a model with a different set of coefficients for all categories of the outcome variable. The null hypothesis states that parameter estimates are equal across all response levels. Table 4.2.1. below presents the results of the test.

Table 4.2.1.
Test of Parallel Lines

Model	-2 Log-Likelihood	Chi-square	df	*p*
Null Hypothesis	157.012			
General	146.572	10.440	15	0.791

Notes: This table provides the results of the Test of Parallel Lines. Given statistics are the -2 Log-Likelihood value, the Likelihood Ratio Chi-square Test, and the p-value pertaining to this test.

In Table 4.2.1., we are interested in the Chi-square value ($X^2(15, N=132)=10.440$, $p=0.791$) and the p-value of this test statistic. Accordingly, the p-value equals 0.791, suggesting that the null hypothesis cannot be rejected at the 5% significance level. Therefore, the assumption of proportional odds holds. Slope coefficients are identical across all categories of the dependent variable.

4.2.2. Multicollinearity Check

Another assumption for valid ordinal regression analysis is the absence of high multicollinearity. Multicollinearity refers to the linear relationship among two or more explanatory variables (Alin, 2010). In other words, multicollinearity occurs when two or more predictors in the model are correlated (Moore et al., 2016).

Multicollinearity affects the generalisability of the model and the interpretation of the parameter estimates (Schroeder et al., 1990). A central goal of regression analysis is to isolate the impact of each independent variable. In other words, researchers are interested in the movement in the response variable resulting from a one-unit change in each predictor, holding all else constant. In the presence of multicollinearity, this is not possible, as a one-unit change in one predictor also influences the estimate of another predictor.

Besides, the presence of multicollinearity will inflate the variance of each predictor, resulting in larger confidence intervals (Mansfield & Helms, 1982). This, in turn, will lead to wrong conclusions about hypotheses. Thus, multicollinearity is a grave problem and must be examined thoroughly before hypotheses testing.

The first step in assessing multicollinearity is identifying the correlation between explanatory variables. This is done through a bivariate correlation matrix using Spearman's Rank-Order Correlation (rho). Spearmen's rho is the non-parametric alternative of Pearson Correlation. The former assesses the strength of the monotonic relationships between predictors, whereas the latter evaluates linear relationships (Corder & Foreman, 2014).Both correlation coefficients take values ranging from -1 to +1, where -1 suggests a perfect negative association and +1 indicates a perfect positive relationship. Values between 0.6 and 0.8 describe a strong correlation, and coefficients beyond 0.8 suggest a very strong correlation. In case values in this range, severe multicollinearity may be present (Simon Fraser University, n.d.). Table 4.2.2. below presents the coefficients of Spearman's correlation.

Table 4.2.2.
Spearman's Correlation Matrix

Variables	SStatus	Pride	Prestige	Self_ID	AltVal
SStatus	1				
	.				
Pride	.656**	1			
	(0.000)	.			
Prestige	.572**	.725**	1		
	(0.000)	(0.000)	.		
Self_ID	.560**	.594**	.464**	1	
	(0.000)	(0.000)	(0.000)	.	
AltVal	-.297**	-.318**	-.232**	-.266**	1
	(0.001)	(0.000)	(0.007)	(0.002)	.

*Notes: This table provides the Spearman Rank-Order Correlation Coefficients. Numbers in brackets indicate the p-value. ** Correlation is significant at the 1% level (2-tailed).*

The rank-order correlation between altruistic values and social status, pride, prestige, and self-identity ranges from -.232 to -.318. These estimates suggest a negative and weak correlation and do not raise alarms for severe multicollinearity.

The correlation coefficient between self-identity and social status, pride, and prestige suggest a moderate and positive monotonic association, ranging from .464 to .594. Multicollinearity may be present, especially between self-identity and pride. However, given the coefficients, the magnitude of the multicollinearity is likely to be low.

