DETERMINING THE CAUSAL BI-DIRECTIONAL RELATIONSHIP BETWEEN ACTIVE TRAVEL AND HEALTH

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DETERMINING THE CAUSAL BI-DIRECTIONAL RELATIONSHIP BETWEEN ACTIVE TRAVEL AND HEALTH

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PREFACE

In front of you lies the work that signifies the end of my time as a student and the start in my professional life. After working on this thesis, I would like to think that I now possess a full understanding of how scientific research is conducted, yet I feel this has given me only a small insight in the world of science and research. Frankly, I can say: I liked what I saw. I enjoyed my growth as a researcher and I am looking forward to develop my researching skills even further in the future. And will come in handy, as the last step in my journey will be to write a journal article based on this thesis.

I want to express my gratitude to a number of people. I want to thank my committee for their guidance during my thesis process. My committee's members having frequently worked together in the past, have greatly benefitted my work. I experienced that my committee has lots of experience regarding the topic of active travel and were all enthusiastic to examine the topic with me in further extend. This was clearly visible in the advice they gave. I want to thank Prof. Dr. G.P. van Wee, the chairman of my committee, for his sharp comments. His comments gave me a better understanding on how the concepts of active travel and health are connected to each other. I want to thank Dr. C. Maat for his comments on the storyline. This helped me to create a clearer storyline and gave me an understanding of why this research is of importance. I want to thank my daily supervisor Dr.ir. M. Kroesen. You helped me from the beginning of my thesis until the very end. During the meetings you gave me new ideas and directions that had a major contribution to this final product. Furthermore, I would like to thank you for the extra opportunities you handed me. These opportunities eventually led to the possibility to present my thesis at the "Colloquium Vervoersplanologisch Speurwerk" (CVS) congress in November 2018.

Finally, I would like to thank my family for offering me the possibility to educate myself and for both the love they gave me while stockpiling my fridge with food so I did not have to cook every day. I want to thank my friends for providing a distraction from my graduation work. The hours of walking helped me clear my mind and sometimes even gave me new ideas to include in my thesis. The bars of chocolate helped me to stay focussed.

Overall, I really enjoyed working on this project and the five months flew by. Therefore, I hope that you as a reader enjoy the read as well.

Marc Kaelani

Delft, October 2018

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In this paper, we make use of data of the LISS (Longitudinal Internet Studies for the Social sciences) panel. The LISS panel data were collected by CentERdata (Tilburg University, The Netherlands) through its MESS project funded by the Netherlands Organization for Scientific Research. More information about the LISS panel can be found at: www.lissdata.nl.

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1.1 Background

The literature on the relationship between physical activity and health is quite extensive and the subject is well examined (Centers for Disease Control, 2001; Miles, 2007). Physical inactivity has been linked to various health problems such as several chronic diseases (e.g., cardiovascular disease, diabetes, cancer, hypertension, obesity, depression and osteoporosis) and premature death (Warburton, Nicol & Bredin, 2006). But even though the benefits of physical activity are known, physical inactivity is still one of the most important health challenges of the 21st century (Dobbins, DeCorby, Robeson & Tirilis, 2017) and is the fourth leading risk factor in global mortality (World Health Organization, 2010).

To increase overall physical activity, one current popular thought is to stimulate active travel (Winters, Buehler & Götschi, 2017). Active travel is travelling, either for leisure or transport, while using an active mode such as walking or cycling. In countries such as Switzerland, the Netherlands, Germany and Denmark, active travel policy is recognized as a critical way to increase health in the cities (Götschi, Tainio, Maizlish, Schwanen, Goodman & Woodcock, 2015). The World Health Organization (WHO) defines health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (http://www.who.int/suggestions/faq/en/).

Given the fact that people naturally have to travel around in everyday life, policymakers believe that active travel is an attractive and feasible way to increase the overall levels of physical activity in the population and thereby increase the health of the population (De Nazelle, Nieuwenhuijsen, Antó, Brauer, Briggs, Braun-Fahrlander & Hoek, 2011). Active travel is easier to incorporate in everyday life, compared to having someone perform physical activity in their leisure time, such as going to the gym. Exercise during leisure time can be seen as an additional burden and can be difficult to sustain for the long-term (Sallis, Haskell, Fortmann, Vranizan, Taylor & Solomon, 1986).

In addition to the health benefits, active travel also leads to other non-health related benefits such as: increasing accessibility, reducing congestion, decreasing emissions and realizing social and societal goals (De Nazelle et al., 2011). However, the focus of this research is limited to the effects of health, the other effects are not considered in the scope of this research.

1.2 Active travel policy in the Netherlands

In this research, active travel within the Netherlands is researched. Traditionally, cycling is incorporated in the Dutch culture. Dutch schoolchildren take a cycling exam at the elementary school and learn to cycle to and from school at an early age. The cycling culture can also be found in the extensive cycling and walking infrastructure in the Netherlands that is often dedicated to cycling or walking. The Dutch are the leader in the number of trips by bicycle and kilometres of cycling per person (Pucher & Buehler, 2008). With currently an active mode share of 44% in 2017 (CBSa, 2018). The high percentage of active travellers can partly be explained by the Dutch policy aimed at improving the transportation infrastructure for these active modes. For example, creating car-free zones and wide pavements for pedestrians or expanding and improving bicycle facilities for cyclists (Pucher & Dijkstra, 2003).

Although active modes are popular in the Netherlands, the Dutch population has problems reaching the thresholds of the minimum required physical activity. The Health Council of the Netherlands (2017) set three minimum thresholds for physical activity. The “Nederlandse Norm Gezond Bewegen” (NNGB) is met when at least 150 minutes of moderate physical activity per person per week is performed. “Fitnorm” only takes into account vigorous physical activity, these activities must be performed at least three times per week. “The combination norm guideline” is met when one of the two previous mentioned norms are met. In 2016, 55% of the Dutch population met the NNGB, 23.2% met the Fitnorm and 57.2% met the combination norm (RIVM, n.d.).

To increase the amount of physical activity in the population, the Cabinet of the Netherlands aims to realize an increase in active travel between 2017 and 2020. This is established in their program: “Agenda Fiets 2017-2020” (Tour de Force, 2016). On the 12th of June 2018, this goal became more tangible, when the Dutch Secretary of State of Infrastructure and Water Management announced her ambition to realize a mode shift from car to bicycle for 200.000 people. To achieve this goal, a budget of 100 million euro is made available and will be used mainly to build new regional cycling routes and bicycle parking spaces near public transport facilities (Van Veldhoven, 2018).

Two important effects when it comes to active travel policy are: the accessibility effects and the health effects (Decisio, 2017; Van Wee & Börjesson, 2015). Yet, the effect of active travel on the total net health benefits is not completely understood. To be able to compare active travel policy alternatives, the health benefits of active travel first have to be monetized. This is done by research institute Decisio in 2017, in their report called: “Waarderingskengetallen MKBA fiets: State of the Art”. In their report, they only looked at the general health benefits. However, they acknowledge that assumptions had to be made regarding the total net health effect for different individuals, as the size of the health benefits is dependent on the individual itself. People who are active in general, are expected to experience less health benefit from an increase of active travel, compared to inactive people. Furthermore, the total net health benefit is dependent on the transportation mode substituted by active travel. If a kilometre of walking is substituted with a kilometre of cycling, the total net health benefit would be smaller than if the kilometre was intentionally travelled by car. In this research, no distinction between cycling with a e-bike or a non-electric bicycle is made.

In conclusion, the relationship between active travel and health is still unclear. The uncertainties can lead to an over- or underestimation of the total net health effects of transport policy aimed at active travel. Examining these uncertainties can help get a better understanding of the total net health benefits of active travel and thereby support the transport policy decision making.

1.3 The Relationship between Active Travel and Health

That not everything is known about the relationship between active travel and health is also recognized in scientific literature. Van Wee and Ettema (2016) addressed various knowledge gaps in their article, regarding travel behavior and health. Furthermore, they proposed a conceptual model of the complex relationships between travel behavior and health, using literature about public health, land use and transportation in relation to health, travel and their underlying mechanisms. This conceptual model includes the effects of travel behavior on air pollution intake, casualties and well-being. However, given the time available for this research, these effects will not be taken into account and are possible subjects of future research. This research will only focus on the relationship between active travel and health.

Policymakers believe that an increase in active travel will have the same health benefits as an increase in physical activity. However, Van Wee and Ettema (2016) suggest that the relationship is not as simple as that, and conclude that "wrong" conclusions can be made if the complex causal relationships between active travel and health are overlooked. They proposed two hypotheses that could explain why active travel has different health benefits than physical activity. These following two hypotheses are tested in this research:

1. Active travel substitutes for other forms of physical activity;
2. There exists a causal bi-directional relationship between active travel and health.

In the first hypothesis, it is assumed that people substitute active travel for other forms of physical activity that they would have undertaken normally. One could think of cycling to work resulting in not going to basketball practice. Important to remember is that active travel is not the only form of physical activity. Examples of other forms of physical health are: work-related physical activity, household physical activity, physical education and sports. Therefore, policy aimed at increasing active travel could have the unwanted effect of decreasing other forms of physical activity and even decrease the total physical activity. This is unwanted because of the link with physical inactivity and various health problems. Currently, Decisio take into account the possible substitution effect to estimate the health benefits of cycling by correcting the values for this effect. If the substitution effect does not exist, it would mean that the current estimates are overcorrected and therefore, underestimated. In this research, the relation between active travel and leisure physical activity is examined. If people substitute leisure physical activity with active travel, the total net health benefits are lower because the total physical activity does not change or changes only limited. However, research examining the relationship between total physical activity and travel-related physical activity are scarce and show contradicting results (Van Wee & Ettema, 2016). In their review, Xu, Wen and Rissel (2013) found increasing evidence indicating active transport increases physical activity. This would mean that active travel would not substitute physical activity and would add up to the estimated health benefits of physical activity. However, Van Wee and Ettema (2016) found that the spatial setting can impact the amount of transportation, but does not affect the overall physical activity. This would suggest that active travel does indeed substitute other forms of physical activity.

The second hypothesis assumes that there exists a causal bi-directional relationship between active travel and health. Instead of the expected uni-directional relationship from active travel to health. Bi-directional means literally a path directed in two ways, indicating that two variables influence each other. It could be possible that active travel has an effect on health, but health also has an effect on active travel, i.e., people get healthier by cycling or healthier people cycle more. If this hypothesis is true, it could mean that unhealthy people would be less likely to travel with an active mode and stimulating active travel would not lead to the desired health benefits. Furthermore, an increase in active travel for unhealthy people will lead to more health benefit than an increase of active travel for already healthy people (Bauman, 2014). Currently, the estimates by Decisio are based on the health benefits of an average person. Depending on the individuals who increase their active travel, the current values for active travel are under- or overestimated. Currently, this direction of the relationship between active travel and health cannot be established because the majority of the current research is conducted using the cross-sectional approach (Saunders et al., 2013). To examine the causality between two variables, three components should be met: isolation, association and direction of influence (Bollen, 1989). For the direction of influence, the temporal order between two variables should be addressed. However, the cross-sectional approach makes it impossible to examine the causality because the temporal order cannot be addressed (Johnson, 2010) and therefore is it not possible yet to say with certainty that no bi-directional relationship exists.

Another point of interest in this research are the different aspects of health. Currently, research mainly focuses on all-cause mortality and cardiovascular outcome to measure the effects on health (Saunders et al., 2013). However, it has been found that physical activity has a different relationship with physical health and mental health (Centers for Disease Control, 2001). Currently, other aspects of health are neglected in the literature. One of the goals of this research is to enrich the knowledge of health on the different aspects of health. Therefore, the relationship of active travel is tested on physical health, as well as on mental health. Weight is used as an indicator for physical health and general mental health is used to examine the mental health.

Being overweight is defined as weighing more than is regarded as optimally healthy and is often measured using Body Mass Index (BMI). Obesity is the most well-known subgroup of being overweight. Overweight as an indicator is chosen because of the link to other comorbidities (Pozza & Isidori, 2018), and therefore, can act as an intermediating variable. Overweight is relatively easy to measure and can be indicated faster than for example all-mortality or other diseases. Mental well-being or mental health is defined as "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community" (World Health Organization, 2004). General mental health is the international standard in population-based studies for mental health, and is a good indicator of the overall mental health of a person and is also measurable with little effort (Driessen, 2011).

In 2001, mental disorders accounted for 13% of the burden of disease in the world and WHO expects this to increase to 15% in 2020. The main contributor to mental illness is depression, affecting one in three people within their lifetime (Harpham et al., 2003). Yet, the evidence indicating a relationship between active travel and mental health is still limited and weak (Xu, Wen & Rissel, 2013). Although the relationship between active travel and mental health has not been researched yet, the association between improvement in mental health and participation in a physical activity has been proven on several occasions (Paluska & Schwenk, 2000). This gives reason to believe that active travel could improve mental health as well.

The other aspect of health that has not been fully researched with respect to active travel is being overweight. In 2017, 48.7% of the Dutch population of 18 years and older were categorized as overweight and 13.9% of the population were categorized as obese (CBSb, 2018). BMI is simple and commonly used to classify obesity. It is defined as a person's weight in kilogram divided by the square of his or her height in meters (James, Leach, Kalamara & Shayeghi, 2001). A BMI of 25 and over, categorizes a person as overweight and a BMI of 30 and over, categorizes a person as obese. Multiple studies exist examining the relationship between active travel and overweight. However, these studies consist mainly of cross-sectional research (Saunders et al., 2013). Studies about walking during leisure-time and weight loss (Gordon-Larsen et al., 2009) give reason to believe that there could also be an effect of active travel on obesity in adults or vice versa.

1.4 Research Objective and Question

The aim of this research is two-fold. The first objective is to contribute to Dutch transport policy aimed at stimulating active travel for health benefits. More insight into the total net health effects of active travel will make it possible for policymakers to make better decisions, regarding stimulating active travel. The second aim of this research is to contribute to the current knowledge about active travel and health. In this research, the issue of causality is examined. More specifically, the direction of causality between physical activity active travel, and between active travel and health. This is done by answering the main question: "*What is the relationship between active travel and health?*". This main question is divided into three sub-questions:

Q1: What findings have been reported on the relationship between active travel and health?

Q2: What is the direction of causation between physical activity and active travel, and to what extend do the variables influence each other, while being controlled for socio-demographic variables?

Q3: What is the direction of causation between active travel, overweight and mental health, and to what extend do the variables influence each other?

By examining the direction of causation, the two hypotheses can be tested.

1.5 Research Methods

The first research question is examined in the form of a literature review. By using keywords and the snowballing method, relevant literature regarding this topic has been collected and examined. The other research sub-questions is examined using structural equation modelling (SEM). Van Wee and Ettema (2016) recommended the use of advanced research methods, such as SEM, over simple methods to examine the complex relationship between active travel and health. The structural equation model is estimated on the Longitudinal Internet Studies for the Social sciences (LISS) panel data, resulting in a Cross-Lagged Panel Model (CLPM). Panel data is collected by measuring the same respondents at multiple points in time. Therefore, the temporal order can be addressed, in contrast to a cross-sectional study approach (Finkel, 1995). The CLPM model is concerned with the relationship between two variables on each other over time (Hamaker, Kuiper & Grasman, 2015).

SEM is a collection of statistical techniques that allow a set of relationships between one or more independent or dependent variables to be examined. Path diagrams are a fundamental part of SEM, as they allow the researcher to draw the hypothesized set of relationships in the model. This helps to clarify the idea about the relationship and they can be directly translated into equations needed for the analysis. SEM models consist of two parts. The measurement model includes the measured variables and the structural model includes the hypothesized relationships among the constructs. SEM models have a number of advantages. The relationships are free of measurement error when relationships among factors are examined. Reliability of measurement can be accounted for within the analysis and SEM is able to examine complex relationships (Ullman & Bentler, 2012).

To increase comprehensiveness, the difference between structural equation modelling (SEM), structural equation modelling models (SEM models) and Cross-lagged panel models (CLPM) is shortly explained. SEM is the process towards establishing the SEM models. SEM models are the models that are eventually estimated. CLPM is a predefined SEM model and is specifically used for the analysis of longitudinal data.

1.6 Research Structure

In this section, an overview of this research is given, including the coming chapters and the flow of information as presented in this research. The information flow of this research is shown in figure 1. Firstly, this research is put into context, the objectives of this research are explained and the methods are introduced. Chapter 2 elaborates on the theoretical background of this research. In this chapter, the current knowledge is addressed, including what models and data are used in the establishment of the current knowledge. The chapter will conclude with the implications of the current knowledge on this research. In chapter 3, the data and the models used for this research are discussed. The chapter ends with the operationalisation of the data and the specification of the models. Chapter 4 describes the results regarding the substitution hypothesis, where the relationship between physical activity and active travel is examined. In chapter 5, the results of the CLPM are described, concerning the relationship between active travel and health. In chapter 6, the results found in this research are put in the light of previous researches and the limitations of this research are discussed. In the last chapter, the main question of this thesis is answered and discussed. Furthermore, the contributions of this research are discussed and recommendations for policy implications and further research are made. Lastly, the thesis consists of a bibliography containing of all the sources used in the research.

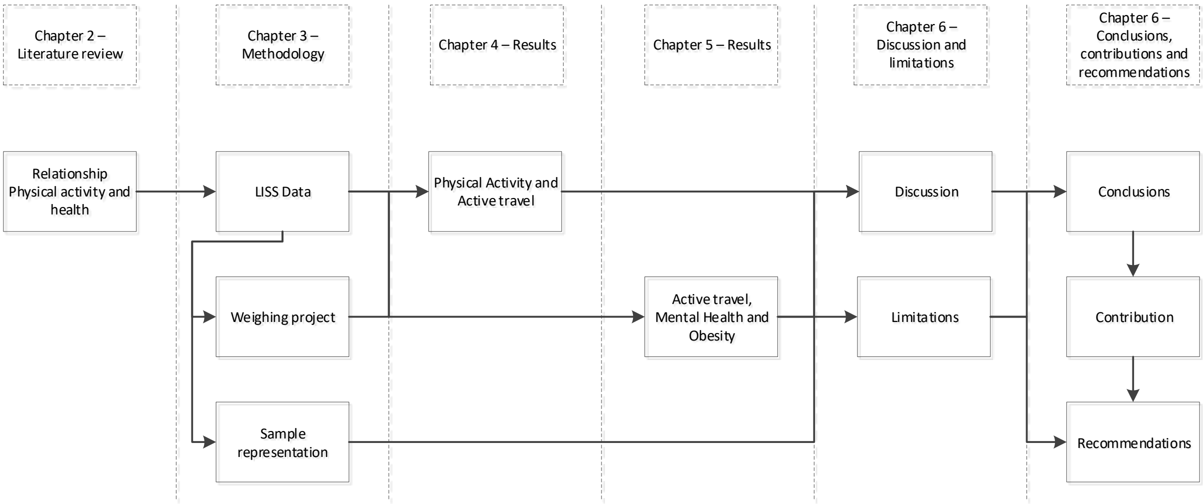


Figure 1 - Research outline and information flow

CHAPTER 2 – LITERATURE REVIEW:

The relationship between physical activity and health

In this chapter, a literature review is conducted regarding the relationship between active travel and health. The aim of the literature review is to get a better understanding of the relationship between active travel and physical activity, and the relationship between active travel, overweight and mental health. By examining what is known about the relationship, how the research is conducted and what data is used, possible limitations of these researches can be addressed. Because this study will elaborate on these limitations, these limitations have implications for this research as well. First, an overview of the relationship between physical activity and health is described. This overall view is used to explain the structure of this chapter. Thereafter, the search methods are discussed. Followed by an introduction of the four main concepts and a discussion about the relationships of interest between the concepts. This chapter ends with a conclusion about the current knowledge gaps that exist in the literature and the implications of these knowledge gaps for this research. The sub-question that is answered in this chapter is: "*What findings have been reported on the relationship between active travel and health?*".

Figure 2 is an overview of the possible relationships between physical activity and health. This figure acts as a guideline through this chapter. The boxes in figure 2 represent the different concepts. The arrows represent the relationships between these concepts. The arrows pointing both ways represent the hypothesized bi-directional relationship. Diamonds indicate the section, in which the relationship or concept is discussed in. Important to note is the link between the conceptual model and the hypotheses mentioned in the previous chapter. This research is interested in testing two hypotheses that could explain why active travel does not have the same health benefits as physical activity. The first hypothesis is the substitution hypothesis and the second hypothesis is the causal bi-directional relationship. The first hypothesis is conceptualized as relationship 2.6 in the conceptual model. Active travel could substitute with other forms of physical activity. Furthermore, it is also possible that other forms of physical activity substitute with each other. In the conceptual model, this process is visualised by the relationships as depicted within the physical activity box. The second hypothesis is a combination of links 2.8 and 2.9. Health has a bi-directional relationship with physical activity. The last relationship is from socio-demographic variables and other individual characteristics towards physical activity. This relationship is depicted as 2.7 in the conceptual model.

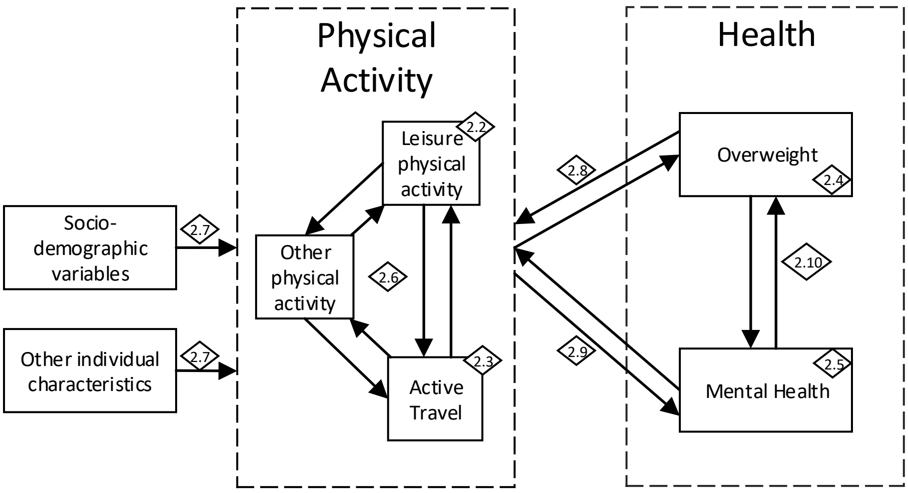


Figure 2 - The conceptual model of this research

The structure of this chapter is as follows. Firstly, the search method used to find the literature is described. This description includes the keywords and databases used. Secondly, the different concepts are defined, starting with physical activity, active travel, overweight and mental health. This is of importance to make sure that the concepts are clear for the reader and different interpretations of the concepts are less likely to occur. Furthermore, the methods used to measure the concepts are discussed. The literature mentions different ways to measure the concepts. The different methods have different advantages and disadvantages, but could also lead to different results. In this literature review, the focus is mainly on methods that are used in panel-based studies, as panel data is necessary to examine the causation issue. Thereafter, the bi-directional relationships between the concepts are examined. The first relationship discussed, is the relationship between active travel and other forms of physical activity. Socio-demographic variables can have an influence on physical activity. Therefore, in section 2.7, the relation between socio-demographic/individual variables and activity is addressed. The second hypothesis is about the bi-directional causal relationship between activity and health and is discussed in section 2.8 and section 2.9. These sections start with a look into the biological reactions linked to the physical activity and health. Thereafter, the relationship between health and physical activity in population studies is discussed. The sections end with a description about the relationship between health and active travel. In section 2.10, the relationship between mental health and overweight is described. As both are used as indicators of health and the relationship can play a role in this research, it is important to know if the two variables are also influenced by each other. This chapter ends with a conclusion about the limitations of the current knowledge and the implications these have for this research. Resulting in a conceptual model of this research.

2.1 Search for literature

Vom Brocke, Simons, Niehaves, Riemer, Plattfaut & Cleven (2009) underline the importance of describing the process of searching comprehensibly, as it will enable the readers to assess the exhaustiveness of the review. For this literature review, four databases were used to find most of the literature: Web of Science, Scopus, ScienceDirect and Google Scholar. Furthermore, the two main search strategies applied were: keyword searching and snowballing. Keyword searching is searching through databases based on certain (key-) words. The keywords that are used in this research are: *physical activity, active travel, active commuting, health, overweight, BMI, mental health, general mental health, MHI-5, Cross-lagged panel model, causal relationship, panel study, longitudinal studies and population study.* Even though keyword searching is the most commonly used strategy for finding literature, keyword searches sometimes fail to find the less cited but relevant papers (Hildreth, 1997). Therefore the second strategy of snowballing is applied, on the literature found using the keyword search strategy. Snowballing means searching for literature by using the bibliography of a paper or the citations to the paper to identify additional papers (Wohlin, 2014). By using this method the less well-known papers about this subject were also searched for and found.

2.2 Leisure physical activity

In general, physical activity is defined as: any muscular movement that increases energy expenditure (Pickett, Kendrick & Yardley, 2017). There are different forms of physical activity and health. Physical activity can be categorized according to domain-specific physical activity, such as: leisure physical activity, work related physical activity or transport related physical activity. Leisure physical activity is defined as: any muscular movement that increases energy expenditure and is not performed with active travel modes, executed during leisure time. For example, playing basketball in the evening.

In population studies, physical activity is mostly self-reported (Shephard, 2003). Often in the form of a survey, people write down the quantity of physical activity performed. The benefit of self-reported physical activity is that it is low cost. However, this method can have implications for the results, as self-report measuring often shows an over- or underestimation with respect to the true amount of physical activity (Prince, Adamo, Hamel, Hardt, Gorber & Tremblay, 2008). Other options to measure physical activity exists. A possible popular alternative is to measure physical activity by using a MTI accelerometer. This device records the time and varying accelerations and is often used for smaller studies, as all the subjects have to wear a MTI accelerometer (Guinhouya, Hubert, Dupont & Durocher, 2005). Physical activity can be divided into different forms varying in intensity, frequency, duration and amount, aerobic and resistance activity and environmental context (Shephard, 2003).

2.3 Active travel

Active travel is defined as: using an active mode, such as walking or cycling, for travelling either for leisure or transport. One can think of commuting by bike instead of using the car. Compared to the literature about physical activity, the literature about active travel is quite limited. Evidence linking the health benefits to active travel have not been examined in depth. Therefore, the relationship between active travel and health is still unclear (Xu et al., 2013). In this research, all trips made cycling or walking are taken as active travel. This includes leisure touring trips and cycling race tours.

Active travel is often measured by self-report for reasons of feasibility, cost and data handling reasons (Lubans, Boreham, Kelly & Foster, 2011). However, again, self-reporting can lack accuracy due to problems with memory, incomplete entries or misreported journeys (Kelly, Krenn, Titze, Stopher & Foster, 2013). As the destination is of importance to measure active travel, the MTI accelerometer alone cannot be used to measure active travel. Combining the acceleration data with the GPS data can be used to identify if someone actively travels (Miller et al., 2015). However, this would be more expensive than self-reporting.

2.4 Overweight

Overweight is defined: as weighing more than is optimally healthy. Mostly being correlation with an excessive accumulation of adipose tissue in the body (Bray & Ryan, 2000). Overweight is an important indicator for general health as it is associated with multiple comorbidities, such as type 2 diabetes, hypertension, cardiovascular disease, osteoarthritis, obstructive sleep apnea, cancer and various psychological disorders (Pozza & Isidori, 2018).

The Quetelet's index is a popular way to measure overweight (World Health Organization, 2016), and is also known as BMI. Quetelet's index calculates Body Mass Index (BMI) using the following formula: weight/height^2 (kg/m^2) (Garrow & Webster, 1985). Given the BMI of a person, someone can be classified as overweight. Table 1 shows the various classifications of weight by BMI. The correlation between weight/height and the amount of adipose tissue is high and overall Quetelet's index is seen as a reliable indicator for overweight (Garrow & Webster, 1985). Other options to measure the adipose tissue are skin measures and waist size. However, measuring these take more time than using BMI and BMI is often simpler to use than other methods.

