The Effects of Risk Factors of Transport Poverty on the Usage of Shared Bicycles and Mopeds: An Explorative Case Study in the City of Rotterdam

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Utrecht University, the Netherlands

Submitted by:
Chayenne T. van de Wouw
Student number 6855989

Under supervision of:
Dr. ir. Stephanie J.L. Geertman
Department of Interdisciplinary Social Science
Faculty of Social and Behavioural Sciences
Utrecht University

In cooperation with:
Gemeente Rotterdam
Cluster of Urban Development
Department of Mobility

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Abstract

In the context of answering sustainability and health challenges as well as addressing increasing pressures on urban infrastructure, shared bicycles and mopeds promise to have many advantages. Simultaneously, there is increasing attention for the concept of transport poverty. It is often presumed that experiencing transport poverty leads to a reduced (perceived) ability to reach key activity locations required for participation in society and a good quality of life. Little remains known about shared bicycles and mopeds in relation to transport poverty, especially in a societal context where cycling is already commonly practised. Therefore, this thesis researched how various risk factors of transport poverty relate to the usage of shared bicycles and mopeds in the municipality of Rotterdam. Based on existing data collected through a survey conducted in Rotterdam, two binary logistic regression models were developed to identify what and how risk factors of transport poverty are related to the usage of shared bicycles and mopeds. The research concluded that risk factors such as socio-economic risk background (age, gender, and education) and competencies (having a driver's license) predicted a significant reduced likeness for having used a shared bicycle or moped. While perceived and objective access to transport options (e.g. perceived traffic flow by car) were not found to be statistically significant for predicting shared bicycle usage, this risk factor was significant for predicting usage of shared mopeds. Neighbourhood of residence was not significant for predicting usage of both shared bicycles and mopeds. Despite these mixed findings, the results of this thesis suggest that shared bicycles and mopeds do not inherently reduce inequity in opportunities to participate in society caused by transport poverty. This highlights the need for public authorities to make further efforts to prevent aggravating inequalities for those at risk of transport poverty.

Introduction

In recent times, increasingly numerous calls are made to set transport poverty on both the political and academic agenda (Lucas et al., 2016; van der Veen, 2017; Martens et al., 2011; VERDUS, 2018). Some population groups are estimated to have limited access to various modes of transportation, which increases the risk of not being able to reach key activity locations required for social inclusion and participation in society (Jorritsma et al., 2018). Someone's likeliness to experience transport poverty is defined by various risk factors of transport poverty such as having a low income or non-western migration background. However, there is only limited and fragmented insight in the prevalence of this phenomenon in the Netherlands (Jorritsma et al., 2018; Kampert et al., 2019).

Simultaneously, a shift from ownership of private vehicles to shared mobility is taking place. This is spurred by the potential of shared mobility to make transportation more sustainable. Shared mobility exists of different modes of transport such as shared cars, bicycles, scooters, e-bikes, and mopeds. Shared bicycles and mopeds promise many benefits including reduced private car usage and lowering the emission of greenhouse gasses (see e.g. Aguilera-García et al., 2020; Zhang & Mi, 2018). This makes shared mobility an important concept for achieving the 11th Sustainable Development Goal (SDG) which refers to creating sustainable cities and communities (United Nations, 2020). Moreover, shared mobility is nested in the notion of healthy cities as it has the potential to increase (health) equity amongst various population groups (Ricci, 2015) and stimulate citizens to make use of active modes of transportation (Martin & Shaheen, 2011).

However, research has also pointed out that shared bicycles and mopeds currently seem to be benefiting specific, already rather advantaged groups in society. In Rotterdam, a survey among users of shared e-bikes and mopeds showed that these are mostly used by young to middle-aged people (53% of the users are aged 18-35, 37% are aged 36-55), males, and (self-)employed citizens (Meijering, 2020), which is in line with academic research (Shaheen et al., 2012).

In this thesis I researched how risk factors of transport poverty relate to ever having used shared bicycles and mopeds, where shared bicycles included both shared e-bikes and regular bicycles. This thesis contributed to gaining more knowledge on the relationship between risk factors that are still underrepresented in existing academic literature on transport poverty and shared bicycles and mopeds. Moreover, more insight was gained in the potential risk of shared bicycles and mopeds aggravating transport poverty and, in turn, inequity. After all, if those at risk of transport poverty are less likely to use shared bicycles and mopeds, they cannot reap the presumed benefits from these shared vehicles. It was hypothesised that people who experience risk factors of transport poverty are less likely to use shared bicycles and mopeds.

The municipality of Rotterdam has expressed its interest in gaining more knowledge on transport poverty in relation to shared bicycles and mopeds. Hence, this research can help determine what role local governments could have in relation to these developments.

Literature Review

Defining Transport Poverty

Over the last two decades, various definitions of and concepts related to transport poverty emerged in academic literature and policy programmes (Kuttler & Moraglio, 2021; Lucas et al., 2016). This creates the risk that addressing the issue is marked by “inadequacy, fragmentation, inconsistency and tokenistic treatment” (Lucas et al., 2016, p. 353), which is disadvantageous considering the impact that transport poverty has on potential victims’ subjective wellbeing (Churchill & Smyth, 2019).

In their literature review on transport poverty, Lucas et al. (2016) addressed that transport poverty can be considered an umbrella term where transport poverty is composed of (a combination of) aspects including transport affordability (inability to afford the costs of transport), mobility poverty (a systemic lack transportation and mobility options), accessibility poverty (having difficulty reaching key activities such as employment, education, healthcare services, shops), and exposure to transport externalities (facing disproportionate negative exposures to the transport system itself). Lucas et al. (2016) argued that an individual can be considered transport poor if at least one of the following conditions apply:

- There is no transport option available that is suited to the individual's physical condition and capabilities.
- The existing transport options do not reach destinations where the individual can fulfil his/her daily activity needs, in order to maintain a reasonable quality of life.
- The necessary weekly amount spent on transport leaves the household with a residual income below the official poverty line.
- The individual needs to spend an excessive amount of time travelling, leading to time poverty or social isolation.
- The prevailing travel conditions are dangerous, unsafe or unhealthy for the individual (p. 356).

To establish a common definition of transport poverty that is relevant to the Dutch context, the Institute for Policy Transport Analysis (hereafter KiM) developed a conceptualisation of transport poverty (Jorritsma et al., 2018). In this research, the works of many prominent scholars in the field were included such as Kaufmann et al. (2004), Bastiaanssen (2012), Lucas (2012), and Martens (2017). Based on this literature review, Jorritsma et al. (2018) proposed a definition based on three streams in the literature on transport poverty: social exclusion perspective, social capital and capability perspective and the transport justice perspective. Jorritsma et al. (2018) combined these perspectives and proposed the following overarching definition of transport poverty:

> The failure or difficulty of accessing activity locations (in terms of effort expended), owing to inadequate transport options (both objective and perceived), in combination with peoples' socio-economic and spatial conditions and personal abilities. Consequently, their participation in social life is impeded, which negatively impacts their quality of life (p. 37).

Recently, Kuttler & Moraglio (2021) raised various critiques towards the concept of transport poverty, including that it is still insufficiently researched "how exactly and to what degree transport and mobility-related disadvantages contribute to social exclusion, reduced opportunities and well-being" (p. 8). In contrast with Lucas et al.'s (2016) and Jorritsma et al.'s (2018) line of work, Kuttler and Moraglio (2021) argued that transport poverty is a sub-concept of experiencing mobility poverty. Taking a more social constructivist approach, such an approach focussing on mobility poverty is argued to be more "sensitive to questions of access, but also to the skills and capabilities of individuals as well as to personal ambitions and differentiated needs" (Kuttler & Moraglio, 2021, p. 10).

To ensure future comparability with studies situated in the Netherlands, this thesis defined transport poverty according to the KiM's definition. However, the importance of the social constructivist emphasis on including sensitivity for the subjective side of transport poverty is recognised in this thesis by incorporating people's perceptions of available transport options.

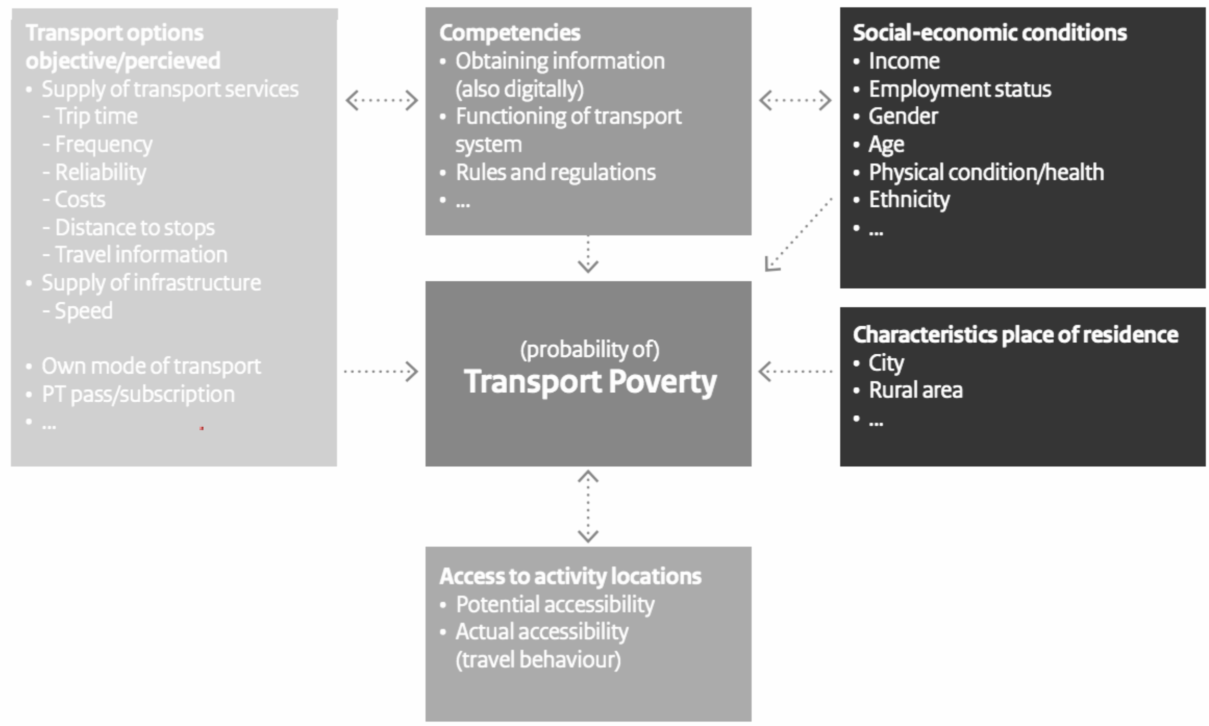
Defining Risk Factors of Transport Poverty

In line with the ongoing debate on a common definition of transport poverty, measuring transport poverty in an empirical way still faces academic scrutiny. Lucas et al. (2016) concluded that "transport poverty is an extremely under-explored and poorly articulated problem even within developed countries" (p. 362). Moreover, Kuttler & Moraglio (2021) addressed that some risk factors like socio-economic background (gender, disability, old and young age) have received less academic attention compared to factors other risk factors like material poverty. The KiM confirmed these observations through conceding that it is not or hardly possible to define the extent to which transport poverty exists in the Netherlands based on available studies (Jorritsma et al., 2018).

As has become evident in the previous section, the extent to which people are considered transport poor is defined by several risk factors. In the study conducted by the KiM, the main concepts that constitute the risk factors of transport poverty were categorised under the notions of competencies, a real or perceived sense of limited transport possibilities, being socially disadvantaged, and location of residence. These risk factors influence someone's ability to reach key activity locations (Jorritsma et al., 2018). For future quantitative studies, the authors recommended a research model in which (the probability of experiencing) transport poverty is influenced by various additional factors (Figure 1).

Figure 1

Risk Factors of Transport Poverty



Note. Reprinted from Jorritsma et al. (2018).

It must be noted that being mobile and having access to transport does not automatically protect someone from facing transport poverty. Kuttler and Moraglio (2021) addressed, for instance, the lack of attention for "the discrimination that ethnic minorities, migrants and refugees face while being mobile and accessing transport" which illustrated that "the highly contextual and relational nature of mobility disadvantage needs further exploration" (p. 9). While some studies have explored the subjective side of transport poverty, in the Netherlands those studies tend to be commissioned by organisations and municipalities (see e.g. De Verkeersonderneming (2019)).

Shared Bicycles and Mopeds' Value in Urban Settings

Shared bicycles and mopeds have gained increasing attention due to their potential to alleviate practical issues and address challenges put forward by the healthy and sustainable city paradigm that currently prevails amongst academia and practitioners alike (Kent & Thompson, 2020).

First, shared bicycles and mopeds have practical and infrastructural benefits as they take up less urban space by having a smaller safety cushion on the roads and requiring less parking space than (shared) cars (Gemeente Amsterdam, 2017). Besides, bicycles are a mode of transportation that fits well within a Dutch context as a large portion of Dutch citizens know how to cycle (de Haas & Hamersma, 2020). Many Dutch citizens own multiples bikes and a large number of privately owned bikes stand still for a long period of time (Centraal Bureau voor de Statistiek, 2021). This puts pressure on the already limited amount of urban space in dense Dutch cities. Shared bicycles are more space-efficient as they help more people reach their destination per day (Gemeente Rotterdam, 2021a). Furthermore, shared bicycles and mopeds may help to mitigate pressures on the public transport system. Fishman's (2016) synthesis of existing literature illustrated that shared bicycles tend to be used as a replacement for public transport. Also a survey in Rotterdam amongst users of shared bicycles and mopeds found that 27 to 28% would have used public transport if these shared vehices would not have been available (Meijering, 2020).

Second, shared bicycles and mopeds fit into the urban planning theory of sustainable cities. Research shows that the prescence of shared bicycles and mopeds contributed to reducing car usage (Aguilera-García et al., 2020; Campbell et al., 2016; Ma et al., 2020). Shared bicycles and mopeds are also an important component of Mobility as a Service (MaaS) (Machado et al., 2018). MaaS is a concept for a platform on which individuals can search, plan, and pay for trips provided by a variety of transport services, which is argued to have the potential to decrease car use and to a lesser extent car ownership. This leads to a reduction in CO_2 emission and energy consumption as well as air and noise pollution within cities (see e.g. Butler et al., 2021). In Rotterdam, 23% of the trips made by shared mopeds and

10% of the trips made by shared bicycles served as a replacement for a trip by car (Meijering, 2020). As shared mopeds are required to be electric in Rotterdam (Gemeente Rotterdam, 2021b), these trips use less energy resources making it a more sustainable mode of transportation for short trips compared to the car (de Bortoli, 2021). Shared bicycles and mopeds also help cover the ‘first and last miles’, thereby making public transportation more accesible (Cao et al., 2019; Cherry et al., 2009). Where mopeds are used more often as a mode of transporation on their own, shared bicycles tend to be used more in combination with public transport (Meijering, 2020). As a trip using public transportation is more sustainable compared to using a car (de Bortoli, 2021), this contributes to more sustainable mobility patterns for short and long distances. However, the potential environmental contributions of shared e-bikes and mopeds may be compromised by aspects such as limited recycling of batteries (Hung & Lim, 2020).

Third, shared bicycles and mopeds can contribute to the goals of a healthy city approach. The reduction in CO_2 emissions and air pollution more generally can benefit people’s health and decrease the number of lifelong disability adjusted life years (Woodcock et al., 2014). Shared bicycles and to a more limited extend shared e-bikes facilitate physical activity as they are active modes of transportation (Bourne et al., 2018; Otero et al., 2018). However, shared e-bikes and mopeds tend to draw people away from active and/or more sustainable modes of transportation like walking and cycling without electrical support (Bourne et al., 2018; Campbell et al., 2016; Ma et al., 2020). This makes the position of shared e-bikes and shared mopeds more contested in a healthy city approach that emphasises physical activitity. Equity is another key aspect of the healthy cities approach as the health burdens of the existing transportation systems are “likely to be unequally distributed among different population groups, with a higher burden in the more deprived and ethnic minority populations” (Khreis & Nieuwenhuijsen, 2019, p. 140). There are population groups, for instance those with a non-western migration background (de Haas & Hamersma, 2020), who are less likely to ride a bicycle which may limit the usefulness of shared bicycles for these citizens.

Shared Bicycles and Mopeds in Relation to Transport Poverty Risk Factors

This study investigated the risk factors of transport poverty in relation to shared bicycles and mopeds. Table 1 to 5 summarise the integrative literature review and include sources that explicitly or implicitly addressed the risk factors as identified in the research of the KiM (Jorritsma et al., 2018). Note that the risk factors are summarised separately for the sake of readability although the risk factors are interrelated as illustrated in Figure 1.

