Ministry of Infrastructure
and Water Management

The relationship between health and active travel

Mathijs de Haas

Netherlands Institute for Transport Policy Analysis | KiM

Summary

According to the (international) literature, cycling and walking have positive effects on health, including lowering the risk of obesity and cardiovascular diseases. In this study we examine the causal relationship between health and active travel (walking and cycling) in the Netherlands, whereby health is approximated by Body Mass Index (BMI) and perceived health. We examined whether increased exercise leads to lower BMIs (or better perceived health), and whether the opposite is true.

A causal relationship exists between BMI and active travel for non-obese people only (BMI < 30 kg/m^2). The more people walk, the greater the positive impact on BMI – it decreases. Additionally, the BMIs of non-obese people negatively impact bicycle use: increased BMI results in decreased numbers of bicycle trips and distances cycled. No causal relationships were found between e-bikes and BMI.

Only bicycle use has a seemingly significant positive impact on perceived health and active travel: the longer distances people cycle, the more their perceived health increases. We found no significant impact on perceived health from e-bikes and walking.

Background
In 2019, the KiM Netherlands Institute for Transport Policy Analysis published a research study titled, 'The relationship between health and use of active transport modes', which ascertained a clear relationship in the Netherlands between people's health and their travel behaviour. People of healthy body weights seemingly cycle more and use cars less than heavier people, while obese people use e-bikes more frequently than people of healthy body weights. Moreover, daily mobility is a key factor in terms of getting enough exercise: one in three Dutch adults get the minimum recommended 150 minutes of exercise weekly from traveling by bicycle, e-bike or on foot. A full summary of this previous research study can be found at the end of this report.

(International) literature
The relationship between health and active travel features prominently in international literature. Because BMI is a relatively easily measurable health indicator, researchers frequently use BMI to study the relationship between active travel and health. Studies conducted in the UK revealed that BMI decreases if a person more frequently commutes by bicycle or walking instead of by car. Elsewhere, Australian researchers found that adults who routinely use active transport modes have lower BMIs than those of car users. However, most research studies are limited in that they assume the direction of the causal relationship (active travel on BMI), rather than studying the direction. The direction of a causal relationship could in fact differ from those assumed in most studies, such as from BMI on active travel or a reciprocal effect. The causal direction is however examined in studies that consider the relationship between BMI and physical activity in general: such studies show that BMI possibly has a larger impact on the extent of active mobility than vice versa.

Although many studies associate active mobility with positive health effects, including reduced risk of premature death, cardiovascular diseases and Type 2 diabetes, active mobility is however also associated with negative health effects, such as accidents and inhalation of polluted air. Nevertheless, active mobility's net effect on health is seemingly positive. In two studies that examined both positive and negative health effects, researchers found the positive effects to be (much) stronger than the negative ones.

Method and data

In this study we used data from the Netherlands Mobility Panel (MPN), a longitudinal travel survey KiM conducts annually (since 2013) among the same group of households and their members, measuring their travel behaviour. At the time of the previous KiM study in 2019, we were not yet able to answer the question of whether causal relationships exist in the Netherlands between BMI and perceived health on the one hand, and active travel on the other. To answer this question, we performed additional analyses in this present study, using MPN data from 2017, 2018 and 2019.

We used a *Random Intercept Cross-Lagged Panel Model* (RI-CLPM) to study relationships over time. This model allowed us to relate BMI, perceived health and use of active transport modes to the same group of people at three periods of time and at one-year intervals. The analysis reveals whether changes to these indicators, such a change of BMI at time period *t*, impacts other indicators, like the use of active transport modes at time period *t+1*. We are therefore studying lagged effects. A key advantage of an RI-CLPM over a standard cross-lagged panel model (CLPM) is that it allows us to distinguish between interpersonal (between people) and intrapersonal (within one person) variance. The within-person level is of interest in this study, as this is the level where the presumed causal effects actually occur.

Conclusions: For non-obese people, increased walking results in decreased BMI, and increased BMI results in decreased cycling. Furthermore, increased cycling results in increased perceived health.