Table 1 - Classification of weight by BMI (WHO, 2016)

Classification	BMI (kg /m^2)
Underweight	< 18.5
Normal range	18.5-24.9
Overweight:	> 25
Pre-obese	25-29.9
Obese I	30-34.9
Obese II	35-39.9
Obese III	> 40

To calculate the BMI, researchers often use self-reported measures, instead of objectively measuring the weight and height. There exists an increasing concern about the use of self-reporting of body weight in research (Xu, Wen & Rissel, 2013). Comparisons between self-reported heights and weights compared to objectively measured heights and weights, researchers found a trend of over-reporting of the height and under-reporting the weight of the person when the self-report method is used. This results in a lower BMI than would have been measured when measured by a researcher (Gorber, Tremblay, Moher, & Gorber, 2007). To measure overweight, other indicators are also possible. BMI is often criticised for the use of the weight of a person, while other indicators are more focused on the excessive fat mass or the abdominal obesity in a person. The main reason to use excessive fat as an indicator of obesity is the difference in density between fat and muscle (Janssen, Katzmarzyk & Ross, 2004). Muscle has a higher density than fat and therefore weighs more than fat per cm^2. Furthermore, an excessive amount of fat causes health problems but an excessive amount of muscle does not. Even though BMI does not take the difference between muscle and fat into account, BMI is still highly correlated with excessive fat mass and abdominal obesity. Therefore, BMI is often used as an indicator for overweight. An additional benefit of BMI is that weight and height are easier to measure than for example excessive fat mass.

2.5 Mental Health

In the positive sense, mental health is used to indicate a state of emotional, psychological and social well-being. In the negative sense, mental health is used to indicate the opposite, namely, people with mental health problems or a mental disorder (Pilgrim, 2017). Especially the negative definition of mental health has gained increased attention in the recent years. Various common mental disorders are: anxiety disorders, mood disorders, psychotic disorders, eating disorders, impulse control and addiction disorders, personality disorders, and others (Polanczyk, Salum, Sugaya, Caye & Rohde, 2015).

Measuring the mental health of the population is of importance, because it enables the understanding of the population's current state of mental health and to follow the trends over the years (Talala, Huurre, Aro, Martelin, & Prättälä, 2008). The international standard instrument to measure the physical and mental health in the population is the Short Format 12 (SF-12) (Abu-Omar, Rütten, & Lehtinen, 2004), often combined with three additional psychological items from the Short Form Health Survey (SF-36). The MHI-5 is the international standard instrument for general mental health in the population and can be calculated by using three items from the SF-36 and two questions from the SF-12. The answers of the MHI-5 questions are combined and lead to a score between 0 and 100. The lower the score is, the lower the mental health (Driessen, 2011). Important to emphasize is that MHI-5 is not intended to diagnose specific psychological disorders. However, the MHI-5 can be used to measure if someone suffers from any kind of psychological disorder and to measure the current mental health state of the population (Driessen, 2011). The MHI-5 identifies any kind of mood disorder and anxiety disorder better than substance disorders and food disorders (Rumpf, Meyer, Hapke & John, 2001). Overall, MHI-5 shows high correlation with diagnoses from psychiatrists and other instruments to measure the mental health (McCabe, Thomas, Brazier& Coleman, 1996; Rumpf, et al., 2001; Strand, Dalgard, Tambs & Rognerud, 2003), this also holds true for the Dutch population (Hoeymans, Garssen, Westert & Verhaak, 2004).

2.6 The relationship between physical activity and active travel

In the first hypothesis, it is assumed that people substitute cycling to work for other physical activities. Researches examining the relationship between total physical activity and travel-related physical activity are scarce and show contradicting results (Van Wee & Ettema, 2016). The amount of total physical activity is mainly important, because of the link between physical inactivity and various health problems such as several chronic diseases (e.g., cardiovascular disease, diabetes, cancer, hypertension, obesity, depression and osteoporosis) and premature death (Warburton, Nicol & Bredin, 2006).

Xu et al. (2013) found increasing evidence that active transport increases physical activity. This would mean that active travel would not substitute physical activity and would add up to the normal health benefits of physical activity. ChiMón et al. (2011) found similar results and added that active travel had a greater impact on vigorous physical activity for boys than for girls. However, Van Wee and Ettema (2016) found that spatial setting can impact the amount of transportation, but does not affect the overall physical activity. This would suggest that active travel does indeed substitute for other forms of physical activity. Currently, the overall expectation is that there exists some form of substitution effect between active travel and other forms of physical activity (Decisio, 2017).

2.7 The relationship between socio-demographic variables/ individual characteristics and active travel

There are multiple determinants for the choice for active travel. Individual characteristics relate to a person. Socio-demographic variables are part of the individual characteristics and are known to influence active travel and are often used as control variables (Ton, Duives, Cats, Hoogendoorn-Lanser & Hoogendoorn, 2018). In this section, the relationship between various socio-demographic variables are discussed. Young people cycle more (Muñoz, Monzon & Daziano, 2016) and old people cycle less (Fraser & Lock, 2010). People with a higher income tend to cycle less than people with a lower income (Muñoz et al., 2016). In the Netherlands, women are found to cycle more often than men (Heinen, Van Wee & Kroesen, 2010). Land use has a strong relationship with active modes. Mixed land use environment have an attracting effect on active modes. In contrast, low residential density has a discouraging effect on active mode use (Mitra, 2013; Wang, Chau, Ng & Leung, 2016). Furthermore, areas with a high population density are attractive for active mode use (Wang et al., 2016). People with a higher education level tend to cycle less (Heinen et al., 2010). Next to the mentioned socio-demographics, other individual characteristics may also play a role, such as: attitude towards health or cycling (Panter, Jones, Van Sluijs & Griffin (2010). As these socio-demographic variables are known to have an effect on active travel, it is important to take these relationships into account.

2.8 The relationship between activity and overweight

The biological reactions leading to overweight are quite complex, involving interactions between genetics, hormones and the environment (Kaila & Raman, 2008). Given the aim of this research this will not be discussed in high detail, however, the basic principle behind body weight change can help to understand the problem and can be explained simply. Body weight change is affected by two factors: energy intake and energy expenditure (Church & Martin, 2018). Taking in more energy/food than total daily energy expenditure over a longer period of time, results in an increase of adipose tissue. Total daily energy expenditure can be divided into three categories and is the sum of: resting energy expenditure, thermic energy expenditure and nonresting energy expenditure. The first category is used to maintain the basic body functions and uses approximately 60% of the total energy. The second category is the thermic effect used for feeding. This is the energy expended in the digestion, transport and deposition of nutrients. This category uses approximately 10% of the total energy. The third category is nonresting energy expenditure. This is the remaining energy expenditure often used for physical activity, using approximately 30% of the total energy (Ravussin & Bogardus, 1989). Of the three categories, nonresting energy expenditure is the most variable and changeable. Therefore, increasing the amount of nonresting energy expenditure in the form of physical activity can counter the extra energy intake, resulting in a loss of adipose tissue (Wiklund, 2016).

The influence of physical activity on overweight is almost common knowledge. Overall, active travel is expected to result in a lower weight. Nonetheless, the scientific evidence is not that straightforward and conclusive. The first studies regarding this topic were cross-sectional studies. Overall they reported lower BMI among people with higher levels of physical activity (Reiner, Niermann, Jekauc & Woll, 2013). Cross-sectional studies study the relationship at one point in time. Therefore it is not possible to draw conclusions about the long-term relationship between physical activity and overweight. To study this relationship longitudinal studies are necessary. DiPietro, Dziura & Blair (2004) conducted a longitudinal study, focussing on men between the age of 22 and 55 years. They concluded that daily physical activity was positively related to weight loss over time. Hankinson et al., (2010) did a similar study, using a different longitudinal database, including women in the research. They found similar results as DiPietro et al., men and women with higher physical activity lost weight over time. Petersen, Schnohr & Sørensen (2004) found a contradicting result in their longitudinal study. Namely, a significant direct correlation between physical activity for men and an increasing risk of becoming obese. This correlation was not found for women. They proposed that overweight influences physical inactivity, but did not discuss the causal relationship between physical activity and overweight.

Within the active travel domain, most research has been done with regards to children. Children are chosen because physical activity declines in adolescence and because travel patterns are established in childhood. In their review about active school transport and body weight of children, Faulkner, Buliung, Flora & Fusco (2009) found that most researches regarding this topic were cross-sectional, except for one prospective research by Rosenberg, Sallis, Conway, Cain& McKenzie (2006). The cross-sectional design does not allow examination of the causal relationship. In general, they concluded that active school commuters do not differ in BMI compared to passive school commuters. Loucaides & Jago (2008) did find a difference, but only for overweight children.

In 2013, Saunders et al. reviewed four longitudinal cohort studies about active travel and overweight in children with contradicting results. Bere, Oenema, Prins, Seiler, & Brug (2011) did such a longitudinal cohort study, using data from Norway and The Netherlands measured at two points in time, with two years in between. They used the multilevel logistic regression to analyse the data and did not examine the causal relationship between the two variables. The aim of this analysis is to estimate the odds that an event will occur (Sommet, & Morselli, 2017). They concluded that children who cycle to school are less likely to be overweight compared to children who were brought by car. The other three longitudinal cohort studies found no significant relationship between active travel and overweight in children and did not examine the causal relationship between the two variables either (Rosenberg, 2006; Pabayo, Gauvin, Barnett, Nikiéma & Séguin, 2010; Heelan, Donnelly, Jacobsen, Mayo, Washburn & Greene, 2005).

Xu et al. (2013) reviewed the relationship between active travel and body weight. They included researches focused on adolescents and found that the evidence that active travel lowers body weight is weak to moderate. Similar to research about children, most studies used cross-sectional design. Furthermore, the results of the studies are contradicting. 40 of the 69 studies reported associations with lower weight, 24 studies found no association and 4 studies even found associations with higher weight.

2.9 The relationship between activity and mental health

Not much is known about how, why, in whom and when physical activity influences the mental health (Pickett, Kendrick, & Yardley, 2017). In general, the various mechanisms can be classified in two mechanisms: physiological and psychological (Peluso & Andrade, 2005). The physiological mechanisms are focused on the internal biological reactions in the body. During physical activity two different neurotransmitters are released, monoamines (Morgan, 1985) and endogenous opioids (Allen, 2000), where both could be responsible for the improved mental health. Monoamine works in a similar way as antidepressant drugs (Dunn & Dishman, 1991). Endogenous opioids affect the central nervous system and are responsible for a sensation of calm and improved mood (Allen, 2000). The psychological mechanisms are: distraction, self-efficacy and social interaction (Pickett, Kendrick, & Yardley, 2017). The first mechanism suggests that physical activity takes the attention away from negative stimuli (Morgan, 1985). Self-efficacy proposes that physical exercise is a challenging activity, undertaking this activity regularly leads to an improved mood and self-confidence (North, McCullagh, & Tran, 1990). The last mechanism states that physical activity is often combined with social interaction (Ransford, 1982), these interactions lead to a better mental health.

Daskapan, Tuzun & Eker (2005) found a positive correlation between physical activity and general mental health under university students, using the SF-36 to measure mental health. Abu-Omar et al., (2004) found similar results, using data from 15 different member states of the European Union and the MHI-5 to measure mental health. Korge and Nunan (2018), found an association between higher participation in physical activity and the reduced use of mental health service. A negative correlation has also been found between intense physical activity and mental health (Peluso & Andrade, 2005). Excessive exercise and overtraining syndrome have a bad influence on the mental health. Kim, Park, Allegrante, Marks, Ok, Cho, & Garber (2012) concluded that the optimal dose to benefit the general mental health is within the range of 2.5 to 7.5 hours of physical activity per week. Besides general mental health, more specific relationships have also been researched. Most researches have focused on depression and anxiety. Physical activity has a positive effect on both disorders (Dinas, Koutedakis, & Flouris, 2011; Park et al., 2011). However, Biddle and Asare (2011) concluded that the association that was found were often small to moderate and the research designs were weak.

Overall, a causal relationship from active travel towards mental health is expected. White et al., (2017) examined the difference of domain-specific physical activity on mental health. Using a Meta-analysis, they examined studies ranging from 1988 to 2015. In their research, they included various domain-specific physical activities, including work-related physical activity. Commuting with an active mode showed a strong positive relationship with mental health. In the reviewed articles, 76% of the researches were cross-sectional. Four articles included longitudinal studies, whereas three of these were focussed on leisure physical activity and the one article about commuting explored the relationship between active travel and psychological well-being. This article of Martin, Goryakin and Suhrcke (2014) explored the relationship between active travel and psychological well-being. Using the data of 17,985 adult commuters in eighteen waves, they estimated the relationships using the fixed effects regression model. They found a significant association between active travel and overall psychological wellbeing when compared to car travel.

2.10 The relationship between overweight and mental health

The last relationship that is described is the relationship between overweight and mental health, and is thus the relationship between both health indicators of this study. De Wit, Van Straten, Van Herten, Penninx & Cuijpers (2009) found a U-shaped association between general mental health and overweight. People with underweight had the highest MHI-5 score, followed by people who were obese and normal. People who were overweight had the lowest MHI-5 score and were therefore mentally the healthiest. This same result has been found for the specific mental health disorders, such as: anxiety and depressive disorders (Scott et al., 2008). However, socio-demographic variables are important moderators, females are more likely to be affected by this relationship than male. Age is also an important moderator, as the relationship was stronger among younger and older people (Scott et al., 2008). Luppino, De Wit, Bouvy, Stijnen, Cuijpers, Penninx & Zitman (2010) reviewed studies that looked at the longitudinal association between overweight and mental health. They concluded that there is a reciprocal relationship between overweight and mental health. Meaning that overweight increases the risk of depression and depression can act as an indicator to develop overweight.

2.11 Conclusions and implications for this research

In conclusion, a few knowledge gaps have been found in the current literature. In this section, these knowledge gaps are discussed together with the implications these knowledge gaps have for this research.

First of all, limited research has been done regarding the effect of active travel on the total physical activity. Contradicting results make that the relationship is not well-understood. To overcome this knowledge gap, the relationship between active travel and other physical activity forms have to be examined. There are different forms of physical activity that could be substituted by active travel. In this research, the choice is made to only examine one of these forms, namely, leisure physical activity. This means that the other forms of physical activity are excluded from the scope of this research. Examples of other forms are: work-related physical activity, household physical activity and physical education. This choice is made because of the available time for this research, but it could be interesting to examine these in future research.

Secondly, a difference has been found for activity and physical or mental health outcome. Therefore, physical health and mental health should be examined specifically in relationship with active travel. The relationship between activity and mental health is not well-known, with only weak evidence for the relationship on a population level. Experiments show more promising results. On the contrary, the relationship between active travel and overweight is well-examined. A limitation of the majority of these researches, is that they are conducted with cross-sectional studies. Cross-sectional study design is able to study the association and to some extent the isolation to define a causal relationship. However, the data is measured at one point in time. Direction of influence states that one must also ensure that the variation in the independent variable came before the variation in the dependent variable (Bollen, 1989). In other words, one must ensure that the time order is correct. The direction of influence is not possible to derive using a cross-sectional study approach (Setia, 2016). As this research is interested in the causality, the cross-sectional study design does not fulfil the requirements to conduct this research with. Another disadvantage of single-moment surveys is that they are unable to measure the mode alteration accurately, especially for car and bicycles. Repeated measures may be a solution (Heinen & Maat, 2012). Of the small body of longitudinal researches, contradicting results have been found. Furthermore, no advanced research methods such as SEM are used to examine the complex relation between active travel and health. The longitudinal researches were mainly conducted with simple methods such as multilevel logistic regression. SEM could provide an possible method to examine the complex relation with.

One possibility to examine the direction of influence, is to conduct an experiment with randomization and control. By manipulating a particular factor and looking at what outcome occurs, insight can be provided in the cause and effect. However, an experiment is often not practical nor feasible, as it could create ethical dilemmas. Furthermore, the results of an experiment are difficult to generalize to the population (Kearney, 2017). Using panel data or longitudinal data is an effective way to address the time order issue in population studies. Furthermore, as respondents are not manipulated, ethical dilemmas are avoided. “A panel dataset is one that follows a given sample of individuals over time, and thus provides multiple observations on each individual in the sample” (Hsiao, 2003). Because panel data involves measures of the same variables of the same individuals observed at least at two points in time, the time order between variables can be tested empirically and all three requirements of a causal relationship can be tested. Therefore, the use of panel data, provides stronger evidence for the causality between active travel and health. Other advantages of panel data for research are described in more detail in the paper by Hsiao 2007.

Thirdly, a relation between different socio-demographic variables and individual characteristics has been found. These could have an influence on the estimated relations and, if possible, should be included in the model. The decision is made to limit the inclusion of the socio-demographic variables to only the most used socio-demographics: age, income, gender, civil status, urban character of residence and level of education. This choice is made, given the available time for this research. However, other socio-demographic variables could be interesting to include in future research.

The final conclusion and implication of this study, various ways exists to measure the variables exists. In the literature, an increasing amount of research can be found with more objective and more precise measurements. However, these measurement instruments are often more expensive and therefore less feasible for large samples. In general, one could say that self-reported data is a feasible option to examine the relationships with for population studies.

In figure 3, the conceptual model of this research is presented consisting of only the relationships that are examined in this research. Because the direction of influence will be examined, the variables have to be measured at least twice. Panel data is suited for this purpose. Self-reported data can be used to examine the complex relationship, as it is more feasible than other forms of data gathering. Furthermore, the hypotheses are examined with a SEM model. To estimate the relationship between active travel and leisure physical activity, the model is controlled for socio-demographic variables. The second SEM model regarding relationship between active travel and health, will include overweight and mental health as indicators of health.

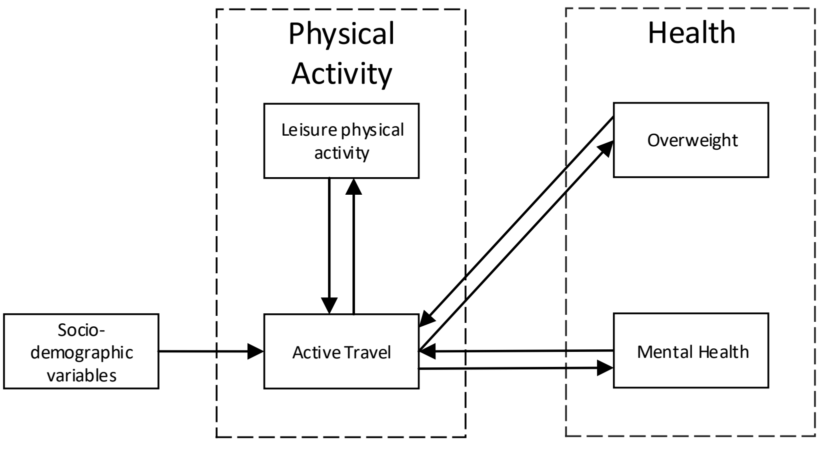


Figure 3 - The conceptual model that is examined

In this chapter, the methodology of this research is described. First, the data is described that fit the requirements as described in the previous chapter. This is followed by a description of the respondent selection in section 3.2 and a description of the sample in section 3.3. To analyse the data, a model should be applied. In section 3.4, the Cross-Lagged Panel Model is proposed to analyse the data. This model is able to analyse panel data. An explanation of the CLPM is given in section 3.4. This is followed by an explanation of the programs that are used to estimate the models. In section 3.6, the operationalization of the variables is described. In section 3.7, the models are specified. The last section of this chapter, describes the different sensitivity analyses.

3.1 LISS Panel data

This research is conducted with the Longitudinal Internet Studies for the Social sciences (LISS) Panel data. The surveys for this panel data are conducted by the CentERdata research institute. The panel consists of 4500 households, including 7000 individuals living in the Netherlands. The data is based on a true probability sample of households drawn from the population register by Statistics Netherlands (CBS). Households complete online questionnaires and are paid for each completed questionnaire. In case a household cannot participate otherwise, CentERdata provides a computer and an internet connection (LISS panel, n.d.). The LISS Panel consists of multiple studies. In this research the LISS Core Study, the travel behavior, well-being and transport-related attitudes study and the Weighing Project are used.

The LISS Core Study is a longitudinal study and the aim is to be repeated yearly. Included in the Core Study are questions about the background, health and sports habits of the panel members (LISS panel, n.d.). Additional to the core study, researchers can send in extra surveys to collect data for different research purposes. One of these additional surveys named: “travel behavior, well-being and transport-related attitudes”, is sent in by Handy, Van Wee and Kroesen (2013). This additional survey includes questions about the active travel behavior of the respondents.

The Weighing Project is another ongoing project linked to the LISS panel. The project consists of two parts: a questionnaire and a weighing part. The questionnaire of this project is sent to selected households on a monthly base. The second part consists of measuring the respondents using a weighing scale provided by CentERdata. These scales send the weight data directly to CentERdata. This project has two advantages over the self-reported weight that can be found in the LISS Core Study. First of all, the scale sends the data directly to the researchers. This means that the respondent cannot adjust their weight. The second advantage is that the researchers can test the weighing scales they send on reliability. Using different weighing scales could lead to different results, and therefore, more measurement error. In this research, The Weighing Project is used to estimate the measurement error of the BMI of the Core Study.

Due to expiring of the financing period not all the years of the LISS Core Study are available (M. Marchand, personal communication, May 25, 2018). The LISS Core study regarding health in 2014 is missing. However, the additional Travel-behavior survey was only conducted in 2013 and 2014. Therefore, the waves of 2012, 2013 and 2015 are used in this research to examine health. Table 2 depicts an overview of the LISS panel studies. The effect of the missing waves on the models is explained in more detail in section 3.7.

Table 2 - LISS panels with corresponding wave dates and total amount of respondents

LISS panel study	Wave start date	Total Amount of respondents
Background Variables	Jul - 2012	11,211
	Jul - 2013	9,720
	Jul - 2014	12,381
	Jul - 2015	10,957
LISS Core Study – Health	6 (05-11-2012)	5,780
	7 (04-11-2013)	5,379
	8 (06-07-2015)	5,975
LISS Core Study - Social Integration and Leisure	6 (04-02-2013)	5,759
	7 (03-02-2014)	6,643
Travel behavior, well-being and transport-related attitudes	1 (01-07-2013)	2,380
	2 (07-07-2014)	1,383
The Weighing Project	Nov - 2012	1,162
	Nov - 2013	1,258

Important to note about the LISS panel studies, is that the same studies are done in the same month for different years. However, different studies are conducted in different months. For example, the LISS Core Study is conducted in November and Travel behavior in July. This is of importance, because this means that even if two variables are measured in the same year. It could be that in reality there is a lag between the measurements, and therefore, not the model does not estimate an instantaneous effect, but a lagged effect. In this research, an instantaneous effect or synchronous effect is assumed when the variables are measured in the same month. If variables are measured in different months, a lagged effect is assumed.

3.2 Respondent selection and missing data

This research is conducted with almost all of the respondents who filled in the active travel questions for wave 1 of the Travel behavior survey. This way the active travel of the respondents is measured at least one time. Within the data, there are some responses that are not very likely or even plausible. Especially for the variable active travel, it is difficult establish the difference between valid responses or possible mistakes. For this problem, the decision is made to make use of an arbitrary threshold. The choice for this threshold is justified for each variable in Appendix A. Based on the reported physical activity and MHI no respondents were deleted, as there were no outliers found or indications that the responses were invalid. For the variables active travel and BMI, some outliers are found. Eventually, the decision is made to take these outliers out of the data, based on correlations in a different direction than expected and the place of these outliers on the histogram. In Appendix A, the process of outliers is described in more detail. This means that the main research is conducted with the outliers taken out of the data and the results, as presented in this research, are without the outliers. In the sensitivity analysis, the effect of outliers is examined and the possible effects of these outliers on the results is reflected on.

The analyses are conducted with 2,214 respondents. To test if the respondents filled the survey carefully, a simple test is conducted and the correlation of age, year of birth and gender are examined for the waves of 2013 and 2014. In all cases, the correlation was 1. This gives reason to believe the respondents filled in the survey carefully.

Important to note is that wave 2 of the Travel behavior survey is completed by only 1,273 respondents. That is 941 respondents less than wave 1. Furthermore, the data show that not all the respondents of the travel behavior survey filled in the Core Study (whole-wave missing data) or did only fill in the survey partly (within-wave missing data). There are various ways to handle missing data. The simplest way is to delete all the respondents with missing data. However, this could lead to loss of information and reduce the statistical power of the analysis (Collins, Schafer & Kam, 2001). For that reason, the choice has been made to use a missing data procedure to handle the missing data. Procedures such as pairwise deletion, substitution of means and regression predictions perform poorly in general (Little & Rubin, 1987). Full information maximum-likelihood (FIML or simply ML) and multiple imputation (MI) are missing data procedures that are both able to produce efficient estimates and accurate measures of statically uncertainty (Collins, Schafer & Kam, 2001). Moreover, both procedures do yield similar results (Collins, Schafer & Kam, 2001). The choice is made to use the ML procedure in the main analyses, for convenience reasons. As this procedure is integrated in AMOS, the same program that is used to estimate the CLPM with.

The ML method chooses parameter values that assign the highest possible probability to the data values, under well-defined parametric probability models (Rubin, 1987). The method assumes that the missing data is missing at random (MAR) (Little, 1995). When the missingness of a variable is not depending on the variable itself, it is called MAR. Under MAR the missingness of a variable and the variable itself may be related but only indirectly through another variable. If the missing data are MAR, the missing data values are removed from the likelihood by summation or integration. Therefore, they are treated as unknown random variables to be averaged over (Collins, Schafer & Kam, 2001). Once a model is specified and the raw data with the missing values is put in, the ML procedure computes the parameters estimates based on the available data. To test the effect of the ML procedure, the model is also estimated using the listwise method in the sensitivity analysis.

3.3 Sample data

In section 3.3.1 the sample composition per year is discussed. Thereafter, the representativeness of the sample is discussed in section 3.3.2.

3.3.1 Sample composition (2012, 2013, 2014 and 2015)

In this section, the socio-demographic variables of the dataset are discussed, combined with the changes of these variables over the time. In the dataset, there are missing values. Especially, the income questions is not filled in by all the respondents. Therefore, the total number of respondents per year is shown. For income, the net monthly personal income is used. The categories for the other variables are mainly based on the CBS categories. This gives the opportunity to compare the data of this sample with the CBS data.

Table 3 presents the socio-demographic variables of the sample. Most socio-demographic variables change in the expected direction. As the data is of the same respondent, the age is expected to go up after a year. Interestingly, income in 2014 decreases compared to the years before. This difference can partly be explained by examining the responses of one specific respondent. This respondent filled in that he had an income of 310,000 euro in 2012 and 2013. However, his income dropped to 3560 euro in 2014 and 2015. Overall, gender does not change over the years as expected. Through the years, more people become a couple and less stay single. The urban character of the respondents almost does not change over the years. The level of education with a degree increases, the older respondents get, the higher the chance that the respondents finished a (higher) degree.

Table 3 - Key variables in 2012, 2013, 2014 and 2015

Variable	**Description**	**Mean (Standard deviation)**			
Year		**2012**	**2013**	**2014**	**2015**
N	Total amount of respondents	2196	2214	2151	2051
Age	Average age	49.54 (17.19)	50.41 (17.22)	51.32 (17.11)	52.36 (16.98)
Income	Personal net income per month	1728 (7510)	1792 (8873)	1577 (4459)	1623 (4580)
Gender	Female	53.3 %	53.5 %	53.3 %	53.3 %
	Male	46.7 %	46.5 %	46.7 %	46.7 %
Civil status	Couple	59.7 %	59.2 %	59.7 %	61.0 %
	Single	40.3 %	40.8%	40.3 %	39.0 %
Urban character of place of residence	Extremely urban	11.5 %	11.6 %	11.7 %	11.8 %
	Very urban	25.3 %	25.4 %	25.5 %	25.6 %
	Moderate urban	24.5 %	24.4 %	24.4 %	24.3 %
	Slightly urban	23.0 %	22.9 %	22.6 %	22.2 %
	Not urban	15.8 %	15.6 %	15.8 %	16.0 %
Level of education with diploma	Primary school	10.0 %	8.6 %	7.7 %	6.7 %
	Vmbo (intermediate secondary education)	23.1 %	23.3 %	23.1 %	22.4 %
	Havo/Vwo (higher secondary education)	10.9 %	11.3 %	10.8 %	11.2 %
	Mbo (intermediate vocational education)	24.4 %	24.6 %	25.2 %	25.9 %
	Hbo (higher vocational education)	23.4 %	23.6 %	24.2 %	24.4 %
	Wo (university)	8.3 %	8.6 %	9.0 %	9.5 %

3.3.2 Representativeness of the LISS Panel

Representativeness of the LISS panel is important to be able to draw conclusions for the Dutch population. As the socio-demographic variables do not differ much over the years, the representativeness of the LISS Panel is only tested once, with the 2013 data. Sample selectivity occurs when the sample is a nonrepresentative sample for the population. As explained in the previous chapter, the panel is based on a true probability sample of households. However, not all the households answered all the questions in all the LISS panel datasets. Therefore, the representativeness has to be examined specifically for the dataset that is used in this research. The representativeness is tested based on: age, income, gender, civil status, urban character of residence and level of education. These percentages of the sample and the population percentages are depicted in table 4. Data from Statistics Netherlands (CBS) is used to test the representativeness of the sample with and to assess whether the sample composition differs significantly from the Dutch population.