Table 1

Socio-Economic Risk Factors of Transport Poverty in Relation to Shared Bicycles and Mopeds

Variables (per risk factor)	Effect of risk factor on usage shared bicycles (country of sample)	Source	Effect of risk factor on usage shared mopeds (country of sample)	Source
Gender (female)	Less usage of shared bicycles (UK, Australia, Ireland)	Fishman (2016)		
	Potentially not significant for usage of shared bicycles (US)	Fishman (2016)		
	Less likely to start using shared e-bikes (Spain)	Munkácsy & Monzón (2018)		
Ethnicity (migrants and ethnic minorities)	Caucasian citizens used shared bicycles more than African American (USA, UK)	Fishman (2016)		
Income (low income)	Less usage of shared bicycles (Greece; Australia, UK)	Efthymiou et al. (2013); Fishman (2016)	Those having high incomes were less likely to use shared mopeds frequently (Spain)	Aguilera-García et al. (2020)
	Less likely to start using shared e-bikes (Spain)	Munkácsy & Monzón (2018)		
	More likely to start using shared e-bikes (China)	Campbell et al. (2016)		
Employment status (unemployed)	Less usage of shared bicycles (UK)	Fishman (2016)	Students were more likely to use shared mopeds than employees (Spain)	Aguilera-García et al. (2020)
	Less likely to start using shared e-bikes (Spain)	Munkácsy & Monzón (2018)		
Education (low education level)	Less usage of shared bicycles (Australia, USA, Canada)	Fishman (2016)	Less likely to use shared mopeds (Spain)	Aguilera-García et al. (2020)
Age (children and elderly)	Elderly (55+) tended to prefer bicycle sharing over e-bike sharing. Young to middle aged males preferred using shared e-bikes (China)	Campbell et al. (2016)	Elderly used shared mopeds less while those aged 26-35 were more likely to use them (Spain)	Aguilera-García et al. (2020)

Table 2

Location of Residence Risk Factors of Transport Poverty in Relation to Shared Bicycles and Mopeds

Variables (per risk factor)	Effect of risk factor on usage shared bicycles (country of sample)	Source	Effect of risk factor on usage shared mopeds (country of sample)	Source
City (deprived neighbourhood)	Shared bicycles were used more in less-affluent urban areas (UK)	Goodman & Cheshire (2014)	Safety was not influential in research on reasons for using a shared moped	Aguilera-García et al. (2020)
	Users of shared bicycles made less arrivals in areas with higher crime rates, but crime rates were not significantly related to location of departure (USA)	Sun et al. (2017)		
	Shared bicycles were used less when air quality is poor. This relation was not significant for shared e-bikes (China)	Campbell et al. (2016)		

Table 3

Competency Risk Factors of Transport Poverty in Relation to Shared Bicycles and Mopeds

Variables (per risk factor)	Effect of risk factor on usage shared bicycles (country of sample)	Source	Effect of risk factor on usage shared mopeds (country of sample)	Source
Knowledge of the public transport system's functioning (lack of familiarity with the public transport system)	Those who already used public transport were more likely to start using shared bicycles (Austria) and e-bikes (Spain)	Bachand-Marleau et al. (2012); Munkácsy & Monzón (2018)		

Variables (per risk factor)	Effect of risk factor on usage shared bicycles (country of sample)	Source	Effect of risk factor on usage shared mopeds (country of sample)	Source
Physical capability (transport system being physically demanding)	Unpleasant circumstances like high temperatures (China) and high wind speeds had a negative impact on shared bicycle usage (Australia)	Campbell et al. (2016); Mateo-Babiano et al. (2016)		
	Shared e-bikes reduce required physical effort for cycling (China)	Campbell et al. (2016)		
Having the skills to ride a bicycle (not being able to ride a bicycle)	Users of shared bicycles (Canada) and e-bikes already cycled regularly (Denmark)	Bachand-Marleau et al. (2012); Haustein & Møller (2016)		
Rules and regulations (not having a car/moped driver's license)	Having a car driver's license increased likeness of using shared bicycles (Canada)	Bachand-Marleau et al. (2012)	Those without a car/moped driver's license were less likely to use a shared moped (Spain)	Aguilera-García et al. (2020)

Table 4

Transport Option Risk Factors of Transport Poverty in Relation to Shared Bicycles and Mopeds

Variables (per risk factor)	Effect of risk factor on usage shared bicycles (country of sample)	Source	Effect of risk factor on usage shared mopeds (country of sample)	Source
Trip time (long travel time)	In combination with public transport, travel time could be decreased by shared bicycles (Finland) and e-bikes (China)	Jäppinen et al. (2013); Campbell et al. (2016)	Avoiding congestion was not significant for using shared mopeds (Spain)	Munkácsy & Monzón (2018)
	For bus commuters, time saved in transit was not a decisive factor to use shared e-bikes (Norway)	Finsveen et al. (2020)		

Variables (per risk factor)	Effect of risk factor on usage shared bicycles (country of sample)	Source	Effect of risk factor on usage shared mopeds (country of sample)	Source
	Traffic congestion did not significantly increase usage shared bicycles (China; USA)	Campbell et al. (2016); Sun et al. (2017)		
	Traffic congestion increased the probability of using shared e-bikes for females, but decreased the probability for males (China)	Campbell et al. (2016)		
Frequency public transport (infrequent public transport)	Metro frequency was negatively related to usage of shared bicycles, bus frequency was positively related to this (USA)	Sun et al. (2017)	Access to flexible mobility was a reason to use shared mopeds (Spain)	Munkácsy & Monzón (2018)
	Higher bus frequency may help shift car commuters to using a shared e-bike for the last mile to bus stops (Norway)	(Finsveen et al., 2020)		
Reliability public transport (unreliable public transport)			Users of shared moped were less likely to combine their trip with public transport compared to shared bicycles (the Netherlands)	Meijering (2020) [a]
Safety transport system (unsafe traffic system)	Shared bicycles were used less in unsafe traffic situations (Australia)	Fishman et al. (2014)	Safety was no significant reason for using a shared moped (Spain)	Aguilera-García et al. (2020)
	The number of traffic accidents was insignificant for using shared bicycles (USA)	Sun et al. (2017)		
Costs (high costs (public) transport)	An attractive price was an important attribute for using a shared e-bike (Norway)	(Finsveen et al., 2020)		
Distance to public transport stops (long distance to stops)	Shared bicycles helped cover the first and last mile to public transport (China)	Cao et al. (2019)	Users of shared moped were less likely to combine their trip with public transport compared to shared bicycles (the Netherlands)	Meijering (2020) [a]
	Distance to bus stops seemed negatively related to usage of shared bicycles (Canada)	Bachand-Marleau et al. (2012)		

Variables (per risk factor)	Effect of risk factor on usage shared bicycles (country of sample)	Source	Effect of risk factor on usage shared mopeds (country of sample)	Source
Supply of infrastructure (lack of supply)	Shared bicycles helped increase available supply through supplementing public transport (Austria)	Leth et al. (2017)	No significant relationship between usage of public transport and shared mopeds (Spain)	Aguilera-García et al. (2020)
	Shared bicycles alleviated first and last mile issues, making public transport more available (China)	Cao et al. (2019);	Shared mopeds were used less in combination with public transport than shared bicycles (the Netherlands)	Meijering (2020) [a]
	Shared bicycles substituted walking and public transportation rather than car trips (Australia, UK, USA)	Fishman et al. (2014)		
Own mode of transport (lack of own mode of transportation)	Those having a privately owned bicycle were less likely to start using a shared bicycle (Canada)	Bachand-Marleau et al. (2012)	Those without a car, moped or motorcycle were less likely to use a shared moped (Spain)	Aguilera-García et al. (2020)
Public transport pass (not having a public transport pass)			Not having a public transport pass was insignificant for using shared mopeds (Spain)	Aguilera-García et al. (2020)

[a] Not a peer-reviewed source

Table 5

Accessibility to Locations and Activities Risk Factors of Transport Poverty in Relation to Shared Bicycles and Mopeds

Variables (per risk factor)	Effect of risk factor on usage shared bicycles (country of sample)	Source	Effect of risk factor on usage shared mopeds (country of sample)	Source
Potential accessibility of key locations (limited potential accessibility)	Shared bicycles helped increase potential accessibility (China; Finland)	Cao et al. (2019); Jäppinen et al. (2013)		
	Shared bicycles were mostly offered in (wealthier) areas with better public transit access (USA)	Jiao & Wang (2020)		
	Shared e-bikes users make longer trips in term of time and distance compared to shared bicycles (USA)	Lazarus et al. (2020)		
Actual accessibility (limited actual accessibility)	The number of new trips made due to shared bicycles was small (Australia, USA, UK)	Fishman (2016)	3% of the users made a new trip due to shared mopeds (the Netherlands)	Meijering (2020)[a]
	5% of the users made a new trip due to shared bicycles (the Netherlands)	Meijering (2020)[a]	Shared mopeds were not related to trip frequency, except for commuting (Spain)	Aguilera-García et al. (2020)
	Inconclusive whether shared e-bikes increased actual accessibility of key activities (Canada; Poland; USA)	Faghih-Imani et al. (2014); Radzimski & Dzięcielski (2021); Sun et al. (2017)		

[a] Not a peer-reviewed source.

Case Study Description

The municipality of Rotterdam has defined in its policy plans to work towards a mobility transition in line with healthy and sustainable city goals, as well as reduce transport poverty (Gemeente Rotterdam, 2019a, 2020). Van der Bijl & Van der Steenhoven (2019) concluded that in 2019 in areas of Rotterdam where more socio-economically disadvantaged residents reside, around 20% of the inhabitants face transport poverty. The municipality of Rotterdam has reiterated several promises of shared bicycles and mopeds such as the potential of shared bicycles to make it easier to reach services, facilities and work sites (Gemeente Rotterdam, 2019b) which could contribute to making citizens more mobile and reduce transport poverty (Gemeente Rotterdam, 2019a). In this document, shared mobility was also named to be a promising development to realise the ambitions towards an active and sustainable mobility transition.

Developments regarding shared mobility are following one another closely in Rotterdam. Shared bicycles were first introduced in Rotterdam in 2016 (Gemeente Rotterdam, 2019a). Since January 2020, 6,500 shared (e-)bikes, mopeds, scooters, cargo-bikes, and other forms of shared mobility (excluding cars and “brommobielen” [microcars]) are allowed in the city (Gemeente Rotterdam, 2019b).

However, the extent to which local governments like Rotterdam are willing and capable to intervene in the shared mobility market is highly political (live meeting attended by the author of this thesis on January 20, 2021 (Gemeente Rotterdam, 2021c)). These factors make the city of Rotterdam an excellent case study for this thesis. The findings of the thesis will inform the municipality in taking either a more stimulating or *laissez-faire* approach to shared bicycles and mopeds in relation to transport poverty.

Conclusion Existing Empirical Research

Although the thesis departs from the KiM's definition of transport poverty, the contributions put forward by social constructivism are acknowledged by including subjective components such as individuals' perceived access to transport options. The key concepts of healthy and sustainable cities helped to contextualise the relation between shared bicycles and mopeds and transport poverty. While shared bicycles and mopeds could contribute to realising the goals of these approaches, also several reservations were made regarding their potential in realising these ambitions.

The overview of existing literature illustrated that the potential of shared bicycles and mopeds to contribute to alleviate transport poverty remain inconclusive and several aspects are insufficiently explored. First, little research has been conducted regarding several risk factors of transport poverty such as objective and perceived transport options in relation to shared bicycles and mopeds. The effects of other socio-economic aspects such as income, gender and the location of residence remained inconclusive, thereby highlighting the need for more insight regarding the various risk factors.

Second, compared to studies on shared bicycles, few studies explored shared e-bikes and mopeds in relation to risk factors of transport poverty. Based on the literature review, differences seemed to exist between shared bicycles and mopeds regarding risk factors such as income, employment status, age, frequency of public transport, distance to public transport stops, and safety of the transport system.

Third, despite the recent surge in literature on shared bicycles, studies mostly focussed on areas where bicycles were not widely used as a mode of transportation, or were just used recreationally (e.g. Campbell et al., 2016; Cao et al., 2019; Goodman & Cheshire, 2014; Woodcock et al., 2014). Few academic studies exist that research the risk factors of transport poverty in relation to shared bicycles and mopeds in a context like the Netherlands where urban design already accommodates to two-wheeled vehicles and cycling is already common practice (de Haas & Hamersma, 2020).

To prevent further exacerbating inequity between those who are and those who are not at risk of transport poverty, more insight is needed in the effects of shared bicycles and mopeds in relation to these various risk factors. Furthermore, the municipality of Rotterdam has expressed its interest for a deeper understanding of the extent to which shared bicycles and mopeds can help to address transport poverty to guide future policy regarding these vehicles. Therefore, the research question of this paper is as following: *how do the various risk factors of transport poverty relate to the usage of shared bicycles and mopeds in the municipality of Rotterdam?* The hypothesis states that people who experience risk factors of transport poverty are less likely to use shared bicycles and mopeds.

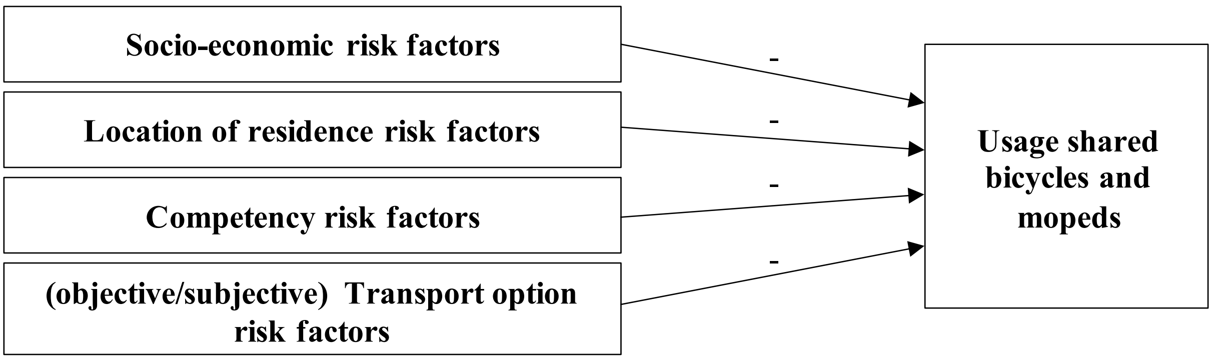
Methods

Research Design

This thesis departed from the risk factors defined in Jorritsma et al.'s (2018) model for further research on transport poverty. Considering this and the integrative literature review, this thesis' research model is illustrated in Figure 2.

Figure 2

Research Model Risk Factors of Transport Poverty and Usage of Shared Bicycles and Mopeds



Note. Adapted from on Jorritsma et al. (2018).

The model illustrates the hypotheses that underlie this thesis:

1. Those who experience socio-economic risk factors of transport poverty are less likely to use shared bicycles and mopeds.
2. Those who live in a disadvantaged neighbourhood are less likely to use shared bicycles and mopeds.
3. Those who experience competency risk factors of transport poverty are less likely to use shared bicycles and mopeds.
4. Those who experience transport option risk factors of transport poverty are less likely to use shared bicycles and mopeds.
5. Risk factors of transport poverty are of different importance for shared bicycles than for shared mopeds.

As this thesis used existing data gathered from the Omnibus survey (de Graaf, 2020), only those concepts and risk factors were included that could be measured using this existing data set. Therefore, *socio-economic* risk factors of transport poverty included being aged 65+, being lowly educated, having a non-western migration background, being female, and not having a paid job.

Location of residence risk factors referred to living in a disadvantaged neighbourhood, which is defined as a neighbourhood that scores low on the indicator called neighbourhood profile Rotterdam. This indicator incorporates social, safety and physical aspects.[1] Charlois, Feijenoord, Rotterdam Centrum scored below average on the combined score of these three domains and were hence considered disadvantaged.

Competency risk factors included not having a car drivers' license and not knowing how to use the public transport system. *Transport option* risk factors described an individual's transport options in two ways: (a) objectively (not owning a(n) (e-)bike, moped,[2] or public transport pass[3] (PT-pass)); and (b) subjectively (experiencing congestion in the city when using the car; experiencing slow, infrequent, unreliable, expensive or socially unsafe public transport; perceiving public transport stops to be far away).

Usage of shared bicycles and mopeds was measured through whether the respondent had ever used a shared bicycle or moped. Though both shared e-bikes and regular bicycles are offered in Rotterdam, the survey did distinguish between these two vehicle types. Therefore, no distinction was made between shared e-bikes and regular bicycles in this thesis. Appendix A contains an overview of the specific survey questions used to operationalise this thesis' variables.

Data Collection and Sample Characteristics

The thesis conducted a binary logistic regression using data acquired from the Omnibus survey held in 2020 (de Graaf, 2020). This survey is conducted yearly and is organised by the research department of the municipality of Rotterdam. Based on a random

[1] See Wijkprofiel Rotterdam (https://wijkprofiel.rotterdam.nl/nl/2020/hulp/themas) for information on the specific variables used to measure the scores in the three domains.
[2] The term "moped" encompass all types of mopeds that can go up to 45km/h.
[3] In the Netherlands, an OV-chipcard (PT-pass) is used as a ticket for all public transport.

sample of the municipality's population registry, 3600 citizens of Rotterdam aged 16 to 85 were invited to participate. 1077 respondents completed the surveys verbally or in written form. Appendix B describes the exact characteristics of the sample. Despite improvements over the past years, certain groups remained underrepresented (e.g. citizens with a migration background and citizens with a lower income). However, the division of respondents from various socio-economic groups was comparable to real population numbers in Rotterdam and different areas of the city were well represented.

Data Analysis Approach

This research used two separate binary logistic regressions to predict the probability of whether someone experiencing certain transport poverty risk factors has ever used a shared bicycle or moped. An inspection of the data was performed to check for normality, multicollinearity, and complete separation. After an initial bivariate check for incomplete information, the number of categories was reduced for several variables. Assumptions of outliers, normally distributed residuals, homoscedasticity, and linearity were met due to the nature of logistic regression on a large sample with only categorical predictors. The descriptive results were based on the variables that remained after these procedures.

Following the procedure suggested by Field (2017), various logistic regressions models were then run to inspect the confidence intervals, standard errors, and significance of predictors. To create a parsimonious model, variables were omitted when they were neither significant nor helped explain variance for both shared bicycles and mopeds. Initial models were fitted based on the significance of the block, proportions of explained variance, absence of extreme confidence intervals and standard errors of predictors, and the model's fit to the data.

This yielded two final models where never having used a shared bicycle or moped were the base cases of the dependent variables. These models were evaluated based on the significance of the models' steps, respective effect sizes (Cox & Snell R Square, Nagelkerke R Square), model fit to the data (Hosmer and Lemeshow Test), significance and odds ratios of individual predictors, influential cases (Cook's distance, leverage and DFBeta), and standardised residuals. As the proportion of respondents having used shared bicycles or mopeds was small compared to those who have not, the thesis focussed on the significance of the different steps and the proportion of variance explained rather than the proportion of correct classifications.