A moderate and positive correlation is present between prestige and social status, with a coefficient of .572. Accordingly, it does not signal high multicollinearity. The relationship between pride and prestige, on the other hand, is worrying. The correlation coefficient of .725

indicates a strong and positive correlation which may imply high multicollinearity. Similarly, the correlation coefficient of .656 also suggests a strong and positive monotonic relationship between pride and social status. To assess whether these strong correlations indicate severe multicollinearity, Variance Inflation Factor (VIF) and Tolerance values are examined.

VIF is the most common diagnostic for detecting collinearity. It describes how much the variances are inflated in an OLS regression analysis (James et al., 2013). A VIF value of one indicates no correlation among the predictors (Penn State, Eberly College of Science, n.d.). The general rule of thumb is that VIF values beyond four caution for further examination and the values exceeding ten signal severe multicollinearity (Penn State, Eberly College of Science, n.d.).

Tolerance is the reciprocal of VIF (Miles, 2014). It assesses the influence of one predictor over all predictors. Tolerance values range from zero to one, and a small tolerance suggests high multicollinearity.

Ordinal logistic regression diagnostics do not include VIF and Tolerance values. Luckily, it is possible to generate these statistics with an OLS regression, even in the case of dichotomous or ordinal outcome variables. The only adjustment, in this case, is dummy coding the different categories in each explanatory variable. Table 4.2.3. presents the results of the OLS regression. Note that the parameter estimates and p-values are irrelevant for assessing multicollinearity.

Table 4.2.3.

Multiple Linear Regression Results for Collinearity Statistics

	Estimate	SE	*p*	95% CI		Collinearity Statistics	
CarUse				LB	UB	Tolerance	VIF
(Constant)	1.626	0.245	0.000	1.141	2.111		
D.SSInd	0.145	0.229	0.527	-0.307	0.597	0.830	1.205
D.SSDis	0.241	0.242	0.322	-0.239	0.721	0.401	2.496
D.PRIInd	-0.033	0.268	0.901	-0.564	0.498	0.433	2.311
D.PRIDis	-0.593	0.410	0.151	-1.405	0.218	0.335	2.984
D.PREAgr	-0.278	0.224	0.218	-0.721	0.166	0.456	2.193
D.PREDis	0.278	0.343	0.419	-0.401	0.958	0.385	2.598
D.IDInd	-0.123	0.296	0.679	-0.708	0.463	0.644	1.553
D.IDDis	0.174	0.237	0.466	-0.296	0.643	0.599	1.668
D.AVInd	0.169	0.199	0.398	-0.225	0.562	0.855	1.169
D.AVDis	-0.036	0.290	0.901	-0.610	0.538	0.907	1.103

Notes: This table provides the multiple linear regression results for collinearity statistics. The dependent variable is car use frequency. Given statistics are parameter estimates, standard errors, p-values, 95% confidence intervals, and tolerance and VIF values.

All VIF values in Table 4.2.3. are well below the caution threshold of ten, and most are reasonably close to the minimum level of one. This suggests that severe multicollinearity is not present in any of the categories of the predictors. The tolerance levels also do not indicate multicollinearity, given the distance from the caution threshold of 0.1. Thus, no high multicollinearity assumption holds across predictors.

4.2.3. Goodness-of-fit

The goodness-of-fit of a model demonstrates how well the observed data compares to the data expected under the model through some fit statistics (Thomson & Emery, 2014). In other words, it explains the disparity between the values expected in the estimated model and observed values (Thomson & Emery, 2014).

Table 4.2.4. below shows the model fitting information. The -2 Log-Likelihood value is the product of -2 and the log-likelihoods of the interceptor only model and final model (UCLA: Statistical Consulting Group, n.d.). It investigates whether all parameter estimates are simultaneously zero (UCLA: Statistical Consulting Group, n.d.). The Chi-square value ($X^2(5, N=132)=12.793$, $p=0.025$) is the outcome of the Likelihood Ratio Chi-square Test. It examines whether all parameter estimates are equal to zero in the model. The test result tells us whether there is a significant improvement in the fit of the full model compared to the null model. In this case, based on the p-value (0.025), we conclude that the final model significantly improves model fit.