Table 4 - Representativeness of the sample

Variable	Description	Sample percentage	Population percentage	P-Value
Age [1]	Average age	50.5	40.8	0.000***
Income [2]	Gross household income per month	5248	4833	0.573
Gender [3]	Female	53.5 %	50.5 %	0.009**
	Male	46.5 %	49.5 %	
Civil status [3]	Married	59.2 %	40.7 %	0.000***
	Single	40.8 %	59.3 %	
Urban character of place of residence [4]	Extremely urban	11.6 %	22.5 %	0.000***
	Very urban	25.4 %	28.6 %	
	Moderate urban	24.4 %	18.7 %	
	Slightly urban	22.9 %	20.5 %	
	Not urban	15.6 %	9.6 %	
Level of education with a diploma [5]	Primary school	8.6 %	11.1 %	0.000***
	Vmbo (intermediate secondary education)	23.3 %	22.3 %	
	Havo/Vwo (higher secondary education)	11.3 %	8.9 %	
	Mbo (intermediate vocational education)	24.6 %	30.9 %	
	Hbo (higher vocational education)	23.6 %	17.2 %	
	Wo (university)	8.6 %	9.6 %	

[1] https://opendata.cbs.nl/statline/#/CBS/en/dataset/37296eng/table?ts=1532684605397
[2] http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=70991ned&D1=a&D2=0-15&D3=0&D4=12&HDR=G3,G2,T&STB=G1&VW=T
[3] https://opendata.cbs.nl/statline/portal.html?_la=nl&_catalog=CBS&tableId=37296ned&_theme=68
[4] http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=82816ned&D1=0&D2=0&D3=0&D4=0&D5=3,5-6,9-11,14,16&D6=a&D7=54,l&HDR=G6,G3,G1,G2,G4&STB=T,G5&VW=T
[5] http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=82816ned&D1=0&D2=0&D3=0&D4=0&D5=3,5-6,9-11,14,16&D6=a&D7=54,l&HDR=G6,G3,G1,G2,G4&STB=T,G5&VW=T

The p-value of the one sample t-test for income is not significant. This indicates that income of the sample is similar to the average income of the population. The significant p-value of the other variables indicates a significant difference between the sample values and the population values. Although the distributions are significantly different, at the generic level the distributions match well with the population. Therefore, no problems with generalization to the Dutch population are assumed.

3.4 Cross-Lagged Panel Model

In section 3.4.1, the main model of this research (CLPM) is explained. Thereafter, possible additions to the model are explained in section 3.4.2.

3.4.1 The basic CLPM

In general, the CLPM is used to investigate a hypothesis regarding the causal directionality of two or more variables (Newsom, 2015). A two wave two variable CLPM is depicted in figure 4. This version of the CLPM can be seen as the basic mode. This model consists of two different dependent variables. In this case, variable X and variable Y. Both variables are being predicted by their previous value, as well as the previous value of the other variable. The term "cross" is used to emphasize the effect of one variable on the other. The term "lagged" emphasizes the usage of data with time in between the measures (Kearney, 2017).

In figure 4, observed variables are represented by squares. Unobserved variables have two or more indicators and are represented by circles. Relationships between variables are indicated by arrows and a lack of an arrow implies that no direct relationship is hypothesized. Arrows can be one- or two-headed. A one-headed arrow implies a direct relationship between two variables. The variable the arrow points towards is the dependent variable. A two-headed arrow indicates a covariance between the two variables. In the case of a covariance, an association is assumed but no particular direction is hypothesed (Ullman & Bentler, 2012).

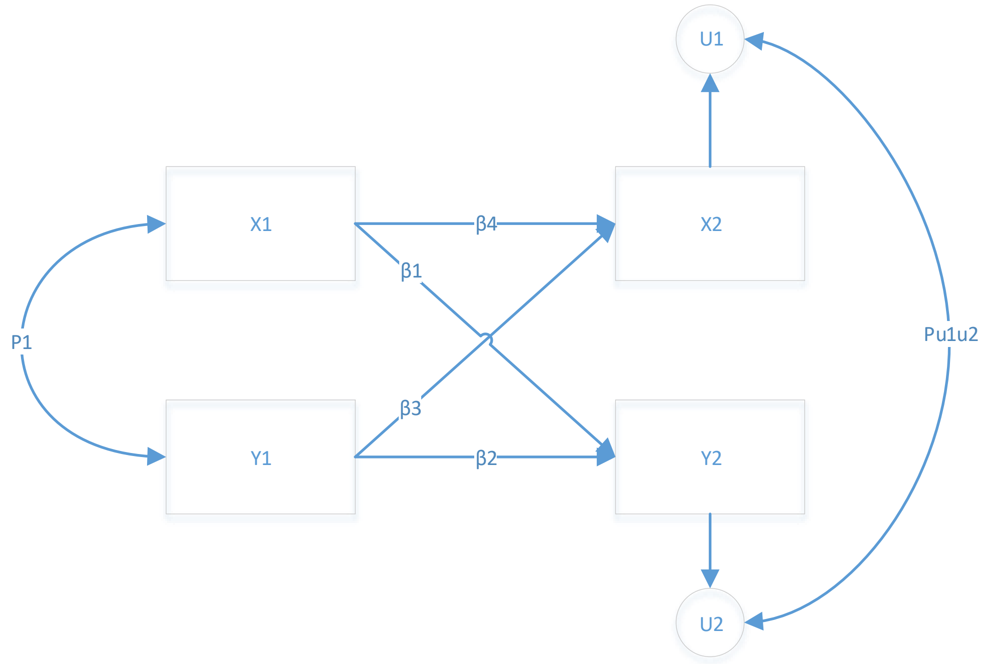


Figure 4 - Example of a Cross-lagged panel model (CLPM).

In figure 4, X1 represents variable X measured at time point 1 and X2 represents the same variable measured at time point 2. Same applies for Y1 and Y2. β2 and β4 are the autoregressive paths and represent the stability of a variable over time. A value closer to 1 indicates relative stability within the variable over time. Assuming that the model is corrected for measurement errors in the measured variables, the remaining unexplained variation in endogenous variables X2 and Y2 is seen as variance from individual changes which have occurred in the period between the two measurements. P1 controls for the initial overlap between X1 and Y1, correcting for the effects of third variables and previous causal influences between both variables. U1 and U2 represent the error terms. The error terms indicate the covariation between variables X2 and Y2 and are associated with variables that are not included in the model. The correlation between the error terms Pu1u2 accounts for possible third variables that influence variables X and Y between the two measurements and a possible synchronous effects between X and Y (Kroesen, Molin, & van Wee, 2010).

In the CLPM, the most important parameters are the cross-lagged paths: β1 and β3 (Rogosa, 1980). The standardized parameters represent the causal effect from one variable to the other (Bentler & Speckart, 1981). These paths try to explain the variance in X2 and Y2 that is not already explained by the stability coefficient (β2 and β4), while controlling for initial overlap (P1), third variables and synchronous causal influences (Pu1u2). Comparing the effects of the parameters β1 and β3 can be used to examine the causal predominance. This can be interpreted in terms of predicting change (Finkel, 1995). If the cross-lagged effect is significant in one direction, but is not significant in the other direction. The results are consistent with the hypothesis that the causal effect works in one direction but not in the other direction. If none of the cross-lagged effects are significant, the results indicate no causation in either direction, given the time lag and the sample size of the study. If both cross-lagged effects are significant, the results suggest that the causal effects work in both ways (Newsom, 2015). The estimated R^2 values represent to which extend the lagged variables explain the variance in the dependent variables. The CLPM can be expressed by following two structural equations:

Equation 1- Structural equation of the CLPM

$$Y_2 = \beta_1 X_1 + \beta_2 Y_1 + U_1$$

$$X_2 = \beta_3 Y_1 + \beta_4 X_1 + U_2$$

A limitation of the two wave CLPM, is that the model is saturated and the model fit cannot be examined. This means that the parameters and standard errors can be estimated, but is it not possible to tell if the model provides a proper description of the actual reciprocal mechanism (Hamaker et al., 2015). Therefore, theory and hypotheses play an important role when applying the CLPM.

In case of an extended CLPM, the model can have degrees of freedom and the model fit can be estimated. Chi-square can be used to determine the model fit. However, this indicator tends to be too large, when the sample size is large. Theoretically, a random sample of the respondents can be taken out of the database, and thereby, the sample size will decrease and Chi-square can be used. However, this will lead to a lower statistical power of the estimations. Another option is the use of additional goodness-of-fit statistics to examine the model fit. Root Mean Square Error of Approximation (RMSEA) and Comparative Fit Index (CFI) are such statistics, which take into account the limitations of Chi-square. A model is defined as well-fitting when it has a value between 0.06 - 0.08 for RSMEA and CFI value larger than 0.95 (Hu & Bentler, 1999). More information about the additional goodness-of-fit statistics can be found in Structural Equation Modelling with AMOS by Byrne (2016).

3.4.2 Adaptions to the CLPM

Additionally to the CLPM, adaption can be made depending on the available data or for theoretical reasons. In the next section, four adaptions are described that are used in this research to improve or fit the CLPM. The adaptations are: reliability, covariates, synchronous path and Random Intercepts-CLPM (RI-CLPM).

3.4.2.1 Reliability

Measurement errors in the observed variables can bias the autoregressive and cross-lagged effects of the CLPM. This can affect the regression coefficient, resulting in an increase in variance. The measurement error can be corrected in the model, by taking the reliability into account. If the reliability of the independent variable is small, the regression coefficient is weaker than estimated. The reliability can be added to the model by adjusting the observed variable into a latent variable with one indicator and chancing the variance of the error term of the indicator. How the measurement error is taken into account in the estimated models and how the reliability is estimated, is explained in detail in section 3.5.

3.4.2.2 Covariates

Covariates can be added to the CLPM and can be used as control variables. Regression coefficients are biased to the extent that a covariate is associated with other predictors, but is excluded from the model. In the case of a CLPM, the autoregressive effect is biased, if a covariate correlates with variable X on both points in time, but is not added to the model. Same can be said for the cross-lagged effect between the two variables X and Y. By adding covariates, the bias of a specific covariate can be taken into account in the model.

3.4.2.3 Synchronous path

A synchronous path is a path between variables measured at the same point in time. It measures the synchronous effect, this is a change in Y at the second point in time resulting from a change in X at a point in time after the first occasion (Kroesen et al., 2010). In the CLPM, only non-directional relationships (covariances and correlations) between variables at the same point in time are estimated. However, uni-directional relationships can be added if there is a theoretical reason to estimate an instantaneous effect. Two-directional paths are difficult to estimate, because of predictor-disturbance dependence and identification issues (Mulaik, 2009). Synchronous effects can also be added for other reasons such as, unavailability of a measurement of a variable at a certain point in time. In this research, a path is assumed to be synchronous if the variables are measured at the exact same time. In all other cases, a cross-lagged effect is assumed.

3.4.2.4 RI-CLPM

The Random Intercepts - Cross-Lagged Panel Model (RI-CLPM) is a new adaptation of the CLPM, introduced in the article of Hamaker, Kuiper and Grasman (2015). Limited researches have used the RI-CLPM and to the best of the knowledge of the author, this is the first research using the RI-CLPM to examine the relationship between BMI and MHI. Therefore, this adaptation is discussed in more detail. First, the within-levels effects is explained. Thereafter, the RI-CLPM is introduced and is explained how the RI-CLPM takes the within-levels into account. This section ends with an explanation of the new meaning of the parameters of the RI-CLPM.

Increasing concerns can be found in the literature about the use and interpretation of the CLPM (Hamaker, et al., 2015; Keijsers, 2015). Their criticism is mainly aimed at the fact that CLPM does not allow to examine the within-person change, but only examines the between-person difference. In the CLPM, the differences are only examined at the population level. However, it is possible that these differences are not necessary true at individual level (Keijsers, 2016).

Hamaker (2012) illustrated this with the following example about the relationship between typing speed (words typed per minute) and typos made (percentage of words typed wrong). At the population level, it is possible to find a negative relationship between typing speed and typos made. In other words, people who type faster make fewer mistakes. A possible explanations for this direction is: people who type faster are more experienced with typing, and therefore, make fewer mistakes. This relationship is depicted in figure 5 on the left side. If this result is generalized to the individual level, one would conclude that a particular person who types faster, make fewer mistakes. This is clearly opposite to the expectation, as one would expect that if a particular person would increase their typing speed, more mistakes would happen. Therefore, on the individual level one would expect a positive relationship rather than a negative relationship. The relationship of multiple individuals are depicted in figure 5 on the right side. Figure 5 depicts that because the individual means differ in the opposite direction and the variability between individuals is larger than the variability in individuals, the relationship as estimated for the population is negative (Hamaker, 2012). In conclusion, relations found at the population level are not necessary true on the individual level.

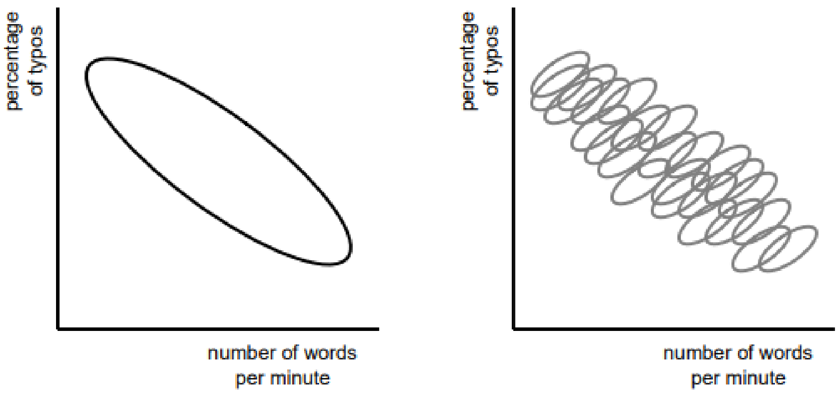


Figure 5 - Relationship between typing speed and typos on population and individual level

Hamaker et al. (2015) investigated the effect further and found three possible wrong results than can be caused by using the CLPM, and not taking into account the within-level effects: 1. No significant cross-lagged paths, while in reality there are; 2. Variable X is causally dominant, while in reality variable Y is dominant; 3. The sign of the cross-lagged paths is estimated negative, while in reality it is positive. Therefore the conclusions of a traditional CLPM can be misleading and are limited.

To address this problem, Hamaker et al. (2015) introduced the Random-Intercepts Cross-Lagged panel model (RI-CLPM). In the RI-CLPM, the variance at the within-level is distinguished from the variance at the between-level. By including random intercepts, this model can control for time-invariant trait-like individual differences (between-person effect) (Hamaker et al., 2015). The random intercepts take out the between-person variance. Therefore, the lagged relationship in the RI-CLPM applies to the within-person effect.

The addition of the random intercepts change the interpretation of the parameters of the model. In the RI-CLPM, the autoregressive parameter does not represent the stability of the variable of individuals from one occasion to the other, but represent the amount of within-person carry-over effect. If the autoregressive parameter is positive, it means when a person scores above the expected score, this person is likely to score an above expected score in the second measurement. The cross-lagged parameters indicate the degree by which deviations from an individual's expected score on Y can be predicted from preceding deviations from one's expected score on X, while controlling for the individual's deviation of the preceding expected score on Y (Hamaker et al., 2015). The correlation between the random intercepts reflects how stable the differences between variable X are linked with stable differences in variable Y.

One of the requirements of the RI-CLPM is that at least three waves of data are needed to be applied, this way there is at least 1 degree of freedom available. Therefore, the model fit of the RI-CLPM can be examined. For this research this means that the RI-CLPM can only be applied between BMI and MHI. An example of a three wave RI-CLPM is depicted in figure 6.

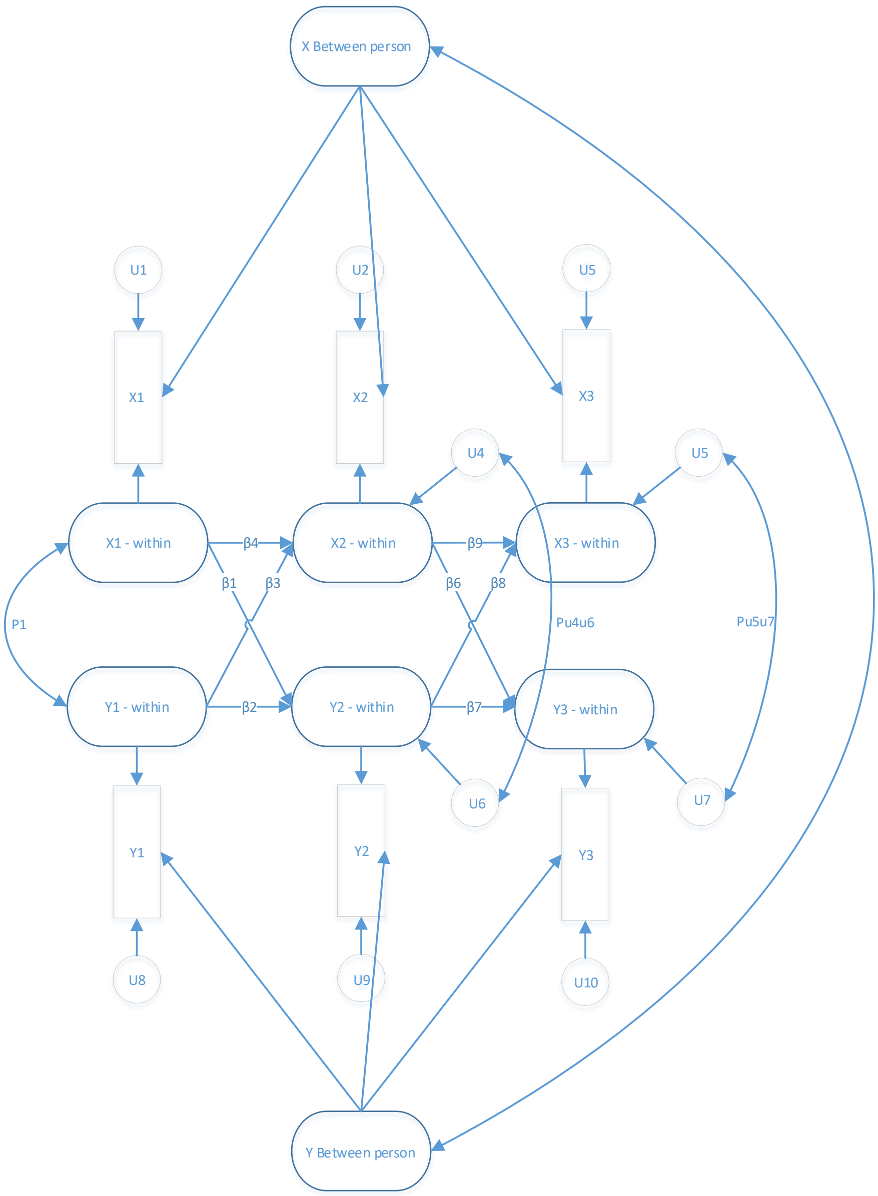


Figure 6 - Example of a Random-Intercepts Cross-Lagged Panel Model (RI-CLPM).

3.5 Data Analysis

To estimate the CLPM, the method of Maximum Likelihood is used. This is the default method in most SEM computer programs. In Maximum Likelihood, the estimates are the ones that maximize the likelihood that the data were drawn from the population. For this method, multivariate normality is assumed for the distribution of the endogenous variables (Kline, 2010).

The CLPM is estimated using AMOS (Analysis of Moment Structures) version 25. In AMOS Graphics, the user can specify the model by drawing the model on the screen. SPSS (Statistical Package for the Social Sciences) version 25 is used to conduct the descriptive and correlational analysis.

3.6 Operationalisation of the variables

In this section, the operationalisation of the variables is discussed. The questions the operationalisation is based on are mentioned and the descriptive of the key variables are depicted.

3.6.1 Leisure physical activity

Leisure physical activity is any muscular movement that increases energy expenditure and is not performed with active travel modes, executed during leisure time. To assess the extent to which responders were physically active, the respondents had to fill in one question: "How many hours do you spend on sports per week, on average?". The answers were measured on a continues scale and are measured in hours.

3.6.2 Active travel

Active travel is defined as walking or cycling for all purposes (e.g., transport or recreational). Active travel has been assessed by two questions: "How many kilometres do you travel (approximately) in a regular week, using the following modes of transport? – By bicycle" and "How many kilometres do you travel (approximately) in a regular week, using the following modes of transport? – On foot". These answers were measured on a continues scale and measured in kilometres per week. Combined with the answers of the two questions, they make up for the total amount of active travel a respondent has travelled per week. In table 5, the mean and standard deviation of physical activity and active travel are depicted for 2013 and 2014.

Table 5 - Key travel variables in 2013 and 2014

Travel variables	Description	2013 (N=2214)	2014 (N= 1285)
		Mean (s.d.)	**Mean (s.d.)**
Active travel	Total active travel	38.42 (44.11)	39.53 (44.46)
	Kilometres someone travelled by bike per week	26.94 (37.07)	27.92 (37.77)
	Kilometres someone travelled on foot per week	11.47 (19.12)	11.54 (15.99)
Physical Activity	Amount of hours someone spends on sport	2.08 (3.10)	2.07 (2.98)

3.6.3 Overweight

Overweight is defined as weighing more than is optimally healthy and can be calculated using the Quetelet's index and the formula: weight/height (kg/m^2) (Garrow & Webster, 1985). The LISS Core Study includes the questions: "How tall are you in cm?" and "How much do you weigh, without clothes and shoes in kilogram?". The answers to these questions are used to calculate the BMI. BMI makes use of meter in the formula. Therefore, the answers for height are divided by 100.

Self-reported measures of height and weight show trends of over-reporting height and under-reporting weight (Xu, Wen & Rissel, 2013). This results in an underestimation of BMI and can eventually influence the estimated effect of the model. Therefore, the measurement error of BMI is taken into account in the model. To do this, the correlation between the self-reported weight from the LISS Core Study and the objectively measured weight of the Weighing Project will act as the reliability measure. This is similar to the test-retest method as described by Bollen (1989). The Weighing Project stopped in 2014, therefore, no reliability data is available for 2015. The correlation for 2015 is set at 0.9, lower than the correlation of the other years. In table 6, the key health variables in 2012, 2013, and 2015 are depicted.

3.6.4 Mental Health

Mental health is used to indicate people with mental health problems or a mental disorder (Pilgrim, 2017). To assess the extent to which respondents are mentally healthy, the MHI-5 test is used. This test is the standardized method to measure general mental health in population based studies. This test does not diagnose specific psychological disorders, but tests if someone suffers from any psychological disorder and measures the general mental health of a person (Driessen, 2011). The MHI-5 questions consists of the following questions: 'This past month I felt very anxious', 'This past month I felt so down that nothing could cheer me up', 'This past month I felt calm and peaceful' 'This past month I felt depressed and gloomy' and 'This past month I felt happy'.

The respondents could choose from a 6-point scale: 1 = never, 2 = seldom, 3 = sometimes, 4 = often, 5 = mostly or 6 = continuously. Each answer is given a score between 0 and 5. However, some questions are formulated negative and some positive. Therefore, question 3 and 5 are scored as follows: 5 = never, 4 = seldom, 3 = sometimes, 2 = often, 1 = mostly and 0 = continuously. The negative formulated questions 1,2 and 4 are valued as follows: 0 = never, 1 = seldom, 2 = sometimes, 3 = often, 4 = mostly and 5 = continuously. By summing the score of the questions, a MHI-5 score between 0 and 25 can be calculated. A low MHI-5 score indicates a low mental health and mental health problems. In this research, the cut-off point of 15 is used to establish if someone is mentally healthy or not, similar to the cut-off point as used by CBS.

Normally the scores on the MHI-5 questions are multiplied by 4 and the MHI score ranges between 0 and 100. However, this is not done in this research, because it makes it problematic to address the measurement error in the models. Therefore, the MHI score in this research ranges between 0 and 25. To address the measurement error in mental health, the reliability is estimated using Cronbach's Alpha (α) of the 5 MHI questions, as described by Bollen (1989).

Table 6 - Key health variables in 2012, 2013 and 2015

Health Variables	Description	2012 (N=2074)	2013 (N=2067)	2015 (N=1841)
		Mean (s.d.)	**Mean (s.d.)**	**Mean (s.d.)**
MHI	I felt very anxious	3.83 (1.06)	3.98 (1.026)	4.02 (0.98)
	I felt so down that nothing could cheer me up	4.30 (0.98)	4.38 (0.948)	4.42 (0.882)
	I felt calm and peaceful	3.28 (1.09)	3.23 (1.14)	3.32 (1.06
	I felt depressed and gloomy	3.93 (1.06)	4.02 (1.06)	4.06 (0.96)
	I felt happy	3.32 (1.04)	3.27 (1.070)	3.28 (1.07)
	Total MHI score (0-25)	18.65 (17.50)	18.87 (16.83)	19.10 (16.17)
MHI reliability	Cronbach's Alpha score	0.859	0.839	0.868
BMI	Body Mass Index	25.76 (8.57)	25.47 (5.12)	25.74 (5.26)
BMI Reliability		0.945	0.913	0.9
Weighing project variable		**2012 (N=208)**	**2013 (N=282)**	**N.A.**
Body Mass Index	BMI as measured in the weighing project	25.32 (4.02)	25.20 (3.75)	
Body fat percentage	Fat percentage as measured in the weighing project	27.27 (6.96)	26.88 (6.94)	

3.6.5 Overlap between leisure physical activity and active travel

In the LISS surveys, there is no clear distinction between the questions: "How many hours do you spend on sports per week, on average?" and "How many kilometres do you travel (approximately) in a regular week, using the following modes of transport? – By bicycle or on foot". This means that overlap is possible between leisure physical activity and active travel. It could be that respondents filled in that they cycled a certain amount of hours as a sport, but also filled in the same amount of kilometres for the active travel questions. This is problematic, because this would mean that the same trip is taken into account twice in the analysis.

In the LISS Core study, the respondents were asked: "What sports do you practice?". The respondents could choose between different options among which: cycling, jogging and walking. In this research, these sports are seen as active travel. In total, 572 respondents filled in they practice either walking, jogging or cycling as a sport in 2013 and 562 respondents in 2014. This is almost 26% of the respondents. Because of the large amount of respondents with possible overlap, the overlap can be problematic if not taken into account in the analysis. Given the data, it is not clear whether the activity is done for travel reasons or as a sport. Furthermore, it is not known whether the same amount of kilometres would have been travelled if another mode should have been used. For example, it could be that people cycle this amount of kilometres because they like cycling or because they just wanted to do any sport. Because the writer cannot think of a solution to overcome the problem of overlap between active travel and leisure physical activity. The decision is made to conduct the main analyses in this research with no adjustments for overlap in the data. However, because of the possible effects of this problem and the large amount of respondents that are linked to this problem, adjusted datasets are made to take the overlap into account. These datasets are examined in the sensitivity analysis and the results are discussed in Appendix B and C. This way the results are based on the available data and the sensitivity analysis makes it possible to give an indication of the effect of the problem.