The Netherlands entered a lockdown due to the COVID pandemic on the 15th of March 2020. The majority of the respondents (70%) filled in the survey after this event (de Graaf, 2020). Significant differences existed between the two groups that filled in the survey before and during the COVID pandemic. Therefore, whether someone filled in the survey before or during the pandemic was initially included as a predictor to help account for any potential consequent variance. However, including the effect of the pandemic did not significantly improve the model nor helped explain variance and is, hence, not further addressed in this thesis.

Ethical Considerations

Special attention was paid to safeguarding the respondents' privacy and anonymity. No personal data was collected that could lead back to individual respondents. Access to the datasets is restricted to a limited number of employees within the municipality of Rotterdam. Usage of this data was approved by the ethical committee of the University of Utrecht.

Results

Descriptive results

Hypothesis 1 and 5: Socio-Economic Background and Usage Shared Bicycles and Mopeds

More males had used a shared moped than females, though differences between genders were smaller for usage of shared bicycles (Table 6). Larger numbers of respondents who are younger, have paid work or have a higher education level had used a shared bicycle. Those classified to have an "other western" ethnicity, had the highest proportion of ever having used a shared bicycle, followed by those classified as Dutch. These observations also held true for users of shared mopeds, implying that population groups who are not typically at risk of transport poverty were more likely to have used these shared vehicles.

Table 6

Socio-Economic Characteristics and Usage of Shared Bicycles and Mopeds (N = 1077)

	Ever used a shared bicycle (n = 1061)		**Ever used a shared moped (n = 1060)**	
	No	Yes	No	Yes
	%	%	%	%
Gender				
Male	89.7	8.4	86.0	12.1
Female	92.8	6.1	91.0	7.7
Has paid work				
Yes	89.2	10.6	85.6	14.1
No	96.0	2.9	94.5	4.5
Education level				
Low	98.1	1.1	95.9	2.6
Middle	94.0	5.2	93.2	6.5
High (HBO/WO)	86.6	13.4	81.6	18.2
Ethnicity				
Dutch	92.0	7.1	88.5	10.1
Other western	84.5	13.6	85.5	12.7
Non-western	92.2	5.4	89.8	8.4

	Ever used a shared bicycle (n = 1061)		Ever used a shared moped (n = 1060)	
	No	Yes	No	Yes
	%	%	%	%
Age				
16-25	78.9	17.1	70.4	26.3
26-35	82.5	15.8	76.3	22.0
36-45	89.9	8.8	90.5	8.8
46-55	96.1	3.2	95.5	3.9
56-65	97.0	2.0	95.0	3.0
66-85	98.8	0.4	98.4	0.4

Hypothesis 2 and 5: Location of Residence and Usage Shared Bicycles and Mopeds

Charlois had a relatively low number of respondents who had used a shared bicycle or moped (Table 7). Although Feijenoord and Rotterdam Centrum were also classified as disadvantaged neighbourhoods, the share of respondents having used a shared bicycle or moped was higher than some neighbourhoods that were not classified as disadvantaged which contradicts Hypothesis 2. Except for two neighbourhoods where the number of respondents who had used a shared moped is equal to those who had used a shared bicycle, more respondents across all remaining neighbourhoods had used a shared moped than a shared bicycle.

Table 7

Neighbourhoods and Usage of Shared Bicycles and Mopeds (N = 1077)

	Ever used a shared bicycle (n = 1061)		Ever used a shared moped (n = 1060)	
	No	Yes	No	Yes
	%	%	%	%
Charlois	96.6	3.4	95.4	4.6
Delfshaven	88.2	8.8	83.8	13.2
Noord	88.3	11.7	87.0	13.0
Hillegersberg-Schiebroek and Overschie	90.3	8.0	89.4	8.8
Kralingen-Crooswijk	86.4	13.6	80.7	19.3
Feijenoord	92.6	5.7	85.2	12.3
IJsselmonde	95.6	3.3	94.5	3.3

	Ever used a shared bicycle (n = 1061)		Ever used a shared moped (n = 1060)	
	No	Yes	No	Yes
	%	%	%	%
Hoogvliet, Pernis, Hoek van Holland and Rozenburg	95.0	3.0	95.0	3.0
Prins Alexander	94.4	5.0	93.3	6.1
Rotterdam Centrum	81.1	13.5	77.0	18.9

Hypothesis 3 and 5: Competencies and Usage Shared Bicycles and Mopeds

Those who have little knowledge regarding the functioning of the public transport system and those who do not have a driver's license less often reported to have used a shared bicycle or moped (Table 8). This indicated a possible negative relationship between competencies related to transport poverty and usage of shared bicycles and mopeds. A larger share of respondents who experience these competency risk factors reported to have used a shared moped rather than a shared bicycle. Moreover, the differences between those who do and do not experience these risk factors were smaller for shared mopeds.

Table 8

Competencies and Usage of Shared Bicycles and Mopeds (N = 1077)

	Ever used a shared bicycle (n = 1061)		Ever used a shared moped (n = 1060)	
	No	Yes	No	Yes
	%	%	%	%
Little knowledge of the public transport system				
Not mentioned	92.0	7.7	89.3	10.3
Mentioned	94.6	3.3	92.4	5.4
Car drivers license ownership				
Yes	90.9	8.6	88.0	11.5
No	97.1	2.1	94.5	4.2

Hypothesis 4 and 5: Transport Options and Usage Shared Bicycles and Mopeds

Amongst respondents who used a shared bicycle, larger shares of respondents reported public transport is not fast, reliable, affordable, or available frequently enough (Table 9). These respondents also reported being unsatisfied with the traffic flow when travelling by car more often. At the same time, however, users of shared bicycles less often reported that transport is too far away, and they often had a PT-pass, a private bicycle or moped. Furthermore, users more often perceived public transport as safe. Table 9 shows the same trends for users of shared mopeds.

In contrast with users of shared bicycles, users of shared mopeds more often reported to consider public transport to be too far away. Besides, compared to users of shared bicycles, more citizens who had used shared mopeds had mixed perceptions towards the safety of public transport.

On the one hand, this indicated that shared bicycles and mopeds were used less when objective risk factors (no ownership of a(n) (e-)bike, moped, or PT-pass) were present. On the other hand, these vehicles appeared to be used more when subjective risk factors related to public transport and traffic flow by car are present.

Table 9

Transport Options Related to Usage of Shared Bicycles and Mopeds (N = 1077)

	Ever used a shared bicycle (n = 1061)		**Ever used a shared moped (n = 1060)**	
	No	Yes	No	Yes
	%	%	%	%
Public transport is perceived as not fast enough				
Not mentioned	92.5	6.9	90.4	8.9
Mentioned	89.2	10.8	81.4	18.6

	Ever used a shared bicycle (n = 1061)		Ever used a shared moped (n = 1060)	
	No	Yes	No	Yes
	%	%	%	%
Public transport is perceived as not frequently enough				
Not mentioned	92.3	7.2	89.8	9.5
Mentioned	90.9	9.1	85.7	14.3
Public transport is perceived as too expensive				
Not mentioned	93.4	6.1	91.8	7.7
Mentioned	90.4	9.1	86.1	13.2
Public transport is perceived as too far away				
Not mentioned	91.9	7.6	89.6	9.7
Mentioned	94.1	5.9	89.3	10.7
Perceived reliability public transport				
No opinion	97.7	1.5	94.7	3.8
(very) negative/unsatisfied	90.0	10.0	88.3	11.7
(very) positive/satisfied	91.6	7.9	88.3	11.2
Perceived safety in public transport				
No opinion	98.1	0.0	93.3	4.8
(very) negative/unsatisfied	95.6	4.4	94.1	5.9
Mixed (A combination of negative and positive)	94.1	5.9	86.8	13.2
(very) positive/satisfied	90.4	9.2	88.1	11.5
Perceived traffic flow by car				
No opinion	92.2	6.4	94.5	4.1
(very) negative/unsatisfied	90.7	9.0	85.1	14.4
(very) positive/satisfied	93.2	6.5	90.4	9.6
Bike and/or e-bike ownership				
Yes	91.0	8.7	88.0	11.4
No	96.2	2.7	94.2	5.4
Moped ownership				
Yes	89.9	10.1	86.1	13.9
No	92.9	6.9	90.1	9.6

	Ever used a shared bicycle (n = 1061)		Ever used a shared moped (n = 1060)	
	No	Yes	No	Yes
	%	%	%	%
PT-pass ownership				
Yes	91.8	7.9	89.0	10.5
No	98.9	1.1	96.8	3.2

Logistic Regression Model: Usage Shared Bicycles

The logistic regression model predicting the likeliness of having used a shared bicycle is shown in Table 11. The model was statistically significant X^2 (df = 18, n = 867) = 109.83, p <.01, Cox and Snell R^2 = .119, Nagelkerke R^2 = .275. Hosmer and Lemeshow test results showed the model was a good fit for the data X^2 (df = 8, n = 867) = 15.002, p > .05.

Looking at the Chi-square per block, adding socio-economic variables X^2 (df = 11, n = 867) = 92.20, p < .01 and competencies X^2 (df = 1, n = 867) = 11.26, p < .01 was significant for predicting usage of shared bicycles. Regarding socio-economic variables, only the lowest and some higher age groups were significant (p < .01). The predicted reduction in likeness to use shared bicycles became steeper with age: for age group 46-55 a reduction of 88.8% in predicted probability was found, where this was 98.1% for age group 66-85. Regarding the competency risk factor of not having a driver's license, the model predicted a decreased likeness of 79.8% for having used a shared bicycle. The block containing transport option risk factors was not significant X^2 (df = 6, n = 867) = 6.36, p >.05.

2.5% of the standardised residuals was higher than 2.5, yet inspecting these respondents yielded no abnormalities. According to the Cook's distance, three influential cases were identified but these values were not problematic according to the leverage and DFBeta values. Assumptions regarding absence of complete separation and under- or overdispersion appear to have been met.

Table 10

Risk Factors of Transport Poverty and Predicting Usage of a Shared Bicycle: Modelling Results (N = 867)

								95% C.I. for Exp(B)	
		B	**SE**	**Wald**	**df**	**Sig.**	**Exp(B)**	**Lower**	**Upper**
Socio-economic variables	Female (baseline: male)	-.302	.276	1.201	1	.273	.739	.431	1.269
	Has no paid work (baseline: has paid work)	.151	.431	.124	1	.725	1.163	.500	2.707
	Education level (baseline: high)			5.542	2	.063			
	Low	-.959	.650	2.177	1	.140	.383	.107	1.370
	Middle	-.686	.330	4.328	1	.037	.504	.264	.961
	Ethnicity (baseline: Dutch)			3.787	2	.151			
	Other western	.529	.368	2.062	1	.151	1.697	.825	3.492
	Non-western	-.314	.365	.740	1	.390	.730	.357	1.495
	Age (baseline: 16-25)			36.941	5	.000**			
	26-35	-.393	.351	1.253	1	.263	.675	.339	1.343
	36-45	-1.157	.424	7.451	1	.006	.314	.137	.722
	46-55	-2.192	.581	14.230	1	.000**	.112	.036	.349
	56-65	-2.463	.592	17.303	1	.000**	.085	.027	.272
	66-85	-3.973	1.086	13.374	1	.000**	.019	.002	.158
Competencies	No car driver's license ownership (baseline: yes)	-1.601	.541	8.762	1	.003**	.202	.070	.582
Transport options	Public transport is perceived as not fast enough (baseline: not mentioned)	-.163	.392	.173	1	.678	.850	.394	1.832
	Public transport is perceived as too expensive (baseline: not mentioned)	.027	.279	.010	1	.921	1.028	.595	1.774
	Perceived traffic flow by car (baseline: no opinion)			2.581	2	.275			
	(very) Negative/unsatisfied	-.405	.400	1.023	1	.312	.667	.305	1.461
	(very) Positive/satisfied	-.670	.420	2.549	1	.110	.512	.225	1.165
	No (e-)bike ownership (baseline: yes)	-.673	.469	2.061	1	.151	.510	.203	1.279
	No PT-pass ownership (baseline: yes)	-1.603	1.040	2.377	1	.123	.201	.026	1.545
	Constant	.001	.491	.000	1	.999	1.001		

* $p < .05$ ** $p < .01$

Logistic Regression Model: Usage Shared Mopeds

The logistic regression model predicting the likeliness of having used a shared moped is shown in Table 12. The model was statistically significant X^2 (df = 18, n = 867) = 164.56, p <.01, Cox and Snell R^2 = .173, Nagelkerke R^2 = .343. Hosmer and Lemeshow test results showed the model was a good fit for the data X^2 (df = 8, n = 867) = 10.109, p > .05.

Looking at the Chi-square per block, adding socio-economic variables X^2 (df = 11, n = 867) = 136.08, p < .01, transport options X^2 (df = 6, n = 867) = 21.28, p < .01 and competencies X^2 (df = 1, n = 867) = 7.19, p < .01 was significant for predicting usage of shared bicycles. For the socio-economic variables, the model predicted a reduction of 40.6% in the probability of females using a shared moped. Those having a middle-level education were predicted to have a 65.6% reduction in the probability of using a shared moped. The predicted reduction in likeness to use shared mopeds became steeper with age: for age group 26-35 a reduction of 46.9% in predicted probability was found, where this was 91.2% for age group 46-55, up to 99.1% for age group 66-85. For competency risk factors, the model predicted a decrease of 66.2% for those not having a driver's license. Regarding transport option risk factors, the model predicted an increase of 177.5% in the probability of using a shared moped for those (very) unsatisfied with the traffic flow by car. However, this predictor's confidence intervals are rather broad.

2.4% of the standardised residuals was higher than 2.5, yet inspecting these respondents yielded no abnormalities. Based on Cook's distance, two influential cases were identified yet these values were not problematic according to the leverage and DFBeta values. Assumptions regarding absence of complete separation and under- or overdispersion appear to have been met.

In short, differences existed in the extent to which the overarching socio-economic, transport option, and competency risk factors as well as specific predictors confirmed that those at risk of transport poverty are less likely to use shared bicycles and mopeds. Moreover, not all overarching risk factors (transport options) nor specific predictors (gender, education level, perceived traffic flow) that were significant for shared mopeds, were significant for shared bicycles.

Table 11

Risk Factors of Transport Poverty and Predicting Usage of a Shared Moped: Modelling Results (n = 867)

		B	SE	Wald	df	Sig	Exp(B)	95% C.I. for Exp(B) Lower	Upper
Socio-economic variables	Female (baseline: male)	-.521	.252	4.295	1	.038*	.594	.363	.972
	Has no paid work (baseline: has paid work)	.450	.377	1.430	1	.232	1.569	.750	3.282
	Education level (baseline: high)			12.554	2	.002**			
	Low	-.825	.499	2.737	1	.098	.438	.165	1.1 65
	Middle	-1.066	.310	11.808	1	.001**	.344	.188	.633
	Ethnicity (baseline: Dutch)			.820	2	.664			
	Other western	-.162	.377	.185	1	.667	.850	.406	1.781
	Non-western	-.282	.319	.781	1	.377	.754	.403	1.410
	Age (baseline: 16-25)			59.801	5	.000**			
	26-35	-.633	.319	3.926	1	.048*	.531	.284	.993
	36-45	-1.762	.402	19.229	1	.000**	.172	.078	.377
	46-55	-2.426	.496	23.931	1	.000**	.088	.033	.234
	56-65	-2.842	.538	27.901	1	.000**	.058	.020	.167
	66-85	-4.685	1.078	18.893	1	.000**	.009	.001	.076
Competencies	No car driver's license ownership (baseline: yes)	-1.086	.432	6.316	1	.012*	.338	.145	.787
Transport options	Public transport is perceived as not fast enough (baseline: not mentioned)	.398	.330	1.451	1	.228	1.488	.779	2.843
	Public transport is perceived as too expensive (baseline: not mentioned)	.299	.250	1.434	1	.231	1.348	.827	2.199
	Perceived traffic flow by car (baseline: no opinion)			6.351	2	.042*			
	(very) Negative/unsatisfied	1.021	.442	5.324	1	.021*	2.775	1.166	6.605
	(very) Positive/satisfied	.587	.453	1.677	1	.195	1.798	.740	4.369
	No (e-)bike ownership (baseline: yes)	-.185	.387	.229	1	.632	.831	.390	1.773
	No PT-pass ownership (baseline: yes)	-2.000	1.034	3.746	1	.053	.135	.018	1.026
	Constant	-.610	.506	1.454	1	.228	.543		

* $p < .05$ ** $p < .01$

Conclusion and Discussion

Main Findings

This thesis investigated how various risk factors of transport poverty relate to the usage of shared bicycles and mopeds in the municipality of Rotterdam. Based on the regression models, mixed evidence was found to support the main hypothesis that those at risk of transport poverty are less likely to use a shared bicycles and mopeds.

The youngest generation of citizens was more likely to use shared bicycles and mopeds. For shared mopeds, the model predicted that males and highly educated citizens were also more likely to use these vehicles. As no significant effects were found for ethnicity and having paid work, the results partially confirmed Hypothesis 1 that those who experience socio-economic risk factors of transport poverty (in terms of age, education, ethnicity, gender and paid work) are less likely to use shared bicycles and mopeds.

The descriptive results indicated no clear relation between living in a disadvantaged neighbourhood and usage of shared bicycles and mopeds. The variable location of residence did not meet the criteria to be included in the model. As will be discussed later, these findings were likely to be influenced by the research design of this thesis. Therefore, Hypothesis 2 that those living in a disadvantaged neighbourhood are less likely to use shared bicycles and mopeds cannot be rejected with confidence.

Though knowledge of the public transport system was not included in the regression models as part of competency risks factors of transport poverty, those without a driver's license were predicted to be less likely to have used shared bicycles and mopeds. This partially confirms Hypothesis 3 that those experiencing these two competency risk factors of transport poverty are less likely to use shared bicycles and mopeds.

Risk factors concerning perceived and objective access to transport options were not significant in predicating usage of shared bicycles (e.g. perceived speed, frequency, reliability, costs, and safety of public transport, and vehicle or PT-pass ownership). While it was significant for shared mopeds, only the variable dissatisfaction with the traffic flow by car was significantly related to an increase in probability of using a shared moped. Therefore, Hypothesis 4 stating that those who experience risk factors of transport poverty related to having (perceived and objective access to) transport options are less likely to use shared bicycles and mopeds cannot be rejected with confidence.