The Akaike Information Criterion (AIC) and Bayesian Information (BIC) values are also given in Table 4.2.4. Both AIC and BIC are closely related and universally accepted measures of fit by assessing relative model qualities. A lower AIC and BIC value indicate a better fit. Accordingly, the AIC and BIC values of the final model are lower than the intercept only model, suggesting that the predictors significantly improve the model fit.

Table 4.2.4.
Model Fitting Information

Model[a]	-2 Log-Likelihood	AIC	BIC	Chi-square	df	*p*
Intercept Only	169.805	179.805	194.219			
Final	157.012	167.012	181.426	12.793	5	0.025

Notes: This table provides the model fitting information of the intercept only model and final model. Given statistics are the -2 Log-Likelihood value, the Likelihood Ratio Chi-square Test, and the p-value pertaining to this test.

Table 4.2.5. provides the results of the Pearson Chi-square and Deviance tests. Both tests assess goodness-of-fit in ordinal regression analysis and examine the difference between the full model and the intercept only model. A non-significant p-value suggests a good model fit (Hosmer et al., 2013).

Sometimes, these two tests do not agree on the level of discrepancy. In this case, both the Pearson Chi-square statistic ($X^2(167, N=132)=192.021$, $p=0.090$) and Deviance statistic ($X^2(167, N=132)=120.258$, $p=0.998$) suggest non-significant results at the 5% significance level, indicating good model fit.

Table 4.2.5.

Goodness-of-fit Tests

	Chi-square	df	*p*
Pearson	192.021	167	0.090
Deviance	120.258	167	0.998

Notes: This table provides the results of the goodness-of-fit tests. Given statistics are the Pearson Chi-square and Deviance Tests, and the subsequent p-values.

The last goodness-of-fit measure this literature considers is the Pseudo R^2 statistic. In OLS regression, the R^2 statistic represents the proportion of the variance of an outcome variable explained by the predictors (Moore et al., 2016). It is a generally accepted measure of the quality of a regression model's fit (Hemmert et al., 2018). However, R^2 values follow from continuous response variables (Smith & McKenna, 2013). Consequently, an exact equivalent of the R^2 statistic does not exist for ordinal logistic regression models. Instead, researchers developed Pseudo R^2 based on maximum likelihood estimates, a rough analogue to the Ordinary Least Squares R^2 (Veall & Zimmerman, 1992). Pseudo R^2 describes the improvement in the model likelihood over the intercept only model, not the proportion of explained variation in the case of OLS regression (Hemmert et al., 2018).

There exist many different measures of Pseudo R^2. Unlike OLS R^2, there is no universal unanimity over a best measure, and each has a distinct interpretation and reporting (Cohen et al., 2014). This study considers three Pseudo R^2 values: McFadden, Cox and Snell, and Nagelkerke. In this setting, a higher value Pseudo R^2, strictly speaking, indicates a better fit (Hemmert et al., 2018).

McFadden R^2 calculates the ratio of the log-likelihood of the null model and the full model (McFadden, 1979). It indicates the improvement the final model offers over the null model (Hemmert et al., 2018). Accordingly, McFadden (1979) argued that values between 0.2 and 0.4 suggest a good model fit.

Cox and Snell R^2 also calculates the ratio of log-likelihoods of the intercept only model and the final model whilst taking sample size into account (Petrucci, 2009). However, it has a severe shortcoming of having an upper bound lower than one. If, for instance, the model predicts the outcome perfectly, then the Cox and Snell R^2 would only be 0.75 (Smith & McKenna, 2013). Consequently, Cox and Snell R^2 is usually not interpreted in logistic regression models. Instead, researchers use Nagelkerke R^2, a correction of the Cox and Snell R^2 that extends the upper limit to one (Petrucci, 2009).

Table 4.3.1. provides the Pseudo R^2 values. McFadden R^2 has a value of 0.047. Cox and Snell R^2 and its correction Nagelkerke R^2 equals 0.092 and 0.106, respectively. Although values are relatively low, the research setting impacts the interpretation. The meta-analysis of Hemmert et al. (2018) showed that almost all Pseudo R^2 are affected to a certain extent by the number of explanatory variables, sample size, and the number of categories of the response variable. Besides, the use of R^2 in logit models is somewhat controversial. Often, publications do not mention Pseudo R^2 values in the results. Interestingly, out of those who report a Pseudo R^2, 80% do not even indicate which measure they used (Hoetker, 2007).