3.7 CLPM Specification

In this section, the CLPM is specified. This means that the CLPM is estimated on the LISS panel data, and specifically on the operationalized variables. In the introduction, two hypotheses are introduced that are examined in this research. The first hypothesis is the substitution hypothesis between active travel and other forms of physical activity. To examine this hypothesis, two models are estimated: the CLPM, and the CLPM controlled for socio-demographic variables. The second hypothesis is the causal bi-directional relationship between active travel and health. To examine this hypothesis, two models are estimated: the CLPM and the RI-CLPM. Additionally, to these models, different datasets are used to examine the effect of the encountered problems with the LISS data. This is done in the form of a sensitivity analysis and are only conducted for the basic CLPM. The sensitivity analysis is explained in more detail in section 3.7.3.

3.7.1 CLPM specification for the relationship between physical activity and active travel

In the first model, the causal relationship between active travel and leisure physical activity is examined. This model is depicted in figure 7. The data from the waves 2013 and 2014 are used for both physical activity and active travel. β2 and β4 are the autoregressive paths and examine the stability over time. β1 and β3 are the cross-lagged paths and give information about the strongest temporal predictor.

Important to note is that the variables are not measured at the same time. Ideally, this would have been the case. However, physical activity is measured in February and active travel in July, for both 2013 and 2014. This impacts the lagged-effects in CLPM, as the time for β1 is estimated for 7 months, whereas β3 is estimated for 17 months. The two waves each have 12 months between them. Given the available data, waves and operationalisation, the model is fit on the situation and is specified as depicted in figure 7. The RI-CLPM cannot be estimated, because only two waves of the data are available and the RI-CLPM can only be estimated with three or more waves.

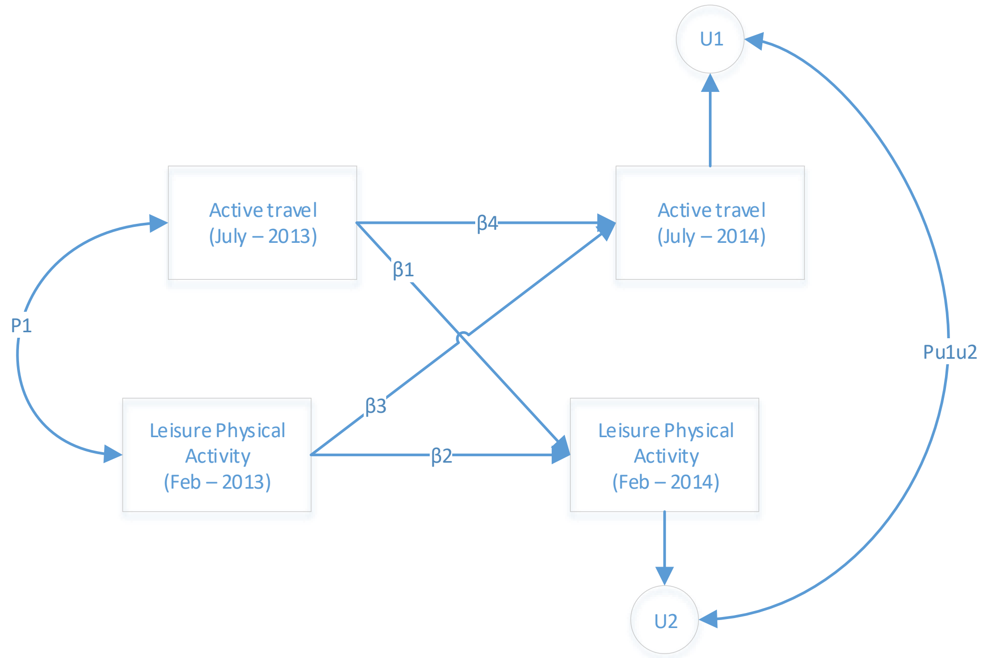


Figure 7 - Specified CLPM of the relationship between active travel and leisure physical activity

To test the hypothesis, two models are estimated. The first model is the basic CLPM and can be seen in figure 7. The second model consists of the basic model, controlled for socio-demographic variables. This model is depicted in figure 8. In general, the importance of socio-economic variables, such as age, gender and education level for travel behavior are recognised (Van Wee & Ettema, 2016). In this model, all the socio-demographic variables described in section 3.4 are tested. However, only the model with significant covariates and paths is examined in the main text. The model with all the covariates and paths can be found in Appendix D. By adding covariates to the model, the variables at time point 1 change into endogenous variables, as they are influenced by the control variables and error terms are added for these variables. Furthermore, a covariance is added to the covariates, controlling for initial overlap.

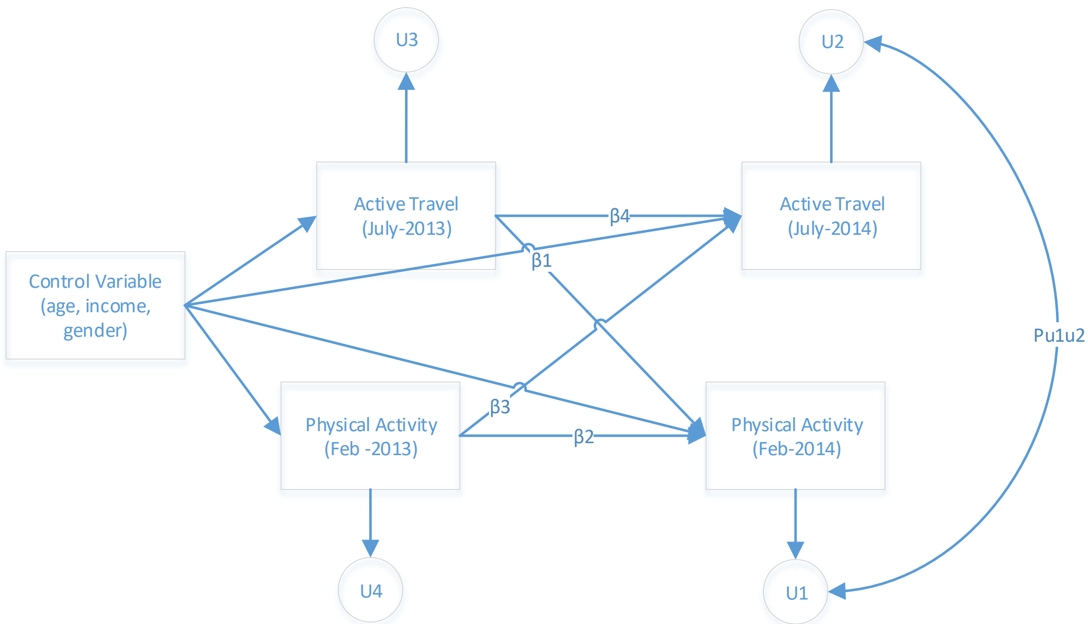


Figure 8 - Specified CLPM of the relationship between active travel and leisure physical activity.

3.7.2 Model specification for the relationship between active travel and health

In this research, the choice has been made to divide health into physical health and mental health and to examine both relationships with active travel. At first, the idea was to estimate a model with the health indicators separately. These ‘simpler’ models would make it easier to test the effect of the addition of covariates for these models. However, these models tested unidentified. Therefore, the decision is made to add physical health and mental health in one model and not to test the influence of covariates for this relationship.

The specification of the CLPM for the relationship between active travel and health is more complicated than the previous specification. This is caused by the missing wave of health in 2014, as explained in section 3.1 “LISS Panel data”. In the ideal situation, the CLPM would be estimated with two variables measured at two points in time. However, given the available data, the available waves and the operationalisation, some adjustments had to be made. Furthermore, for this relationship it is possible to estimate the RI-CLPM, because of the three available waves.

3.7.2.1 CLPM for active travel and health

To estimate the relationship between active travel and health, the CLPM uses three data waves (2012, 2013 and 2015) for health and two waves (2013 and 2014) for active travel. Both health indicators are regressed on their own latent factor, with each loading set at 1. Resulting in 6 latent variables, with 6 error terms. The variances of the error terms of BMI are set equal to (1 – α) * Var(x). The variance of the error terms of the latent variable MHI are set equal to (1 – reliability) * Var(x). Active travel is added in the model as an observed variable. The specified model is depicted in figure 9.

In the model, there are five autoregressive paths. Β14 and β15 are the autoregressive paths between health in 2012 and 2013. β4 is the autoregressive path between active travel. These paths are estimated for 12 months. The autoregressive paths β2 and β6 are estimated for 20 months. The model has 8 cross-lagged paths. β12 and β13 are estimated for 1 year and β8 and β9 are estimated for 24 months. β10 and β11 are estimated for 4 months and β1 and β5 are estimated for 24 months.

In the model, the decision is made to add covariance paths (P1 and P2) between active travel 2013 and health 2012. This corrects for initial causal influence between both variables. It can be theoretically justified to estimate a lagged effect between health 2012 and active travel 2013. However, this led to an unidentified model. Because the covariance is measured between two different points in time, it may be that each predictor only partially controls for the other variable. The correlation P3 between the health indicators correct for the initial causal influence between the health indicators. The last paths that are in the model are β10 and β11. These paths are lagged paths measured in the same year, but with 4 months in between and model effect between active travel and both health indicators. In addition to this model.

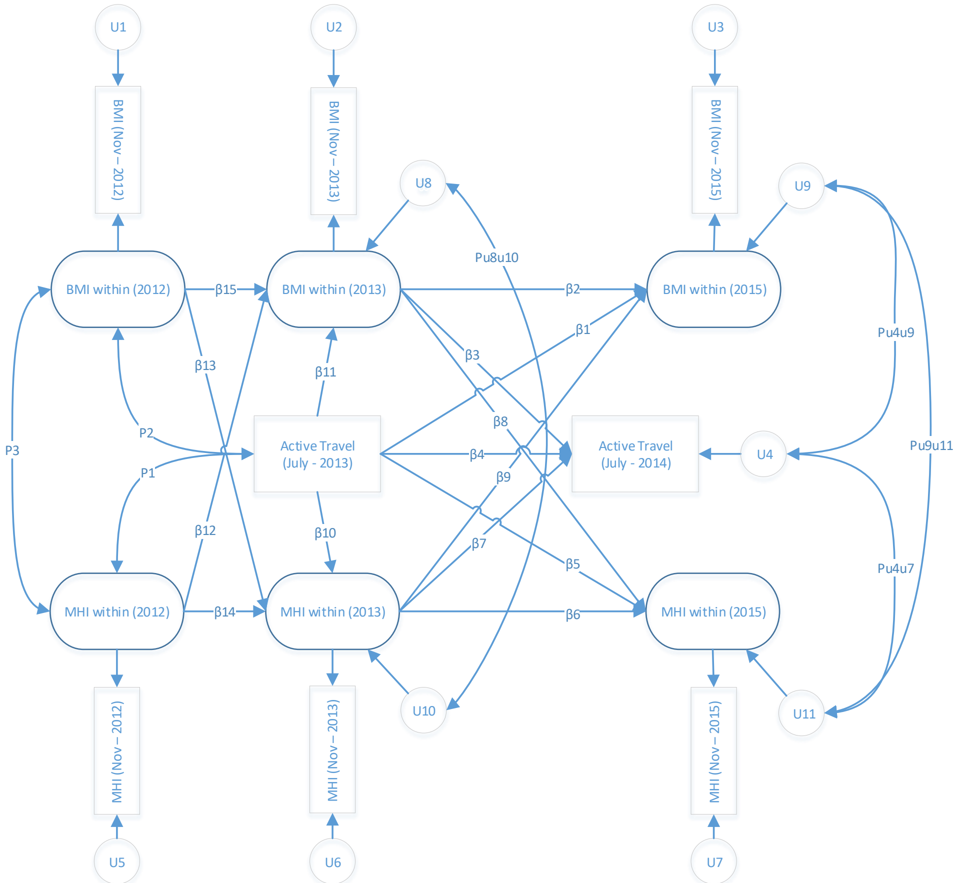


Figure 9 - CLPM of the relationship between active travel and BMI and MHI

3.7.2.2 RI-CLPM model for active travel and health

Because three waves of data are available, the RI-CLPM can be estimated. This model takes into account the difference between variance at the within-level, from the variance at the between-level. To model the RI-CLPM, the procedure as described by Hamaker et al. (2015) is followed. Additional to the CLPM, two random intercepts are added for BMI and MHI. These are used to control for the stable between-level variance. The observed variables act as indicators of these random intercepts, with the factor loadings constrained at 1. Furthermore, a correlation between the random intercepts is added to the model. The specified RI-CLPM is depicted in figure 10.

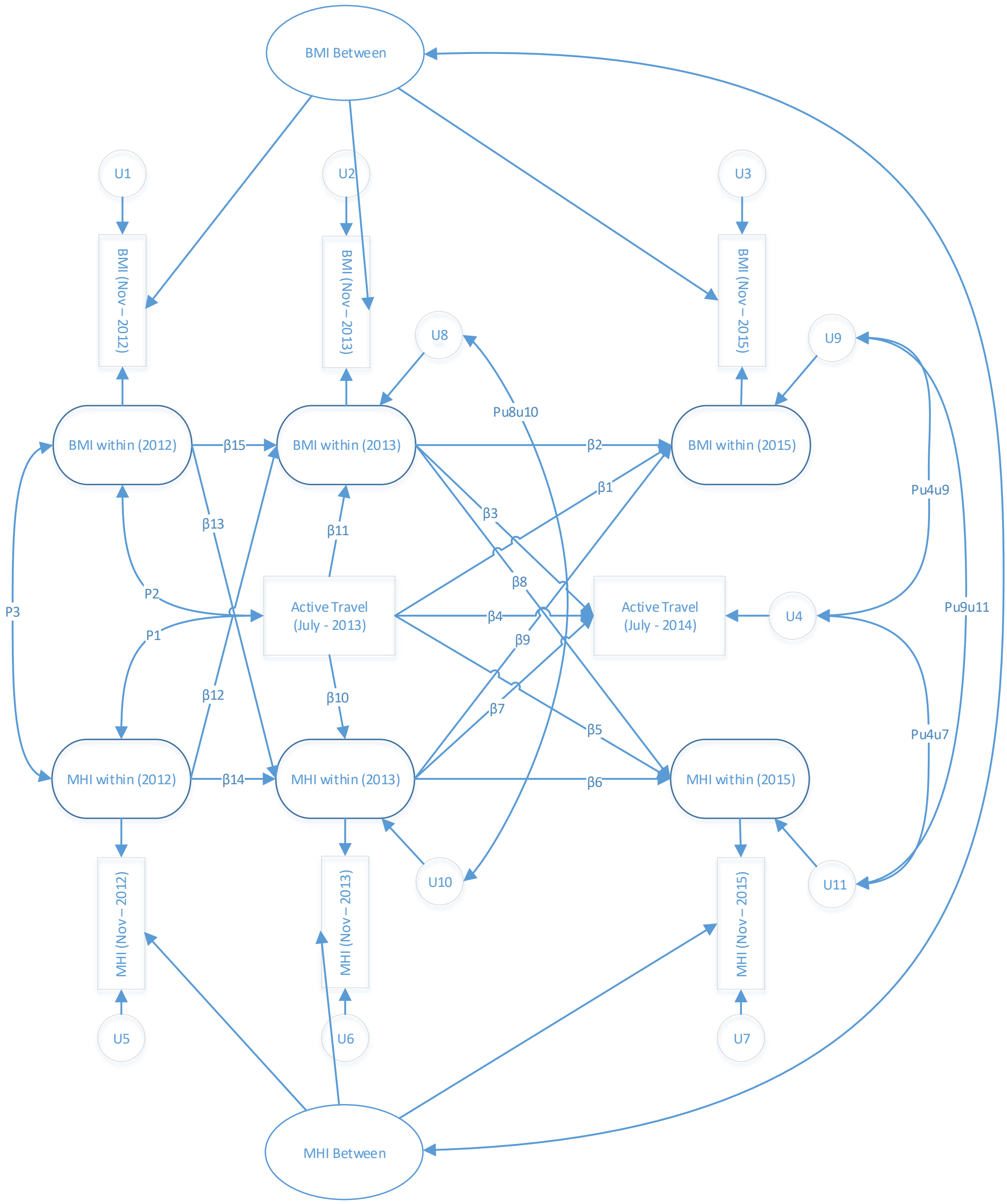


Figure 10 - Specified RI-CLPM of the relationship between active travel and BMI and MHI

3.8 Sensitivity analysis

Some problems have been encountered linked to the LISS panel data. In this research, these problems are overcome in various ways. To understand the effect of these problems, different scenarios are tested in the sensitivity analysis. The sensitivity analysis models and their estimations can be found in Appendix B for the relationship between active travel and leisure physical activity and in Appendix C for the relationship between active travel and health.

3.8.1 Overlap

In the data, an overlap is possible between active travel and leisure physical activity. To take the overlap into account, it is unknown whether active travel should be subtracted from leisure physical activity or leisure physical activity should be subtracted from active travel. Therefore, both ways are examined in the analysis. For the respondents who filled in they only practice one sport, it can be assumed that the responded hours of sport are all performed doing this specific sport. This is the case for 117 respondents in 2013 and 126 respondents in 2014. By taking into account the average speed of walking, cycling or jogging, the amount of hours can be converted into kilometres and vice versa and thereby subtracted from the other. In this calculation, the following average speed per mode are used: 5km/h for walking, 10km/h for jogging/running and 25 km/h for cycling.

For the respondents who filled in they practice more than one sport, this method cannot be used. For these respondents it is not possible to know how many hours are put in which sport. This is the case for 451 respondents in 2013 and 432 respondents in 2014. For this group the decision is made to examine the extremes. Therefore, in the first analysis active travel is set at 0. In the other analysis, leisure physical activity is set at 0.

3.8.2 Outliers

Another problem with the data, is that possible outliers are encountered. Based on the unexpected direction of the relations in the correlation analysis, as depicted in Appendix A, and the plausibility of the values, the values are taken out of the dataset for the main analysis. However, it could be that the variables are indeed correct and that some people travel more than 700 kilometres per week actively. Therefore, the basic CLPM will also be estimated with the outliers, to test the effect of the outliers on the results. Another option to address the outliers is by dividing active travel into ordinal categories. By dividing active travel in 5 groups, with in each group 20% of the respondents, the outliers are categorized in the same group, resulting in less effect of the outliers.

3.8.3 Missing data

In the LISS panel data, data is missing between the waves. This means that not all the respondents who filled in the survey in 2013, filled in the survey in 2014. Therefore, the FIML procedure is used to estimate the models. This way all the available information can be used. To test the effect of this procedure, the models will also be estimated with the listwise procedure. This means that the model will also be estimated with only respondents who filled in all the variables of interest. By comparing the results of the different missing value procedures, the effect of the FIML on the results can be examined.

3.8.4 Conclusion

In conclusion, 5 extra models are estimated for the sensitivity analysis. For the first hypothesis, twice the overlap model, twice the outlier model and once the missing value model is estimated. For the second hypothesis, 3 extra models are estimated. Twice the outlier model and once the missing value model. Table 7 shows the different models and the different data that is used to estimate the models.

Table 7 - Sensitivity analysis models

Model	Data changes
Overlap model	To test the overlap, active travel is subtracted from leisure physical activity or leisure physical activity is set at 0 for the respondents with possible overlap
Overlap model	To test the overlap, leisure physical activity is subtracted from active travel or active travel is set at 0 for the respondents with possible overlap
Outlier model	To test the outliers, the CLPM is estimated with all the data, including the outliers.
Outlier model	To test the outliers, active travel is reconstructed on an ordinal scale, with 20% of the respondents in every group.
Missing value model	To test the missing values, the model is estimated with only the respondents who filled in all the variables of interest in all the waves.

CHAPTER 4 – RESULTS:

The relationship between leisure physical activity and active travel

In this chapter the results of the CLPM are discussed regarding the relationship between physical activity and active travel. The sub-question that is key in this chapter is: "*What is the direction of causation between physical activity and active travel and to what extend do the variables influence each other?".* To answer this question, first the correlations between physical activity and active travel across the two waves are examined in section 4.1. This gives a first impression on how the two concepts are linked. Thereafter, the CLPM and the CLPM controlled for socio-demographic variables are applied to examine the reciprocal relationship, while taking into account the stability of the variables across the years. For parsimonious reasons, only the socio-demographic variables and paths with a significant influence on the model are included in the model. Additionally, the sensitivity analysis is applied in section 4.3. In section 4.4, the results are interpreted and a short recap of this chapter is given in more understandable terms.

The hypothesis that is tested in this chapter is: Active travel substitutes for other forms of physical activity. Leisure physical activity is used as an indicator for other forms of physical activity. This hypothesis predicts that active travel will have a negative influence on leisure physical activity and can be tested by examining the relationship between active travel and leisure physical activity.

4.1 Correlations

The correlational analysis reveals high correlations between the waves, as can be seen in table 8. Especially the correlation between the same variable over the years are high and. This indicates a high stability over time within the variables. Also the correlation between the different variables for the successive years are significant. This indicates a possible lagged relationship between active travel and leisure physical activity. The correlation between the two variables in the same year is significant as well. This indicates a possible instantaneous relationship between the two variables.

Table 8 - Correlation between active travel and leisure physical activity

	Active travel 2013	Active travel 2014	Leisure physical activity 2013
Active travel 2013	1	-	-
Active travel 2014	0.612**	1	-
Leisure physical activity 2013	0.217**	0.206**	1
Leisure physical activity 2014	0.244**	0.254**	0.733**

** Correlation is significant at the 0.01 level.
* Correlation is significant at the 0.05 level.

4.2 CLPM

Tables 9 and 11 present the unstandardized and standardized estimates of the two models. In figure 11 and 12, the blue arrow indicates the effect from leisure physical activity to active travel. The blue value indicates the corresponding standardized estimation between leisure physical activity towards active travel. The red arrow indicates the effect from active travel towards leisure physical activity and the red value indicates the standardized estimation.

The model fit of the first model cannot be examined because the model is saturated. Model 1 indicates significant autoregressive effects for active travel (0.631***) and leisure physical activity (0.732***), indicating that the variables are stable and do not change much over time. More interesting are the cross-lagged effects, as can be seen in figure 11. The model indicates a significant effect of leisure physical activity on active travel (1.128**). Someone who spends more hours sporting in 2013 travels more kilometres on an active mode in 2014. The other cross-lagged effect from active travel to physical activity is also significant (0.005***). Someone who spends more kilometres traveling on an active mode spends more hours sporting.

Both correlations in the model are significant, as shown in table 9. The correlation between active travel 2013 and leisure physical activity 2013 indicates an initial overlap. Furthermore, the correlation between the error terms of leisure physical activity 2014 and active travel 2014 is significant. This correlation indicates influence of a third variable not included in the model or a synchronous effect. However, it is not possible to indicate which of the two causes the effect.

Table 9 - Estimates of the CLPM

	Active travel 2014		**Leisure physical activity 2014**	
	b	β	b	β
Active travel 2013	0.631***	0.613	0.005***	0.067
Leisure physical activity 2013	1.128**	0.077	0.732***	0.737
R^2	0.403		0.570	

*** Effect is significant at the 0.001 level.
** Effect is significant at the 0.01 level.

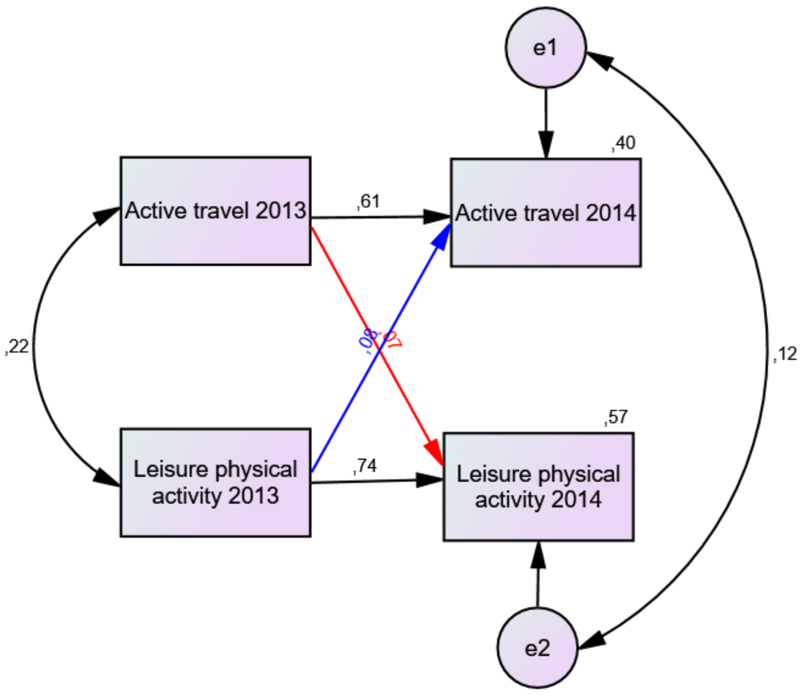


Figure 11 - Standardized estimates of the Leisure physical activity – active travel CLPM.

Table 10 - Covariates between the key variables and their error terms

	Estimate
Active travel – Leisure physical activity 2013	29.781***
e1 – e2	8.282***

*** Covariates is significant at the 0.001 level.

4.3 CLPM with control variables

To examine the control variables, multiple models are estimated. These are depicted in Appendix D. The model that is presented in this section is the parsimonious model. The model fit of the second model is presented at the bottom of table 11. The model has to be rejected based on the Chi-squared. However, the Chi-square test has been found to be sensitive to large sample sizes. This causes that the model may fit the data, but is rejected because of the large sample size. In this case, the sample size is 2,214. Therefore, other model fit indicators are used as leading indicators to address the model fit. The RMSEA value is within the range of 0.06 and 0.08. The CFI score is just above the required 0.95, indicating a good fit.

The addition of the control variables affects the relationship between leisure physical activity and active travel only slightly. The same paths remain significant and the direction of the paths stays the same. Gender has a significant effect on active travel. Women in 2013 travel less actively compared to man. Age, gender and income have a significant effect on leisure physical activity. The higher the age, the less leisure physical activity is undertaken. Men exercise more often than women and the higher the income the more sport someone undertakes. Furthermore, income has a negative influence on active travel in 2014.

Similar to the first model, the correlation between the error terms of leisure physical activity 2014 and active travel 2014 significant. This indicates influence of a third variable not included in the model or a synchronous effect. Furthermore, the correlation between the control variables age and gender, and age and income is significant. This indicates an initial overlap between these variables.

Table 11 - Estimates of the CLPM with control variables

	Active travel 2013		**Leisure physical activity 2013**		**Active travel 2014**		**Leisure physical activity 2014**	
	b	β	b	β	b	B	b	β
Active travel 2013					0.623***	0.593	0.005***	0.070
Leisure physical activity 2013					1.244***	0.083	0.731***	0.745
Age			-0.023***	-0.128				
Gender	-5.942**	-0.067	-0.517***	-0.083				
Income			0.000**	0.072	-0.002***	-0.338		
R^2	0.005		0.026		0.469		0.561	
	Chi-square: 113.647, df:8, P:0.000, RMSEA: 0.077, CFI: 0.954							

*** Effect is significant at the 0.001 level.
** Effect is significant at the 0.01 level.

Table 12 - Covariates between the key variables and their error terms

	Estimate
e1 – e2	8.532***
Gender – Age	-0.622***
Age - Income	9299.948*
Gender - Income	-38.699

*** Covariates is significant at the 0.001 level.

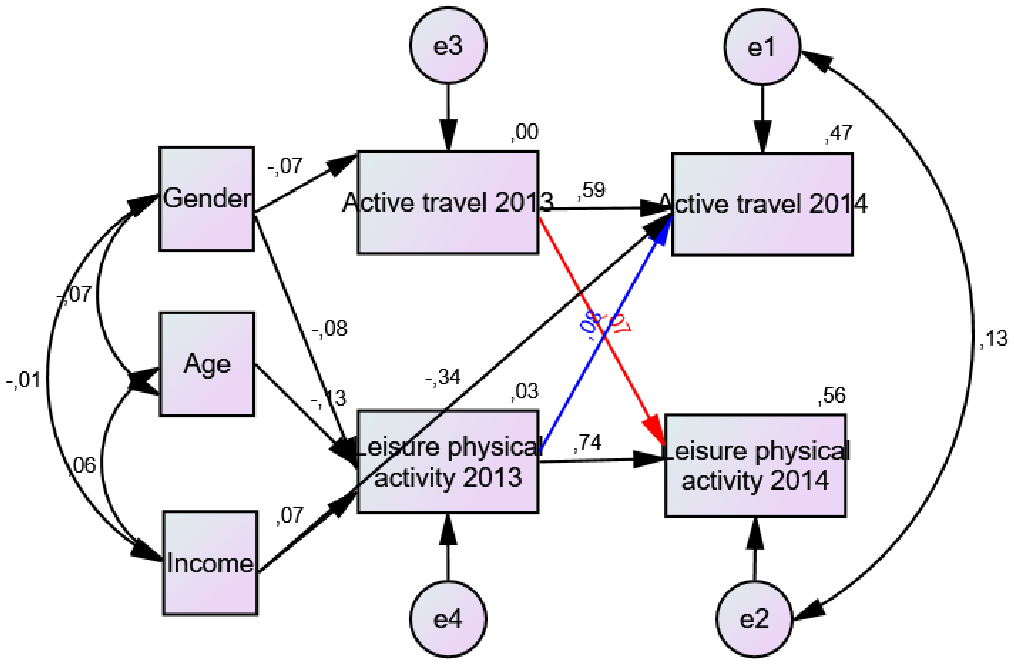


Figure 12 - Standardized estimates of the CLPM controlled for gender, age and income.