We found significant effects between BMI and distances travelled by bicycle and on foot for non-obese people (BMI < 30 kg/m^2). We did not find such significant effects for e-bikes and for obese people. For non-obese people, the distance travelled positively (= negative) impacts BMI: the further people walk, the more their BMI decreases (Figure 1). We did not find the opposite effect of BMI to walking distance.

We did however observe this opposite effect for bicycles. For non-obese people, BMI has a significantly negative impact on distance cycled (Figure 1): hence, increased BMI results in decreased distance cycled. As for the relationship between BMI and numbers of trips, we found that BMI only negatively effects the number of bicycle trips (Figure 1). In other words, if people's BMIs increase, they cycle less often.

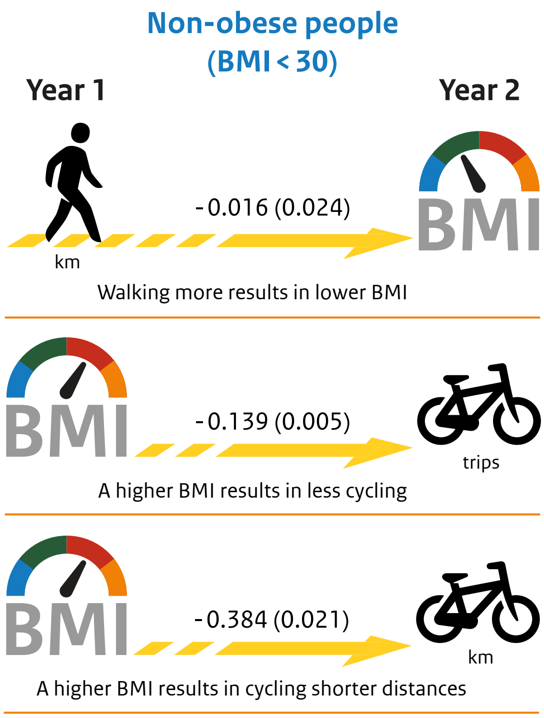

Figure 1 Significant effects between BMI and active travel (the parameter shows how a 1-point change to the variable in Year 1 impacts the variable in Year 2; hence, for example, a 1 km increase in walking in Year 1 results in a 0.016 kg/m^2 decrease in Year 2. The p-value is stated between brackets.)

We found that bicycle use has no impact on BMI, which implies that promoting bicycle use in the Netherlands will not decrease the average BMI. Given that the number of overweight people in the Netherlands is rising, this will result in a relative decrease in bicycle use in future. Conversely, bicycle use could be positively impacted by policy aimed at reducing the number of overweight and obese Dutch people, such as through commitments to eating healthy food and encouraging participation in sports and exercise.

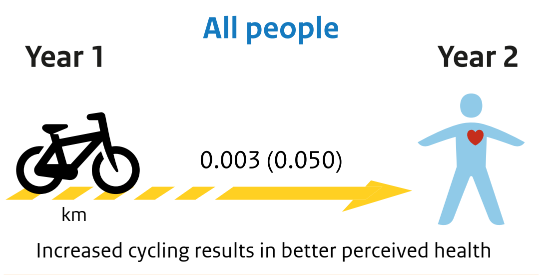

Figure 2 Significant effects between active travel and perceived health

Regarding the relationship between perceived health and distance travelled, we found a significant effect for bicycles. The distance a person cycles has a significantly positive impact on their perceived health (Figure 2); consequently, Dutch people's perceived health increases if they cycle greater distances. We found no significant effects between perceived health and distance travelled by e-bike or on foot, nor pertaining to the relationship between perceived health and number of trips via active transport modes.

Walking is thus the only active travel that leads to decreased BMI, while cycling results in increased perceived health. However, this does not mean that these are the only health benefits of active travel, as much of the available literature reveals the positive impact that active travel or exercise in general has on subjective health, the burden of diseases and life expectancy, for example.

Follow-up research

This research is limited in that we had only limited available information about health. The MPN provides detailed insights into the respondents' travel behaviour, but health-related information is limited to BMI and perceived health. Consequently, it is impossible to reveal the full extent of the relationship between active travel and health, and thus we recommend follow-up research. Potential subjects for further research could include the relationship between mental health and active mobility in the Netherlands, which remains unclear, as does the precise impact that active travel has on absenteeism or vitality.