The regression models demonstrated that risk factors of transport poverty related to socio-economic background, (perceived and objective) access to transport options and competency were of significance in predicting usage of shared mopeds. However, (perceived and objective) access to transport options was not a significant risk factor for shared bicycles. This confirmed Hypothesis 5 that risk factors of transport poverty have different effects on the use of shared bicycles than the use of shared mopeds.

Discussion and Limitations

Similar to existing literature, this thesis yields no absolute verdict on whether those at risk of transport poverty are less likely to use shared bicycles and mopeds. The thesis confirms findings from other studies (e.g. Campbell et al., 2016; Fishman, 2016) that socio-economic risk factors like a higher age are negatively related to usage of shared bicycles and mopeds. The results also confirm earlier findings relating to shared mopeds, transport options and competencies by Aguilera-García et al. (2020).

However, the thesis also found results that contradict existing research. Gender was not significant for usage of shared bicycles, which is in contrast with findings from Fishman (2016) and Munkácsy and Monzón (2018). These differences may be caused by cycling being common practice regardless of gender in the Netherlands (de Haas & Hamersma, 2020) which may not be the case in the countries examined in aforementioned studies.

Considering existing literature (e.g. Goodman & Cheshire, 2014; Jiao & Wang, 2020) and the increased availability of shared vehicles in more central neighbourhoods (Gemeente Rotterdam, 2021a), the supply of shared vehicles in particular neighbourhoods likely acted as a confounding variable which explains the insignificance of location of residence in this thesis.

Additionally, no significant relationships were found for variables like ethnicity, having paid work, or frequency and speed of public transport. This may be influenced by the operationalisation of these variables using few categories which left little room for potentially required nuance. Furthermore, the variables for perceived transport options agglomerated bus, tram, metro, and train. These modes of transport can influence the usage of shared bicycles and mopeds in different ways (e.g. Finsveen et al., 2020; Sun et al., 2017).

Regarding the external validity of this study, the significance of risk factors and predictors must be interpreted with caution as the dataset contains more respondents who have never used a shared bicycle or moped compared to those who have.

Conclusion and Implications

The thesis contributes to more academic insight in the relationship between transport poverty risks and usage of shared bicycles and mopeds. This relationship appears to be different for shared bicycles and mopeds. While the hypotheses regarding risk factors of living in a disadvantaged neighbourhood as well as objective and perceived transport options are (partially) rejected, the hypotheses concerning socio-economic and competency risk factors are accepted. This suggests shared bicycles and mopeds do not inherently reduce inequity in opportunities to participate in society caused by transport poverty.

The thesis includes risk factors of transport poverty and shared vehicles that have not been researched (extensively) in existing research. Furthermore, it is one of the few studies conducted in a context where cycling is already prevalent amongst a large share of the population (de Haas & Hamersma, 2020). The different influence of risk factors (like gender) that were found in this thesis compared to similar research in other locations, underscores the need for more research in a context where cycling is already commonly practiced.

The findings of this thesis, despite its limitations, provides a basis for further research on usage of shared bicycles and mopeds which would explore interaction effects, the until now insufficiently researched competency risk factors like health impairments and subjective aspects of experiencing transport poverty. To recognise the different attributes of the two vehicle types, it is recommended that future studies on transport poverty distinguish between shared bicycles and e-bikes.

The practical value of this thesis lies in multiple aspects. First, the results confirm a consistent trend that particular groups of citizens (which are often not the ones experiencing transport poverty) use shared bicycles and shared mopeds more often. This highlights the need for governmental intervention to prevent an increase in inequity in real and perceived accessibility of transport options.

Second, differences in predicted likeliness to use shared bicycles and mopeds underscore the need for pragmatic solutions for various risk groups when seeking to address transport poverty through policy and interventions. Fewer transport poverty risk factors are related to using shared bicycles than using shared mopeds. This suggests that, for people experiencing transport poverty, barriers to using shared bicycles are lower. This entails bicycles can be of greater value than shared mopeds for those at risk of transport poverty and could, hence, be given priority in policies designed to reduce transport poverty.

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Appendix A

Questions in the Omnibus Survey Used to Measure Socio-Economic Risk Factors

Socio-economic variable in dataset	Socio- economic risk factor	Question in survey	Categorical values used in the analysis
Age	Old age (aged 65+)	This variable is already known through the sampling procedure of the survey. In case age is missing, the value reported by the respondent is filled in.	16-25, 26-35, 36-45, 46-55, 56-65, 66-85
Paid work	Having no paid occupation	Do you have paid work?	Yes, no
Education	Being lowly educated	A recoded variable exists in the dataset that is recommended by the research department of the municipality of Rotterdam. Highly educated is defined as everything above having followed an (applied) academic study.	Lowly educated, middle educated, highly educated
Gender	Being female	This variable is already known through the sampling procedure of the survey. In case this is missing, the value reported by the respondent is filled in.	Male, female
Ethnicity	Having a non-western migration background	This variable is already known through the sampling procedure of the survey. In case this is missing, the value reported by the respondent is filled in.	Dutch, non-western (Surinamese, Antillean, Cape Verdean, Turkish, Moroccan, non-western migration background), other western (other European (based on membership of the EU in 2007, other western)

Questions in the Omnibus Survey Used to Measure Location of Residence Risk Factors

Characteristics location of residence variables in dataset	Characteristics location of residence risk factor	Question in survey	Categorical values used in the analysis
Neighbourhood	Living in a disadvantaged neighbourhood	This variable is already known through the sampling procedure of the survey. Neighbourhoods are identified based on the standard used by the Dutch central office of statistics (CBS)	Charlois; Delfshaven; Noord; Hillegersberg-Schiebroek and Overschie; Kralingen-Crooswijk; Feijenoord; IJsselmonde; Hoogvliet, Pernis, Hoek van Holland and Rozenburg; Prins Alexander; Rotterdam Centrum

Questions in the Omnibus Survey Used to Measure Competency Risk Factors

Competency variables in dataset	Competency risk factors	Question in survey	Categorical values used in the analysis
Car license	Having no car driver's license	Do you have a car driver's license?	Yes, no
KnowledgePT	Not having enough knowledge of the public transport system	Why do you not travel more often by bus, tram, metro and/or train [you can pick multiple answers?	Not mentioned, mentioned not having enough knowledge of the system to use the bus, tram, metro and/or train more frequently

Questions in the Omnibus Survey Used to Measure Limited Transportation Options Risk Factors

Limited transportation options variables in dataset	Limited transportation options risk factors	Question in survey	Categorical values used in the analysis
Congestion	Experiences congestion in the city when using the car	What do you think about the following subjects in Rotterdam: Traffic flow by car in the city?	No opinion, (very) negative/unsatisfied, (very) positive/satisfied

Limited transportation options variables in dataset	Limited transportation options risk factors	Question in survey	Categorical values used in the analysis
SpeedPT	Perceives that public transport is slow	Why do you not travel more often by bus, tram, metro and/or train [you can pick multiple answers]?	Not mentioned, mentioned bus, tram, metro and/or train are not fast enough
FrequencyPT	Perceives that public transport is not frequently available	Why do you not travel more often by bus, tram, metro and/or train [you can pick multiple answers]?	Not mentioned, mentioned bus, tram, metro and/or train are not going frequently enough
ReliabilityPT	Perceives that public transport is unreliable	What do you think about the following subjects in Rotterdam: Public transport being on time?	No opinion, (very) negative/unsatisfied, (very) positive/satisfied
CostPT	Perceives that public transport is expensive	Why do you not travel more often by bus, tram, metro and/or train [you can pick multiple answers]?	Not mentioned, mentioned bus, tram, metro and/or train are too expensive
DistancePT	Perceives public transport stops to be far away	Why do you not travel more often by bus, tram, metro and/or train [you can pick multiple answers]?	Not mentioned, mentioned bus, tram, metro and/or train stops are too far away
SafetyPT	Experiences social unsafety when using public transport	What do you think about the following subjects in Rotterdam [you can pick multiple answers]?	No opinion, (very) negative/unsatisfied, mixed (a combination of negative and positive), (very) positive/satisfied
Moped	Having no moped	Do you have a moped?	Yes, no
E.bike	Having no (e-)bike	Do you have a bike and/or e-bike?’	Yes, no
PTpass	Having no PT chipcard	Do you have an OV-chipcard?	Yes, no

Questions in the Omnibus Survey Used to Measure Usage of Shared Bicycles and Mopeds

Usage shared vehicles variables in dataset	Question in survey	Categorical values used in the analysis
Shared bike	Do you ever use a “shared bike” in Rotterdam, such as an OV bicycle, Mobike, Jump or Donkey Republic bicycle?	Yes, no
Shared moped	Have you ever used a "shared moped", such as those from Felyx?	Yes, no

Appendix B

Respondents' Socio-Economic Characteristics

	Sample (N = 1077)
	%
Gender	
Male	47.6
Female	51.5
Has paid work	
Yes	53.5
No	35.2
Education level	
Low	25.1
Middle	34.1
High (HBO/WO)	36.8
Ethnicity	
Dutch	57.9
Other western	10.2
Non-western	31.0
Age	
16-25	14.1
26-35	16.4
36-45	13.7
46-55	14.3
56-65	18.6
66-85	22.8

Respondents' Neighbourhood of Residence

	Sample (N = 1077)
	%
Charlois	8.1
Delfshaven	12.6
Noord	7.1
Hillegersberg-Schiebroek and Overschie	10.5
Kralingen-Crooswijk	8.2
Feijenoord	11.3
IJsselmonde	8.4
Hoogvliet, Pernis, Hoek van Holland and Rozenburg	9.3
Prins Alexander	16.7
Rotterdam Centrum	6.9

Respondents' (Subjective and Objective) Transport Options

	Sample (N = 1077)
	%
Public transport is perceived not fast enough	
Not mentioned	87.2
Mentioned	9.5
Public transport is perceived as not frequently enough	
Not mentioned	89.5
Mentioned	7.1
Public transport is perceived too expensive	
Not mentioned	57.9
Mentioned	38.7
Public transport is perceived too far away	
Not mentioned	81.0
Mentioned	15.7
Perceived reliability public transport	
No opinion	12.3
(very) Negative/unsatisfied	11.1
(very) Positive/satisfied	71.6
Perceived safety public transport	
No opinion	9.7
(very) Negative/unsatisfied	12.5
Mixed (a combination of negative and positive)	6.3
(very) Positive/satisfied	66.9
Perceived traffic flow by car	
No opinion	20.2
(very) Negative/unsatisfied	38.0
(very) Positive/satisfied	35.7
Bike and/or e-bike ownership?	
Yes	74.4
No	24.1
Moped ownership	
Yes	7.3
No	91.1
OV-chipcard ownership	
Yes	89.9
No	8.6

Respondents' Competencies

	Sample (N = 1077)
	%
Little knowledge of the public transport system	
Not mentioned	88.1
Mentioned	8.5
Car drivers license ownership	
Yes	76.6
No	22.1

Respondents' Usage of Shared Bicycles and Mopeds

	Sample (N = 1077)
	%
Ever used a shared (e-)bike	
Yes	7.1
No	91.4
Ever used a shared moped	
Yes	9.7
No	88.7

Appendix C

SPSS syntax

```
* Encoding: UTF-8.
****************************************************************************
RETRIEVE DATA
****************************************************************************
* Retrieve original data and save under a new name.
GET
  FILE='P:\SO\VV_Fiets\06 Fietsdelen\14. Stage Chayenne\Scriptie\Data
analyse\Omnibus\omni20b.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.

* Variables that are not used in the analysis are removed, save and work in new dataset.
SAVE OUTFILE='P:\SO\VV_Fiets\06 Fietsdelen\14. Stage Chayenne\Scriptie\Data
analyse\Omnibus\05062021 omni20b kopie omnibus data.sav'.
GET FILE='P:\SO\VV_Fiets\06 Fietsdelen\14. Stage Chayenne\Scriptie\Data
analyse\Omnibus\05062021 omni20b kopie omnibus data.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.

****************************************************************************
INSPECT DATA
****************************************************************************
* Check frequencies for first inspection of relevant variables.
FREQUENCIES
corona
Q54 Q49 OPL3 GSL ETNICBS LFT
WIJKCBS SS2020CAT VS2020CAT FS2020CAT
Q25_10 Q26_9 Q25_6 Q26_5 Q32a Q32p Q25_3 Q26_3 Q25_2 Q26_2 Q13 Q21 Q16 Q17
Q24 Q32l Q32m
Q12 Q25_9 Q26_8 Q25_5 Q19_23 Q34a
Q22 Q23.

* Check frequencies for a first inspection of relevant variables.
DESCRIPTIVES
corona
Q54 Q49 OPL3 GSL ETNICBS LFT
WIJKCBS SS2020CAT VS2020CAT FS2020CAT
Q25_10 Q26_9 Q25_6 Q26_5 Q32a Q32p Q25_3 Q26_3 Q25_2 Q26_2 Q13 Q21 Q16 Q17
Q24 Q32l Q32m
Q12 Q25_9 Q26_8 Q25_5 Q19_23 Q34a
Q22 Q23.

****************************************************************************
RECODE AND ORGANISE DATA
****************************************************************************
* Recode corona. 'During' is baseline because it has a higher frequency.
RECODE corona (0 = 999) (1 = 1) (2=0) INTO COVID.
VALUE LABELS
COVID
```

0 'During'
1 'Before'
999 'Missing value'.
VARIABLE LABELS
COVID
'Survey taken before or during corona'.
FREQUENCIES COVID.

* Recode [Q22] Maakt u in Rotterdam wel eens gebruik van een “deelfiets”, zoals een OV-fiets, Mobike, Jump of Donkey Republic fiets? into yes/no question.
* 'No' is baseline because it has a higher frequency.
RECODE Q22 (1=0) (2 3=1) (0 4 19 999 = 999) INTO SHAREDBIKE.
VALUE LABELS
SHAREDBIKE
0 'No'
1 'Yes'
999 'Missing value'.
VARIABLE LABELS
SHAREDBIKE
'Ever used a shared bicycle'.
FREQUENCIES SHAREDBIKE.

* Recode [Q23] Wist u dat er tegenwoordig ook ‘deelscooters’ bestaan, zoals bijvoorbeeld van Felyx? into yes/no question.
* Respondents could originally answer with "yes, but I've never used one"; "yes, and I have used one"; or "no".
* This recoding is based on the assumption that when someone hasn't heard of shared mopeds, they also have not used one.
* 'No' is baseline because it has a higher frequency.
RECODE Q23 (1 2 = 0) (3 =1) (0 4 19 999 = 999) INTO SHAREDMOP.
VALUE LABELS
SHAREDMOP
0 'No'
1 'Yes'
999 'Missing value'.
VARIABLE LABELS
SHAREDMOP
'Ever used a shared moped'.
FREQUENCIES SHAREDMOP.

* Combine into one variable: [Q25_10] bus, tram en metro gaan niet snel genoeg; Waarom reist u niet vaker met bus, tram of metro?
and [Q26_9] de trein gaat niet snel genoeg; Waarom reist u niet vaker met de trein?.
* Baseline = not mentioned as it is most frequent.
FREQUENCIES Q26_9 Q25_10.
COMPUTE SPEEDPT= MEAN(Q26_9, Q25_10).
FREQUENCIES SPEEDPT.
RECODE SPEEDPT (0 = 0) (0.50 1 = 1) (19 = 999).
VALUE LABELS
SPEEDPT

0 'Not mentioned'
1 'Mentioned'
999 'Missing value'.
VARIABLE LABELS
SPEEDPT
'Public transport is perceived as not fast enough'.
FREQUENCIES SPEEDPT.

* Combine into one variable: [Q25_6] bus, tram en metro rijden niet vaak genoeg; Waarom reist u niet vaker met bus, tram of metro?
and [Q26_5] de treinen rijden niet vaak genoeg; Waarom reist u niet vaker met de trein?.
*Baseline = not mentioned as it is most frequent.
FREQUENCIES Q25_6, Q26_5.
COMPUTE FREQPT= MEAN(Q25_6, Q26_5).
RECODE FREQPT (0 = 0) (0.50 1 = 1) (19 = 999).
VALUE LABELS
FREQPT
0 'Not mentioned'
1 'Mentioned'
999 'Missing value'.
VARIABLE LABELS
FREQPT
'Public transport is perceived as not frequently enough'.
FREQUENCIES FREQPT.

* Combine into one variable: [Q25_3] bus, tram en metro zijn te duur; Waarom reist u niet vaker met bus, tram of metro?
and [Q26_3] de trein is te duur; Waarom reist u niet vaker met de trein?.
* Baseline = not mentioned as it is most frequent.
FREQUENCIES Q25_3, Q26_3.
COMPUTE COSTPT= MEAN(Q25_3, Q26_3).
RECODE COSTPT (0 = 0) (0.50 1 = 1) (19 = 999).
VALUE LABELS
COSTPT
0 'Not mentioned'
1 'Mentioned'
999 'Missing value'.
VARIABLE LABELS
COSTPT
'Public transport is perceived as too expensive'.
FREQUENCIES COSTPT.

* Combine into one variable: [Q25_2] de haltes zijn te ver weg; Waarom reist u niet vaker met bus, tram of metro?
and [Q26_2] het station is te ver weg; Waarom reist u niet vaker met de trein?.
* Baseline = not mentioned as it is most frequent.
FREQUENCIES Q25_3, Q26_3.
COMPUTE DISTANCEPT= MEAN(Q25_2, Q26_2).
RECODE DISTANCEPT (0 = 0) (0.50 1 = 1) (19 = 999).
VALUE LABELS

DISTANCEPT
0 'Not mentioned'
1 'Mentioned'
999 'Missing value'.
VARIABLE LABELS
DISTANCEPT
'Public transport is perceived as too far away'.
FREQUENCIES DISTANCEPT.