4.4 Sensitivity Analysis

In Appendix B, the sensitivity analysis models are depicted regarding the relationship between active travel and leisure physical activity. In this section, the main model is the model as described in section 4.2. Both overlap models indicate that both cross-lagged parameters are not significant between active travel and leisure physical activity. This is problematic because the main model indicates that these parameters are significant. Because the extremes are tested, we believe that the effect is less strong than these models make believe. However, these models do show the importance of taking overlap into account. This is discussed in more detail in section 6.3 "limitations" and section 7.3 "recommendations for future research". In the first outlier model with no outliers taken out of the dataset, the cross-lagged parameter from active travel 2013 to leisure physical activity 2014 is not significant. This indicates that the choice for inclusion or exclusion of the outliers has an effect on the results. In the outlier model where active travel is divided in 5 ordinal scales, the model depicts similar significant paths as the main model. Based on both outlier models, we conclude that taking out the outliers was the right choice to make for the main model. The last estimated sensitivity analysis is the missing value model. This model gives the same significant parameters as the main model.

The most important conclusion based on the sensitivity analysis, is that the relationship between active travel and leisure physical activity does not become negatively significant, as expected by the hypothesis. This is of importance, as this means that the different problems do not give an indication to believe that the hypothesis is true and cannot be falsified.

4.5 Interpretation of the results

The first hypothesis predicts that active travel substitutes for other forms of physical activity, i.e., has a negative influence on total physical activity. The correlation between active travel 2013 and physical activity 2014 show a positive significant correlation. This same result has been found once the stability is taken into account in the CLPM, the control variables are included into the model and the sensitivity analysis is conducted. These findings do not support hypothesis 1.

Surprisingly, an effect is found in the opposite direction from the hypothesized effect. The results indicate that instead of a substitution effect, active travel has a positive effect on leisure physical activity. Therefore, an increase in active travel would lead to an increase in leisure physical activity. This would mean that active travel will not decrease the overall physical activity, but will lead to a higher overall physical activity. The model also indicates a positive effect from leisure physical activity to active travel. Someone who spends more time sporting, also spends more time travelling actively.

In short, we tested whether active travel has an influence on physical activity. In this research, we found that active travel will stimulate physical activity. Furthermore, physical activity also has a stimulating effect on active travel. Therefore, these findings support the idea that active travel has a positive influence on health.

Chapter 5 – Results:

The bi-directional relationship between Active travel and health

In this chapter the results of the specified models are discussed regarding the relationship between active travel and health. The sub-question that is key in this chapter is: "*What is the direction of causation between active travel, overweight and mental health and to what extend do the variables influence each other?* ". Firstly, the correlations are examined between active travel, BMI and MHI in section 5.1. This gives a first insight into how the two concepts are linked. Thereafter, the results of the CLPM are examined in section 5.2 and the results of the RI-CLPM in section 5.3. Additionally, the sensitivity analysis is applied in section 5.4. The chapter ends with the interpretation of the results and a short recap of the findings in this chapter in more understandable terms.

In this chapter, the hypothesis that is examined is: there exists a causal bi-directional relationship between active travel and health. This hypothesis predicts not only an effect of active travel on BMI and MHI, but also an effect of BMI and MHI on active travel.

5.1 Correlations

The correlational analysis revealed high significant correlation between the same variables over the years, indicating a high stability of the variables over the years for active travel, BMI and MHI. The results of the correlational analysis can be seen in table 13. The correlation between active travel 2013 and MHI 2012 and MHI 2013 are also significant. Indicating a possible positive relation between active travel and MHI. The other correlations are not significant, indicating no relationship between active travel and BMI.

Furthermore, the correlations are in the expected directions. In general, active travel has a negative correlation with BMI, someone who travels more actively has a lower BMI. Active travel has a positive correlation with MHI, someone who travels more actively has a higher MHI, indicating a better general mental health.

Table 13 - Correlation between active travel, BMI and MHI

	AT 2013	AT 2014	BMI 2012	BMI 2013	BMI 2015	MHI 2012	MHI 2013
AT 2013	1	-	-	-	-	-	-
AT 2014	0.612***	1	-	-		-	
BMI 2012	-0.031	-0.018	1	-	-	-	-
BMI 2013	-0.024	-0.006	0.911**	1	-	-	-
BMI 2015	-0.007	-0.004	0.913**	0.894**	1	-	-
MHI 2012	0.055*	0.043	0.020	0.022	0.034	1	-
MHI 2013	0.046*	0.035	0.025	0.018	0.035	0.642**	1
MHI 2015	0.045	0.037	0.011	0.006	0.032	0.600**	0.643**

*** Correlation is significant at the 0.001 level.
** Correlation is significant at the 0.01 level.
AT = Active travel

5.2 CLPM

Table 14 presents the unstandardized and standardized estimates of the CLPM. The standardized estimates are presented in figure 13. The model fits the data well. Only the Chi-square indicated a non-fitting model. However, this can be explained by the large sample size that is used in this research.

The autoregressive paths are significant at the 0.001 level, indicating a high stability over the years for active travel, BMI and MHI. Even though the correlations between active travel and MHI are significant, none of the cross-lagged paths are significant. These results indicate that there is no relationship between active travel and either obesity or mental health. A change in active travel has no effect on obesity or mental health. Furthermore, a change in mental health or obesity has no effect on active travel.

Two correlations are significant and are shown in table 15. The first significant correlation is between MHI 2012 and active travel 2013. This correlation indicates an initial overlap between the two variables. The other significant correlation is between the error terms of BMI 2015 and MHI 2015. This indicates influence of a third variable not included in the model or a synchronous effect. However, it is not possible to indicate which of the two causes the effect.

In the results three points stand out. The first is the weak cross-lagged effects, indicating no effect between active travel, BMI and MHI. The second point that stands out is the significant correlation between the error terms of BMI 2015 and MHI 2015. This indicates the influence of a third variable not included in the model or a synchronous effect. However, it is not possible to indicate which of the two causes the effect. The last point that stands out is the high stability of the variables. Especially, BMI has a high stability. For a cross-lagged path to have a significant effect, this cross-lagged effect has to be very strong to overcome this suppressor. These points are discussed in more detail in chapter 6 "Discussion and limitations".

Table 14 - Estimates of the CLPM

	AT 2014		BMI 2012	BMI 2013		BMI 2015		MHI 2012	MHI 2013		MHI 2015	
	b	β		b	β	b	β		b	β	b	β
AT 2013	0.649***	0.631		0.000	0.003	0.002	0.017		0.001	0.014	0.001	0.012
BMI 2012				1.008***	0.986				0.005	0.006		
BMI 2013	-0.115	-0.012				1.000***	0.993				-0.010	-0.013
MHI 2012				-0.010	-0.008				0.750***	0.776		
MHI 2013	-0.037	-0.003				0.018	0.014				0.781***	0.778
R^2	0.399		0.869	0.913		0.944		0.859	0.839		0.869	
	Chi-square: 71,676, df:6, P:0.000, RMSEA: 0.070, CFI: 0.993											

*** Effect is significant at the 0.001 level.
AT = Active travel

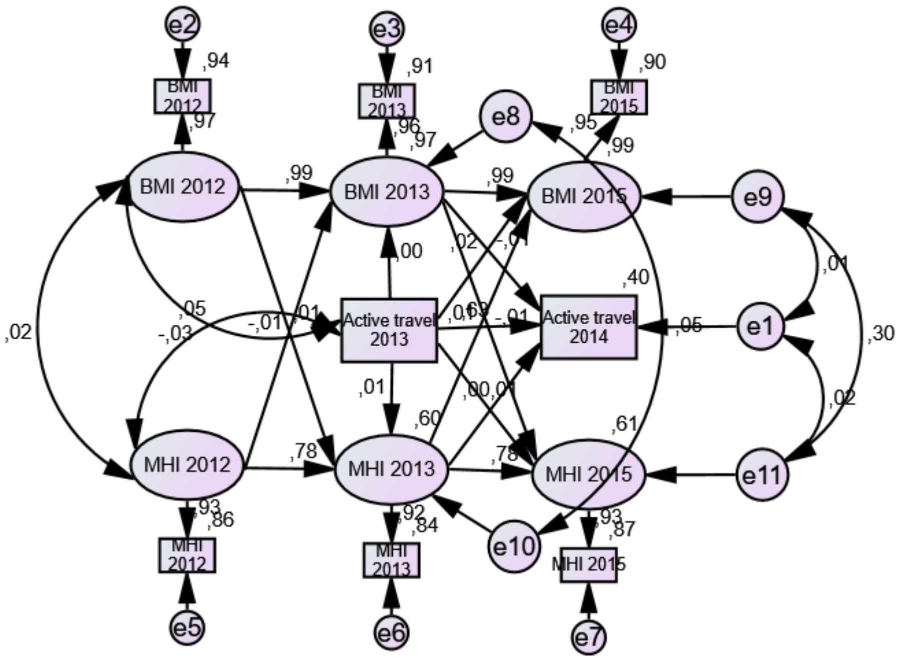


Figure 13 - Standardized estimates of the CLPM.

Table 15 - Covariances between the key variables and their error terms

	Estimate
BMI 2012 – MHI 2012	0.457
BMI 2012 – Active travel 2013	-6.720
MHI 2012 – Active travel 2013	9.275*
e1 – e11	2.058
e1 – e9	0.141
e9 – e11	0.418**
e10 – e8	-0.087

** Covariates is significant at the 0.01 level.
* Covariates is significant at the 0.05 level.

5.3 RI-CLPM

In the second model, the between-level variance is separated from the within-level variance for BMI and MHI. This is done by estimating the RI-CLPM. In this case, the RI-CLPM has an exact fit. This means that the Chi-Square is lower than the amount of degrees of freedom.

Table 16 presents the results of the RI-CLPM and the standardized estimates are presented in figure 14. The autoregressive paths for all the years of MHI and between BMI 2013 and BMI 2015 are significant. This indicates that within-level variance can be predicted by deviations from their own expected score on BMI and MHI. The autoregressive path between BMI 2012 and BMI 2013 is not significant with a p-value of 0.066. All the cross-lagged paths in this model are not significant, similar to the CLPM. This indicates that the variables are not linked reciprocally, and a deviation from their own expected score in BMI, does not predict a deviation from MHI (and vice versa).

Table 17 presents the correlations of the RI-CLPM. The non-significant correlation between BMI between and MHI between, reflects that the between-level variance of BMI is not linked with the between-level variance of MHI. The correlation between MHI 2012 and active travel 2013 reflect an initial overlap. The correlation between e9 (the error term of BMI 2015) and e11 (the error term of MHI 2015) indicates the effect of a third unmeasured variable or a synchronous effect.

Table 16 - Estimates of the RI-CLPM

	AT 2014		BMI 2012	BMI 2013		BMI 2015		MHI 2012	MHI 2013		MHI 2015	
	b	β		b	β	b	β		b	β	b	β
AT 2013	0.654***	0.636		0.000	-0.021	0.000	0.003		0.002	0.037	0.003	0.071
BMI 2012				0.825					-0.539			
BMI 2013	1.440	0.026				0.514***	0.454				-0.150	-0.059
MHI 2012				-0.010	-0.028				0.233*	0.254		
MHI 2013	0.027	0.001				0.060	0.135				0.188*	0.189
R^2	0.399		0.944	0.914		0.898		0.858	0.840		0.868	
	Chi-square: 1.377, df:3, P:0.711, RMSEA: 0.000, CFI: 1.000											

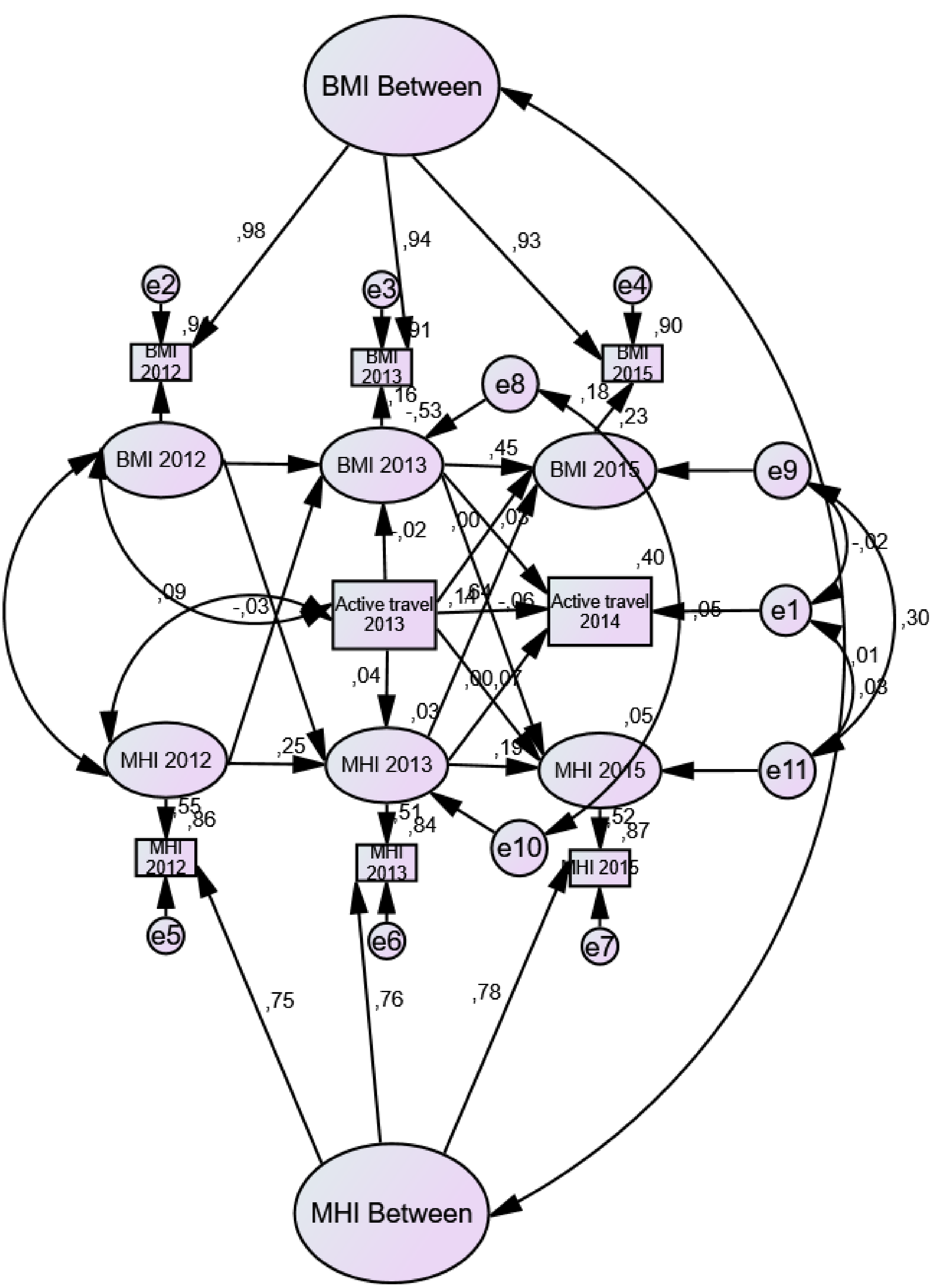
*** Effect is significant at the 0.001 level.
** Effect is significant at the 0.01 level.
AT = Active travel

Table 17 - Covariances between the key variables and their error terms.

	Estimate
BMI between – MHI between	0.169
BMI 2012 – Active travel 2013	-6.618
MHI 2012 – Active travel 2013	9.238*
BMI 2012 – MHI 2012	0.116
e11 – e9	0.489**
e1 – e11	2.434
e10 – e8	-0.113
e1 – e9	-0.578

** Covariates is significant at the 0.01 level.
* Covariates is significant at the 0.05 level.

Figure 14 - Standardized estimates of the RI-CLPM.



5.4 Sensitivity Analysis

In Appendix C, the sensitivity analysis models are depicted regarding the relationship between active travel and health. In general, the sensitivity analyses result in similar estimations as the main model. This indicates that the outliers do not affect the results of the main model. The model fit of the missing data is worse that the main model. This indicates that the FIML is the better choice to handle missing data. Furthermore, the significance of the correlations differs for the different sensitivity models. In the model with the outliers and the model without missing data, the correlation between BMI 2012 and Active travel 2013 is not significant. This indicates no initial overlap. However, in the main model, the RI-CLPM and the outlier model with the ordinal scales, the correlation is significant. A possible explanation is that the outliers influence the variance to the extent that there is no significant initial overlap anymore.

5.5 Interpretation of the results

In this chapter, the hypothesis that is tested is: there exists a causal bi-directional relationship between active travel and health. The hypothesis predicts an effect from active travel on BMI and MHI and an effect of BMI and MHI on active travel. In the correlation analysis, some indication has been found for a cross-lagged effect between active travel and MHI. However, once the stability was taken into account in the CLPM and the RI-CLPM, this effect was not found to be significant. The effect between BMI and active travel or BMI and MHI is not found to be significant in either the correlational analysis, the CLPM, the RI-CLPM or the sensitivity analysis. The findings of the analysis do not support the hypothesis and indicate no causal relationship between active travel and health. This would mean that an increase in active travel would not lead to an increase in MHI or a decrease in BMI.

In short, in this chapter we tested whether active travel has an influence on overweight or mental health and if overweight or mental health influence the amount of kilometres someone travels with an active mode. No influence in either direction has been found. Therefore, these findings do not support the idea that active travel has a positive influence on overweight or mental health and vice versa.

CHAPTER 6 – DISCUSSION AND LIMITATIONS:

In the light of earlier research

In this chapter, the findings are interpreted and placed in the context of earlier research. This is done by comparing the findings of this research to earlier findings and examining the limitations of this research. First, the findings linked to the substitution hypothesis are discussed in section 6.1, followed by the findings regarding the bi-directional causal relationship in section 6.2. The chapter ends with a discussion about the limitations in section 6.3.

6.1 The relationship between active travel and leisure physical activity

In chapter 4, the relationship between active travel and leisure physical activity is examined. Van Wee and Ettema (2016) hypothesized that it is possible for active travel to have a substitutive effect on other forms of physical activity. In case the substitution effect would take place, it would not be possible to add the active travel to the total amount of physical activity. This means that policy aimed at stimulating active travel would have less health benefits than expected. To control for this problem, Decisio currently corrects their estimations for this effect. Given this hypothesis, a negative effect from active travel on leisure physical activity is expected.

No negative effect from active travel on leisure physical activity is found. Not in the CLPM, the CLPM with the control variables or the sensitivity analysis. The findings are quite surprising. Contrary to the hypothesized effect, a significant positive effect from active travel 2013 on leisure physical activity 2014 is found. Therefore, based on the findings the hypothesis is falsified. Furthermore, the findings indicate a positive influence from active travel on other forms of physical activity. This indicates that people who travel with an active mode also practice more leisure physical activity over time. These findings are in line with the majority of cross-sectional studies and literature reviews (Lee, Orenstein & Richardson, 2008; Faulkner, Buliung, Flora & Fusco, 2009; Sluijs et al., 2009; Sahlqvis et al., 2012; Yang et al., 2012; Smith et al., 2017). All these researches reported that an increase in active travel would lead to an increase in physical activity.

In this research, the effect from leisure physical activity on active travel is also taken into account. A significant effect from leisure physical activity 2013 to active travel 2014 is found in the CLPM and the CLPM with control variables. However, in the overlap and the outlier sensitivity analysis, this relationship is not always found to be significant. Therefore, these results should be interpreted with care. The positive significant effect from leisure physical activity 2013 to active travel 2014 indicates a positive influence from other forms of physical activity on active travel, i.e., people who spend more hours to practice a form of physical activity also travel more actively over time. This means that not only active travel stimulates other forms of physical activity, other forms of physical activity also stimulate active travel. In other words, there exists a positive bi-directional relationship between active travel and other forms of physical activity, this can be seen as a multiplier effect for the health benefits. A possible explanation for this multiplier effect could be attitude towards sport. People who like sport will likely make more use of the bike and conduct other sports. For biological factors, genes could play a possible role. For example, genes that make somebody a more active person, lead to more active travel but also more physical activity. In the overlap sensitivity analysis model the relationship from leisure physical activity to active travel was not significant. This could indicate a possible problem with the data used. Further examination of this relationship is necessary to get a better understanding of the relationship.

6.2 The relationship between active travel and health

In chapter 5, the relationships between active travel, BMI and mental health are examined. Van Wee and Ettema (2016) hypothesized that there exists a bi-directional causal relationship between active travel and health. Does active travel contribute to healthier people or are healthier people more likely to use an active mode for transport or leisure reasons? An increase in active travel for unhealthy people will lead to more health benefit than an increase of active travel for already healthy people (Bauman, 2014). Currently, the estimations are based on average health benefits. Depending on the individuals who increase their active travel, the current values for active travel are under- or overestimated. In this research, health is divided into two component, a physical component and a mental component. BMI is used as an indicator for the physical health and the MHI-5 score is used as an indicator for general mental health. First, the relationship regarding BMI is discussed, this is followed by a discussion about the relationship between active travel and mental health.

6.2.1 The relationship between active travel and BMI

The findings of this research regarding the relationship between active travel and BMI are opposite to the expectations and the findings in earlier research. In this research, no significant effects are found from active travel on BMI or vice versa. No significant cross-lagged effect is found in the CLPM, the RI-CLPM or the sensitivity analysis. This indicates that active travel does not affect BMI and that BMI does not affect active travel. In the analysis, a change in active travel in 2013 did not lead to a change in BMI in 2015 and a change in BMI in 2013 did not lead to a change in active travel in 2014. The findings in this research indicate that there exists no bi-directional relationship between active travel and BMI. Therefore, based on the results we would falsify the hypothesis.

In the light of earlier research, the findings in this research do not match the majority of the findings. In general, an inverse association between active travel and BMI is found (Wanner et al., 2012; Lubans et al., 2011). Furthermore, it feels counter-intuitive that there is no effect from active travel on BMI. Wanner et al. (2012) found in their review, that 25 of the 30 researches found an inverse association between active transport and BMI. Similar results are found in the review by Xu et al. (2013). In both reviews, mainly cross-sectional researches were examined. Of the small body of longitudinal researches between active travel and BMI, one article found a significant association between active commuting and a change in BMI. However, after adjusting for the baseline BMI, this effect was not found to be significant anymore (Mytton et al., 2016). Because the effect from active travel on BMI is well-established, chances are that a fundamental problem is encountered in this research.

An important question that could be asked, is whether we could have expected to find a significant effect from active travel on BMI, given the data and methods used. A possible explanation for the findings is the incorrect use of time-lag. Incorrect usage of time-lag can lead to wrong estimates (Gollob & Reichardt, 1987; Voelkle, Oud, Davidov & Schmidt, 2012). This could have resulted in the findings that no relationship was found in this research. Saunders et al. (2013) highlighted this problem in their review on the health benefits of active travel. They mentioned that if the follow-up period is too short it may be that the health effects have not taken place and cannot be measured.

In this research, a time-lag of 4 months and 24 months is used to estimate the cross-lagged effects. This relative short time-lag could be a possible explanation that no significant relationship between active travel and BMI is found. This idea is supported by the high stability that has been found in the analyses for BMI, with standardized autoregressive paths close to 0.99. This means that the BMI of the population is mainly explained by the BMI of previous years. From a methodological standpoint, the high stability suppresses the cross-lagged effects. For a cross-lagged path to have a significant effect, this cross-lagged effect has to be very strong to overcome this suppressor and to become significant. An increase in the time between the measures could increase the chance of more variation in the BMI and thereby decrease the stability of BMI. Another possibility could be, that in the first few years muscle growth results in a higher weight. Even though fat is lost, the muscle growth could lead to no changes in weight.

The exact time-lag that is necessary to examine the relationship between active travel and BMI is difficult to pinpoint and no clear answer is found in the health literature (Krousel-Wood, 1999). However, we found some possible indications. Koursel-Wood (1999) included in her article three different health outcomes based on time. These time outcomes can be used as an indication for time-lag: "Short-time outcomes (e.g., in-hospital mortality for myocardial infarction patients), intermediate outcomes (e.g., 6-12 month functional ability after total knee replacement), or long-term outcomes (e.g., 10-year survival status for patients treated for breast cancer)". For BMI, the health outcome is expected to be long-term, as the body has to adapt to the changes. In their research to examine BMI change, Gebremariam, Arah, Lien, Naess, Ariansen & Kjollesdal (2018) even used a time-lag of 24 years.

Based on the results, we have to falsify the hypothesis of the existence of a bi-directional relationship between active travel and health. However, given that the majority of the literature indicates an inverse relationship between active travel and BMI and the short time-lag of this research, it is difficult to give a definitive answer regarding the hypothesis. Therefore, we suggest that future research should be conducted over a longer period of time to examine the relationship and come to a better understanding of the relationship between active travel and BMI.

6.2.2 The relationship between active travel and mental health

The findings of this research regarding the relationship between active travel and MHI were in disagreement with the hypothesis. However, they do fit some findings of earlier research. In this research, no significant effect is found from active travel on MHI or vice versa. No significant cross-lagged effect is found in the CLPM, the RI-CLPM or the sensitivity analysis. This indicates that active travel does not affect MHI and that MHI does not affect active travel. In the analysis, a change in active travel in 2013 did not lead to a change in MHI in 2015 and changes in MHI in 2013 did not lead to a change in active travel in 2014. The findings in this research indicate that there exists no bi-directional relationship between active travel and MHI. Therefore, based on the results we would falsify the hypothesis.

Compared to the literature regarding the relationship between active travel and BMI, the literature on active travel and mental health is quite limited. In their review, Xu et al. (2013) described the relationship between active travel and mental health as weak. They found that only domain-specific relations were found between activity and mental health. Other research only found an effect on people with a mental disorder (Overdorf, Kollia, Makarec & Alleva Szeles, 2016).

This gives reason to believe that there simply does not exist a bi-directional relationship between active travel and mental health or even an uni-directional relationship from active travel to mental health or vice versa. A possible explanation on why active travel does not influence mental health, in contrast to physical activity, can be found in the differences between active travel and other forms of physical activity (e.g., exercise or team sports). In chapter 2, two mechanisms are mentioned that possibly explain how activity would affect mental health: the physiological and psychological mechanisms. Lubanset et al. (2016) found that the strongest evidence is found for the improvements by the psychological mechanisms. Few studies have examined the neurobiological mechanisms and the role of neurotransmitters on mental health is still to be determined.

Focussing on the psychological mechanisms, it is possible that active travel does not have the same characteristics as other forms of physical activity. Distraction suggests that undertaking activities takes the attention away from the negative stimulus. However, active travel consists of mainly simple activities. Therefore, it may be that the activity is not distracting enough to switch the attention to something else. Self-efficacy proposes that exercise is a challenging activity, undertaking and overcoming these challenges would improve mood and self-confidence. Active travel consists of mainly simplistic activities, this could explain why this effect does not take place for active travel. Social interaction during physical activity would lead to a better mental health. However, active travel is often undertaken alone. These differences between active travel and other forms of physical activity could form a possible explanation on why active travel does not lead to a better mental health.