Thus, given the small sample size and non-experimental nature of the study, a low Pseudo R^2 was expected. Following the results of Hemmert et al. (2018) and considering the research setting, it is argued that a low Pseudo R^2 does not necessarily suggest a poor fit.

4.3. Hypotheses Testing

Assumption testing and goodness-of-fit measures proved that the regression model is suitable for hypotheses testing. In the model, car use frequency is the outcome variable with five rank-ordered categories. Predictors are individuals' perceptions on the relationship between car ownership and social status, pride, prestige, self-identity, and altruistic values. The results of the ordinal regression analysis are given below in Table 4.3.1.

Table 4.3.1.
Ordinal Logistic Regression Results

		Estimate	SE	Wald	df	*p*	95% CI	
CarUse							LB	UB
Threshold	[CarUse = 1]	1.887	0.733	6.628	1	0.010	0.450	3.324
	[CarUse = 2]	3.545	0.787	20.29	1	0.000	2.002	5.087
	[CarUse = 3]	4.907	0.884	30.81	1	0.000	3.174	6.640
	[CarUse = 4]	6.535	1.260	26.91	1	0.000	4.066	9.004
Location	SStatus	0.371	0.263	1.989	1	0.158	-0.145	0.887
	Pride	-0.625	0.448	1.940	1	0.164	-1.504	0.254
	Prestige	0.886	0.379	5.456	1	0.020	0.143	1.630

		Estimate	SE	Wald	df	p	95% CI	
CarUse							LB	UB
	Self_ID	0.091	0.274	0.111	1	0.739	-0.446	0.628
	AltVal	0.137	0.304	0.203	1	0.653	-0.459	0.733
Pseudo R^2								
McFadden	0.047							
Cox and Snell	0.092							
Nagelkerke	0.106							

Notes: This table presents the results of the ordinal logistic regression analysis. The dependent variable is car use frequency. Predictors are social status, pride, prestige, self-identity, and altruistic values. Given statistics are parameter estimates, standard errors, Wald Test results and the subsequent p-values, and 95% confidence intervals. Pseudo R^2 values are also provided.

Threshold values represent the estimates for the different levels of the outcome variable. Each coefficient is the cut-off point between two categories (Liu, 2015). [CarUse = 1] is the cut point between car use frequency of "(Almost) never" and "Once or twice per month". [CarUse = 2] describes the cut-off value between "once or twice per month" and "A few times a week". The threshold estimate of [CarUse = 3] represents the cut point between "A few times a week" and "Several times a week". Finally, [CarUse = 4] is the cut-off value between "Several times a week" and "Every day", which is the reference category in the model.

Threshold estimates are the intercepts in the model (Hosmer et al., 2013). Their explanation, though, is somewhat different from the constant of the OLS regression. For example, the interpretation of [CarUse = 4] is as follows: *Respondents who had a value of 6.535 or higher on the outcome variable would be categorised as "Every day", holding all else constant* (Liu, 2015). However, researchers do not usually interpret these threshold values directly. Instead, they are used to calculate the cumulative logits and odds between two groups (Liu, 2015). Since inter-group comparisons are not part of this research, further analysis on the threshold values is not required.

Before proceeding with parameter interpretation, It is crucial to understand how hypotheses testing is done in an ordered logit model. OLS regression applies *t*-Tests to examine whether slope coefficients significantly influence the response variable. In an ordinal regression analysis, hypotheses testing is carried out by the results of a Wald Test. The test follows an asymptotic X^2 distribution and is also called the Wald Chi-square Test (Hauck Jr. & Donner, 1977). It examines whether slope coefficients are equal to zero (Hauck Jr. & Donner, 1977). If the p-value is greater than 0.05, the test suggests that the predictor in question does not significantly affect the outcome variable.