Content

1 Introduction

People in the Netherlands use cars for a large share of their short trips (up to 7.5 km) (De Haas and Hamersma, 2020). If they instead chose to use active transport modes for these short car trips, this would have positive effects on their health. Encouraging such a modal shift from cars to bicycles would also have a positive impact on accessibility, quality of life and the environment, as would promoting public transport use, in which active transport modes play key roles in access and egress transport.

In 2019, the KiM Netherlands Institute for Transport Policy Analysis published a research study titled, 'The relationship between health and the use of active transport modes' (De Haas en Van Den Berg, 2019). The study, which was based on data from the Netherlands Mobility Panel (MPN), revealed a clear correlation in the Netherlands between people's health and their travel behaviour. People of healthy body weights seemingly cycle more and use cars less than heavier people, for example, while obese people use e-bikes more often than people of healthy body weights. Moreover, the study found that daily mobility is a key factor in terms of getting enough exercise. The Health Council of the Netherlands recommends exercising a minimum of 150 minutes per week, which includes cycling and walking. Approximately one in three Dutch adults already get this much weekly exercise from traveling by bicycle, e-bike or walking. Because people of healthy body weights use these active transport modes more frequently, they are also more likely to meet the recommended exercise standard than overweight and obese people. A full summary of this previous research study can be found at the end of this report.

The question the previous research left unanswered was whether any causal relationships exist between active travel and the health indicators of Body Mass Index (BMI) and perceived health. This current research focused on answering that question, which required additional analyses, compared to the 2019 study, because at that time only two years of MPN health indicator data were available, but now, to conduct the statistical analysis needed to study causal relationships between health and active travel, we require at least three years of health indicator data. These additional analyses should reveal whether active travel results in healthier body weights (lower BMI) or (conversely) whether changes in BMI influence how much a person actively travels. We also conducted the same studies for the relationship between perceived health (how healthy people perceive themselves to be) and active travel behaviour.

1.1 Research objective

The aim of our current research is to answer the following previously unanswered question:

To what extent does a causal relationship exist between health and active travel in the Netherlands?

Our research relied on data from the Netherlands Mobility Panel (MPN). The MPN contains information about two health indicators: BMI and perceived health. We therefore divided the main research question into the following two sub-questions:

- To what extent does a causal relationship exist between BMI and active travel in the Netherlands?
- To what extent does a causal relationship exist between perceived health and active travel in the Netherlands?

1.2 Reader's guide

Before examing the causal relationships between health and active travel, we first discuss in Chapter 2 the relevant literature, briefly summarising the 2019 literature review's main findings, while primarily focusing on literature that appeared after publication of the earlier study. In Chapter 3 we detail the method used to study the causal relationships, and describe the MPN data used in this research.
In addition to detailed information about people's travel behaviour, the MPN also contains information about their health, including BMI and perceived health. In Chapter 4 we present and discuss our findings. In Chapter 5 we summarise the answers to our research questions and make recommendations for further research.

2 Literature

In the 2019 KiM research study on the relationship between active travel and health we examined in detail the available literature pertaining to that relationship. In this chapter we revisit the main findings of that previous literature review while also focusing on more recently published studies. We also examine the negative health effects of active travel. As based on the literature, active mobility's net effect on health is seemingly positive when both positive and negative effects are considered.

2.1 BMI and active mobility

The international literature devotes much attention to the relationship between health and active travel. Because BMI is a relatively easy health indicator to measure, it is often used for studying the relationship between health and active travel. For example, research previously conducted in the UK found that maintaining active travel patterns during puberty positively impacts BMI (Falconer et al., 2015), that adults switching from cars to bicycles for commuting resulted in decreased BMI (Flint et al., 2016), and that decreased BMI is associated with people who walk more frequently (Mytton et al., 2016a). Elsewhere, Australian research found that the BMIs of adults who consistently use active transport modes are lower than those of car users (Turrell et al., 2018). We must note however that many studies assumed, rather than studied, the direction of the causal relationships. Consequently, the assumption is that use of active transport modes caused a change in BMI and not vice versa.