* Combine into one variable: [Q32l] veiligheid in de bus / tram / metro : Hoe denkt u over onderstaande onderwerpen in Rotterdam?
and [Q32m] veiligheid in en om metro- / treinstations : Hoe denkt u over onderstaande onderwerpen in Rotterdam?.
RECODE Q32l (0=999) (1=Copy) (2=Copy) (3=Copy) (4=Copy) (5=Copy) (6=999) (19=999) (999=999) INTO Q32l_1.
RECODE Q32m (0=999) (1=Copy) (2=Copy) (3=Copy) (4=Copy) (5=Copy) (6=999) (19=999) (999=999) INTO Q32m_1.
FREQUENCIES Q32l_1 Q32m_1.
COMPUTE SAFETYPT_proto=MEDIAN(Q32l_1, Q32m_1).
FREQUENCIES SAFETYPT_proto.

* In the case of a value of 4.5, people have no opinion and simoultaniously very postive/satisfied. These answers (2 in total) are recoded as very positive.
* Where a respondent has an answer combined with a missing value, the value of the answer that is known is taken.
* Baseline = No opinion.
RECODE SAFETYPT_proto (1 = 1) (1.5 = 1.5) (2 = 2) (2.5 = 2.5) (3 = 3) (3.5 = 3.5) (4 = 4) (4.5 = 4) (5 = 0) (500 = 1) (500.5 = 2) (501 = 3) (501.5 = 4) (502 = 0) (999 = 999) INTO SAFETYPT.
ADD VALUE LABELS
SAFETYPT
0 'No opinion'
1 'Very negative/unsatisfied'
1.5 'Very negative/unsatisfied to negative/unsatisfied'
2 'Negative/unsatisfied'
2.5 'Mixed (A combination of negative and positive)'
3 'Positive/satisfied'
3.5 'Positive/satisfied to very postive/satisfied'
4 'Very postive/satisfied'
999 'Missing value'.
VARIABLE LABELS
SAFETYPT
'Perceived safety in public transport'.
FREQUENCIES SAFETYPT.

* Combine into even larger categories due to few respondents in some categories.
COMPUTE recSAFETYPT= SAFETYPT.
RECODE recSAFETYPT (0 = 0) (1 1.5 2 = 1) (2.5 =2) (3 3.5 4 = 3) (999 =999).
VALUE LABELS
recSAFETYPT

0 'No opinion'
1 '(Very) negative/unsatisfied'
2 'Mixed (A combination of negative and positive)'
3 '(Very) positive/satisfied'
999 'Missing value'.
VARIABLE LABELS
recSAFETYPT
'Perceived safety in public transport'.
FREQUENCIES recSAFETYPT.

* Combine into one variable: [Q25_9] ik ken het systeem niet goed genoeg om er mee te reizen; Waarom reist u niet vaker met bus, tram of metro?
and [Q26_8] ik ken het systeem niet goed genoeg om er mee te reizen; Waarom reist u niet vaker met de trein?.
* Baseline = not mentioned as it is most frequent.
FREQUENCIES Q25_9, Q26_8.
COMPUTE KNOWLEDGEPT= MEAN(Q25_9, Q26_8).
RECODE KNOWLEDGEPT (0 = 0) (0.50 1 = 1) (19 = 999).
VALUE LABELS
KNOWLEDGEPT
0 'Not mentioned'
1 'Mentioned'
999 'Missing value'.
VARIABLE LABELS
KNOWLEDGEPT
'Little knowledge of the public transport system'.
FREQUENCIES KNOWLEDGEPT.

* Recode [Q16] Heeft u een fiets? and [Q17] Heeft u een elektrische fiets? in preperation of recoding into one variable whether people have a shared bike and/or e-bike.
RECODE Q16 (0 3 19 999= 999) (2 = 0) (1 = 1) INTO BIKE.
VALUE LABELS
BIKE
0 'No'
1 'Yes'
999 'Missing value'.
VARIABLE LABELS
BIKE
'Do you have a bike?'.

RECODE Q17 (0 3 19 999= 999) (2 = 0) (1 = 1) INTO EBIKE.
VALUE LABELS
EBIKE
0 'No'
1 'Yes'
999 'Missing value'.
VARIABLE LABELS
EBIKE
'Do you have an e-bike?'.

```
* Combine into one variable BIKE and EBIKE.
* Yes is basline because it is most frequent.
COMPUTE E.BIKE= MEAN(BIKE, EBIKE).
RECODE E.BIKE (0 = 1) (0.50 1 500= 0) (499.50 999 = 999).
VALUE LABELS
E.BIKE
0 'Yes'
1 'No'
999 'Missing value'.
VARIABLE LABELS
E.BIKE
'Bike and/or e-bike ownership'.
FREQUENCIES E.BIKE.

* Recode [Q54] In welke klasse valt het gezamenlijke netto (= schoon) inkomen van uw
huishouden?
* >3600 is baseline because it is most frequent.
RECODE Q54 (1 THRU 4= COPY) (5 = 0) (19 999 = 999) INTO INCOME.
VALUE LABELS
INCOME
0 '>3600 per month'
1 '< €1200 per month'
2 '€1200-1650 per month'
3 '€1650-2200 per month'
4 '€2200-3600 per month'
999 'Missing value'.
VARIABLE LABELS
INCOME
'Net household income'.
FREQUENCIES INCOME.

* Recode [Q49] Heeft u betaald werk? Zo ja, hoeveel uur per week?
* Yes is baseline because it is most frequent.
RECODE Q49 (1 =0) (2 = 1) (0 3 19 999 = 999) INTO PAIDWORK.
VALUE LABELS
PAIDWORK
0 'Yes'
1 'No'
999 'Missing value'.
VARIABLE LABELS
PAIDWORK
'Has paid work'.
FREQUENCIES PAIDWORK.

* Recode [OPL3] Opleidingsniveau.
* Highly educated is baseline because it is most frequent.
RECODE OPL3 (1 =1) (2 =2) (3 =0) (999 = 999) INTO EDUCATION.
VALUE LABELS
EDUCATION
0 'High (HBO/WO)'
```

```
1 'Low'
2 'Middle'
999 'Missing value'.
VARIABLE LABELS
EDUCATION
'Education level'.

*Recode [GESLACHT] Geslacht (volgens steekproef).
* Male is baseline because literature review shows they are more likely to use shared
mobility.
RECODE GESLACHT (1=0) (2=1) (999 = 999) INTO GENDER.
FREQUENCIES GENDER.
VALUE LABELS
GENDER
0 'Male'
1 'Female'
999 'Missing value'.
VARIABLE LABELS
GENDER
'Gender'.

* Recode [Etnicbs] Etniciteit volgens steekproef.
* Dutch is baseline because it is most frequent.
RECODE Etnicbs (LOWEST THRU 6 = COPY) (7 = 0) (8 = 7) (9 = 8) (999 = 999) INTO
preETHNICITY.
FREQUENCIES preETHNICITY.
VALUE LABELS
preETHNICITY
0 'Dutch'
1 'Surinamese'
2 'Antillian'
3 'Cape Verdian'
4 'Turkish'
5 'Moroccan'
6 'Other non-western'
7 'European (EU_27, 2007)'
8 'Other western'
999 'Missing value'.
VARIABLE LABELS
preETHNICITY
'preETHNICITY'.

* Later onwards in the logistic regression the problem of too few cases in one ore more
categories occurred. Therefore, merge some categories.
RECODE preETHNICITY (0 = 0) (1 = 2) (2 = 2) (3 = 2) (4 =2) (5 = 2) (6 = 2) (7 = 1) (8 = 1)
(999 = 999) INTO ETHNICITY.
FREQUENCIES ETHNICITY.
VALUE LABELS
ETHNICITY
0 'Dutch'
```

1 'Other western'
2 'Non-western'
999 'Missing value'.
VARIABLE LABELS
ETHNICITY
'Ethnicity'.
FREQUENCIES
ETHNICITY.

* Rename LFT into AGE.
COMPUTE AGE=LFT.
VARIABLE LABELS
AGE
'Age in years'.
FREQUENCIES AGE.

* Based on later results on AGE with logistic regression, there are too few participants in relation to shared bicycles. Therefore, recode into categories.
* Baseline is lowest age as younger citizens are more likely to use shared mobility.
RECODE LFT (999=999) (16 thru 25=1) (26 thru 35=2) (36 thru 45=3) (46 thru 55=4) (56 thru 65=5) (66 thru 85=6) INTO catAGE.
VARIABLE LABELS catAGE 'Age'.
ADD VALUE LABELS
catAGE
1 '16-25'
2 '26-35'
3 '36-45'
4 '46-55'
5 '56-65'
6 '66-85'
999 'Missing value'.
FREQUENCIES catAGE.

* Rename variables [SS2020CAT] Sociale Score 2020 buurt (klassenindeling)
and [VS2020CAT] Veiligheidsscore 2020 buurt (klassenindeling)
and [FS2020CAT] Fysieke Score 2020 buurt (klassenindeling).
* Highest categories are reference because they are mostly named most often.
* These variables are not included in the logistic regression itself, but used to determine the type of neighbourhoods people live in.
COMPUTE SOCIALSCORE=SS2020CAT.
RECODE SOCIALSCORE (1 THRU 999 = COPY).
VALUE LABELS
SOCIALSCORE
1 'Far under average'
2 'Under average'
3 'Around average (2014)'
4 'Above average'
5 'Far above average'
999 'Missing value'.
VARIABLE LABELS

```
SOCIALSCORE
'Social score neighbourhood 2020'.
FREQUENCIES SOCIALSCORE.

COMPUTE SAFETYSCORE = VS2020CAT.
RECODE SAFETYSCORE (1 THRU 999 = COPY).
VALUE LABELS
SAFETYSCORE
1 'Far under average'
2 'Under average'
3 'Around average (2014)'
4 'Above average'
5 'Far above average'
999 'Missing value'.
VARIABLE LABELS
SAFETYSCORE
'Safety score neighbourhood 2020'.
FREQUENCIES SAFETYSCORE.

COMPUTE PHYSICALSCORE = FS2020CAT.
RECODE PHYSICALSCORE (1 THRU 999 = COPY).
VALUE LABELS
PHYSICALSCORE
1 'Far under average'
2 'Under average'
3 'Around average (2014)'
4 'Above average'
5 'Far above average'
999 'Missing value'.
VARIABLE LABELS
PHYSICALSCORE
'Physical score neighbourhood 2020'.
FREQUENCIES PHYSICALSCORE.

* Recode variable [WIJKCBS] CBS-wijk (Gebied).
* Pernis only has 3 respondents, combine this with Hoogvliet due to geographical proximity
and similarity in characteristics.
* In the original dataset no area is assigned to the value 2, 9, 11 and 20.
* Use Charlois as a baseline because it scores the lowest on the three neighbourhood
classifications in terms of social, physical and safety scores.
RECODE WIJKCBS (LOWEST THROUGH HIGHEST = COPY) INTO
preCBSNEIGHBOURHOOD.
FREQUENCIES preCBSNEIGHBOURHOOD.
RECODE preCBSNEIGHBOURHOOD (1 = 10)(3 = 1) (4 = 2) (5 = 3) (6 = 4) (8 = 5)
(10 = 6) (12 = 7) (13 = 8) (14 = 9)  (15 = 0) (16 = 8) (17 = 11) (18 = 12)
(19 = 13) (21 = 14) (22 = 15) (23 = 16) (24 = 17) (25 =18) (26 = 19) (27 = 20) (999 = 999)
INTO CBSNEIGHBOURHOOD.
VARIABLE LABELS
CBSNEIGHBOURHOOD
'Neighbourhood of residence'.
```

VALUE LABELS
CBSNEIGHBOURHOOD
0 'Charlois'
1 'Delfshaven'
2 'Overschie'
3 'Noord'
4 'Hillegersberg-Schiebroek'
5 'Kralingen-Crooswijk'
6 'Feijenoord'
7 'IJsselmonde'
8 'Hoogvliet and Pernis'
9 'Prins Alexander'
10 'Rotterdam Centrum'
11 'Hoek van Holland'
12 'Spaanse Polder'
13 'Nieuw Mathenesse'
14 'Waalhaven-Eemhaven'
15 'Vondelingenplaat'
16 'Botlek-Europoort-Maasvlakte'
17 'Bedrijvenpark Rotterdam N-W'
18 'Rivium'
19 'Bedrijventerrein Schieveen'
20 'Rozenburg'
999 'Missing value'.
FREQUENCIES
CBSNEIGHBOURHOOD.

* Recode CBSNEIGHBOURHOOD because later in the logistic regression concerning usage of shared bicycles, Overschie is problematic, as well as Hoek van Holland and Rozenburg.
* Therefore, merge Overschie with Hillegersberg-Schiebroek due to locational proximity and merge Hoek van Holland and Rozenburg for the same reason.
RECODE CBSNEIGHBOURHOOD (0 = 0)(1 = 1) (2 = 4) (3 = 3) (4 = 4) (5 THRU 10 = COPY) (11 = 8) (12 THRU 19= COPY) (20 =8) (999 = 999) INTO recCBSNEIGHBOURHOOD.
VARIABLE LABELS
recCBSNEIGHBOURHOOD
'Neighbourhood of residence'.
VALUE LABELS
recCBSNEIGHBOURHOOD
0 'Charlois'
1 'Delfshaven'
3 'Noord'
4 'Hillegersberg-Schiebroek and Overschie'
5 'Kralingen-Crooswijk'
6 'Feijenoord'
7 'IJsselmonde'
8 'Hoogvliet, Pernis, Hoek van Holland and Rozenburg'
9 'Prins Alexander'
10 'Rotterdam Centrum'
12 'Spaanse Polder'

13 'Nieuw Mathenesse'
14 'Waalhaven-Eemhaven'
15 'Vondelingenplaat'
16 'Botlek-Europoort-Maasvlakte'
17 'Bedrijvenpark Rotterdam N-W'
18 'Rivium'
19 'Bedrijventerrein Schieveen'
999 'Missing value'.
FREQUENCIES
recCBSNEIGHBOURHOOD.

* Recode variable [Q32a] doorstroming van de auto in de stad: Hoe denkt u over onderstaande onderwerpen in Rotterdam?.
* No opinion is baseline.
COMPUTE CONGESTION = Q32a.
RECODE CONGESTION (0 6 19 999 = 999) (1 =1) (2 = 2) (3 =3) (4 = 4) (5 = 0).
FREQUENCIES CONGESTION.
VALUE LABELS
CONGESTION
0 'No opinion'
1 'Very negative/unsatisfied'
2 'Negative/unsatisfied'
3 'Positive/satisfied'
4 'Very positive/satisfied'
999 'Missing value'.
VARIABLE LABELS
CONGESTION
'Perceived traffic flow by car'.
FREQUENCIES CONGESTION.

* Due to later issues in expected frequencies, merge into larger categories.
RECODE CONGESTION (999 = 999) (0 = 0) (1 2 =1) (3 4 =2) INTO recCONGESTION.
FREQUENCIES CONGESTION.
VALUE LABELS
recCONGESTION
0 'No opinion'
1 '(Very) negative/unsatisfied'
2 '(Very) positive/satisfied'
999 'Missing value'.
VARIABLE LABELS
recCONGESTION
'Perceived traffic flow by car'.
FREQUENCIES recCONGESTION.

* Recode and rename variable [Q32p] het op tijd rijden van het openbaar vervoer : Hoe denkt u over onderstaande onderwerpen in Rotterdam?.
* No opinion is baseline.
COMPUTE RELIABILITYPT = Q32p.
RECODE RELIABILITYPT (0 6 19 999= 999) (1 THRU 4 = COPY) (5 = 0).
FREQUENCIES RELIABILITYPT.

VALUE LABELS
RELIABILITYPT
0 'No opinion'
1 'Very negative/unsatisfied'
2 'Negative/unsatisfied'
3 'Positive/satisfied'
4 'Very positive/satisfied'
999 'Missing value'.
VARIABLE LABELS
RELIABILITYPT
'Perceived reliability public transport'.
FREQUENCIES RELIABILITYPT.

* During the logistic regression with sharedbike and sharedmop only, rather high confidence intervals were found.
* To see if this improves with larger categories, a new variable with less categories is coded.
RECODE RELIABILITYPT (999= 999) (0 =0) (1 2 = 1) (3 4 =2) INTO
recRELIABILITYPT.
VALUE LABELS
recRELIABILITYPT
0 'No opinion'
1 '(very) negative/unsatisfied'
2 '(very) positive/satisfied'
999 'Missing value'.
VARIABLE LABELS
recRELIABILITYPT
'Perceived reliability public transport'.
FREQUENCIES recRELIABILITYPT.