SStatus represents the log-odds estimate for a single unit change in respondents' view on car use as a symbol of social status on the expected car use frequency, holding all other predictors constant. The estimated effect is 0.371 (%95 CI, [-0.145, 0.887]). The accompanying Wald test statistic is $X^2(1) = 1.989$, $p = 0.158$. Given the p-value, which is above the significance level of 5%, social status is not a significant determinant of car use frequency. Thus, further interpretation of the impact of social status is meaningless.

Pride represents the log-odds estimate for a single unit change in respondents' view on deriving pride from car ownership on the expected car use frequency, holding all other predictors constant. The estimated effect is -0.625 (%95 CI, [-1.504, 0.254]). The accompanying Wald test statistic is $X^2(1) = 1.940$, $p = 0.164$. Given the p-value, which is greater the significance level of 5%, pride is not a significant determinant of car use frequency. Thus, further interpretation of the impact of pride is meaningless.

Prestige represents the log-odds estimate for a single unit change in subjects' view on deriving prestige from driving a car on the expected car use frequency, holding all other predictors constant. The estimated effect is 0.886 (%95 CI, [0.143, 1.630]). The accompanying Wald test statistic is $X^2(1) = 5.436$, $p = 0.02$. The p-value is lower than the significance level of 5%, indicating that prestige is a significant determinant of car use frequency. The slope coefficient of 0.886 demonstrates a positive relationship between car use frequency and prestige. Accordingly, for every single unit increase in this predictor, the log-odds of being in a higher category in the dependent variable increases on average by 0.886. In other words, respondents that perceive prestige from car ownership are more frequently using their cars compared to those who do not.

Self_ID represents the log-odds estimate for a single unit change in respondents' view on expressing their identity with their car on the expected car use frequency, holding all other predictors constant. The estimated effect is 0.091 (%95 CI, [-0.446, 0.628]). The accompanying Wald test statistic is $X^2(1) = 0.111$, $p = 0.739$. Given the p-value, which is greater than the significance level of 5%, identity expression is not a significant determinant of car use frequency. Thus, further interpretation of the impact of self-identity is meaningless.

Finally, *AltVal* represents the log-odds estimate for a single unit change in subjects' view on altruistic values on the expected car use frequency, holding all other predictors constant. The estimated effect is 0.137 (%95 CI, [-0.459, 0.733]). The accompanying Wald test statistic is $X^2(1) = 0.203$, $p = 0.653$. Given the p-value, which is larger than the significance level of 5%, holding altruistic values is not a significant determinant of car use frequency. Thus, further interpretation of the impact of altruistic values is meaningless.

Chapter 5: Concluding Thoughts

5.1. Discussion

The ordinal regression analysis failed to provide evidence for the relationships between social status, pride, self-identity, altruistic values, and car use frequency. Thus, associations described in hypotheses one, two, four, and five do not hold for the sample in question. These findings imply that other factors that are unaccounted for in the model provide a better explanation to respondents' car use.

Non-significant findings, though, does not imply that no impact exists. It simply suggests that the hypothesised relationship is not significant at the 5% significance level. For instance, the p-value of social status (0.158) indicates that the positive effect of social status on car use frequency is only 84.2% true (1 - 0.158), instead of being 95% true. Therefore, a relationship does indeed exist. We should investigate why this relationship is not significant at the level of 5%.

Firstly, the sample size is a crucial determinant of the power of a model. For ordinal regression analysis, sample size requirements are stricter than OLS regression. According to Bujang et al. (2018), a sample of 500 is the minimum for valid parameter estimates. They further their argument by suggesting the following rule of thumb; $n = 100 + 50i$ where i represents the number of predictors in the model. Using this rule, the sample size requirement for this research would be 600. The sample size in this study is only 132, which can remarkably alter the regression estimates. Also, collapsing categories in small samples influence regression results. To meet the proportional-odds assumption, the adjacent categories in the predictors were combined into three levels. This is a common practice in proportional odds models (Murad et al., 2003). However, this procedure produces Wald statistics that are very conservative, leading to wrong conclusions about the hypotheses (Murad et al., 2003).