Studies of the relationship between BMI and physical activity generally have indeed examined the direction of the causal relationship: a Danish study of the relationship between leisure time, physical activity and obesity among adults found no evidence that physical inactivity results in obesity, but that a high BMI does result in physical inactivity (Petersen et al., 2004), while Bak et al. (2004) and Mortensen et al. (2006) also found that higher BMIs determine the extent of people's physical activity or sedentary behaviour, yet found no evidence that physical activity or sedentary behaviour impacted BMI. These studies indicate that BMI may have a greater impact on active mobility than vice versa.

Recent Dutch research specifically focused on the direction of the causal relationship between walking and BMI, finding that the amount a person walks has no effect on changes in BMI, but that BMI does negatively impact the amount of walking (Kroesen and De Vos, 2020). When people gain weight, they walk less. This research was however limited in the sense of how walking was measured, as the researchers only knew on how many days the respondents walked for at least 10 minutes during a 7-day time span. Consequently, no distinction could be made between people who walked for 10 minutes a day and those who walked for longer.

A Japanese cohort study involving some 30,000 participants found that active commuting does not result in decreased BMI, but that it does help limit weight gain (Kuwahara et al., 2019). People's BMIs are known to increase with age. The Japanese study found that the BMIs of people commuting actively over a 5-year period increased significantly less than those of people who commuted inactively during that same period. Those who switched from an active transport mode to an inactive mode experienced significantly larger increases in BMI than the group that had been inactive for the entire period. Active travel therefore helps maintain body weight.

2.2 Other positive health effects of active mobility

There are, in addition to BMI, numerous other health indicators, including subjective health and disease burden, and much research has focused on the relationships between these indicators and active travel. Previous research in the UK found a significant relationship between psychological well-being and active travel (Martin et al., 2014); incidentally, researchers subsequently found no such relationship in the Dutch context (Scheepers et al., 2015). Other UK research determined that people who commute by bicycle report sick less often (Mytton et al., 2016b). Dutch people who commute by bicycle also report sick less often (Hendriksen and Van Gijlswijk, 2010), although this study did not examine the causal relationships. Consequently, such findings do not necessarily prove that absenteeism rates decrease if employees cycle to work more frequently.

In addition to BMI, the aforementioned Dutch study by Kroesen and De Vos (2020) focused on the causal relationship between walking and subjective well-being, with subjective well-being measured according to the Mental Health Inventory (MHI-5) (Berwick et al., 1991). This study found that walking significantly impacts subjective well-being, yet the opposite effect was insignificant (the opposite effect was however significant at a significance level of 10%).

In addition to effecting subjective health, active travel impacts life expectancy and disease burden. Much available literature pertains to the relationships between physical activity (including active travel) and health: for example, risk of premature death decreases as physical activity increases (Arem et al., 2015; Ekelund et al., 2015; Hupin et al., 2015), which, according to a meta-analysis, also specifically applies to cycling and walking (Kelly et al., 2014); and physical activity lowers risks of disease such as cardiovascular disease (Dobbins et al., 2013; Janssen and Leblanc, 2010; Kelley et al., 2003; Murtagh et al., 2015), type 2 diabetes (Aune et al. , 2015; Cloostermans et al., 2015), and various cancers (Liu et al., 2016; Wu et al., 2013). Additionally, according to a meta-analysis focusing specifically on active travel, cycling to work is associated with lower risks of cardiovascular disease and cancer, and a lower overall mortality risk (Celis-Morales et al., 2017); moreover, this study found that walking to/from work is associated with lower risks of cardiovascular disease, but not of cancer and a lower overall mortality risk.

A recent meta-analysis based on 23 (non-Dutch) prospective studies involving some 500,000 participants endorsed these relationships (Dinu et al., 2019). The participants who actively commuted (walking or cycling) to/from work had an 8% lower overall mortality risk, a 9% lower risk of developing cardiovascular disease and a 30% lower risk of diabetes. Moreover, people commuting to work by bicycle enjoy a greater reduction in overall mortality risk and death due to cancer than those who walk to work.

2.3 Negative health effects of active mobility

Active mobility has both positive and some negative effects on health, such as higher risk of accidents and inhalation of polluted air.