* Recode and rename variable [Q34a] de prijs van een parkeervergunning voor een auto bij uw woning? : Wat vindt u van ...
* There are only few people (10) who say permit is too low. Probably combine this into a binomial variable from people who think it is or isn't too expensive.
* No opinion is baseline.
COMPUTE PARKPERMIT=Q34a.
RECODE PARKPERMIT (0 6 7 19 999 = 999) (1 = 1) (2 = 1) (3 = 2) (4 = 2) (5 =0).
FREQUENCIES PARKPERMIT.
VALUE LABELS
PARKPERMIT
0 'No opinion'
1 'Not too high (too low or just fine)'
2 'Too high (a little or much too high)'
999 'Missing value'.
VARIABLE LABELS
PARKPERMIT
'Perceived price parking permit.'.
FREQUENCIES PARKPERMIT.
* There are a lot of people for whom this question is not applicable (606 in total, formerly coded by 6). Drop this from further analysis.

```
* Recode and rename car ownership [Q13] Beschikt u gewoonlijk zelf over een auto?.
* Yes always is baseline because it is most frequent.
COMPUTE CAR = Q13.
RECODE CAR (0 6 19= 999) (1 = 0) (2 = 1) (3 4 = 2) (5 = 3).
FREQUENCIES CAR.
VALUE LABELS
CAR
0 'Yes, always'
1 'Yes, sometimes'
2 'No, but I regularly use a shared or rented car'
3 'No'
999 'Missing value'.
VARIABLE LABELS
CAR
'Car ownership'.
FREQUENCIES CAR.

* Recode and rename moped ownership [Q21] Heeft u een bromfiets, snorfiets of scooter?.
* No is baseline because it is most frequent.
COMPUTE MOPED = Q21.
RECODE MOPED (0 3 19 999= 999) (2 = 0) (1 = 1).
VALUE LABELS
MOPED
0 'No'
1 'Yes'
999 'Missing value'.
VARIABLE LABELS
MOPED
'Moped ownership'.
FREQUENCIES MOPED.

* Recode and rename OV-chipcard ownership [Q24] Heeft u een OV-chipkaart?. Yes is
baseline because it is most frequent.
COMPUTE PTPASS = Q24.
RECODE PTPASS (0 3 19 999= 999) (2 = 1) (1 = 0).
VALUE LABELS
PTPASS
0 'Yes'
1 'No'
999 'Missing value'.
VARIABLE LABELS
PTPASS
'PT-pass ownership'.
FREQUENCIES PTPASS.

* Rename variables [Q12] Heeft u een autorijbewijs? about ownership carlicenses.
* Yes is baseline because it is most frequent.
COMPUTE CARLICENSE = Q12.
RECODE CARLICENSE (0 3 19 999= 999) (2 = 1) (1 = 0).
VALUE LABELS
```

CARLICENSE
0 'Yes'
1 'No'
999 'Missing value'.
VARIABLE LABELS
CARLICENSE
'Car drivers license ownership'.
FREQUENCIES CARLICENSE.

* Rename variables [Q25_5] ik weet niet waar de haltes zijn; Waarom reist u niet vaker met bus, tram of metro?.
* No is baseline because it is most frequent.
COMPUTE LOCATIONPT = Q25_5.
RECODE LOCATIONPT (0 = 0) (1 = 1) (19 = 999).
VALUE LABELS
LOCATIONPT
0 'No'
1 'Yes'
999 'Missing value'.
VARIABLE LABELS
LOCATIONPT
'I do not know where the stops are; Why do you not travel more often by bus, tram or metro?'.
FREQUENCIES LOCATIONPT.
* Only 4 people do not know where stops are, remove from analysis.

*Rename variable [Q19_23] gezondheid/leeftijd/kan niet fietsen; Wat zou er moeten veranderen zodat u méér zou gaan fietsen?.
* Not mentioned is baseline because it is most frequent.
COMPUTE BIKEABILITY = Q19_23.
RECODE BIKEABILITY (0 = 0) (1 = 1) (19 = 999).
VALUE LABELS
BIKEABILITY
0 'Not mentioned'
1 'Mentioned'
999 'Missing value'.
VARIABLE LABELS
BIKEABILITY
'Health / age / unable to cycle; What should change so that you can cycle more?'.
FREQUENCIES BIKEABILITY.
* In the original dataset, no difference was made between the variable not being named or wether the answer was missing. Therefore, the variable will be dropped from further analysis.

* Copy some variables containing background information about the way the survey was filled in and translate their descriptions.
VARIABLE LABELS
id 'Anonymous identification number'
MODE 'Mode of survey'
Status 'Survey completed or not'
datum 'Date'
duur 'Duration of filling in the survey'

apparaat 'Device used for filling in the survey'.
VALUE LABELS
MODE
1 'Online'
2 'On paper'
3 'Face-to-face'.
VALUE LABELS
Status
1 'Succesfully completed'
2 'Active/ongoing'
3 'Broken off'
4 'Stopped by script'
5 'Stopped by respondent'
6 'Interview system closed'
7 'Revised'
8 'Signal'.
VALUE LABELS
apparaat
0 'Unknown'
1 'PC'
2 'Tablet'
3 'Smartphone'.

* Define Variable Properties of newly created variables with the right number of decimals, specification of missing values and type of measure.
FORMATS COVID SHAREDBIKE SHAREDMOP SPEEDPT FREQPT COSTPT DISTANCEPT SAFETYPT recSAFETYPT KNOWLEDGEPT E.BIKE
INCOME PAIDWORK EDUCATION GENDER preETHNICITY ETHNICITY AGE catAGE CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD SOCIALSCORE SAFETYSCORE PHYSICALSCORE CONGESTION recCONGESTION RELIABILITYPT recRELIABILITYPT PARKPERMIT CAR MOPED PTPASS CARLICENSE (F8.0).
MISSING VALUES COVID SHAREDBIKE SHAREDMOP SPEEDPT FREQPT COSTPT DISTANCEPT SAFETYPT recSAFETYPT KNOWLEDGEPT E.BIKE
INCOME PAIDWORK EDUCATION GENDER preETHNICITY ETHNICITY AGE catAGE CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD SOCIALSCORE SAFETYSCORE PHYSICALSCORE CONGESTION recCONGESTION RELIABILITYPT recRELIABILITYPT PARKPERMIT CAR MOPED PTPASS CARLICENSE (999).
VARIABLE LEVEL COVID SHAREDBIKE SHAREDMOP SPEEDPT FREQPT COSTPT DISTANCEPT SAFETYPT recSAFETYPT KNOWLEDGEPT E.BIKE
PAIDWORK GENDER preETHNICITY ETHNICITY CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD CONGESTION recCONGESTION RELIABILITYPT recRELIABILITYPT PARKPERMIT CAR MOPED PTPASS CARLICENSE INCOME EDUCATION (NOMINAL)
catAGE SOCIALSCORE SAFETYSCORE PHYSICALSCORE (ORDINAL)
AGE (SCALE).

* Save as a new dataset, with only the variables that are relevant for further analysis.

```
SAVE OUTFILE='P:\SO\VV_Fiets\06 Fietsdelen\14. Stage Chayenne\Scriptie\Data
analyse\Omnibus\omni20b  kopie omnibus VARS READY.sav'
/KEEP id MODE Status datum duur apparaat COVID
SHAREDBIKE SHAREDMOP
GENDER INCOME PAIDWORK EDUCATION preETHNICITY ETHNICITY AGE
catAGE
SPEEDPT FREQPT COSTPT DISTANCEPT SAFETYPT recSAFETYPT  E.BIKE
CONGESTION recCONGESTION RELIABILITYPT recRELIABILITYPT CAR MOPED
PTPASS
KNOWLEDGEPT CARLICENSE
CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD
SOCIALSCORE SAFETYSCORE PHYSICALSCORE.

*Get the newly made copy of the original dataset.
GET
  FILE='P:\SO\VV_Fiets\06 Fietsdelen\14. Stage Chayenne\Scriptie\Data
analyse\Omnibus\omni20b  kopie omnibus VARS READY.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.

****************************************************************************
ASSUMPTIONS CHECK
****************************************************************************
* 1. Check the potential effect of COVID since part of the data was collected before and
another part after the lockdown.
DATASET ACTIVATE DataSet1.
T-TEST GROUPS=COVID(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=INCOME PAIDWORK EDUCATION GENDER preETHNICITY
ETHNICITY AGE catAGE
SOCIALSCORE SAFETYSCORE PHYSICALSCORE
CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD
SPEEDPT CONGESTION recCONGESTION FREQPT RELIABILITYPT
recRELIABILITYPT COSTPT DISTANCEPT CAR MOPED E.BIKE PTPASS SAFETYPT
recSAFETYPT
CARLICENSE KNOWLEDGEPT
SHAREDBIKE SHAREDMOP
  /CRITERIA=CI(.95).
* There are some significant differences between the groups of people who filled in the
survey before and after the lockdown situation occurred in the NL
   *Both 1- and 2-tailed significant differences for: having paid work, education level,
ethnicity, perceived price, distance, speed & frequency PT,
    bicycle and moped ownership, driver's license ownership.
* Some can be explained like bike ownership (people may have started cycling more since
pandemic).
* But also some differences can't easily be explained, e.g.  education level, ethnicity.
* But the sample would become rather small if only pre-COVID can be included.
* Moreover, it's unclear whether people filled it in according to old habits or new.
* Therefore, the groups  before and after the pandemic are analysed as one group.
* However, any potential effect of the pandemic will be taken into account by including
COVID as a predictor to see if it improves the model.
```

```
* 2. Inspect which neighbourhoods score low on the social, safety and physical
neighbourhood scores.
* Calculate combined average social, physcial and safety score for the neighbourhoods.
COMPUTE Tot_scoresneighbourhood_mean=(SOCIALSCORE + SAFETYSCORE +
PHYSICALSCORE)/3.
FORMATS Tot_scoresneighbourhood_mean (F8.2).
MISSING VALUES Tot_scoresneighbourhood_mean (999).

* Create table to the average neighbourhood score as well as average neighbourhood score per
social, physical and safety indicator per neighbourhood.
MEANS TABLES=SOCIALSCORE SAFETYSCORE PHYSICALSCORE
Tot_scoresneighbourhood_mean BY CBSNEIGHBOURHOOD
  /CELLS=MEAN COUNT.
* Neighbourhoods that score below average (3.0) on the combined social, safety and physical
score are (from low to high):
    * Charlois, Feijenoord, Rotterdam Centrum.
 * Neighbourhoods that score above average (3.0) on the combined social, safety and physical
score are:
    * Delfshaven, Ijsselmonde, Noord, Overschie, Kralingen-Crooswijk, Hoogvliet and Pernis,
Rozenburg,  Prins Alexander, Hoek van Holland, Hillegersberg-Schiebroek.

MEANS TABLES=SOCIALSCORE SAFETYSCORE PHYSICALSCORE
Tot_scoresneighbourhood_mean BY recCBSNEIGHBOURHOOD
  /CELLS=MEAN COUNT.
* Neighbourhoods are classified below or above the combined average score in the same way
as the variable CBSNEIGHBOURHOOD.
* The analysis can thus be continued with recCBSNEIGHBOURHOOD.

* 3. Check for multicollinearity.
* Check correlations between predictors using spearman because there are ordinal variables
and there are only categorical predictors.
* Bootstrap should ideally be used to get more robust confidence intervals, but this isn't
included in the available version of SPSS available to the author of the thesis.
NONPAR CORR
  /VARIABLES= COVID
  INCOME PAIDWORK EDUCATION GENDER preETHNICITY ETHNICITY AGE
catAGE
  CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD
  SPEEDPT CONGESTION recCONGESTION FREQPT RELIABILITYPT
recRELIABILITYPT COSTPT DISTANCEPT CAR MOPED E.BIKE PTPASS SAFETYPT
recSAFETYPT
  CARLICENSE KNOWLEDGEPT
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.
OUTPUT MODIFY
  /REPORT PRINTREPORT=NO
  /SELECT TABLES
  /IF COMMANDS=[LAST]
```

```
  /TABLECELLS SELECT=[CORRELATION] SELECTDIMENSION=ROWS
SELECTCONDITION="Abs(x)>=0.5"
    BACKGROUNDCOLOR=RGB(248, 152, 29) APPLYTO=CELL.
* As can be expected, the variables that have been recoded are highly related.
* Later on, the (recoded) variables that works best for the logistic regression will be chosen.
* Having access to a car, and having a driver's license are highly correlated.
* Use having a driver's license because this is important for being able to use shared mopeds.

* Test absence of multicollinearity for shared bicycles.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT SHAREDBIKE
  /METHOD=ENTER COVID PAIDWORK EDUCATION GENDER ETHNICITY catAGE
recCBSNEIGHBOURHOOD
    SPEEDPT recCONGESTION FREQPT recRELIABILITYPT COSTPT DISTANCEPT
MOPED E.BIKE PTPASS CARLICENSE
    KNOWLEDGEPT recSAFETYPT.
* No VIF values larger than 10 or tolerance fewer than 0.1.

* Test absence of multicollinearity for shared mopeds respectively.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT SHAREDMOP
  /METHOD=ENTER COVID PAIDWORK EDUCATION GENDER ETHNICITY catAGE
recCBSNEIGHBOURHOOD
    SPEEDPT recCONGESTION FREQPT recRELIABILITYPT COSTPT DISTANCEPT
MOPED E.BIKE PTPASS CARLICENSE
    KNOWLEDGEPT recSAFETYPT.
* No VIF values larger than 10 or tolerance fewer than 0.1.

* To see whether the usage of shared bicycles and mopeds are related, a correlation test
between the outcome variables is run.
NONPAR CORR
  /VARIABLES=SHAREDMOP SHAREDBIKE
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.
OUTPUT MODIFY
  /REPORT PRINTREPORT=NO
  /SELECT TABLES
  /IF COMMANDS=[LAST]
  /TABLECELLS SELECT=[CORRELATION] SELECTDIMENSION=ROWS
SELECTCONDITION="Abs(x)>=0.5"
    BACKGROUNDCOLOR=RGB(248, 152, 29) APPLYTO=CELL.
* The two outcome variables are highly correlated.
```

* Nevertheless, differences may exist in the extent to which specific predictors influence shared bicycles and mopeds respectively.
* These potential differences will be examined later on in two seperate logistic regressions.

* 4. Check for incomplete information.
* Because of the large number of predictors, bivariate contingency tables are created.
* Examine expected frequencies to see they are more than 1 and no more than 20% is less than 5.
* Expected frequencies for shared bikes.

```
CROSSTABS
  /TABLES=COVID INCOME PAIDWORK EDUCATION GENDER preETHNICITY
ETHNICITY AGE catAGE
CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD
SPEEDPT CONGESTION recCONGESTION FREQPT RELIABILITYPT
recRELIABILITYPT COSTPT DISTANCEPT MOPED E.BIKE PTPASS SAFETYPT
recSAFETYPT
CARLICENSE KNOWLEDGEPT BY SHAREDBIKE
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ CC PHI LAMBDA CORR
  /CELLS=COUNT EXPECTED RESID SRESID
  /COUNT ROUND CELL.
```

* Expected frequencies are alright expect for:
   * preETHNICITY 6 cells <5: Min expected count 1.46 but makes up 33.3% --> Possibly not alright
   * AGE 73 cells <5: Min expected count .22 and makes up 52.1% --> Not alright.
   * CBSNEIGHBOURHOOD 4 cells <5: Min expected count 1.32 making up 15.4% --> Possibly not alright
   * Congestion 1 cell < 5: Min exp. count 1.59 making up 10% --> Possibly not alright
   * SafetyPT 3 cells <5: Min exp. count .67 making up 18.8% --> Not alright.
   * Reliability PT 1 cell < 5: Min exp. count 1.18 making up 10% --> Possibly not alright.

* Expected frequencies for shared mopeds.

```
CROSSTABS
  /TABLES=COVID INCOME PAIDWORK EDUCATION GENDER preETHNICITY
ETHNICITY AGE catAGE
CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD
SPEEDPT CONGESTION recCONGESTION FREQPT RELIABILITYPT
recRELIABILITYPT COSTPT DISTANCEPT MOPED E.BIKE PTPASS SAFETYPT
recSAFETYPT
CARLICENSE KNOWLEDGEPT BY SHAREDMOP
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ CC PHI LAMBDA CORR
  /CELLS=COUNT EXPECTED RESID SRESID
  /COUNT ROUND CELL.
```

* Expected frequencies are alright expect for:
   * preETHNICITY 3 cells <5: Min exp. count 2.00, making up 16.7% --> Possibly not alright.
   * AGE 73 cells <5: Min expected count .30 and makes up 52.1% --> Not alright
   * CBSNEIGHBOURHOOD 3 cells <5: Min expected count 1.80 making up 11.5% --> Possibly not alright.

```
   * Congestion 1 cell < 5: Min exp. count 2.19 making up 10% -->  Possibly not alright.
   * recCBSNEIGHBOURHOOD 1 cells <5: Min expected count 3.70 making up 4.5% -->
Possibly not alright.
   * Reliability PT 1 cell < 5: Min exp. count 1.65 making up 10% --> Possibly not alright.
   * Safety PT <5: Min exp. count .92 making up 12.% -->  Possibly not alright.

* 5. Check normality.
DATASET ACTIVATE DataSet1.
PPLOT
  /VARIABLES=COVID
  INCOME PAIDWORK EDUCATION GENDER preETHNICITY ETHNICITY AGE
catAGE
  CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD
  SPEEDPT CONGESTION recCONGESTION FREQPT RELIABILITYPT
recRELIABILITYPT COSTPT DISTANCEPT CAR MOPED E.BIKE PTPASS SAFETYPT
recSAFETYPT
  CARLICENSE KNOWLEDGEPT
  /NOLOG
  /NOSTANDARDIZE
  /TYPE=P-P
  /FRACTION=BLOM
  /TIES=MEAN
  /DIST=NORMAL.
* Visually, preETHNICITY, perceived reliability  (the variable that is not recoded), car
ownership, perceived safety in PT (both recoded and not) seem skewed.

* Check normality statistically.
FREQUENCIES VARIABLES=COVID
  INCOME PAIDWORK EDUCATION GENDER preETHNICITY ETHNICITY AGE
catAGE
  CBSNEIGHBOURHOOD recCBSNEIGHBOURHOOD
  SPEEDPT CONGESTION recCONGESTION FREQPT RELIABILITYPT
recRELIABILITYPT COSTPT DISTANCEPT CAR MOPED E.BIKE PTPASS SAFETYPT
recSAFETYPT
  CARLICENSE KNOWLEDGEPT
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV VARIANCE RANGE MINIMUM MAXIMUM SEMEAN
MODE SKEWNESS SESKEW KURTOSIS SEKURT
  /BARCHART FREQ
  /ORDER=ANALYSIS.

* Interpretation based on numbers of skewness and kurtosis.
    * Some variables are not/little skewed (Skewness -0.5-0.5) like: INCOME, PAIDWORK,
EDUCATION, GENDER, AGE, catAGE, recNEIGHBOURHOOD, CONGESTEION,
recCONGESTION,
      PRICEPT.
    * Some variables are moderately skewed (Skewness -1.0- -0.5 // 0.5 - 1) like: COVID,
preETHNICITY, ETHNICITY, NEIGHBOURHOOD, PARKPERMIT
```

* Some varibales are highly skewed (Skewness -1<->1) like: SPEEDPT, FREQPT, RELIABILITYPT, recRELIABILITY, DISTANCEPT, CAR, MOPED, E.BIKE, PTPASS, SAFETYPT, recSAFETYPT, CARLICENSE
KNOWLEDGEPT.