Sample characteristics also impact results. For example, Nordfjærn & Rundmo (2019) argued that women are more environmentally conscious about their transport mode choice. Our sample consists mainly of males, which, in turn, may lead to the underestimation of the relationship between altruistic values and car use frequency. Hiscock et al. (2002) showed that people with less lavish and more localised lifestyles do not derive symbolic satisfaction from car use. Given the income distribution of the sample and localised lifestyles in the Netherlands, a similar impact to the findings of Hiscock et al. (2002) is probable in the study. According to Murray et al. (2010), symbolic variables do not influence the mobility decisions of current and previous public transport users. Given the public transport consumption in the Netherlands, especially in the school-age, it is likely that our sample consists of current or previous users of public transport.

Survey design can also influence results. In this study, the data of each predictor reflects subjects' perceptions of a given statement. The definition provided for each variable could, in turn, influence people's opinion toward the variable. For instance, the question on social status asks respondents to agree or disagree with the following statement: *"Using public transport lowers my status in society".* This is a considerably strong statement that could alter the actual opinion of the respondents who are, for example, concerned about their image in society. Inclination towards acting in a socially desirable way also influenced the results of Bergstad et al. (2011). For example, it is not socially desirable to express that one's car symbols its status in society or see your car as an achievement and take pride in its ownership (Bergstad et al., 2011). Thus, image concerns can greatly influence respondents' intention to express their true opinion.

Some literature also questioned the impact of symbolic variables in general. Steg et al. (2001) studied the influence of transport facility factors and symbolic variables in the Netherlands. They found that people value the practical advantages of driving like convenience and safety much more than its symbolic consumption. Lois & López-Sáez (2009) found a significant but weak relationship between symbolic motivations and car use. Their results showed that people's affective link with their cars only explains about 12% of their driving frequency.

Unlike the rest, prestige turned out to be a significant determinant of car use frequency. The relationship described in hypothesis three, therefore, holds at the 5% significance level. Deriving prestige from car ownership is estimated to increase the log-odds of being in a higher category in the car use frequency by 0.886, holding all else constant. There is overwhelming evidence for such an effect in the existing literature. Şimşekoğlu et al. (2015) and Li et al. (2019) showed that individuals derive prestige from owning a car. Similarly, Heffner et al. (2007) found that owners of electric cars identify their vehicles as a source of prestige because, for example, they own the newest technology. Ellaway et al. (2003) also argued that having a luxurious car results in greater prestige for their owner.

To sum up, the regression model did not provide evidence for a significant relationship between social status, pride, self-identity, altruistic values, and car use frequency. However, this does not mean that no effect exists. Some of the many explanations for our non-significant results include sample size and characteristics and inclination to act in a socially acceptable way. Prestige, on the other hand, turned out to be a strong influencer of car use frequency, which is in line with the findings of existing literature. Accordingly, it is concluded that the influence of symbolic motivators on car use frequency depends on the symbolic variable in question. Social status, pride, self-identity, and altruistic values do not impact subjects' travel behaviour in this sample, whereas prestige does.

5.2. Limitations and Future Research

This research is subject to certain limitations. Firstly, the sample size and characteristics substantially reduce the power of our model in finding truly significant estimates. Second, capturing data on symbolic motivators through statements may interfere with respondents' genuine opinions. Besides, the cross-sectional surveys also limit the extent to which one can appropriately determine the actual characteristics of the participants. Third, the non-experimental nature of this study limits the generalisability of the findings. Our findings, strictly speaking, are correlational, not causal. Thus, the results must be interpreted cautiously.

These limitations naturally open room for further research. Future research should expand the sample size and capture a more evenly distributed population. Survey design should also be improved to avoid interfering with individuals' genuine opinions on these symbolic influences. Besides, a longitudinal study could be better for capturing the actual characteristics of the respondents. Then, future research could analyse the impact of symbolic motivators in the presence of other influences on transport mode choice. This could be done through structural equation modelling. Another compelling research could be studying individuals' opinions on these symbolic motivators before and after becoming a car owner, which can be, for instance, carried out with a difference-in-differences analysis.