Cyclists account for around one-third of all traffic fatalities in the Netherlands. The total number of traffic fatalities was higher in recent years as compared to 2013 (the lowest number of traffic fatalities in 10 years) (CBS, 2020c). Bicycle-related traffic fatalities are clearly on the rise. In 2018, 228 cyclists died in traffic accidents, the highest number since 2000. In 2019 that figure was lower at 203 deaths, and included 65 people riding e-bikes, although, according to Statistics Netherlands (CBS), that latter figure is the lower limit, because reporting is not always accurate in terms of whether the bicycles involved were electric or regular (CBS, 2020b). It is therefore likely that e-cyclists account for a higher percentage of all bicycle fatalities. Previous research revealed that the increase in bicycle traffic fatalities in the Netherlands was largely attributed to an increased number of accidents in which no motorised vehicles were involved, such as people falling from their bicycles (Schepers et al., 2017).

The same study found this increase partly attributable to increased bicycle use among senior citizens. The number of fatalities involving pedestrians had been decreasing annually until 2013, but since then pedestrian fatalities have fluctuated between 50 and 60 per year (CBS, 2020c).

According to the number of traffic fatalities per distance travelled (the risk of death), cyclists and pedestrians are relatively vulnerable road users compared to car occupants. In 2017, 10.7 pedestrians and 14.2 cyclists died per billion passenger-kilometres, while for car occupants that figure was 1.5 fatalities per billion passenger-kilometres (KiM Netherlands Institute for Transport Policy Analysis, 2019). The difference in risk levels between cars and active mobility is not the same for everyone: the risk of death associated with active mobility is higher for elderly people than younger people, which is also reflected in the proportion of elderly people among traffic fatalities. In 2019, some 38% of traffic fatalities involved people aged 70 or older, while for cyclists and pedestrians those figures were 58% and 53%, respectively. For illustrative purposes, in 2019 approximately 8% of the Dutch population was aged 70 or older (CBS, 2020a).

In addition to higher incidences of fatal road accidents, cyclists and pedestrians also account for more visits to hospital Accident & Emergency (A&E) departments due to accidents than motorists (Safetynl, 2020). In 2019, road accidents accounted for more than 124,000 A&E visits, with more than half the victims (56%) suffering serious injury (MAIS2+). Some two-thirds of these road accident victims were riding bicycles when the accidents occurred, while 13% of A&E visits involved motorists and 3% pedestrians. The reason why pedestrians account for such a low percentage is that single pedestrian accidents (like a person tripping and falling in the street) are not considered traffic accidents. In 2019, 21,200 pedestrians visited the A&E due to falling in the street.

Inhaling polluted air (like nitrogen and particulate matter) also adversely affects health. Inhaling fine particles smaller than 2.5 µm (PM2.5) has the most severe impact on human health (De Hartog et al., 2010), and not only cyclists and pedestrians inhale particulate matter but also people traveling via passive transport modes (like cars and buses). The local context determines the concentration of particulate matter (PM2.5). De Nazelle et al. (2017), conducting a meta-analysis based on various European studies, found that PM2.5 concentrations are on average higher for car users than for cyclists and pedestrians. Two Dutch studies were part of this meta-analysis and also arrived at the same conclusion (Boogaard et al., 2009; Zuurbier et al., 2010). However, because pedestrians and cyclists inhale more air than car users, owing to their physical exertion, they inhale more particulate matter than car users (Kahlmeier et al., 2017; Panis et al., 2010).

2.4 Conclusion literature study

There is ample evidence that active mobility positively impacts health, especially due to the increased physical activity. KiM's 2019 research study of the relationship between active travel and health also arrived at the same conclusion. Nevertheless, certain negative effects persist, including higher risks of accidents and exposure to polluted air.

Active mobility's net effect on health is seemingly positive when both positive and negative effects are considered. De Hartog et al. (2010) concluded that the increased life expectancy due to the extra physical exercise deriving from switching from cars to bicycles (+3 to +14 months) is far greater than decreases due to increased risk of accidents (-5 to -9 days) and inhalation of polluted air (-0.8 to -40 days). Rabl and De Nazelle (2012) also found that the benefits of stimulating active mobility (improved health and reduced air pollution, for instance) outweigh the risks (higher accident risk rates), as based on various scenarios in several large European cities.