Yet, this research cannot rule out that other factors influenced the findings and that there exists a relationship between active travel and mental health. A possible explanation for the findings could be found in the time-lag of this research. Contrary to BMI, the time-lag in this research of 4 months and 24 months is expected to be too long to measure the changes in mental health. If the physiological mechanisms would be correct and the release of neurotransmitters would lead to a better mental health, one would expect that the neurotransmitters are released shortly after the active travel took place. Looking at intervention research regarding mental health, we see that the common follow-up time is around the 10 days till 12 weeks (Rosenbaum, Tiedemann & Ward, 2014).

Another possible explanation for the findings of this research is the ceiling effect. In this research, the mean MHI score of the sample is around the 76 points out of the possible 100. In general, one is expected to have mental health problems if they score below the 60 points MHI-5 test. It could be that the mental health of this sample is too high to find a certain effect and that active travel would only result in a significant effect on mental health for people who are mentally unstable. For people with already a good mental health, it could be that active travel will not lead to a significant change in mental health. The ceiling effect is supported by research regarding physical activity or active travel and people with a mental disorder. These researches reported a relationship between physical activity or active travel and an increase in mental health for people with a mental disorder (Overdorf et al., 2016; Rosenbaum, Tiedemann & Ward, 2014).

In this research, no findings were derived to indicate a bi-directional relationship between active travel and mental health. Based on the results we have to falsify the hypothesis of the existence of a bi-directional relationship between active travel and health. However, given the limited literature regarding this topic, it is difficult to establish whether there exists a relationship between active travel and mental health or not. It is therefore difficult to give a definitive answer regarding the hypothesis. Therefore, we suggest that future research should be conducted over a shorter period of time to examine the relationship and come to a better understanding of the relationship between active travel and MHI.

6.3 Limitations

Although the longitudinal approach of this research provides additional information for the causal relationship between active travel and health. This research should be interpreted with some care due to several limitations. The limitations of this research are described in this section. Based on these limitations, future research directions are identified in the following chapter. First, the limitations regarding the method are discussed, this is followed by the limitations regarding the LISS panel data.

6.3.1 CLPM

In this section, the limitations linked to the CLPM are discussed.

6.3.1.1 Third unobserved variable

CLPM is often used to examine the causality between two or more factors. However, there is a possibility that the cross-lagged effects are caused by a third unobserved variable that influences both variables. In this research, this is possible for active travel, as well as for leisure physical activity. This could be, for example, a biological factor that developed in the early youth and that may account for an increase of active travel at time 1 and physical activity at time 2 or vice versa. For example, genes that make somebody a more active person lead to more active travel but also more physical activity. Despite that this research took into account the influence of some socio-demographical variables, there are still other unobserved variables possible that are not included in this study. The influence of a third unobserved variable or a synchronous effect is indicated by the significant correlation between the error terms of the endogenous variables. This was the case in the CLPM in the 4th chapter, as well as in the CLPM in the 5th chapter.

For the relationship between active travel and leisure physical activity, no indication has been found that could indicate if the covariance is caused by the influence of a third unobserved variable or a synchronous effect. For the relationship between active travel and BMI, we can reason that the influence of a third variable seems more likely than the influence of a synchronous effect. As explained, the outcomes of health often take longer to establish and a synchronous effect seems less likely. Therefore, it seems that the influence of a third unmeasured variable is more likely. For the relationship between active travel and mental health, a synchronous effect seems more likely.

6.3.1.2 RI-CLPM

Another limitation of the CLPM, is that the CLPM only takes into account the between-level change, but not the within-level change. In a CLPM, the effects are only examined at the population level and not at the individual level (Keijsers, 2016). In chapter 3, the problems caused by this limitation are explained in more detail. To solve this problem, Hamaker et al. (2015) proposed the RI-CLPM. This model is able to take into account the within-level change. However, the RI-CLPM could not be applied in all the analyses, as this model can only be estimated if three or more waves of data are available.

In this research, three waves were only available for BMI and the general mental health. The other variables only had two waves available. Therefore, the RI-CLPM could not be estimated for these variables. As explained in the methodological implications, the use of the RI-CLPM did influence the results. Therefore, the RI-CLPM is found to be a fruitful approach. Based on this finding, we would recommend doing a follow-up study for both hypotheses with three or more waves of data for each variable. By taking into account the between-level change and the within-level change a better understanding of the relationships between active travel and health at the individual level can be established.

6.3.2 LISS Data

In this sections, the limitations regarding the LISS data are discussed.

6.3.2.1 Indicators

Given the available time and data, the decision is made to use certain indicators in this research. To test the substitution hypothesis, the relationship between active travel and leisure physical activity is examined. However, other forms of physical activity also exist (e.g., work-related physical activity, household physical activity and physical education). It is possible that active travel would substitute with other forms of physical activity. For health, BMI is used as an indicator for physical health and general mental health is used as an indicator for mental health. In both cases, other indicators could possibly lead to other results. BMI could be substituted by: cardiovascular disease, diabetes, cancer or hypertension. General mental health only gives an indication whether people suffer from mental health illness or not. It could be possible that active travel only has an effect on specific kinds of mental health disorders. This is not taken into account in this research.

6.3.2.2 Measuring instruments and operationalization

In this research, self-reported data is used. In self-reported data, active travel can lack accuracy due to problems with memory, incomplete entries or misreported journeys (Kelly, Krenn, Titze, Stopher & Foster, 2013). Furthermore, weight tends to be underestimated and the height tends to be overestimated in self-reported data. This leads to an underestimated BMI (Gorber, Tremblay, Moher, & Gorber, 2007). In this research, the underestimation of weight is taken into account. However, this was not possible for the height. Even though the correlation between the self-reported weight and the scale reported weight was high, the underestimation of the weight was also visible.

One of the limitations of the operationalisation of physical activity is that only the hours a sport is conducted is measured. This gives no information about the intensity of the specific sport. Because the intensity of a sport can affect the health, this can influence the estimations. BMI is one of the most common indicators for physical health. However, this indicator is not always seen as the most precise indicator because BMI does not take into account the difference between fat and muscle. Another problem with the operationalisation, is that in this research overlap between leisure physical activity and active travel is possible. It could be that respondents filled in that they travelled a certain amount of kilometres with a bicycle for active travel and also filled this trip in as hours spend on the bicycle as a sport. Counting the same activity double leads to wrong estimations. An important question regarding the overlap is if people would spend similar hours doing another sport, if they could not cycle. Or if these people only prefer cycling and would not have spent the same amount of time sporting per week if they had to choose another sport. The amount of additional travel of active modes should be examined to solve this limitation.

6.3.2.3 Generalization, missing waves and dropout

For this research, data collected in the Netherlands is used. Infrastructure, culture and other factors play an role in the choice for bicycle usage (Ton et al., 2018). Possibly, the results are only valid in the Netherlands. Another limitation is caused by the missing waves of data. Due to the expiring of the financing period, not all the data is available for health. This is described in more detail in chapter 3. Therefore, the standard CLPM was adjusted to fit the available data. This led to the fact that some relationships are estimated over different time-lags. Furthermore, the travel behavior is only measured for two waves with one year in between. The last limitation is regarding the dropout of respondents. In 2014, there was a dropout of almost 950 respondents for the travel behavior survey, compared to the 2013 survey. It could be possible that the findings are based on a systematic dropout. In this research, the sample was still sufficiently large and the findings of the correlations are similar over the years. Furthermore, the FIML is used to address the missing values. These aspects combined, we concluded that the dropout did not affect the results significantly.

6.3.3 Conclusion

Despite the mentioned limitations, we believe that this study provides a significant contribution to the field. The majority of the earlier researches investigated the relationship by cross-sectional methods. This research adds stronger evidence for causality, because of the longitudinal nature. Some of the limitations are already taken into account. The RI-CLPM is applied where possible, some of the overlap between leisure physical activity and active travel has been taken into account in the sensitivity analysis, the data is fitted on the models and the FIML is used to address the missing values. About the use of self-reported data it can be said that most of the researches regarding these topics use self-reported data (Saunders et al., 2013). In conclusion, we can state that there is room for improvement. Yet, we think that this research gives new insights into the causal relationship between active travel and health. In the following chapter, the limitations are used for future research directions.

CHAPTER 7 – CONCLUSIONS, CONTRIBUTION AND RECOMMENDATIONS:

In this last chapter, an answer to the main question is formulated. Section 7.1 starts with a small recap of the context of this research and the findings of this research. Eventually, resulting in an answer on the main question: "What is the relationship between active travel and health?". This is followed by the contributions this research has brought to science and practise. The chapter ends with recommendations for possible future research directions in section 7.3.

7.1 Conclusion

Physical inactivity has been linked to various health problems. However, 55% of the Dutch population does not meet the norm of 150 minutes per week of moderate physical activity. To tackle this problem, policymakers want to increase the amount of active travel. Hereby, they assume that the increase in active travel will lead to the same health benefits as an increase in physical activity. Nonetheless, there are reasons to believe that the relationship between active travel and health is more complex than currently is expected. Specifically, the substitution hypothesis and the causal bi-directional relationship hypothesis could be reasons why active travel does not have the same effect on health as physical activity. If these effects are not taken into account, the health benefits of travel policy could be overestimated.

Currently, the evidence for the relationship between active travel and total physical activity is scarce. The relationship between active travel and health has mostly been examined with cross-sectional studies. However, cross-sectional studies are not able to examine the direction of influence. In this research, panel data is used to overcome this problem. Panel data provides an opportunity to examine the causal relationship. To estimate the possible substitution effect between physical activity and active travel and the causal bi-directional relationship between active travel and health, a Cross-Lagged Panel Model (CLPM) is estimated on the LISS (Longitudinal Internet Studies for the Social sciences) Panel data. The aim of this research is to contribute to the Dutch transport policy aimed at stimulating active travel for health benefits and to contribute to the current knowledge about active travel and health. More insight into the total net health effects of active travel will make it possible for policymakers to make better decisions aimed at stimulating active travel.

In this research, the findings indicate a bi-directional positive relationship between active travel and leisure physical activity. This means that active travel does not substitute for other forms of physical activity. Contrary, active travel has a positive effect on other forms of physical activity. Furthermore, physical activity stimulates active travel. No significant relationship has been found between active travel and either BMI or mental health, neither uni- nor bi-directional. This indicates that active travel does not influence overweight nor mental health and that overweight and mental health do not influence active travel. In figure 15, an overview of the relationships and the variables is depicted. This figure can be seen as a summary of the findings. The arrows between active travel and the health indicators, depicted as dots, show that no relationship is found between these variables in this research.

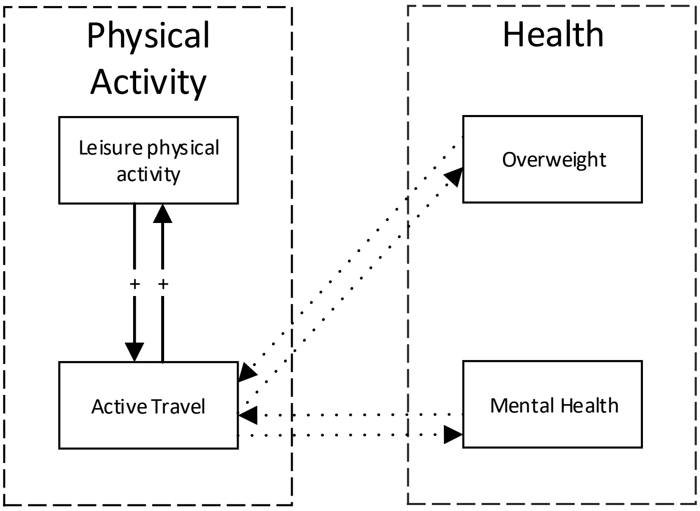


Figure 15 - Conceptual model with the found relationships

The main question of this research is: *"What is the relationship between active travel and health?".*

Overall, the findings show the complexity of the relationship between active travel and health. However, we can conclude that active travel has a positive effect on health. The positive effect of active travel on physical activity is of importance, as a lack of physical activity is linked to various health problems. Furthermore, even though no indications for the relationship between active travel and health has been found, there are good reasons to believe that a fundamental problem has been encountered in this research and that an uni- or bi-directional relationship between active travel and health does exist.

7.2 Scientific and practical contributions

In this section, the scientific and practical contributions are discussed.

7.2.1 Scientific contribution

One of the aims of this research is to contribute to the current knowledge about active travel and health. Therefore, a few knowledge gaps have been examined. Especially, the findings regarding the relationship between active travel and other forms of physical activity can be seen as an important scientific contribution of this research. Furthermore, the relationship between active travel and health is found not to be significant in this research. However, this research can still be seen as a first step in providing knowledge on the long-term effect between active travel and health, and a first indication for time-lag is now provided. The last scientific contribution, is a methodological contribution. The use of the RI-CLPM has proven to be a fruitful approach to examine the causal relationship.

7.2.1.1 Substitution effect between active travel and other forms of physical activity

Within the knowledge of the writer, this is one of the first longitudinal research concerning the substitution effect between active travel and other forms of physical activity. The findings in this research do not only indicate that active travel does not have a negative effect on other forms of physical activity, but even indicate an additional effect on other forms of physical activity. Furthermore, a bi-directional relationship between active travel and leisure physical activity have been found. The practical implications of this finding are discussed in more detail in the section "practical contributions".

7.2.1.2 Time-lag and longitudinal approach

The choice of time-lag was found to be an important factor in health-related research. In the current literature, a causal effect from active travel towards health is expected by most writers (Saunders et al., 2013). Most literature examining the relationship between active travel and health applied cross-sectional analysis, making it impossible to examine the causal relationship between the variables. To overcome this problem, a longitudinal approach is applied in this research. Longitudinal data was available regarding active travel and health. This gave us the opportunity to test the bi-directional causal relationship and add evidence for causality between the variables. Now, we can state that the time-lags of 4 months and 24 months, as used in this research, are too limited and future research should address the hypothesis with other time-lags. For BMI the time-lag should probably be longer and we expect that the time-lag for MHI should be shorter.

7.2.1.3 RI-CLPM

This research has proven that the RI-CLPM is a fruitful approach to examine the causal relationship between two health variables. The distinction between the between-level and within-level variation allowed for more specific estimations for the relationship between BMI and MHI. These estimations differed from the CLPM estimations. The stability of BMI and MHI decreased and in the case of BMI, the stability was not significant anymore between 2012 and 2013. These findings inidicate that once the between-level is taken into account, the within-level of BMI did not prove to have a significant effect on the future BMI anymore. In their article, Hamaker et al. (2015) have shown that the CLPM may lead to wrong conclusions about the relationship between two variables. This same effect is also found in this research, and therefore, this research can be seen as a confirmation of the described effects of Hamaker et al. (2015). Given these results, we do believe that the RI-CLPM is the better alternative to examine the relationship between health-related variables and, in general, variables that are supposed to occur on a within-level over time.

7.2.2 Practical contributions

Additional to the scientific contribution, this research also aimed to contribute to the Dutch transport policy aimed at stimulating active travel for health benefits. The practical contribution mainly exists of recommended changes for the current health benefit estimations. At the moment, the estimations that are used in a Cost-Benefit analysis are based on the current knowledge about active travel. This research provides new insights into the relationship between active travel and health. At first, the impact of these new insights on the estimations is discussed. Thereafter, a short link is made between Dutch transport policy and stimulating active travel in general.

7.2.2.1 Impact of the findings on the current health benefit estimations

In the Netherlands, the estimations of Decisio are used to estimate the health benefits of cycling. These values can be found in the report “Waarderingskengetallen MKBA fiets: State of the Art”. In the light of the new insights of this research, the estimations are examined and the estimations that possible need to be estimated again are pinpointed. Decisio distinguished five possible health benefits of policy aimed at stimulating cycling: fitness, productivity, health care cost, quality of life and life expectancy. The distinction is of importance as cycling influences the different health benefits differently.

The most important effect that currently causes an underestimation of the health benefits, is caused by the correction for a substitution effect. In the report, both healthcare cost and life expectancy are corrected for a substitution effect between active travel and other physical activity forms (Decisio, 2017, p28; Decisio, 2017, p30). In none of the estimated models, a substitution effect between active travel and leisure physical activity is found. Contrary, an additional effect of active travel on leisure physical activity is found. The correction of the current estimations makes that these estimations in the report of Decisio are underestimated. A substitution effect between active travel and other forms of physical activity is still possible (e.g., work-related physical activity or household related physical activity). This possibility is discussed in more detail in the recommendations for future research.

Another important effect not taken into account for the estimations, is the positive bi-directional effect between active travel and physical activity. Not only do other forms of physical activity stimulate active travel, but active travel also stimulates other forms of physical activity. In all five health benefits, physical activity is mentioned as an important factor of influence. In the current estimations, the stimulating effect of active travel on physical activity and the stimulating effect of physical activity on active travel is not taken into account. Because this positive bi-directional effect is not taken into account, all the five estimated health benefits can be assumed to be underestimated.

An increase in active travel will also lead to an increase in some of the negative effects on health. A mode switch from the car to the bicycle, leads to an increase in air pollution intake and increases the chance of traffic accidents. De Hartog, Boogaard, Nijland & Hoek (2010) estimated that the health benefits of increased physical activity are larger than the potential mortality effect of the increased inhaled air pollution and the increase of traffic accidents in the Netherlands.

In general, we can state that the findings of this research are uplifting for policy aimed at stimulating active travel. In general, in the light of the findings of this research the health benefits in the report of Decisio are assumed to be underestimated. Mainly because some values are corrected for a substitution effect and the stimulating effect between active travel and physical activity is not taken into account. Therefore, we would propose that the health benefits should be changed in a second version of the Decisio report or a similar report used to estimate the cost and benefits of active travel related policy. On the other hand, an increase in active travel will lead to some negative effects on health. However, the health benefits of active travel outweigh the negative effects on health in general.

7.2.2.2 Conclusion

Overall, the findings of this study provide support for policy to stimulate active travel with the aim to increasing the health of the population. The positive influence of active travel on other forms of physical activity is encouraging. It implies that the stimulation of active travel will lead to a greater total physical activity. This is of importance, as the Netherlands are currently not reaching the physical activity norms and physical inactivity is linked to various health problems such as several chronic diseases (e.g., cardiovascular disease, diabetes, cancer, hypertension, obesity, depression and osteoporosis) and premature death (Warburton, Nicol & Bredin, 2006). Furthermore, stimulating physical activity will also lead to an increase in active travel. The positive bi-directional influence leads to a multiplier effect, as both factors have a positive influence on each other. In addition, an increase in active travel will lead to non-health related benefits such as increasing accessibility, reducing congestion, decreasing emissions and realizing social goals. Therefore, we can conclude that this research can be seen as an extra support for policy aimed at stimulating active travel and we recommend to keep on stimulating active travel with transport policy.

7.3 Recommendations for future research

The last part of this chapter, consists of recommendations for possible future research directions. These are discussed in three different categories. The first category of recommendations is based on this research. In this section, future research directions are discussed regarding the limitations of this research and how these limitations can be overcome. These recommendations describe what the ideal version of this research would look like if no limitations were encountered. The second category of recommendations is based on practical needs. In this section, future research directions are discussed based on reports by people who make use of the estimations of the health benefits of active travel. The last category of recommendations is based on the needs of policymakers, what do we still need to examine to achieve the most effective transport policy linked to active travel and health.

7.3.1 Recommendations based on this research

In chapter 6, the limitations of this research are discussed. Based on these limitations, future research directions are identified. For the recommendations, the order of the limitations is followed. This means that first the future research directions regarding the method are discussed, followed by future research directions regarding the data.

To examine the relationship between active travel and health, experimental studies will play an important role. In the ideal research, the relationship is examined in an experimental study. Experimental studies make it possible to examine the direction of influence and can provide insight into the cause and effect. Furthermore, it is possible to exclude influence of third variables with an experiment. However, an experiment is often not practical or infeasible option, because it could create ethical dilemmas. Moreover, the results of an experiment are difficult to generalize to the population (Kearney, 2017). Therefore, we will discuss the ideal research within the limits of longitudinal research.

The first recommendation is linked to the influence of third variables. An interesting future research direction is to study the impact of other determinants for active travel, such as the effect of other socio-economic and demographic variables on travel behavior and health. In this research, only a limited set of socio-demographic variables are examined. Health-related attitudes and self-selection processes related to travel behavior are an important topic to examine and currently, empirical knowledge is still limited (Van Wee & Ettema, 2016). To examine the health-related attitudes, qualitative methods could be applied to get a better understanding of the health-related attitudes of the respondents. Interviews with respondents make it possible to do an in-depth exploration of the processes and for example include lifestyle in the study. Other possible determinants that could be included are: household characteristics, season and weather characteristics, built environment and work conditions. Ton et al. (2018) found that all these have an influence on the choice for an active travel mode.

The second recommendation is related to the use of RI-CLPM. The RI-CLPM has proven to be fruitful and this research showed that it can be useful in a health-related context. Furthermore, the results have shown that the findings can differ compared to the CLPM. To apply the RI-CLPM, three or more waves are necessary. Moreover, the choice of time-lag is found to be of importance to examine the relationship. For BMI, a time-lag of at least 5 years is recommended between the waves. For MHI, a short time-lag between the 10 days till 12 weeks is recommended.

The third recommendation is related to the indicators used. Simply said, other indicators should also be examined to get a better understanding of the relationship between active travel and health. We recommend examining the relationship between active travel and other forms of physical activities such as work-related physical activity, household physical activity and physical education. These could have a substitutional effect on active travel. For mental health, we recommend examining specific disorders in future research. The link between specific disorders and active travel could be different. Therefore, analysing mental health based on the specific Diagnostic and Statistical Manual of Mental Disorders (DSM) criteria could be a possibility to get a better insight into the relationship between active travel and mental health. Furthermore, examining respondents with a specific disorder will help overcome the problem of the ceiling effect.

The fourth recommendation is regarding the measuring of the indicators and the operationalisation. In general, more precise measure instruments are preferred. Feasible options are available to increase the preciseness of the measures. For active travel, a travel diary could help overcome the problem of forgetting to measure all the trips. Another possibility is the usage of more advanced technology such as GPS combined with accelerometers. Accelerometers make it possible to make assumptions on which mode is used. New research regarding the topic of measuring active travel has been conducted (Procter et al., 2017) with exciting results. For physical activity, it would be interesting to include what kind of sport is conducted. This way the Metabolic Equivalent Task (MET) score can be calculated. MET score has the benefit of taking into account the intensity of a specific sport. As the health outcome is dependent on intensity, the usage of MET hours per week could be a feasible option to examine the effect of intensity on active travel. Objectively measuring physical activity is challenging and costly. GPS and wearable cameras could give future possibilities to measure physical activity within specific domains. To measure BMI, a body weight scale that sends the data to the researchers directly, as used in the Weighing project, could be provided to all respondents. This will help overcome the problems of self-reporting bias. To overcome the limitation of the height, researchers could choose to measure the participants themselves. In the discussion, the possibility of an decrease of fat but an increase of muscle is mentioned. This could possibly explain why no difference in BMI is found after 2 years. Measuring the excessive fat of a person instead of the weight, could be a feasible option to get a better insight in the relationship and overcome this problem. To overcome the problem of overlap between active travel and leisure physical activity, the survey should explicitly mention that walking and cycling should be added to active travel and not to leisure physical activity. The additional effect of cycling on active travel can be examined by conducting qualitative research and could give a helping hand. For example, respondents could be asked whether they would have done sports the same amount of hours if they had not used an active travel mode.

Because for this research only data collected in the Netherlands is used, it is possible that the results are only valid in the Netherlands. To examine the generalizability of the results, data of other countries is needed. As mentioned in the introduction, the Netherlands has an extended cycling infrastructure and has one of the highest trips made by bicycles in the world. This means that other countries still have lots of possibilities to extend their cycling infrastructure and increase their active travel share. Therefore, it can be speculated that the potential health benefits in other countries could even be higher than the ones estimated for the Netherlands. Furthermore, in the ideal situation, the survey would have no dropout and the time between the measures would be constant.

7.3.2 Recommendations based on practical needs

Another possibility to examine research needs and possible future research directions, is to examine the current grey literature. In this case, the reports, in which the estimations regarding the health benefit of cycling are used, are examined. Together with the accessibility benefits, the health benefits are of the utmost importance for the benefits of new cycling infrastructure. Therefore, the recommendations will mainly be aimed at increasing the knowledge regarding the estimations of the health benefits. The report of Goudappel Coffeng by Beenker (2018): "Samenwerken aan meer fiets", is the most recent report that uses the estimations of Decisio. In this report, a non-infrastructure related Cost-Benefit Analysis is conducted aimed at estimating the benefits of stimulating the use of bicycles in the South of Limburg (a province of the Netherlands). While estimating the benefits, they encountered three knowledge gaps. The influence of the e-bike, the difference in health benefits per individual and the internalized effect of health.

The first knowledge gap is related to the effect of the e-bike on the health benefits estimations. The current health benefit estimations are based on the non-electric bike. Currently, there is an increase in popularity for the e-bike (Fishman & Cherry, 2016). This e-bike has different characteristics compared to the non-electric bike. Therefore, it is important to examine the health benefits of the e-bike specifically. Regarding the effect of the e-bike on health, Kroesen (2017) found that e-bike ownership reduces non-electric bike use and to a lesser extent car use. However, it is not yet known to what extent the e-bike usage substitutes non-electric bike usage. Therefore, it is currently difficult to draw conclusions regarding the health benefits of e-bikes. On the upside, Simons, Van Es & Hendriksen (2009) provided evidence that the intensity levels on an e-bike are high enough to reach the intensity standard of 3-6 MET. This intensity level is similar to the intensity of non-electric bicycle users. Furthermore, Jones, Harms & Heinen (2016) found that the e-bike provides new opportunities for people who could not use the non-electric bike anymore, allowing them to maintain some sort of physical activity. These findings indicate that the e-bike could have the same health benefit or in some cases even leads to more health benefits that the non-electric bike. To examine this possible substitution effect between e-bikes and non-electric bikes, one could apply a CLPM. A possible data source is the Netherlands Mobility Panel (MPN) of the Kennisinstituut voor Mobiliteitsbeleid (Hoogendoorn-Lanser, Schaap & OldeKalter, 2015). This panel includes trip data for the e-bike and bike. Possible other future research directions linked to e-bikes and health are: the duration of e-bike trips, the modal shift and e-bike users and their travel motives (Decisio, 2017). All these factors could influence the estimated health benefits. To assess the e-bike users and their travel motives, the Latent Class Analysis (LCA) could be applied to get an insight into the different classes that exist for the e-bike users (Vermunt & Magidson, 2002). This can also be examined using the MPN.

The second recommendation is focussed on the difference in health effect per individual. Currently, the estimations are based on the average of the population. However, the health benefits differ per individual. For example, people who are inactive and become more active, will have higher health benefits compared to people who are already active. Ideally, the values would be estimated specifically per group. Furthermore, it is important to know what kind of people are going to travel actively. Research, specifically aimed at certain groups could give a better insight. For example, it could be that active travel has a positive significant effect on people who have a low mental health, but does not affect the mental health of people with a good mental health. This could also be the case for people with a high BMI or a low BMI. Additionally, the negative effects of health per individual are unknown. De Hartog et al. (2010) estimated that the health benefits of increased physical activity are larger than the potential mortality effect of the increased inhaled air pollution and the increase of traffic accidents in the Netherlands. However, studies that examine this relationship on an individual level are lacking (Van Wee & Ettema, 2016). Because the focus, in this case, is on specific groups of individuals, we would recommend conducting experiments specifically focussed on certain groups. Another possibility is the usage of the RI-CLPM with longitudinal data.

The last limitation is regarding the internalized relation of health on itself. Currently, the effect of health on itself is not taken into account. This is a very complex subject and limited research has been done regarding this topic. In general, the existence of an internalized effect is acknowledged. Findings of Ohrnberger, Fichera & Sutton (2017a) indicate a bi-directional relationship between mental and physical health (Ohrnberger, Fichera & Sutton, 2017b). Better past mental health increases present physical health and better past physical health has a positive effect on present mental health (Ohrnberger et al., 2017a). A similar effect is found for body weight and subjective well-being. In the research by Wootton et al. (2018) subjective well-being was defined as subjective happiness and life satisfaction. They found an increase in BMI caused by a reduction in subjective well-being. The current findings for the existence of an internalized health effect indicate that currently the effect of health is underestimated. Kim et al. (2012) found that the relationship between physical activity and mental health is not linear but curvilinear. The optimal physical activity for mental health benefit was between 2.5 and 7.5 hours of weekly physical activity. SEM combined with panel data could be applied to examine the complex relationship between physical health and mental health. LISS data includes both indicators and could be used to examine the internalized relationship. An important factor, to keep in mind to conduct such a research, is the time-lag between the measurements.