* Some variables are not/little skewed (Kurtosis -0.5 // 0.5-) like: CAR, recSAFETYPT, CARLICENSE.
* Some variables are moderately skewed (Kurtosis -1.0 - 0.5 // 0.5 - 1) like: preETHNICITY, RELIABILITY, recRELIABILITY, E.BIKE
* Some varibales are highly skewed (Kurtosis -1<->1): COVID, INCOME, PAIDWORK, EDUCATION, GENDER, ETHNICITY, AGE, catAGE, NEIGHBOURHOOD, recNEIGHBOURHOOD, SPEEDPT, FREQPT,
CONGESTION, recCONGESTION, SPEEDPT, PRICEPT, PARKPERMIT, DISTANCEPT, MOPED, PTPASS, SAFETYPT, KNOWLEDGEPT.

* There is some inconsistency between whether variables are skewed using Skewness or Kurtosis measure.
* Both measures agree on variables being moderately skewed for: preETHNICITY.
* Both measures agree on variables being highly skewed for: SPEEDPT, FREQPT, DISTANCEPT, MOPED, PTPASS, SAFETYPT, KNOWLEDGEPT.
* For the other variables, the measures disagree whether they are little, moderatly or highly skewed.
* However, as the sample size is rather large (>1000 respondents), no further adaptations are made to the data. Take the distortions into account though for intepretating significance.

* CONCLUSION ASSUMPTIONS.
* Based on the checking of the assumptions:
* Caricense remains included in the analysis but owning a car is removed due to the high correlation between the two predictors.
* ETHNICITY is chosen, preETHNICITY is removed due to the phenomenon of incomplete information.
* catAGE instead of Age is chosen due to problems in relation to the phenomenon of incomplete information.
* recCBSneighbourhood is chosen instead of CBSneighbourhood due to problems in relation to the phenomenon of incomplete information..
* recSafetyPT is chosen instead of SafetyPT due to problems in relation to the phenomenon of incomplete information.,
* recRELIABILITYPT is chosen instead of RELIABILITYPT due to problems in relation to the phenomenon of incomplete information.

****
FINAL DESCRIPTIVES
****
* Distribution COVID.

```
CTABLES
  /VLABELS VARIABLES=COVID DISPLAY=LABEL
  /TABLE COVID [C][COLPCT.TOTALN COMMA40.1]
  /CATEGORIES VARIABLES=COVID ORDER=A KEY=VALUE EMPTY=INCLUDE
    MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.
```

```
* Distribution socio-economic  variables.
CTABLES
  /VLABELS VARIABLES=GENDER PAIDWORK EDUCATION ETHNICITY catAGE
DISPLAY=LABEL
  /TABLE GENDER [C][COLPCT.TOTALN COMMA40.1] + PAIDWORK
[C][COLPCT.TOTALN COMMA40.1] + EDUCATION
    [C][COLPCT.TOTALN COMMA40.1] + ETHNICITY [C][COLPCT.TOTALN
COMMA40.1] + catAGE [C][COLPCT.TOTALN
    COMMA40.1]
  /CATEGORIES VARIABLES=GENDER PAIDWORK EDUCATION ETHNICITY
catAGE ORDER=A KEY=VALUE EMPTY=INCLUDE
    MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Distribution neighbourhood residence.
CTABLES
  /VLABELS VARIABLES=recCBSNEIGHBOURHOOD DISPLAY=LABEL
  /TABLE recCBSNEIGHBOURHOOD [COLPCT.TOTALN COMMA40.1]
  /CATEGORIES VARIABLES=recCBSNEIGHBOURHOOD ORDER=A KEY=VALUE
EMPTY=INCLUDE MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Distribution transport options variables.
CTABLES
  /VLABELS VARIABLES=SPEEDPT FREQPT COSTPT DISTANCEPT
recRELIABILITYPT recsafetyPT recCONGESTION E.BIKE MOPED
    PTPASS
    DISPLAY=LABEL
  /TABLE SPEEDPT [COLPCT.TOTALN COMMA40.1] + FREQPT [COLPCT.TOTALN
COMMA40.1] + COSTPT
    [COLPCT.TOTALN COMMA40.1] + DISTANCEPT [COLPCT.TOTALN COMMA40.1]
+ recRELIABILITYPT [COLPCT.TOTALN
    COMMA40.1] + recsafetyPT [COLPCT.TOTALN COMMA40.1] + recCONGESTION
[COLPCT.TOTALN COMMA40.1] + E.BIKE [COLPCT.TOTALN COMMA40.1] +
MOPED
    [COLPCT.TOTALN COMMA40.1] + PTPASS [COLPCT.TOTALN COMMA40.1]
  /CATEGORIES VARIABLES=SPEEDPT FREQPT COSTPT DISTANCEPT
recRELIABILITYPT recCONGESTION E.BIKE MOPED
    PTPASS ORDER=A KEY=VALUE EMPTY=INCLUDE MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Distribution competencies variables.
CTABLES
  /VLABELS VARIABLES=KNOWLEDGEPT CARLICENSE DISPLAY=LABEL
  /TABLE KNOWLEDGEPT [COLPCT.TOTALN  'Sample (n = 1077)' COMMA40.1] +
CARLICENSE [COLPCT.TOTALN 'Sample (n = 1077)' COMMA40.1]
  /CATEGORIES VARIABLES=KNOWLEDGEPT CARLICENSE ORDER=A
KEY=VALUE EMPTY=INCLUDE MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.
```

```
* Distribution usage shared bicycles and mopeds.
CTABLES
  /VLABELS VARIABLES=SHAREDBIKE SHAREDMOP DISPLAY=LABEL
  /TABLE SHAREDBIKE [COLPCT.TOTALN  'Sample (n = 1077)' COMMA40.1]  +
SHAREDMOP [COLPCT.TOTALN  'Sample (n = 1077)' COMMA40.1]
  /CATEGORIES VARIABLES=SHAREDBIKE SHAREDMOP ORDER=A KEY=VALUE
EMPTY=INCLUDE MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

*************************************************************************
DESCRIPTIVE RESULTS
*************************************************************************
* COVID.
CTABLES
  /VLABELS VARIABLES=COVID SHAREDBIKE SHAREDMOP
    DISPLAY=LABEL
  /TABLE COVID [ROWPCT.TOTALN '' COMMA40.1] BY SHAREDBIKE [C] +
SHAREDMOP [C]
  /CATEGORIES VARIABLES=COVID SHAREDBIKE SHAREDMOP
    ORDER=A KEY=VALUE EMPTY=INCLUDE MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Socio-economic variables.
CTABLES
  /VLABELS VARIABLES= GENDER PAIDWORK EDUCATION ETHNICITY catAGE
SHAREDBIKE SHAREDMOP
    DISPLAY=LABEL
  /TABLE GENDER [ROWPCT.TOTALN '' COMMA40.1] + PAIDWORK
    [ROWPCT.TOTALN '' COMMA40.1] + EDUCATION [ROWPCT.TOTALN ''
COMMA40.1] + ETHNICITY [ROWPCT.TOTALN ''
    COMMA40.1] + catAGE [ROWPCT.TOTALN '' COMMA40.1] BY SHAREDBIKE [C] +
SHAREDMOP [C]
  /CATEGORIES VARIABLES=GENDER PAIDWORK EDUCATION ETHNICITY
catAGE SHAREDBIKE SHAREDMOP
    ORDER=A KEY=VALUE EMPTY=INCLUDE MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Frequencies neighbourhoods.
CTABLES
  /VLABELS VARIABLES=recCBSNEIGHBOURHOOD SHAREDBIKE SHAREDMOP
DISPLAY=LABEL
  /TABLE recCBSNEIGHBOURHOOD [ROWPCT.TOTALN '' COMMA40.1] BY
SHAREDBIKE [C] + SHAREDMOP [C]
  /CATEGORIES VARIABLES=recCBSNEIGHBOURHOOD SHAREDBIKE
SHAREDMOP ORDER=A KEY=VALUE EMPTY=INCLUDE
    MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Frequencies transport options variables related to mobility poverty.
```

```
CTABLES
  /VLABELS VARIABLES=SPEEDPT FREQPT COSTPT DISTANCEPT
recRELIABILITYPT recSAFETYPT recCONGESTION E.BIKE MOPED
    PTPASS SHAREDBIKE SHAREDMOP
    DISPLAY=LABEL
  /TABLE SPEEDPT [C][ROWPCT.TOTALN '' COMMA40.1] + FREQPT
[C][ROWPCT.TOTALN '' COMMA40.1] + COSTPT
    [C][ROWPCT.TOTALN '' COMMA40.1] + DISTANCEPT [C][ROWPCT.TOTALN ''
COMMA40.1] + recRELIABILITYPT
    [C][ROWPCT.TOTALN '' COMMA40.1] + recSAFETYPT [C][ROWPCT.TOTALN ''
COMMA40.1] + recCONGESTION
    [C][ROWPCT.TOTALN '' COMMA40.1] + E.BIKE [C][ROWPCT.TOTALN ''
COMMA40.1] + MOPED
    [C][ROWPCT.TOTALN '' COMMA40.1] + PTPASS [C][ROWPCT.TOTALN ''
COMMA40.1]
    BY SHAREDBIKE [C] + SHAREDMOP [C]
  /CATEGORIES VARIABLES=SPEEDPT [0, 1, OTHERNM] EMPTY=INCLUDE
  /CATEGORIES VARIABLES=FREQPT COSTPT DISTANCEPT recRELIABILITYPT
recSAFETYPT recCONGESTION E.BIKE MOPED PTPASS
    SHAREDBIKE SHAREDMOP ORDER=A KEY=VALUE EMPTY=INCLUDE
MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Frequencies competencies related to mobility poverty.
CTABLES
  /VLABELS VARIABLES=KNOWLEDGEPT CARLICENSE SHAREDBIKE
SHAREDMOP DISPLAY=LABEL
  /TABLE KNOWLEDGEPT [ROWPCT.TOTALN '' COMMA40.1] + CARLICENSE
[ROWPCT.TOTALN '' COMMA40.1] BY SHAREDBIKE [C]
    + SHAREDMOP [C]
  /CATEGORIES VARIABLES=KNOWLEDGEPT CARLICENSE SHAREDBIKE
SHAREDMOP ORDER=A KEY=VALUE EMPTY=INCLUDE
    MISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

****************************************************************************
TOWARDS LOGISTIC REGRESSION
****************************************************************************
* PRE-LOG REGRESSION SHARED BICYCLES.
* Check for each variable what its regression model looks like.
* COVID.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER COVID
  /CONTRAST (COVID)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
```

```
* 16 missing cases
* initial model classifies 92.7% right
* constant is  p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .001 and Nagelkerke .003
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1

* INCOME.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER INCOME
  /CONTRAST (INCOME)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 330 missing cases
* initial model classifies 91.4% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.05
* Cox & Snells R .013 and Nagelkerke .029
* Classification percentage correct 91.4%
* Variables in euqation (Wald) p < 0.05, CI does not include 1
* Small confidence intervals.

* PAIDWORK.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER PAIDWORK
  /CONTRAST (PAIDWORK)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 127 missing cases
* initial model classifies 92.4% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .022 and Nagelkerke .054
* Classification percentage correct 92.4%
* Variables in euqation (Wald) p < 0.00, CI does not include 1
* Small confidence intervals.
* Choose paid work over income, because it has less missing values and classifies better.
```

```
* EDUCATION.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER EDUCATION
  /CONTRAST (EDUCATION)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 49 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .041 and Nagelkerke .101
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p < 0.00, CI does not include 1
* Small confidence intervals.

* GENDER.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER GENDER
  /CONTRAST (GENDER)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 25 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .002 and Nagelkerke .005
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1

* preETHNICITY had too few participants in each category. Try again with ETHNICITY.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER ETHNICITY
  /CONTRAST (ETHNICITY)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 25 missing cases
```

```
* initial model classifies 92.7% right
* constant is p <.01.
* BLOCK 1.
* Model is p < .05
* Cox & Snells R .007  and Nagelkerke .026
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p <.05 , CI does not include 1
* Confidence interval is rather small.

* AGE --> too few particiapnts across the various ages so try again with catAGE.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER catAGE
  /CONTRAST (catAGE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 16 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .071 and Nagelkerke .175
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p < 0.05 and p < .01, CI does not include 1
* Small CI"s.

* CBSNEIGHBOURHOOD too high CI, try again with recCBSNEIGHBOURHOOD.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER recCBSNEIGHBOURHOOD
  /CONTRAST (recCBSNEIGHBOURHOOD)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 25 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.05
* Cox & Snells R .021 and Nagelkerke .051
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p < 0.05, CI does not include 1
* High CI.

* SPEEDPT.
```

```
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER SPEEDPT
  /CONTRAST (SPEEDPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 41 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .002 and Nagelkerke .004
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

* FREQPT.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER FREQPT
  /CONTRAST (FREQPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 41 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .002 and Nagelkerke .004
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

* RELIABILITYPT has very high CI's, try again with recRELIABILITYPT.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER recRELIABILITYPT
  /CONTRAST (recRELIABILITYPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* Still very large confidence interval, remove from analysis.

* COSTPT.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
```

```
  /METHOD=ENTER COSTPT
  /CONTRAST (COSTPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 41 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .003 and Nagelkerke .008
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

* DISTANCEPT.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER DISTANCEPT
  /CONTRAST (DISTANCEPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 41 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .001 and Nagelkerke .001
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

*MOPED.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER MOPED
  /CONTRAST (MOPED)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 19 missing cases
* initial model classifies 92.8% right
* constant is p < .01.
* BLOCK 1.
```

```
* Model is p > 0.05
* Cox & Snells R .001 and Nagelkerke .002
* Classification percentage correct 92.8%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

*E.BIKE.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER E.BIKE
  /CONTRAST (E.BIKE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 21 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .012 and Nagelkerke .029
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p < 0.01, CI does not include 1.
* Somewhat high CI.

*PTPASS.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER PTPASS
  /CONTRAST (PTPASS)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 19 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .008 and Nagelkerke .020
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p < 0.05, CI does not include 1.
* Very high confidence interval though.

*SAFETYPT nor recSafetyPT can be run because no opinion has no participants in this
category. Remove from further analysis.

*KNOWLEDGEPT.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
```

```
  /METHOD=ENTER KNOWLEDGEPT
  /CONTRAST (KNOWLEDGEPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 41 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .003 and Nagelkerke .007
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

*DISTANCEPT.
 LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER DISTANCEPT
  /CONTRAST (DISTANCEPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 58 missing cases
* initial model classifies 92.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .001 and Nagelkerke .001
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

* CARLICENSE.
 LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER CARLICENSE
  /CONTRAST (CARLICENSE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 20 missing cases
* initial model classifies 92.8% right
* constant is p < .01.
* BLOCK 1.
```

```
* Model is p < 0.01
* Cox & Snells R .014 and Nagelkerke .035
* Classification percentage correct 92.8%
* Variables in euqation (Wald) p < 0.01, CI does not include 1.
* High CI's.

* CONGESTION.
 LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER CONGESTION
  /CONTRAST (CONGESTION)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 71 missing cases
* initial model classifies 92.4% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.01
* Cox & Snells R .004 and Nagelkerke .010
* Classification percentage correct 92.4%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

* recCONGESTION.
 LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER recCONGESTION
  /CONTRAST (recCONGESTION)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 71 missing cases
* initial model classifies 92.4% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.01
* Cox & Snells R .002 and Nagelkerke .005
* Classification percentage correct 92.4%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

* PRE-LOG REGRESSION SHARED MOPEDS. Check for each variable what it regression
model does.
* COVID.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER COVID
  /CONTRAST (COVID)=Indicator(1)
```

```
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 17 missing cases
* initial model classifies 90.1% right
* constant is  p < .01.
* BLOCK 1.
* Model is p < .05
* Cox & Snells R .005 and Nagelkerke .012
* Classification percentage correct 90.1%
* Variables in euqation (Wald) p < 0.05, CI does not include 1
* Small confidence intervals.

* INCOME.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER INCOME
  /CONTRAST (INCOME)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 333 missing cases
* initial model classifies 88.2% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.05
* Cox & Snells R .025 and Nagelkerke .048
* Classification percentage correct 88.2%
* Variables in euqation (Wald) p < 0.05 and p <.01, CI does not include 1
* Small confidence intervals.

* PAIDWORK.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER PAIDWORK
  /CONTRAST (PAIDWORK)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 128 missing cases
* initial model classifies 89.7% right
* constant is p < .01.
* BLOCK 1.
```

```
* Model is p < 0.01
* Cox & Snells R .026 and Nagelkerke .053
* Classification percentage correct 89.7%
* Variables in euqation (Wald) p < 0.01, CI does not include 1
* Small confidence intervals.
* Choose paid work over income, because it has less missing values and classifies better.

* EDUCATION.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER EDUCATION
  /CONTRAST (EDUCATION)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 50 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .049 and Nagelkerke .103
* Classification percentage correct  90.0%
* Variables in euqation (Wald) p < 0.01, CI does not include 1
* Small confidence intervals.

* GENDER.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER GENDER
  /CONTRAST (GENDER)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 26 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.05
* Cox & Snells R .006 and Nagelkerke .012
* Classification percentage correct 90.0%
* Variables in euqation (Wald) p < 0.05, CI does not include 1
* Small confidence intervals.

* preETHNICITY --> too few participants in each category. Try again with ETHNICITY.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER ETHNICITY
```

```
  /CONTRAST (ETHNICITY)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 26 missing cases
* initial model classifies 90.0% right
* constant is p <.01.
* BLOCK 1.
* Model is p >.05
* Cox & Snells R .002  and Nagelkerke .004
* Classification percentage correct 90.0%
* Variables in euqation (Wald) p >.05 , CI does include 1

* AGE too few particiapnts so try again with catAGE.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER catAGE
  /CONTRAST (catAGE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 17 missing cases
* initial model classifies 90.1% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .0109and Nagelkerke .229
* Classification percentage correct 90.1%
* Variables in euqation (Wald) p < 0.01, CI does not include 1
* Small confidence intervals.

* CBSNEIGHBOURHOOD too few particiapnts, use recCBSNEIGHBOURHOOD.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER recCBSNEIGHBOURHOOD
  /CONTRAST (recCBSNEIGHBOURHOOD)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 16 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
```

```
* Model is p < 0.01
* Cox & Snells R .034and Nagelkerke .072
* Classification percentage correct 90.0%
* Variables in euqation (Wald) p < 0.05 and p < .01, CI does not include 1
* Big CI's

* SPEEDPT.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER SPEEDPT
  /CONTRAST (SPEEDPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 42 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
* Model is p <.01
* Cox & Snells R .008 and Nagelkerke .016
* Classification percentage correct 90.0%
* Variables in euqation (Wald) p < 0.01, CI does not include 1.
* Small CI interval.

* FREQPT.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER FREQPT
  /CONTRAST (FREQPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 42 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .002 and Nagelkerke .003
* Classification percentage correct 90.0%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

* RELIABILITYPT too few particiapnts, so use recRELIABILITYPT.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER recRELIABILITYPT
  /CONTRAST (recRELIABILITYPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
```

```
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 59 missing cases
* initial model classifies 89.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.05
* Cox & Snells R .008 and Nagelkerke .017
* Classification percentage correct 89.7%
* Variables in euqation (Wald) p < 0.05, CI does not include 1.
* Large confidence interval.

* COSTPT.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER COSTPT
  /CONTRAST (COSTPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 42 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .008 and Nagelkerke .017
* Classification percentage correct 90.0%
* Variables in euqation (Wald) p < 0.01, CI does not include 1.
* Small confidence interval.

* DISTANCEPT.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER DISTANCEPT
  /CONTRAST (DISTANCEPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 42 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
```

```
* Cox & Snells R .000 and Nagelkerke .000
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p > 0.05, CI does include 1.

*MOPED.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER MOPED
  /CONTRAST (MOPED)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 20 missing cases
* initial model classifies 90.1% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .001 and Nagelkerke .003
* Classification percentage correct 90.1%
* Variables in euqation (Wald) p > 0.05, CI does include 1.
* Small CI.

*E.BIKE.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER E.BIKE
  /CONTRAST (E.BIKE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 21 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .008 and Nagelkerke .018
* Classification percentage correct 92.7%
* Variables in euqation (Wald) p < 0.01, CI does not include 1.
* Small confidence interval.

*PTPASS.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER PTPASS
  /CONTRAST (PTPASS)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
```

```
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 20 missing cases
* initial model classifies 90.1% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.05
* Cox & Snells R .006 and Nagelkerke .013
* Classification percentage correct 90.1%
* Variables in euqation (Wald) p < 0.05, CI does not include 1.
* High confidence interval though.

*SAFETYPT large CI's, try with recSAFETYPT.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER recSAFETYPT
  /CONTRAST (recSAFETYPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 55 missing cases
* initial model classifies 89.7% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .38 and Nagelkerke .078
* Classification percentage correct 89.7%
* Variables in euqation (Wald) p < 0.01, CI does not include 1.
* Very high confidence interval

*KNOWLEDGEPT.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER KNOWLEDGEPT
  /CONTRAST (KNOWLEDGEPT)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 42 missing cases
* initial model classifies 90.0% right
* constant is p < .01.
* BLOCK 1.
* Model is p > 0.05
* Cox & Snells R .002 and Nagelkerke .005
```

```
* Classification percentage correct 90.0%
* Variables in euqation (Wald) p > 0.05, CI does  include 1.

* CARLICENSE.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER CARLICENSE
  /CONTRAST (CARLICENSE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 21 missing cases
* initial model classifies 90.1% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .012 and Nagelkerke .025
* Classification percentage correct 90.1%
* Variables in euqation (Wald) p < 0.01, CI does not include 1.
* CI is somewhat on the higher side.

* CONGESTION high CI's, try again with recCONGESTION.
 LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER CONGESTION
  /CONTRAST (CONGESTION)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(999) CUT(0.5).
* BLOCK 0.
* 71 missing cases
* initial model classifies 89.6% right
* constant is p < .01.
* BLOCK 1.
* Model is p < 0.01
* Cox & Snells R .020 and Nagelkerke .040
* Classification percentage correct 89.6%
* Variables in euqation (Wald) p < 0.05 and p < 0.01, CI does not include 1.
* CI is still somewhat high.

* Based on this first exploration, the following variables are included in the inititial logistic regression as they are significant for either
shared bicycles and/or mopeds:
* COVID, GENDER, PAIDWORK, EDUCATION, ETHNICITY, catAGE
SPEEDPT, COSTPT, recCONGESTION, recRELIABILITYPT, E.BIKE, recSAFETYPT, PTPASS
CARLICENSE
```