3 Method and data

In our research of the causal relationship between BMI, perceived health and active transport mode use, we used a statistical method that allowed us to study this relationship over time. Our research relied on data from the Netherlands Mobility Panel (MPN). In this chapter we explain the applied statistical method and data.

3.1 Method

We used a *Random Intercept Cross-Lagged Panel Model* (RI-CLPM) to study relationships over time (Hamaker et al., 2015). This model allowed us to relate the BMIs, perceived health and active transport mode use of the same group of people to each other at multiple points in time, thereby establishing whether changes to these indicators, like a change in BMI at time *t*, impacted other indicators, such as use of active transport modes at time *t+1*. This model allowed us to study the delayed effects. Compared to a regular Cross-Lagged Panel Model (CLPM), an RI-CLPM offers a key advantage: we could distinguish between interpersonal (between persons) and intrapersonal (within one person) variance, and thus study the effects within one person. At this level the assumed causal effects also come into play. The RI-CLPM is described in greater detail in Appendix A.

The relationship between BMI and active transport mode use can differ among groups: for example, a large-scale US study (15,000 participants) found an inverse relationship between extent of physical activity and weight gain (Littman et al., 2005), or, in other words, the people who were more physically active gained less weight than the people who were less active. That relationship was stronger among obese people than non-obese people. Consequently, if a causal relationship exists between BMI and active transport mode use, the relationship differs for obese people and non-obese people. To study this, we also estimated models for the relationship between BMI and active travel, specifically distinguishing between these two groups – obese and non-obese people.

We distinguished between bicycles, e-bikes and walking as transport modes, examining the relationships between health indicators and the numbers of trips people made with those three transport modes, as well as the distances they travelled. To prevent the model from becoming too complex we estimated separate models for each transport mode. Had we estimated all transport modes in the same model, we would have also gained insights into the transport modes' various substitution effects, but KiM had already researched this aspect in 2019 (De Haas, 2019), and, moreover, it is beyond the scope of this current research. When analysing the distances travelled, we removed from the sample the 0.5% of respondents who travelled the greatest distances, as a small number of outliers can have a relatively large impact on model estimations. Outliers would include people who cycle more than 200 km or walk more than 60 km over the course of three days, for example.

3.2 Netherlands Mobility Panel

The Netherlands Mobility Panel (MPN), KiM's longitudinal travel survey, allows us to map changes in the travel behaviour of fixed groups of people and households. KiM has conducted this annual survey since 2013. MPN participants complete various questionnaires, and all participating household members aged 12 and older keep travel diaries, recording all the trips they make over a period of three consecutive days. In 2017, MPN questionnaires also started to include certain questions about health. Consequently, for our current study we used MPN data from 2017, 2018 and 2019.

Children and young people aged 12 to 18 also participate in the MPN, but for our study we only used data for adult respondents aged 18 and older. Children are still developing physically and hence their BMIs reveal relatively large changes regardless of whether they travel actively. We therefore excluded children from our study.

To measure active travel, we used distance travelled and number of trips by bicycle, e-bike and walking. Cycling or walking are deemed moderately intensive exercises (World Health Organization, 2010). Although e-bikes demand less physical exertion than regular bicycles, both Dutch and international research concluded that traveling by e-bike also qualifies as moderately intensive exercise and hence e-bikes are deemed an active transport mode (Bourne et al., 2018; Simons et al., 2009).

Our current study includes all respondents who participated in the MPN for at least one full year in 2017, 2018 or 2019; that is, respondents who completed both the questionnaire and 3-day travel diary during at least one of those years. Additionally, we only used respondents who had completed the health questions, as respondents have the option of not answering those questions. Our sample consisted of 6,745 respondents. Table 1 shows the composition of the respondents participating in the MPN in 2019 (the compositions in 2017 and 2018 are comparable to 2019). The Gold Standard reflects the composition of Dutch society (Moa, 2019). The table further shows that many of MPN sample's variables are representative of Dutch society. Notably, underrepresented in the sample are young adults aged 18 to 30, people with secondary educations, and households in highly urbanised areas, while adult households are slightly overrepresented. Because we used the RI-CLPM to study the effects within a person, we automatically corrected for time-constant variables. We can, to a certain extent, consider the variables in the table as time constant, and hence minor deviations in the sample are not expected to impact the findings.