7.3.3 Recommendations based on policy needs

In light of the conclusion to stimulate active travel, there is one last step that we would like to touch upon. Namely, the effectiveness of policies aimed at stimulating active travel. Currently, there exists limited knowledge regarding the exact effect of specific policies on levels of active travel. In general, there exists evidence that policy efforts are positively related to health benefits gained from an increase in active travel (Winters, Buehler & Götschi, 2017). However, different possible strategies exist to stimulate active travel, i.e. travel-related infrastructure, end-of-trip facilities, transit integration, promotional and other programs, bicycle access and regulations (Pucher, Buehler, Bassett & Dannenberg, 2010). Policy-makers can benefit from research that examine which strategies are more likely to increase active travel. An evidence-based approach can help policy-makers limit the waste of resources and can help avoid failures that undermined public support (Heinen, Van Wee, & Maat, 2010). Therefore, we recommend that more studies examine the effectiveness of different strategies to quantify the impact of specific policies on active travel.

Bibliography

Abu-Omar, K., Rütten, A., & Lehtinen, V. (2004). Mental health and physical activity in the European Union. *Sozial-und Präventivmedizin*, *49*(5), 301-309.

Allen, M. (2000). The psychobiology of athletic training. *Sport psychiatry: theory and practice. New York: WW Norton & Company*, 22-44.

Bauman, A. E. (2004). Updating the evidence that physical activity is good for health: an epidemiological review 2000–2003. *Journal of science and medicine in sport*, *7*(1), 6-19.

Beenker, J. (2018). *Samenwerken aan meer fiets*. Retrieved October 1, 2018, from: http://www.verkeerskunde.nl/Uploads/2018/9/20180630---Eindevaluatie-Fietsimpuls-MB---def.pdf

Bentler, P. M., &Speckart, G. (1981). Attitudes" cause" behaviors: A structural equation analysis. *Journal of Personality and Social Psychology*, *40*(2), 226.

Bollen, K. A. (1989). *Structural equations with latent variables.* Oxford, England: John Wiley & Sons.

Bouchard, C. (2007). BMI, fat mass, abdominal adiposity and visceral fat: where is the 'beef'?. *International journal of obesity, 31*(10), 1552.

Bray, G. A., & Ryan, D. H. (2000). Clinical evaluation of the overweight patient. *Endocrine, 13*(2), 167-186.

Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. Routledge.

CBSa, 2018, July 03. Personenmobiliteit in Nederland; vervoerwijzen en motieven; regio's. Retrieved September 10, 2018, from: https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83500ned/table?ts=1533718250585

CBSb, 2018, April 06. Leefstijl en (preventief) gezondheidsonderzoek; persoonskenmerken. Retrieved September 17, 2018, from: https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83021NED/table?ts=1522312658353

Centers for Disease Control (2001). Effects of physical activity on health and disease: a report from the Surgeon General. Retrieved April 25, 2018, from: http://www.mkba-informatie.nl/mkba-voor-gevorderden/richtlijnen/waarderingskengetallen-mkba-fiets-state-art/http://www.cdc.gov/nccdphp/sgr/prerep.htm.

ChiMón, P., Ortega, F. B., Ruiz, J. R., De Bourdeaudhuij, I., Martínez-Gómez, D., Vicente-Rodriguez, G., ... & Ward, D. S. (2011). Active commuting and physical activity in adolescents from Europe: results from the HELENA study. *Pediatric exercise science*, *23*(2), 207-217.

Church, T., & Martin, C. K. (2018). The Obesity Epidemic: A Consequence of Reduced Energy Expenditure and the Uncoupling of Energy Intake?. *Obesity*, *26*(1), 14-16.

Cole, T. J., Freeman, J. V., & Preece, M. A. (1995). Body mass index reference curves for the UK, 1990. *Archives of disease in childhood*, *73*(1), 25-29.

Collins, L. M., Schafer, J. L., & Kam, C. M. (2001). A comparison of inclusive and restrictive strategies in modern missing data procedures. *Psychological methods*, *6*(4), 330.

Cools, M., & Creemers, L. (2013). The dual role of weather forecasts on changes in activity-travel behavior. *Journal of Transport Geography*, *28*, 167-175.

Daskapan, A., Tuzun, E. H., & Eker, L. (2005). Relationship between physical activity level and health related quality of life among university students. *Saudi medical journal*, *26*(6), 1026-1028.

Decisio (2017). *Waarderingskengetallen MKBA Fiets: state-of-the-art.* Retrieved from http://www.mkba-informatie.nl/mkba-voor-gevorderden/richtlijnen/waarderingskengetallen-mkba-fiets-state-art/

De Hartog, J. J., Boogaard, H., Nijland, H., & Hoek, G. (2010). Do the health benefits of cycling outweigh the risks?. *Environmental health perspectives*, *118*(8), 1109.

De Nazelle, A., Nieuwenhuijsen, M. J., Antó, J. M., Brauer, M., Briggs, D., Braun-Fahrlander, C., & Hoek, G. (2011). Improving health through policies that promote active travel: a review of evidence to support integrated health impact assessment. *Environment international*, *37*(4), 766-777.

De Wit, L. M., Van Straten, A., Van Herten, M., Penninx, B. W., & Cuijpers, P. (2009). Depression and body mass index, a u-shaped association. *BMC public health*, *9*(1), 14.

Dinas, P. C., Koutedakis, Y., & Flouris, A. D. (2011). Effects of exercise and physical activity on depression. *Irish journal of medical science*, *180*(2), 319-325.

Dipietro, L. (1995). Physical activity, body weight, and adiposity: an epidemiologic perspective. *Exercise and sport sciences reviews*, *23*, 275-303.

DiPietro, L., Dziura, J., & Blair, S. N. (2004). Estimated change in physical activity level (PAL) and prediction of 5-year weight change in men: the Aerobics Center Longitudinal Study. *International journal of obesity*, *28*(12), 1541.

Dobbins, M., DeCorby, K., Robeson, P. H., & H and Tirilis, D. (2017). School-based physical activity programs for promoting physical activity and fitness in children and adolescents aged 6-18. *Cancer*.

Driessen, M. (2011). Geestelijke ongezondheid in Nederland in kaart gebracht. *Den Haag, The Netherlands: Centraal Bureau voor de Statistiek.*

Dunn, A. L., & Dishman, R. K. (1991). 2 Exercise and the Neurobiology of Depression. *Exercise and sport sciences reviews*, *19*(1), 41-98.

Faulkner, G. E., Buliung, R. N., Flora, P. K., & Fusco, C. (2009). Active school transport, physical activity levels and body weight of children and youth: a systematic review. *Preventive medicine*, *48*(1), 3-8.

Fishman, E., & Cherry, C. (2016). E-bikes in the Mainstream: Reviewing a Decade of Research. *Transport Reviews*, *36*(1), 72-91.

Flegal, K. M., Carroll, M. D., Kit, B. K., & Ogden, C. L. (2012). Prevalence of obesity and trends in the distribution of body mass index among US adults, 1999-2010. *Jama*, *307*(5), 491-497.

Fraser, S. D., & Lock, K. (2011). Cycling for transport and public health: a systematic review of the effect of the environment on cycling. *European journal of public health*, *21*(6), 738-743.

Garrow, J. S., & Webster, J. (1985). Quetelet's index (W/H2) as a measure of fatness. *International journal of obesity*, *9*(2), 147-153.

Gibbons, L. W., Blair, S. N., Cooper, K. H., & Smith, M. (1983). Association between coronary heart disease risk factors and physical fitness in healthy adult women. *Circulation*, *67*(5), 977-983.

Gollob, H. F., & Reichardt, C. S. (1987). Taking account of time lags in causal models. *Child development*, 80-92.

Gorber, S. C., Tremblay, M., Moher, D., & Gorber, B. (2007). A comparison of direct vs. self-report measures for assessing height, weight and body mass index: a systematic review. *Obesity reviews*, *8*(4), 307-326.

Gordon-Larsen, P., Hou, N., Sidney, S., Sternfeld, B., Lewis, C. E., Jacobs Jr, D. R., & Popkin, B. M. (2008). Fifteen-year longitudinal trends in walking patterns and their impact on weight change–. *The American journal of clinical nutrition*, *89*(1), 19-26.

Götschi, T., Tainio, M., Maizlish, N., Schwanen, T., Goodman, A., & Woodcock, J. (2015). Contrasts in active transport behaviour across four countries: How do they translate into public health benefits? *Preventive medicine*, *74*, 42-48.

Gebremariam, M. K., Arah, O. A., Lien, N., Naess, O., Ariansen, I., & Kjollesdal, M. K. (2018). Change in BMI Distribution over a 24-Year Period and Associated Socioeconomic Gradients: A Quantile Regression Analysis. *Obesity*, *26*(4), 769-775.

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. (2015). A critique of the cross-lagged panel model. *Psychological methods*, *20*(1), 102.

Handy, S., Van Wee, B., & Kroesen, M. (2014). Promoting cycling for transport: research needs and challenges. *Transport reviews*, *34*(1), 4-24.

Hankinson, A. L., Daviglus, M. L., Bouchard, C., Carnethon, M., Lewis, C. E., Schreiner, P. J., ... & Sidney, S. (2010). Maintaining a high physical activity level over 20 years and weight gain. *Jama*, *304*(23), 2603-2610.

Harpham, T., Reichenheim, M., Oser, R., Thomas, E., Hamid, N., Jaswal, S., & Aidoo, M. (2003). Measuring mental health in a cost-effective manner. *Health policy and planning*, *18*(3), 344-349.

Haskell, W. L., Lee, I. M., Pate, R. R., Powell, K. E., Blair, S. N., Franklin, B. A., …& Bauman, A. (2007). Physical activity and public health: updated recommendation for adults from the American College of Sports Medicine and the American Heart Association. *Circulation*, *116*(9), 1081.

Health Council of the Netherlands (2017). Dutch physical activity guidelines 2017. The Hague: Health Council of the Netherlands.

Heelan, K. A., Donnelly, J. E., Jacobsen, D. J., Mayo, M. S., Washburn, R., & Greene, L. (2005). Active commuting to and from school and BMI in elementary school children–preliminary data. *Child: care, health and development*, *31*(3), 341-349.

Heinen, E., & Maat, K. (2012). Are longitudinal data unavoidable? Measuring variation in bicycle mode choice. *Transportation research record*, *2314*(1), 72-80.

Heinen, E., Van Wee, B., & Maat, K. (2010). Commuting by bicycle: an overview of the literature. *Transport reviews*, *30*(1), 59-96.

Hoeymans, N., Garssen, A. A., Westert, G. P., & Verhaak, P. F. (2004). Measuring mental health of the Dutch population: a comparison of the GHQ-12 and the MHI-5. *Health and quality of life outcomes*, *2*(1), 23.

Hoogendoorn-Lanser, S., Schaap, N. T., & OldeKalter, M. J. (2015). The Netherlands Mobility Panel: An innovative design approach for web-based longitudinal travel data collection. *Transportation research procedia*, *11*, 311-329.

Hsiao, C. (2003). Analysis of panel data, 2nd. *Cambridge: Cambridge University Press. Kose, MA, ES Prasad and ME Terrones (2003), Financial Integration and Macroeconomic Volatility, IMF Staff Papers*, *50*, 119-142.

Hsiao, C. (2007). Panel data analysis—advantages and challenges. *Test*, *16*(1), 1-22.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.

James, P. T., Leach, R., Kalamara, E., & Shayeghi, M. (2001). The worldwide obesity epidemic. *Obesity*, *9*(S11).

Johnson, S. L. (2010). A question of time: Cross-sectional versus longitudinal study designs. *Pediatrics in review*, *31*(6).

Jones, T., Harms, L., & Heinen, E. (2016). Motives, perceptions and experiences of electric bicycle owners and implications for health, wellbeing and mobility. *Journal of transport geography*, *53*, 41-49.

Kaila, B., & Raman, M. (2008). Obesity: a review of pathogenesis and management strategies. *Canadian Journal of Gastroenterology and Hepatology*, *22*(1), 61-68.

Kearney, M. W. (2017). Cross Lagged Panel Analysis. *The SAGE Encyclopedia of Communication Research Methods. Thousand Oaks, CA: Sage*.

Keijsers, L. (2016). Parental monitoring and adolescent problem behaviors: How much do we really know?. *International Journal of Behavioral Development*, *40*(3), 271-281.

Kelly, P., Krenn, P., Titze, S., Stopher, P., & Foster, C. (2013). Quantifying the difference between self-reported and global positioning systems-measured journey durations: a systematic review. *Transport Reviews*, *33*(4), 443-459.

Kim, Y. S., Park, Y. S., Allegrante, J. P., Marks, R., Ok, H., Cho, K. O., & Garber, C. E. (2012). Relationship between physical activity and general mental health. *Preventive medicine*, *55*(5), 458-463.

Kline, R. B. (1998). Software review: Software programs for structural equation modeling: Amos, EQS, and LISREL. *Journal of psychoeducational assessment*, *16*(4), 343-364.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.

Korge, J., & Nunan, D. (2018). Higher participation in physical activity is associated with less use of inpatient mental health services: A cross-sectional study. *Psychiatry research*, *259*, 550-553.

Krizek, K. J., Forsyth, A., & Baum, L. (2009). Walking and cycling international literature review.

Kroesen, M. (2017). To what extent do e-bikes substitute travel by other modes? Evidence from the Netherlands. *Transportation Research Part D: Transport and Environment*, *53*, 377-387.

Kroesen, M., Molin, E. J., & van Wee, B. (2010). Determining the direction of causality between psychological factors and aircraft noise annoyance. *Noise and Health*, *12*(46), 17.

Krousel-Wood, M. A. (1999). Practical considerations in the measurement of outcomes in healthcare. *The Ochsner Journal,* 1(4), 187-194.

Lee, M. C., Orenstein, M. R., & Richardson, M. J. (2008). Systematic review of active commuting to school and children's physical activity and weight. *Journal of Physical Activity and Health*, *5*(6), 930-949.

LISS panel. (n.d.) About the Panel. Retrieved from https://www.lissdata.nl/about-panel

Little, R. J. (1995). Modeling the drop-out mechanism in repeated-measures studies. *Journal of the American Statistical Association*, *90*(431), 1112-1121.

Little, R. J. A., & Rubin, D. B. (1987). Statistical Analysis with Missing Data.

Loucaides, C. A., & Jago, R. (2008). Differences in physical activity by gender, weight status and travel mode to school in Cypriot children. *Preventive medicine*, *47*(1), 107-111.

Lubans, D. R., Boreham, C. A., Kelly, P., & Foster, C. E. (2011). The relationship between active travel to school and health-related fitness in children and adolescents: a systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *8*(1), 5.

Lubans, D., Richards, J., Hillman, C., Faulkner, G., Beauchamp, M., Nilsson, M., ... & Biddle, S. (2016). Physical activity for cognitive and mental health in youth: a systematic review of mechanisms. *Pediatrics*, e20161642.

Luppino, F. S., de Wit, L. M., Bouvy, P. F., Stijnen, T., Cuijpers, P., Penninx, B. W., & Zitman, F. G. (2010). Overweight, obesity, and depression: a systematic review and meta-analysis of longitudinal studies. *Archives of general psychiatry*, *67*(3), 220-229.

Martin, A., Goryakin, Y., & Suhrcke, M. (2014). Does active commuting improve psychological wellbeing? Longitudinal evidence from eighteen waves of the British Household Panel Survey. *Preventive Medicine*, *69*, 296-303.

McCabe, C. J., Thomas, K. J., Brazier, J. E., & Coleman, P. (1996). Measuring the mental health status of a population: A comparison of the GHQ–12 and the SF–36 (MHI–5). *The British Journal of Psychiatry*, *169*(4), 517-521.

Miles, L. (2007). Physical activity and health. *Nutrition bulletin*, *32*(4), 314-363.

Miller, H. J., Tribby, C. P., Brown, B. B., Smith, K. R., Werner, C. M., Wolf, J., ... & Oliveira, M. G. S. (2015). Public transit generates new physical activity: evidence from individual GPS and accelerometer data before and after light rail construction in a neighborhood of Salt Lake City, Utah, USA. *Health & place*, *36*, 8-17.

Mitra, R. (2013). Independent mobility and mode choice for school transportation: a review and framework for future research. *Transport reviews*, *33*(1), 21-43.

Morgan, W. P. (1985). Affective beneficence of vigorous physical activity. *Medicine & Science in Sports & Exercise*.

Mulaik, S. A. (2009). *Linear causal modeling with structural equations*. Chapman and Hall/CRC.

Muñoz, B., Monzon, A., & Daziano, R. A. (2016). The Increasing Role of Latent Variables in Modelling Bicycle Mode Choice. *Transport Reviews*, *36*(6), 737-771.

Newsom, J. T. (2015). *Longitudinal structural equation modeling: A comprehensive introduction*. Routledge.

North, T. C., McCullagh, P. E. N. N. Y., & Tran, Z. V. (1990). Effect of exercise on depression. *Exercise and sport sciences reviews*, *18*(1), 379-416.

Ohrnberger, J., Fichera, E., & Sutton, M. (2017a). The dynamics of physical and mental health in the older population. *The Journal of the Economics of Ageing*, *9*, 52-62.

Ohrnberger, J., Fichera, E., & Sutton, M. (2017b). The relationship between physical and mental health: A mediation analysis. *Social Science & Medicine*, *195*, 42-49.

Overdorf, V., Kollia, B., Makarec, K., & Alleva Szeles, C. (2016). The relationship between physical activity and depressive symptoms in healthy older women. *Gerontology and Geriatric Medicine*, *2*, 2333721415626859.

Pabayo, R., Gauvin, L., Barnett, T. A., Nikiéma, B., & Séguin, L. (2010). Sustained active transportation is associated with a favorable body mass index trajectory across the early school years: findings from the Quebec Longitudinal Study of Child Development birth cohort. *Preventive medicine*, *50*, S59-S64.

Paluska, S. A., & Schwenk, T. L. (2000). Physical activity and mental health. *Sports medicine*, *29*(3), 167-180.

Panter, J. R., Jones, A. P., Van Sluijs, E. M., & Griffin, S. J. (2010). Attitudes, social support and environmental perceptions as predictors of active commuting behaviour in school children. *Journal of Epidemiology & Community Health*, *64*(01), 41-48.

Park, S., Cho, M. J., Cho, S. J., Bae, J. N., Lee, J. Y., Park, J. I., ... & Hong, J. P. (2011). Relationship between physical activity and mental health in a nationwide sample of Korean adults. *Psychosomatics*, *52*(1), 65-73.

Peluso, M. A. M., & Andrade, L. H. S. G. D. (2005). Physical activity and mental health: the association between exercise and mood. *Clinics*, *60*(1), 61-70.

Petersen, L., Schnohr, P., & Sørensen, T. I. A. (2004). Longitudinal study of the long-term relation between physical activity and obesity in adults. *International journal of obesity*, *28*(1), 105.

Pickett, K., Kendrick, T., & Yardley, L. (2017). “A forward movement into life”: A qualitative study of how, why and when physical activity may benefit depression. *Mental Health and Physical Activity*, *12*, 100-109.

Pilgrim, D. (2017). *Key concepts in mental health*. London: Sage.

Planbureau voor de Leefomgeving (2012). Gezondheid in maatschappelijke kosten-batenanalyses van omgevingsbeleid. Retrieved from: http://www.mkba-informatie.nl/mkba-basics/eerste-hulp-bij-mkba/

Polanczyk, G. V., Salum, G. A., Sugaya, L. S., Caye, A., & Rohde, L. A. (2015). Annual Research Review: A meta-analysis of the worldwide prevalence of mental disorders in children and adolescents. *Journal of Child Psychology and Psychiatry, 56(*3), 345-365.

Pozza, C., & Isidori, A. M. (2018). What’s Behind the Obesity Epidemic. In *Imaging in Bariatric Surgery* (pp. 1-8). Springer, Cham.

Procter, D., Nightingale, C., Rudnicka, A., Ram, B., Ellaway, A., Cooper, A., ... & Whincup, P. (2017). Identification of Travel Behaviour from Objective Physical Activity Data. *Journal of Transport & Health*, *5*, S39.

Prince, S. A., Adamo, K. B., Hamel, M. E., Hardt, J., Gorber, S. C., & Tremblay, M. (2008). A comparison of direct versus self-report measures for assessing physical activity in adults: a systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *5*(1), 56.

Pucher, J., & Buehler, R. (2008). Making cycling irresistible: lessons from the Netherlands, Denmark and Germany. *Transport reviews*, *28*(4), 495-528.

Pucher, J., Buehler, R., Bassett, D. R., & Dannenberg, A. L. (2010). Walking and cycling to health: a comparative analysis of city, state, and international data. *American journal of public health*, *100*(10), 1986-1992.

Pucher, J., & Dijkstra, L. (2003). Promoting safe walking and cycling to improve public health: lessons from the Netherlands and Germany. *American journal of public health*, *93*(9), 1509-1516.

Ransford, C. P. (1982). A role for amines in the antidepressant effect of exercise: a review. *Medicine and science in sports and exercise*, *14*(1), 1-10.

Ravussin, E., & Bogardus, C. (1989). Relationship of genetics, age, and physical fitness to daily energy expenditure and fuel utilization. *The American Journal of Clinical Nutrition*, *49*(5), 968-975.

Reiner, M., Niermann, C., Jekauc, D., & Woll, A. (2013). Long-term health benefits of physical activity–a systematic review of longitudinal studies. *BMC public health*, *13*(1), 813.

RIVM (n.d.). Beweeggedrag bij personen van 12 jaar en ouder in 2016. Retrieved May 14, 2018, from https://www.rivm.nl/dsresource?objectid=98b648a1-49b5-45d4-9a43-9e1b2931c16c&type=pdf&disposition=inline

Rogosa, D. (1980). A critique of cross-lagged correlation. *Psychological Bulletin*, *88*(2), 245.

Rosenberg, D. E., Sallis, J. F., Conway, T. L., Cain, K. L., & McKenzie, T. L. (2006). Active transportation to school over 2 years in relation to weight status and physical activity. *Obesity*, *14*(10), 1771-1776.

Rosenbaum, S., Tiedemann, A., & Ward, P. B. (2014). Meta-analysis physical activity interventions for people with mental illness: a systematic review and meta-analysis. *J Clin Psychiatry*, *75*(0), 1-11.

Rubin, D. B. (1987). Multiple Imputation for Nonresponse in Surveys (Wiley Series in Probability and Statistics).

Rumpf, H. J., Meyer, C., Hapke, U., & John, U. (2001). Screening for mental health: validity of the MHI-5 using DSM-IV Axis I psychiatric disorders as gold standard. *Psychiatry research*, *105*(3), 243-253.

Sallis, J. F., Haskell, W. L., Fortmann, S. P., Vranizan, K. M., Taylor, C. B., & Solomon, D. S. (1986). Predictors of adoption and maintenance of physical activity in a community sample. *Preventive medicine*, *15*(4), 331-341.

Saunders, L. E., Green, J. M., Petticrew, M. P., Steinbach, R., & Roberts, H. (2013). What are the health benefits of active travel? A systematic review of trials and cohort studies. *PloS one*, *8*(8), e69912.

Scott, K. M., Bruffaerts, R., Simon, G. E., Alonso, J., Angermeyer, M., de Girolamo, G., ... & Kessler, R. C. (2008). Obesity and mental disorders in the general population: results from the world mental health surveys. *International journal of obesity*, *32*(1), 192.

Setia, M. S. (2016). Methodology series module 3: Cross-sectional studies. *Indian journal of dermatology*, *61*(3), 261.

Shephard, R. J. (2003). Limits to the measurement of habitual physical activity by questionnaires. *British journal of sports medicine*, *37*(3), 197-206.

Simons, M., Van Es, E., & Hendriksen, I. (2009). Electrically assisted cycling: a new mode for meeting physical activity guidelines?. *Medicine & Science in Sports & Exercise*, *41*(11), 2097-2102.

Slattery, M. L., McDonald, A., Bild, D. E., Caan, B. J., Hilner, J. E., Jacobs, D. R., & Liu, K. (1992). Associations of body fat and its distribution with dietary intake, physical activity, alcohol, and smoking in blacks and whites. *The American journal of clinical nutrition*, *55*(5), 943-949.

Sommet, N., & Morselli, D. (2017). Keep Calm and Learn Multilevel Logistic Modeling: A Simplified Three-Step Procedure Using Stata, R, Mplus, and SPSS. *International Review of Social Psychology*, *30*(1).

Stevens, James (1996). *Applied Multivariate Statistics for Social Sciences.* Mahwah, NJ: Lawrence Erlbaum Associates

Strand, B. H., Dalgard, O. S., Tambs, K., & Rognerud, M. (2003). Measuring the mental health status of the Norwegian population: a comparison of the instruments SCL-25, SCL-10, SCL-5 and MHI-5 (SF-36). *Nordic journal of psychiatry*, *57*(2), 113-118.

Talala, K., Huurre, T., Aro, H., Martelin, T., & Prättälä, R. (2008). Socio-demographic differences in self-reported psychological distress among 25-to 64-year-old Finns. *Social Indicators Research*, *86*(2), 323-335.

Ton, D., Duives, D. C., Cats, O., Hoogendoorn-Lanser, S., & Hoogendoorn, S. P. (2018). Cycling or walking? Determinants of mode choice in the Netherlands. *Transportation Research Part A: Policy and Practice*.

Tour de Force (2016). *Agenda Fiets 2017-2020*. Retrieved from http://tourdeforce2020.nl/wp-content/uploads/2016/12/AgendaFiets-2017-2020.pdf

Ullman, J. B., &Bentler, P. M. (2012). Structural equation modeling. *Handbook of Psychology, Second Edition*, *2*.

Van Veldhoven, S. (2018, 12 June). *Ambities fiets*. Retrieved from https://www.rijksoverheid.nl/documenten/kamerstukken/2018/06/12/kamerbrief-ambities-fiets

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. *Applied latent class analysis*, *11*, 89-106.

Voelkle, M. C., Oud, J. H., Davidov, E., & Schmidt, P. (2012). An SEM approach to continuous time modeling of panel data: relating authoritarianism and anomia. *Psychological methods*, *17*(2), 176.

Voorrips, L. E., Meijers, J. H., Sol, P., Seidell, J. C., & van Staveren, W. (1992). History of body weight and physical activity of elderly women differing in current physical activity. *Int J Obes Relat Metab Disord*, *16*(3), 199-205.

Wang, Y., Chau, C. K., Ng, W. Y., & Leung, T. M. (2016). A review on the effects of physical built environment attributes on enhancing walking and cycling activity levels within residential neighborhoods. *Cities*, *50*, 1-15.

Wanner, M., Martin, B. W., Autenrieth, C. S., Schaffner, E., Meier, F., Brombach, C., ... & Kriemler, S. (2016). Associations between domains of physical activity, sitting time, and different measures of overweight and obesity. *Preventive medicine reports*, *3*, 177-184.

Warburton, D. E., Nicol, C. W., & Bredin, S. S. (2006). Health benefits of physical activity: the evidence. *Canadian medical association journal*, *174*(6), 801-809.

Ware, J. E., & Gandek, B. (1998). Overview of the SF-36 health survey and the international quality of life assessment (IQOLA) project. *Journal of clinical epidemiology*, *51*(11), 903-912.

Van Wee, B., & Börjesson, M. (2015). How to make CBA more suitable for evaluating cycling policies. *Transport Policy*, *44*, 117-124.

Van Wee, B., & Ettema, D. (2016). Travel behaviour and health: A conceptual model and research agenda. *Journal of Transport & Health*, *3*(3), 240-248.

White, R. L., Babic, M. J., Parker, P. D., Lubans, D. R., Astell-Burt, T., & Lonsdale, C. (2017). Domain-specific physical activity and mental health: a meta-analysis. *American journal of preventive medicine*, *52*(5), 653-666.