recCBSNEIGHBOURHOOD.

* Note that recCONGESTION is chosen because it did not yield as high confidence interval in the regression with shard mopeds
For constistency with this, recCONGESTION is also used for shared bicycles.

* The variables that were not significant were inspected to see whether they accounted for a notable proportion of variance explained
As they had very small proportions of variance explained, these variables are not included for the sake of parsimony.

```
*****************************************************************************
LOGISTIC REGRESSION: INITIAL MODELS
*****************************************************************************
* LOGISTIC REGRESSION USAGE SHARED BICYCLES.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER COVID
  /METHOD=ENTER GENDER PAIDWORK EDUCATION ETHNICITY catAGE
  /METHOD=ENTER recCBSNEIGHBOURHOOD
  /METHOD=ENTER SPEEDPT COSTPT recSAFETYPT recCONGESTION
recRELIABILITYPT E.BIKE PTPASS
  /METHOD=ENTER CARLICENSE
  /CONTRAST (COVID)=Indicator(1)
  /CONTRAST (GENDER)=Indicator(1)
  /CONTRAST (PAIDWORK)=Indicator(1)
  /CONTRAST (EDUCATION)=Indicator(1)
  /CONTRAST (ETHNICITY)=Indicator(1)
  /CONTRAST (recCBSNEIGHBOURHOOD)=Indicator(1)
  /CONTRAST (SPEEDPT)=Indicator(1)
  /CONTRAST (COSTPT)=Indicator(1)
  /CONTRAST (recSAFETYPT)=Indicator(1)
  /CONTRAST (recCONGESTION)=Indicator(1)
  /CONTRAST (recRELIABILITYPT)=Indicator(1)
  /CONTRAST (E.BIKE)=Indicator(1)
  /CONTRAST (PTPASS)=Indicator(1)
  /CONTRAST (KNOWLEDGEPT)=Indicator(1)
  /CONTRAST (CARLICENSE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(30) CUT(0.5).
* Upon inspection recSAFETYPT yielded extreme SE's which is a sign of an insufficient
sample to predictor ratio.

* Therefore, the model is re-run without recSAFETYPT.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER COVID
  /METHOD=ENTER GENDER PAIDWORK EDUCATION ETHNICITY catAGE
  /METHOD=ENTER recCBSNEIGHBOURHOOD
```

```
  /METHOD=ENTER SPEEDPT COSTPT recCONGESTION recRELIABILITYPT E.BIKE
PTPASS
  /METHOD=ENTER CARLICENSE
  /CONTRAST (COVID)=Indicator(1)
  /CONTRAST (GENDER)=Indicator(1)
  /CONTRAST (PAIDWORK)=Indicator(1)
  /CONTRAST (EDUCATION)=Indicator(1)
  /CONTRAST (ETHNICITY)=Indicator(1)
  /CONTRAST (recCBSNEIGHBOURHOOD)=Indicator(1)
  /CONTRAST (SPEEDPT)=Indicator(1)
  /CONTRAST (COSTPT)=Indicator(1)
  /CONTRAST (recCONGESTION)=Indicator(1)
  /CONTRAST (recRELIABILITYPT)=Indicator(1)
  /CONTRAST (E.BIKE)=Indicator(1)
  /CONTRAST (PTPASS)=Indicator(1)
  /CONTRAST (KNOWLEDGEPT)=Indicator(1)
  /CONTRAST (CARLICENSE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(30) CUT(0.5).
* recRELIABILITYPT has unrealistically  high confidence intervals, remove this variable.

* SHARED MOPEDS LOG REGRESSION.
* recSAFETYPT did not extraordinary SE's for shared mopeds
* For consistency with the shared bicycles, recSAFETYPT is also left out of the model for
shared mopeds.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER COVID
  /METHOD=ENTER GENDER PAIDWORK EDUCATION  ETHNICITY catAGE
  /METHOD=ENTER recCBSNEIGHBOURHOOD
  /METHOD=ENTER SPEEDPT COSTPT recCONGESTION recRELIABILITYPT E.BIKE
PTPASS
  /METHOD=ENTER CARLICENSE
  /CONTRAST (COVID)=Indicator(1)
  /CONTRAST (GENDER)=Indicator(1)
  /CONTRAST (PAIDWORK)=Indicator(1)
  /CONTRAST (EDUCATION)=Indicator(1)
  /CONTRAST (ETHNICITY)=Indicator(1)
  /CONTRAST (recCBSNEIGHBOURHOOD)=Indicator(1)
  /CONTRAST (SPEEDPT)=Indicator(1)
  /CONTRAST (COSTPT)=Indicator(1)
  /CONTRAST (recCONGESTION)=Indicator(1)
  /CONTRAST (recRELIABILITYPT)=Indicator(1)
  /CONTRAST (E.BIKE)=Indicator(1)
  /CONTRAST (PTPASS)=Indicator(1)
  /CONTRAST (KNOWLEDGEPT)=Indicator(1)
  /CONTRAST (CARLICENSE)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
```

```
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(30) CUT(0.5).
* recRELIABILITYPT has unrealistically high confidence intervals, remove this variable for the final model

* The blocks with COVID and recNEIGHBOURHOOD are removed for the final model
    For both shared bicycles and mopeds, the blocks of COVID and recNEIGHBOURHOOD have non-significant Omnibus tests
    Adding these two variables also only explain a very small portion of variance
    For shared mopeds, the addition of recNEIGHBOURHOOD into the model increases the percentage of correct classifications with 1.2%, for shared bicycles it reduced it by 0.1%.
* Transport related risk factors remain included in both final models for constincy
    The block with transport related risk factors is not significant for bicycles, but it is for shared mopeds.
* recRELIABILITYPT is removed for the final model due to high confidence intervals.
* recCONGESTION is kept in the analysis for consistency, even though it has quite high confidence intervals for shared mopeds too. Take this into account when interpretating this variable's significance.

* Before continuing, manually clear all saved PRED PGROUP COOK LEVER DFBETA ZRESID from variable list.

****************************************************************************
LOGISTIC REGRESSION: FINAL MODELS
****************************************************************************
* Log regression shared bicycles.
LOGISTIC REGRESSION VARIABLES SHAREDBIKE
  /METHOD=ENTER GENDER PAIDWORK EDUCATION ETHNICITY catAGE
  /METHOD=ENTER CARLICENSE
  /METHOD=ENTER SPEEDPT COSTPT recCONGESTION E.BIKE PTPASS
  /CONTRAST (GENDER)=Indicator(1)
  /CONTRAST (PAIDWORK)=Indicator(1)
  /CONTRAST (EDUCATION)=Indicator(1)
  /CONTRAST (ETHNICITY)=Indicator(1)
  /CONTRAST (catAGE)=Indicator(1)
  /CONTRAST (CARLICENSE)=Indicator(1)
  /CONTRAST (SPEEDPT)=Indicator(1)
  /CONTRAST (COSTPT)=Indicator(1)
  /CONTRAST (recCONGESTION)=Indicator(1)
  /CONTRAST (E.BIKE)=Indicator(1)
  /CONTRAST (PTPASS)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(30) CUT(0.5).

* Inspect:
```

* The extent to which people get classified more accurately (Check that is doesnt get lower %)
Always 91.8, except for transport options 91.6%.

* The significance of the steps and model based on chi squared
Transport options not significant, socio-economic block and competencies block are significant
Model is always significant

* Standardised residual (only 5% should lie outside 2, 1 % should lie outside 2,5. Cases with a value of more than 3 need inspection as this could be an outlier).

```
FREQUENCIES VARIABLES=ZRE_1
  /STATISTICS=MINIMUM MAXIMUM
  /ORDER=ANALYSIS.
```

* 3.5% has a value above 2 which is fine. 2.5% is above 2.5.
* 1.8% is above 3, but upon inspection, the values on the various questions do not show any abnormalities.

* Cook's distance (should be less than 1).

```
FREQUENCIES VARIABLES=COO_1
  /STATISTICS=MINIMUM MAXIMUM
  /ORDER=ANALYSIS.
```

* There are 3 cases with a Cook's distance >1. The cases did not have unusual values so they are not removed

* Leverage (should be between 0 and 1).

```
DESCRIPTIVES VARIABLES=LEV_1
  /STATISTICS=MEAN STDDEV MIN MAX.
```

* All cases are between 0 and 1.

* Look at -2LL, Cox & Snell R Square, Nagelkerke R Square for evaluation effect sizes of the model
These are 381. // .119 // .275.

* Model fit to the data
The model fits well, the Hosmer and Lemeshow Test is not significant.

* DFbeta for constant and first predictor should be less than 1.

```
FREQUENCIES VARIABLES=DFB0_1 DFB1_1 DFB2_1 DFB3_1 DFB4_1 DFB5_1
DFB6_1 DFB7_1 DFB8_1 DFB9_1 DFB10_1
    DFB11_1 DFB12_1 DFB13_1 DFB14_1 DFB15_1 DFB16_1 DFB17_1 DFB18_1
  /STATISTICS=MINIMUM MAXIMUM MEAN
  /ORDER=ANALYSIS.
```

* 1 case is more than 1 for PTPASS, but no more than 2 so that is alright.

* Complete separation / overdispersion
There do not appear to be too large or too small standard errors.

* Observed groups and probability plot should be clustered most neatly at both sides
The predicted probability plot does not show a neat clustering at both sides

This is to be expected due to the high number of people who have not used a shared bicycle in the sample compared to those who have.

```
 * Log regression shared mopeds.
LOGISTIC REGRESSION VARIABLES SHAREDMOP
  /METHOD=ENTER GENDER PAIDWORK EDUCATION ETHNICITY catAGE
  /METHOD=ENTER CARLICENSE
  /METHOD=ENTER SPEEDPT COSTPT recCONGESTION E.BIKE PTPASS
  /CONTRAST (GENDER)=Indicator(1)
  /CONTRAST (PAIDWORK)=Indicator(1)
  /CONTRAST (EDUCATION)=Indicator(1)
  /CONTRAST (ETHNICITY)=Indicator(1)
  /CONTRAST (catAGE)=Indicator(1)
  /CONTRAST (CARLICENSE)=Indicator(1)
  /CONTRAST (SPEEDPT)=Indicator(1)
  /CONTRAST (COSTPT)=Indicator(1)
  /CONTRAST (recCONGESTION)=Indicator(1)
  /CONTRAST (E.BIKE)=Indicator(1)
  /CONTRAST (PTPASS)=Indicator(1)
  /SAVE=PRED PGROUP COOK LEVER DFBETA ZRESID
  /CLASSPLOT
  /CASEWISE OUTLIER(2)
  /PRINT=GOODFIT CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(30) CUT(0.5).
* Inspect:
* The extent to which people get classified more accurately
```

In block 0, people are classified 88.8% correctly. This is 88.5% for socio-economic variables in block 1, 89.4% for transport options block 2, 89.5% for competencies block 3.

* The significance of the steps based on chi squared
Socio-economic variables, transport options, competencies are significant
Model is always significant

* Standardised residual (only 5% should lie outside 2, 1 % should lie outside 2.5. Cases with a value of more than 3 need inspection as this could be an outlier).

```
FREQUENCIES VARIABLES=ZRE_2
  /STATISTICS=MINIMUM MAXIMUM
  /ORDER=ANALYSIS.
```

* 3.5% has a value above 2 which is fine. 2.4% is above 2.5
* Upon inspection, the values on the various questions do not show any abnormalities.

* Cook's distance (should be less than 1).

```
   FREQUENCIES VARIABLES=COO_2
  /STATISTICS=MINIMUM MAXIMUM
  /ORDER=ANALYSIS.
```

* There are 2 cases with a Cook's distance >1.

* Leverage (should be between 0 and 1).

```
DESCRIPTIVES VARIABLES=LEV_2
```

/STATISTICS=MEAN STDDEV MIN MAX.
* All cases are between 0 and 1.

* Look at -2LL, Cox & Snell R Square, Nagelkerke R Square for evaluation effect sizes of the model
443.082 // .173 // .343

* Model fit to the data
The model fits well, the Hosmer and Lemeshow Test is not significant.

* DFbeta for constant and first predictor should be less than 1.
FREQUENCIES VARIABLES=DFB0_2 DFB1_2 DFB2_2 DFB3_2 DFB4_2 DFB5_2 DFB6_2 DFB7_2 DFB8_2 DFB9_2 DFB10_2
DFB11_2 DFB12_2 DFB13_2 DFB14_2 DFB15_2 DFB16_2 DFB17_2 DFB18_2
/STATISTICS=MINIMUM MAXIMUM MEAN
/ORDER=ANALYSIS.
* 1 is more than 1 for PTPASS, but no more than 2 so still alright.

* Complete separation / overdispersion
There do not appear to be too large or too small standard errors.

* Observed groups and probability plot should be clustered most neatly at both sides, with neat clusters at each sides
The predicted probability plot does not show a neat clustering at both sides
This is to be expected due to the high number of people who have not used a shared bicycle in the sample compared to those who have.