Table 1 Composition of sample and Dutch society (MPN 2019, n = 4.511)

		MPN (2019)	Gold Standard (2019)	Differential (share MPN – share Gold Standard)
Gender	Male	47.8%	49.3%	-1.5%
	Female	52.2%	50.7%	1.5%
Age	18-30	14.5%	20.4%	-5.9%
	31-40	17.1%	15.0%	2.1%
	41-50	14.9%	17.3%	-2.4%
	51-64	27.0%	24.4%	2.6%
	65+	26.4%	22.9%	3.5%
Education level	Low	27.0%	28.5%	-1.5%
	Medium	39.0%	42.9%	-3.9%
	High	34.0%	28.6%	5.4%
Employment status	Employed	54.6%	54.6%	0.0%
	Unemployed	11.1%	12.0%	-0.9%
	Occupationally disabled	6.3%	3.9%	2.4%
	Student	4.9%	6.8%	-1.9%
	Pensioner	23.1%	22.6%	0.5%
Household situation	One-persons household	22.3%	22.0%	0.3%
	Adult household	54.0%	49.6%	4.4%
	Household with youngest child aged ≤ 12	17.6%	20.3%	-2.7%
	Household with youngest child aged 13 to 17	6.1%	8.1%	-2.0%
Degree of Urbanisation*	Non-urban (< 500 addresses/km^2)	8.0%	7.8%	0.2%
	Slight (500 to 1,000 addresses/km^2)	21.5%	21.6%	-0.1%
	Moderate (1,000 to 1,500 addresses/km^2)	18.8%	15.6%	3.2%
	High (1,500 to 2,500 addresses/km^2)	31.9%	30.3%	1.6%
	Very high (≥ 2,500 addresses/km^2)	19.9%	24.6%	-4.7%

3.3 BMI and perceived health

In 2017, MPN questionnaires began to include several questions about health, and from that resulting information we can determine people's BMIs. From the following MPN question we measure perceived health: 'What is your opinion of your own health generally?'. Respondents choose from response categories, ranging from poor to excellent. Perceived health is a subjective measure of health, but the literature does establish perceived health's relation to overall mortality risk (Desalvo et al., 2006; Idler and Benyamini, 1997).

BMI is a person's weight in kilograms divided by the square of height in meters. BMI indicates whether a person is of a healthy body weight, overweight or obese. High BMIs do not necessarily indicate poor health, but high BMIs are key risk factors for diseases like type 2 diabetes, cardiovascular disease and certain types of cancer (Pozza and Isidori, 2018; Visscher and Seidell, 2001). Table 2 presents the various categories and associated limit values, as prescribed by the World Health Organization (2019).

* Distribution of degree of urbanisation based on the Gold Standard shows the distribution among all Dutch people aged 13 and older. A distribution for Dutch people aged 18 and older is unavailable.

Table 2 Various weight classifications according to the World Health Organisation

Weight classification	BMI
Underweight	Lower than 18.5
Healthy weight	18.5 – 24.9
Overweight	25.0 – 29.9
Obesity class 1	30.0 – 34.9
Obesity class 2	35.0 – 39.9
Obesity class 3	Higher than 40.0

Previous research found that people who self-report their heights and weights routinely report greater heights and lower weights (Gorber et al., 2007). If MPN respondents do the same then BMI will be underestimated; nevertheless, this issue is not expected to significantly impact the findings. Because we use the same person's BMI in different years, any measurement error will be constant over time.

Respondents themselves specify their own heights and weights; consequently, we cannot verify if such data are indeed correct. We therefore remove extreme values from the data; namely, people with BMIs below 15 kg/m^2 (extremely underweight) and above 50 kg/m^2 (extremely overweight). We ultimately removed eight respondents from the sample. The heights that respondents report in the different years should be relatively constant, and while this was the case for most respondents, we did ultimately remove 22 respondents who had reported large height differences (their heights varying by more than 15 cm between the years).

Table 3 presents the distribution of Dutch people across the various weight classifications; this distribution is consistent with that of the MPN, where overweight and obese people are slightly over-represented.