Wiklund, P. (2016). The role of physical activity and exercise in obesity and weight management: Time for critical appraisal. *Journal of Sport and Health Science*, *5*(2), 151-154.

Winters, M., Buehler, R., & Götschi, T. (2017). Policies to promote active travel: evidence from reviews of the literature. *Current environmental health reports*, *4*(3), 278-285.

Wootton, R. E., Lawn, R. B., Millard, L. A., Davies, N. M., Taylor, A. E., Munafò, M. R., ... & Haworth, C. M. (2018). Evaluation of the causal effects between subjective wellbeing and cardiometabolic health: mendelian randomisation study. *BMJ*, *362*.

World Health Organization (2004). Promoting mental health: concepts, emerging evidence, practice (Summary Report) Geneva: World Health Organization

World Health Organization (2010). Global recommendations on physical activity for health. Geneva: World Health Organization; 2010.

World Health Organization. (2016). World Health Organization obesity and overweight fact sheet.

Xu, H., Wen, L. M., & Rissel, C. (2013). The relationships between active transport to work or school and cardiovascular health or body weight: a systematic review. *Asia Pacific Journal of Public Health*, *25*(4), 298-315.

Appendices

Appendix A – Outliers

In this appendix, the handling of the outliers for this research is discussed. Because it is difficult to establish whether the active travel responses are outliers or mistakes, various steps had to be taken to examine the possible outliers for active travel. The first step is to examine the data. This is done by creating a histogram of the data. This gives a first indication of the outliers and if the outliers are still within the limits of plausible variables. Furthermore, the correlation analysis gives an indication on the effect of these outliers. Based on both indications, a decision is made to take the outliers out of the data. Furthermore, the threshold is discussed that is used to take the responses out of the dataset. For BMI, outliers are easier to pinpoint. Therefore, these BMI outliers are only based on the change of BMI over the years.

A.1 Active travel

In the dataset, there are some reported active travel distances that are very unlikely and even implausible. Figure 6 depicts a histogram on a logarithmic scale with a normal distribution pictured over the histogram. As can be seen, active travel follows the normal distribution quite well in general. The left peak are the people who do not travel actively, with an active travel of 0 kilometres per week. However, the long tail on the right indicates possible outliers. As can be seen in both histograms, the tails are long. These values in the right peak are likely to be mistakes as they range between 7000 and 750 kilometres per week, which are relatively high if not implausible distances to travel actively per week. Looking at the individual respondents with the outliers on active travel and their general answers in the LISS data, no indication for deliberately made errors were found. However, it could be that a mistake is made between kilometre and metre. Because the values are far from the mean, it could be that their answers could have a large and unwanted influence on the estimations of the relationships. To test this, the correlation between all the variables is analysed and depicted in table 4. The correlation between active travel 2014 and MHI is found to be negative. Suggesting that traveling actively would lead to a lower mental health. This is the opposite direction as one would expect based on the literature in chapter 2. This indicates possible influence of the outliers. Once the outliers are taken out of the dataset, the correlations are in the expected direction as can be seen in chapter 5, table 14. For this reason, the outliers are taken out in the main analysis. However, in the sensitivity analysis the effect of the outliers is taken into account.

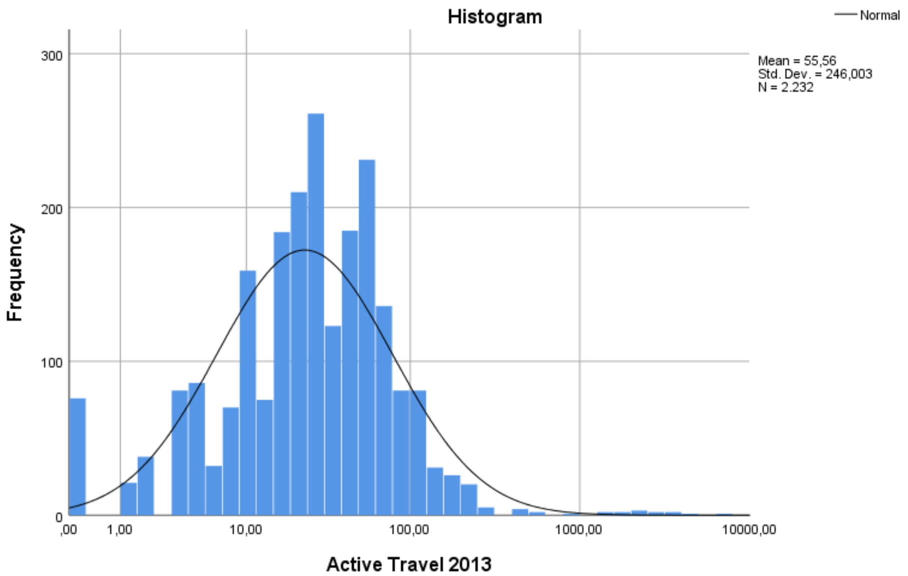


Figure A.1 - Histogram of active travel 2013

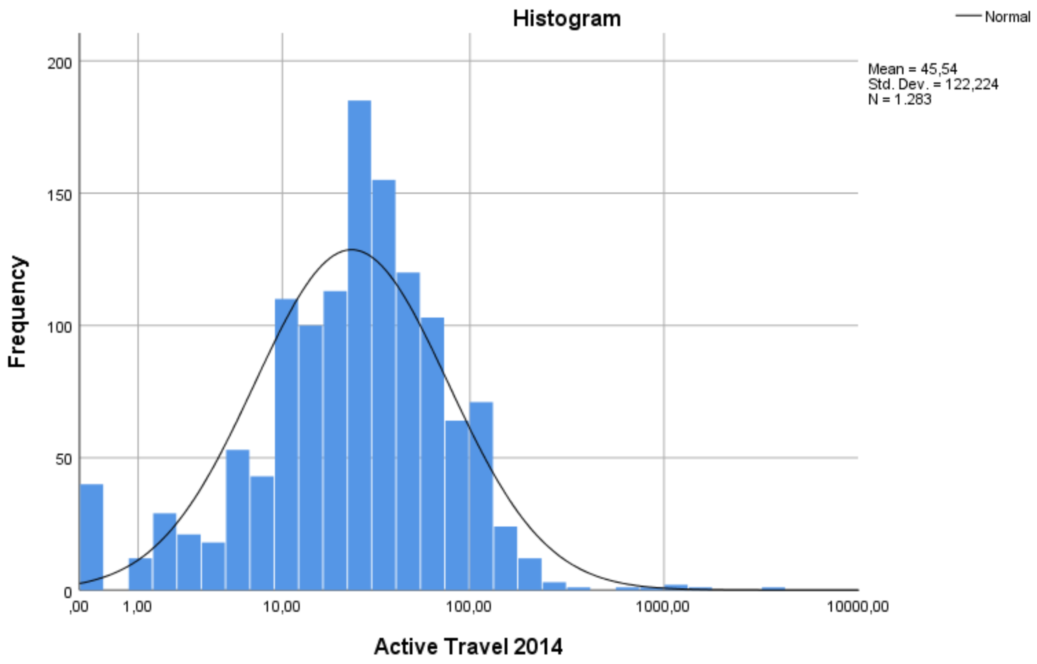


Figure A.2 - Histogram of active travel 2014

Table A.1 - Correlation between active travel, leisure physical activity, BMI and MHI

	Active Travel 2013	Active Travel 2014	Leisure physical activity 2013	Leisure physical activity 2014	BMI 2012	BMI 2013	BMI 2015	MHI 2012	MHI 2013	MHI 2015
Active Travel 2013	1	0.528**	0.043*	0.037	0.018	0.009	0.014	0.025	0.010	0.001
Active Travel 2014	0.528**	1	0.144**	0.169**	0.012	0.026	0.025	-0.039	-0.022	-.063*
Leisure physical activity 2013	0.043*	0.144**	1	0.723**	-0.086 **	-0.079 **	-0.069 **	0.056*	0.045*	0.061**
Leisure physical activity 2014	0.037	0.169**	0.723**	1	-0.086 **	-0.078 **	-0.065 **	0.049*	0.070**	0.073**
BMI 2012	0.018	0.012	-0.086 **	-0.086 **	1	0.912**	0.913**	0.019	0.024	0.010
BMI 2013	0.009	0.026	-0.079 **	-0.078 **	0.912**	1	0.895**	0.021	0.017	0.004
BMI 2015	0.014	0.025	-0.069 **	-0.065 **	0.913**	0.895**	1	0.032	0.033	0.030
MHI 2012	0.025	-0.039	0.056*	0.049*	0.019	0.021	0.032	1	0.642**	0.601**
MHI 2013	0.010	-0.022	0.045*	0.070**	0.024	0.017	0.033	0.642**	1	0.643**
MHI 2015	0.001	-0.063*	0.061**	0.073**	0.010	0.004	0.030	0.601**	0.643**	1

** Correlation is significant at the 0.01 level.
* Correlation is significant at the 0.05 level.

The choice is made to set the threshold for active travel at 700 kilometres per week. That is 100 kilometres per day. To reach this limit a person should travel more than 4 hours actively every day, with an average speed of 25 km/hour. This is relative high, as the average commuting time is 34 minutes and this is one of the main reasons for travel (CBS, 2016). Furthermore, the average speed of a bicycle is 20km/h (Tranter, 2004). The threshold of 700 kilometres is just on the inside of the normal distribution of active travel 2013 and 2014 as can be seen in figure 6 and 7. Based on this guideline, 18 respondents are taken out of the dataset, because of extreme and implausible points. 14 respondents reported a higher amount of kilometres per week actively travelled in 2013 and an additional 4 respondents reported a higher amount of kilometres in 2014.

A.2 BMI

For BMI the decision is made to take respondents out of the database based on the BMI change over the years. There are three specific cases where the respondents reported a change in height and weight. Two respondents reported a weight of respectively 712 and 600 kilograms in 2012, resulting in a BMI of 229.86 and 223.08. However, they reported a weight of respectively 22.60 and 24.17 in 2013. This large changes indicate a mistake and are therefore taken out of the data. Another respondent filled in a height of 63 cm resulting in a BMI of 168.81. However, in the following years the respondent reported a height of 165 cm and a BMI of 24.98 in 2015, this indicates a reporting mistake. These large changes in BMI are unrealistically large and these respondents are taken out of the dataset.

In this research, some problems have been encountered linked to the LISS panel data. These problems are overcome in various ways. To understand the effect of these problems, different scenarios are tested in the sensitivity analysis. Because these problems and the effect of these problems are discussed in detail in the main text, this will not be repeated in this appendix. In section 3.7.3, these problems are discussed. This appendix is only used to depict the results of the sensitivity analysis models regarding the relationship between leisure physical activity and active travel. The models as depicted in this appendix are saturated. Therefore, the model fit of these models cannot be examined. The comparison between the models and the effect of the results of these models on the conclusion is discussed in the main text in section 4.3. An overview of the different sensitivity analyses is depicted in table B.1.

Table B.118 - Overview sensitivity analysis

Model	Data changes
Overlap model	To test the overlap, active travel is subtracted from leisure physical activity or leisure physical activity is set at 0 for the respondents with possible overlap
Overlap model	To test the overlap, leisure physical activity is subtracted from active travel or active travel is set at 0 for the respondents with possible overlap
Outlier model	To test the outliers, the CLPM is estimated with all the data, including the outliers.
Outlier model	To test the outliers, active travel is reconstructed on an ordinal scale, with 20% of the respondents in every group.
Missing value model	To test the missing values, the model is estimated with only the respondents who filled in all the variables of interest in all the waves.

Overlap subtracted from leisure physical activity

Table B.2 presents the unstandardized and standardized estimates. The model indicates significant autoregressive effects for active travel (0.648***) and leisure physical activity (0.517***), indicating that the variables are stable and do not change much over time. The model indicates no significant effect of leisure physical activity on active travel (-0.315) or from active travel on leisure physical activity (0.001). These estimations indicate that someone who spends more hours sporting in 2013 does not travel more kilometres on an active mode in 2014 and someone who spends more kilometres traveling on an active mode spends does not practises more hours sporting. Both correlations in the model are not significant, as shown in table B.3. This indicates no initial overlap and no influence of a third variable not included in the model, or a synchronous effect.

Table B.219 - Estimates of the CLPM

	Active travel 2014		Leisure physical activity 2014	
	b	β	b	β
Active travel 2013	0.648***	0.631	0.001	0.020
Leisure physical activity 2013	-0.315	-0.015	0.517***	0.549
R^2	0.398		0.302	

*** Effect is significant at the 0.001 level.

Table B.3 - 20Covariates between the key variables and their error terms

	Estimate
Active travel – Leisure physical activity 2013	-2.059
e1 – e2	1.562

Overlap subtracted from active travel

Table B.4 presents the unstandardized and standardized estimates. The model indicates significant autoregressive effects for active travel (0.269***) and leisure physical activity (0.754***), indicating that the variables are stable and do not change much over time. More interesting are the cross-lagged effects. The model indicates no significant effect of leisure physical activity on active travel (-0.148), but the effect from active travel on leisure physical activity is significant (0.003*). These estimations indicate that someone who spends more hours sporting in 2013 does not travel more kilometres on an active mode in 2014. However, someone who spends more kilometres traveling on an active mode spends does not practises more hours sporting. Both correlations in the model are significant, as shown in table B.5. This indicates initial overlap and influence of a third variable not included in the model or a synchronous effect.

Table B.421 - Estimates of the CLPM

	Active travel 2014		Leisure physical activity 2014	
	b	β	b	β
Active travel 2013	0.269***	0.319	0.003*	0.031
Leisure physical activity 2013	-0.148	-0.015	0.754***	0.757
R^2	0.089		0.513	

*** Effect is significant at the 0.001 level.
* Effect is significant at the 0.05 level.

Table B.5 - 22Covariates between the key variables and their error terms

	Estimate
Active travel – Leisure physical activity 2013	-18.194***
e1 – e2	-5.566***

*** Covariates is significant at the 0.001 level.

Outlier model

Table B.6 presents the unstandardized and standardized estimates. The model indicates significant autoregressive effects for active travel (0.359***) and leisure physical activity (0.716***), indicating that the variables are stable and do not change much over time. The cross-lagged effects indicate a significant effect of leisure physical activity on active travel (3.941***), indicating that someone who spends more hours sporting in 2013 does not travel more kilometres on an active mode in 2014. The cross-lagged parameters between active travel and leisure physical activity are not significant (0.000). This indicates that someone who spends more kilometres traveling on an active mode spends does not practises more hours sporting the following year. Both correlations in the model are significant, as shown in table B.7. This indicates initial overlap and influence of a third variable not included in the model or a synchronous effect.

Table B.623 - Estimates of the CLPM

	Active travel 2014		Leisure physical activity 2014	
	b	β	b	β
Active travel 2013	0.359***	0.646	0.000	0.003
Leisure physical activity 2013	3.941***	0.095	0.716***	0.739
R^2	0.546		0.432	

*** Effect is significant at the 0.001 level.

Table B.7 - Covariates between the key variables and their error terms

	Estimate
Active travel – Leisure physical activity 2013	55.556***
e1 – e2	2.125***

*** Covariates is significant at the 0.001 level.

Outlier (ordinal scale)

Table B.8 presents the unstandardized and standardized estimates. The model indicates significant autoregressive effects for active travel (0.641***) and leisure physical activity (0.707***), indicating that the variables are stable and do not change much over time. Both cross lagged effects are significant. The model indicates a significant effect of leisure physical activity on active travel (0.036***) and from active travel on leisure physical activity (0.104**). This indicates that someone who spends more hours sporting in 2013 travels more kilometres on an active mode in 2014 and someone who spends more kilometres traveling on an active mode practises more hours sporting. Both correlations in the model are significant, as shown in table B.9. This indicates initial overlap and influence of a third variable not included in the model or a synchronous effect.

Table B.824 - Estimates of the CLPM

	Active travel 2014		Leisure physical activity 2014	
	b	β	b	β
Active travel 2013	0.641***	0.646	0.104**	0.046
Leisure physical activity 2013	0.036***	0.084	0.707***	0.729
R^2	0.309		0.564	

*** Effect is significant at the 0.001 level.
** Effect is significant at the 0.01 level.

Table B.9 - Covariates between the key variables and their error terms

	Estimate
Active travel – Leisure physical activity 2013	0.920***
e1 – e2	0.236***

*** Covariates is significant at the 0.001 level.

No Missing Data (Full data)

Table B.10 presents the unstandardized and standardized estimates. The model indicates significant autoregressive effects for active travel (0.631***) and leisure physical activity (0.732***), indicating that the variables are stable and do not change much over time. Both cross lagged effects are significant. The model indicates a significant effect of leisure physical activity on active travel (0.956***) and from active travel on leisure physical activity (0.005**). This indicates that someone who spends more hours sporting in 2013 travels more kilometres on an active mode in 2014 and someone who spends more kilometres traveling on an active mode practises more hours sporting. Both correlations in the model are significant, as shown in table B.11. This indicates initial overlap and influence of a third variable not included in the model or a synchronous effect.

Table B.10 - Estimates of the CLPM

	Active travel 2014		Leisure physical activity 2014	
	b	β	b	β
Active travel 2013	0.631***	0.541	0.005**	0.072
Leisure physical activity 2013	0.956***	0.057	0.732***	0.731
R^2	0.546		0.432	

*** Effect is significant at the 0.001 level.
** Effect is significant at the 0.01 level.

Table B.11 - Covariates between the key variables and their error terms

	Estimate
Active travel – Leisure physical activity 2013	28.075***
e1 – e2	7.479**

*** Covariates is significant at the 0.001 level.
** Covariates is significant at the 0.01 level.

In this research, some problems have been encountered linked to the LISS panel data, these problems are overcome in various ways. To understand the effect of these problems, as encountered in this research, different scenarios are tested in the sensitivity analysis. Because these problems and the effect of these problems are discussed in detail in the main text, this will not be repeated in this appendix. In section 3.7.3, these problems are discussed. This appendix is, only used to depict the results of the sensitivity analysis models regarding the relationship between active travel and health. The comparison of the models is discussed in the main text in section 5.4. Three different models are tested: twice the outlier model and one time a model with no missing data. An overview of the different sensitivity analyses is depicted in table C.1.

Table C.125 - Overview sensitivity analysis

Model	Data changes
Outlier model	To test the outliers, the CLPM is estimated with all the data, including the outliers.
Outlier model	To test the outliers, active travel is reconstructed on an ordinal scale, with 20% of the respondents in every group.
Missing value model	To test the missing values, the model is estimated with only the respondents who filled in all the variables of interest in all the waves.

Outliers (Full data)

Table C.2 presents the unstandardized and standardized estimates. The model indicates significant autoregressive effects for active travel, BMI and MHI, indicating that the variables are stable and therefore do not change much over time. None of the cross-lagged effects are significant. This indicates that active travel does not influence BMI and mental health or vice versa. The only significant correlation is between error terms e9 and e11. This indicates a possible influence of a third variables not included in the model or a synchronous effect.

Table C.226 - Estimates of the CLPM

	AT 2014		**BMI 2012**	**BMI 2013**		**BMI 2015**		**MHI 2012**	**MHI 2013**		**MHI 2015**	
	b	β		b	β	b	β		b	β	b	β
AT 2013	0.365***	0.655		0.000	0.003	0.000	0.006		0.000	0.011	0.000	-0.005
BMI 2012				1.008***	0.987				0.005	0.006		
BMI 2013	-0.114	-0.004				1.001***	0.993				-0.011	-0.014
MHI 2012				-0.010	-0.008				0.751***	0.778		
MHI 2013	-0.784	-0.021				0.019	0.014				0.783***	0.779
R²	0.399		0.869	0.913		0.944		0.859	0.839		0.869	
	Chi-square: 72.363, df:6, P:0.000, RMSEA: 0.070, CFI: 0.993											

****** Effect is significant at the 0.001 level.*

Table C.3 - 27Covariates between the key variables and their error terms

	Estimate
BMI 2012 – MHI 2012	0.425
BMI 2012 – Active travel 2013	6.732
MHI 2012 – Active travel 2013	28.129
e1 – e11	-15.983
e1 – e9	2.401
e9 – e11	0.406**
e10 – e8	-0.095

** Covariates is significant at the 0.01 level.

Outliers (Ordinal scale)

Table C.2 presents the unstandardized and standardized estimates. The model indicates significant autoregressive effects for active travel, BMI and MHI, indicating that the variables are stable and therefore do not change much over time. None of the cross-lagged effects are significant. This indicates that active travel does not influence BMI and mental health or vice versa.

There are two significant correlations. The first significant correlation is between BMI 2012 and active travel 2013. This correlation indicates an initial overlap between the two variables. The second significant correlation is between error terms e9 and e11. This indicates a possible influence of a third variables not included in the model or a synchronous effect between BMI 2015 and MHI 2015.

Table C.428 - Estimates of the CLPM

	AT 2014		BMI 2012	BMI 2013		BMI 2015		MHI 2012	MHI 2013		MHI 2015	
	b	β		b	β	b	β		b	β	b	β
AT 2013	0.657***	0.661		-0.041	-0.012	0.043	0.012		0.067	0.025	0.084	0.031
BMI 2012				1.007***	0.986				0.006	0.007		
BMI 2013	-0.004	-0.014				1.002***	0.994				-0.009	-0.012
MHI 2012				-0.009	-0.007				0.750***	0.777		
MHI 2013	0.013	0.034				0.018	0.014				0.782***	0.777
R^2	0.399		0.869	0.913		0.944		0.859	0.839		0.869	
	Chi-square: 71.426, df:6, P:0.000, RMSEA: 0.070, CFI: 0.993											

*** Effect is significant at the 0.001 level.

Table C.5 - 29Covariates between the key variables and their error terms

	Estimate
BMI 2012 – MHI 2012	0.429
BMI 2012 – Active travel 2013	-0.380*
MHI 2012 – Active travel 2013	0.225
e1 – e11	0.072
e1 – e9	-0.017
e9 – e11	0.400**
e10 – e8	-0.088

** Covariates is significant at the 0.01 level.
* Covariates is significant at the 0.05 level.

Missing data

Table C.2 presents the unstandardized and standardized estimates. The model indicates significant autoregressive effects for active travel, BMI and MHI, indicating that the variables are stable and therefore do not change much over time. None of the cross-lagged effects are significant. This indicates that active travel does not influence BMI and mental health or vice versa. There only significant correlation is between error terms e9 and e11. This indicates a possible influence of a third variables not included in the model or a synchronous effect between BMI 2015 and MHI 2015.

Table C.630 - Estimates of the CLPM

	AT 2014		BMI 2012	BMI 2013		BMI 2015		MHI 2012	MHI 2013		MHI 2015	
	b	β		b	β	b	β		b	β	b	β
AT 2013	0.362***	0.542		0.000	-0.002	0.000	0.000		0.000	-0.009	0.000	0.031
BMI 2012				0.971***	0.992				0.003	0.004		
BMI 2013	-0.040	-0.002				1.018***	1.026				-0.014	-0.019
MHI 2012				-0.004	-0.004				0.746***	0.805		
MHI 2013	-0.137	-0.032				-0.007	0.014				0.817***	0.800
R^2	0.399		0.869	0.913		0.944		0.859	0.839		0.869	
	Chi-square: 60.402, df:6, P:0.000, RMSEA: 0.091, CFI: 0.992											

*** Effect is significant at the 0.001 level.

Table C.7 - 31Covariates between the key variables and their error terms

	Estimate
BMI 2012 – MHI 2012	0.617
BMI 2012 – Active travel 2013	41.161
MHI 2012 – Active travel 2013	-5.552
e1 – e11	-17.581
e1 – e9	0.249
e9 – e11	0.347*
e10 – e8	0.046

* Covariates is significant at the 0.05 level.

Appendix D – CLPM with control variables

In this appendix, the steps towards the presented parsimonious CLPM with control variables in the main text are discussed. In this case, this means that all the non-significant paths are taken out of the model. This way a good-fitting model is established. Three steps are conducted to come to the main model. The first step is to include all the socio-demographic variables that have possible influence on activity and are in the scope of this research. The socio-demographic variables are described in section 2.7 and section 3.3. The model and the results of the first step are depicted in section "all covariates". The second step is to delete the control variables with no significant effect on either active travel or leisure physical activity. This model and the results of this model are depicted in section "Only significant covariates". The last step is to delete the non-significant paths between the control variables and active travel and leisure physical activity. This last step results in the model as depicted in the main text. The results of the other two models are depicted in this appendix. The comparison of the CLPM and the CLPM with control variables can be found in section 4.3.

All covariates

In this model, all the socio-demographic variables of interest are included in the model. Age, gender and income are found to have a significant effect on either active travel or leisure physical activity, as can be seen in table D.1. Therefore, in the following model, these socio-demographics are included. The covariates of the model are depicted in table D.2.

Table D.132 - Estimates of the CLPM with control variables

	Active travel 2013		**Leisure physical activity 2013**		**Active travel 2014**		**Leisure physical activity 2014**	
	b	β	b	β	b	Β	b	β
Active travel 2013					0.630***	0.602	0.005***	0.071
Leisure physical activity 2013					1.031**	0.069	0.729***	0.743
Age	0.032	0.012	-0.020***	-0.113	-0.009	-0.003	-0.003	-0.019
Civil status	-0.571	-0.006	0.223	-0.035	0.421	0.004	-0.099	-0.016
Gender	-5.986**	-0.068	-0.505***	-0.081	-2.152	-0.023	-0.127	-0.021
Income	0.000	0.027	0.000*	0.064	0.001**	0.254	0.000	-0.015
Level of education	-0.587	-0.020	0.016	0.008	0.362	0.011	0.007	0.003
Urban character	-0.841	-0.024	0.048	0.0219	0.789	0.694	0.038	0.039
R^2	0.006		0.026		0.446		0.562	
	Chi-square: 191.826, df:1, P:0.000, RMSEA: 0.232, CFI: 0.957							

*** Effect is significant at the 0.001 level.
** Effect is significant at the 0.01 level.
* Effect is significant at the 0.05 level.

Table D.233 - Covariances between the key variables and their error terms

	Estimate
Gender – Civil status	0.008
Civil status – Urban character	-0.076***
Urban character - Gender	-0.002
Urban character – Level of education	-0.185***
Civil status – Level of education	-0.019
Gender – Level of education	-0.078***
Age – Level of education	-2.213***
Age – Urban character	0.914*
Age – Civil status	-3.269***
Age – Gender	-0.622***
Income – Gender	-89.868
Income – Urban character	-54.232
Income – Level of education	103.881
Income – Civil status	145.902
Income – Age	10151.916*
e1 – e2	8.700***

*** Covariates is significant at the 0.001 level.
* Covariates is significant at the 0.05 level.

Only significant covariates

In this model, only the significant covariates of the previous model are included in the model. As can be seen the same socio-demographic variables are significant as in the previous model. The estimations can be seen in table D.3. Because not all the paths are significant, these can be taken out of the model. The covariates of this model can be found in table D.4. Taking out the non-significant paths results in the model as discussed in the main text.

Table D.3 - Estimates of the CLPM with control variables

	Active travel 2013		Leisure physical activity 2013		Active travel 2014		Leisure physical activity 2014	
	b	β	b	β	b	Β	b	β
Active travel 2013					0.629***	0.601	0.005***	0.070
Leisure physical activity 2013					1.048***	0.070	0.728**	0.743
Age	0.040	0.016	-0.023***	-0.127	-0.016	-0.006	-0.002	-0.013
Gender	-5.792**	-0.066	-0.507***	-0.082	-2.251	-0.024	-0.130	-0.021
Income	0.000	0.026	0.000**	0.066	0.001**	0.257	0.000	-0.016
R^2	0.005		0.025		0.447		0.561	
	Chi-square: 117.373, df:1, P:0.000, RMSEA: 0.229, CFI: 0.949							

*** Effect is significant at the 0.001 level.
** Effect is significant at the 0.01 level.

Table D.434 - Covariances between the key variables and their error terms

	Estimate
Gender – Age	-0.622***
Age - Income	10210.357**
Gender - Income	-96.086
e1 – e2	8.752***

*** Covariates is significant at the 0.001 level.
** Covariates is significant at the 0.01 level.