5.3. Policy Recommendations

The results suggest that the impact of symbolic motivators can vary depending on the variable in question. First, authorities should identify which of these symbolic influencers are significant determinants of mobility decisions. After establishing these influences, authorities should try to understand why the symbolic consumption of cars exists. Depending on the outcome, certain educational and psychological measures could be taken, as defined by Loo & Banister (2016). Despite the non-significant results, there is still evidence for significant relationships between symbolic motivators and travel behaviour, both in this research in the form of prestige and previous literature. Authorities should therefore consider symbolic consumption in their efforts to achieve more sustainable transportation. This, in turn, will allow them to spend their limited tax-payer money and labour more effectively.

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Appendix A: Survey Transcript

Section 1

1. Do you have a car?

(1) Yes
(2) No

2A: If *"yes"* to question 1, what type of car do you have?

(1) Company leased car
(2) Privately owned or privately leased car

2B: If *"no"* to question 1: Survey ends.

Section 2

3. Think of your life before COVID-19. Generally speaking, how frequently did you use your **car** for travelling to work/school and leisure activities (E.g. Shopping)?

(1) (Almost) never
(2) Once or twice a month
(3) A few times a week
(4) Several times a week
(5) Every day

4. Think of your life before COVID-19. Generally speaking, how frequently did you use **public transport (bus, metro, tram, and train)** for travelling to your work/school and leisure activities (E.g. Shopping)?

(1) (Almost) never
(2) Once or twice a month
(3) A few times a week
(4) Several times a week
(5) Every day

Section 3

5. To what extent do you agree with the following statement: "Using public transport lowers my status in society".

(1) Strongly agree
(2) Somewhat agree
(3) Neither agree nor disagree
(4) Somewhat disagree
(5) Strongly disagree

6. To what extent do you agree with the following statement: “Driving a car gives me a sense of pride”. (E.g. A feeling of pleasure you derive from driving a car because it symbolises an achievement)

(1) Strongly agree
(2) Somewhat agree
(3) Neither agree nor disagree
(4) Somewhat disagree
(5) Strongly disagree

7. To what extent do you agree with the following statement: “Driving a car gives me prestige”. (E.g. People respect or admire me because of my car)

(1) Strongly agree
(2) Somewhat agree
(3) Neither agree nor disagree
(4) Somewhat disagree
(5) Strongly disagree

8. To what extent do you agree with the following statement: “A car is a part of my identity and a reflection of my personal traits and lifestyle”.

(1) Strongly agree
(2) Somewhat agree
(3) Neither agree nor disagree
(4) Somewhat disagree
(5) Strongly disagree

9. To what extent do you agree with the following statement: “Driving a car gives me a feeling of power and superiority”.

(1) Strongly agree
(2) Somewhat agree
(3) Neither agree nor disagree
(4) Somewhat disagree
(5) Strongly disagree

10. To what extent do you agree with the following statement: “Using public transport is good because it decreases congestion, accidents, and environmental damage”.

(1) Strongly agree
(2) Somewhat agree
(3) Neither agree nor disagree
(4) Somewhat disagree
(5) Strongly disagree

Section 4

11. What is your current employment status?

(1) Employed full-time
(2) Employed part-time
(3) Unemployed
(4) Student
(5) Retired
(6) Prefer not to say

12. If answered "Student" to question 14: Do you have the student travel product by DUO which allows you to use public transport for free in weekdays or weekends depending on your choice?

(1) Yes
(2) No

13. What is your gross yearly income?

(1) Less than €13,700
(2) €13,700 – €28,600
(3) €28,600 – €42,400
(4) €42,400 – €71,000
(5) €71,000 – €84,700
(6) More than €84,700
(7) Prefer not to say

14. What is your gender?

(1) Female
(2) Male
(3) Non-binary / third gender
(4) Prefer not to say

15. What is your age?

(1) 18-24
(2) 25-34
(3) 35-44
(4) 45-54
(5) 55-64
(6) 65+
(7) Prefer not to say

16. What is your highest level of education?

(1) Less than high school
(2) High school graduate
(3) Bachelor's degree
(4) Master's degree
(5) Doctorate
(6) Prefer not to say