Table 3 Distribution weight classifications 2019 Netherlands (CBS and Rivm, 2019) and MPN (MPN 2019, n = 4.511)

Weight classification	Share Netherland 2019	Share MPN 2019
Underweight (BMI < 18.5)	1.8%	1.7%
Healthy weight (18.5 ≤ BMI < 25)	48.1%	45.2%
Overweight (25 ≤ BMI < 30)	35.4%	36.6%
Obese (BMI ≥ 30)	14.7%	16.4%

Table 4 shows perceived health per weight classification. Perceived health seemingly correlates to people's BMIs. People of healthy weights are more likely to have better perceptions of their own health than those in higher weight classifications. (X^2 (16, N = 4511) = 329.371, p = 0.000).

Table 4 Correlation and perceived health of MPN respondents (MPN 2019, n = 4.511)

	Perceived health				
Weight classification	**Poor**	**Average**	**Good**	**Very good**	**Excellent**
Underweight (BMI < 18.5)	3.8%	12.8%	44.9%	19.2%	19.2%
Healthy weight (18.5 ≤ BMI < 25)	1.5%	9.1%	43.7%	29.4%	16.3%
Overweight (25 ≤ BMI < 30)	2.0%	14.9%	53.0%	22.4%	7.7%
Obese (BMI ≥ 30)	4.7%	23.7%	56.1%	11.5%	4.0%
Total	**2.2%**	**13.7%**	**49.1%**	**23.7%**	**11.2%**

4 Causal relationship between BMI, perceived health and active travel

This chapter presents the results of our statistical analyses, providing insight into the extent to which causal relationships exist between BMI and active travel (section 4.1), and between perceived health and active travel (section 4.2). We measure active travel based on distance travelled and number of trips. Distance travelled is likely a better reflection of the relationship between BMI and active travel than number of trips, because distance travelled is a better indicator of physical exertion. Table 5 presents per section the examined health indicator and active travel indicator.

Table 5 Reader's guide to Chapter 4

Section	Health indicator	Indicator for active travel
4.1.1	BMI	Distance travelled
4.1.2	BMI	Number of trips
4.2.1	Perceived health	Distance travelled
4.2.2	Perceived health	Number of trips

We consider the model fit of all presented models to be good, as based on the chi-square test (X^2), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardised Root Mean Square Residual (SRMR) (Brown, 2014). This means the models fit the data well. The fit indices are presented in Appendix B. The model estimation results are depicted in this chapter. The parameter estimates are tabulated in Appendix B.

4.1 BMI and active travel

As described in section 3.1, for the relationship between BMI and active travel, we estimate models in which the effects are assumed to be the same for everyone included in the sample, and models in which we specifically distinguish between groups of obese and non-obese people. We found no significant effects in models in which no distinction was made between groups. Therefore, we only discuss models where distinctions were made. The findings for the other models are presented in Appendix B.

4.1.1 BMI and distance travelled by bicycle, e-bike and walking

For the relationship between BMI and distances travelled by active transport modes, we found significant effects for cycling and walking but not for e-bikes.

Figure 3 Parameter estimates RI-CLPM relationship BMI and distance travelled per three days with active transport modes (in km), p-values in brackets

For non-obese people, BMI has a significant negative effect on distance cycled (see Figure 3). The negative parameter indicates that when BMI increases, distance cycled decreases. And conversely, when BMI decreases, distance cycled increases. To illustrate the impact of the effect, we take as an example a person 1.80m tall and weighing 75 kg: a 1-point increase or decrease in this person's BMI equals 3.24 kg (1.802). For every 3.24 kg that this person gains he or she will cycle 0.384 km less per three days, and vice versa, and hence the effect is relatively minor.

For walking, the only significant relationship with BMI pertains to non-obese people. Walking distance has a negative effect on BMI. The BMIs of people who walk longer distances decrease, but again the effect is minor. To illustrate the point, we again take as an example a person 1.80 m tall and weighing 75 kg: if this person walks an additional 2 km per day, his or her BMI will decrease by 0.096 kg/m^2 (the parameter pertains to walking distance per three days, so we multiply the parameter by 6 (3 days * 2 km)), which is equal to a decrease of approximately 0.3 kg. We found no inverse effect for BMI on distance travelled. Consequently, a change in BMI does not result in someone walking a different distance.

We found no significant results for obese people (see Figure 3). We did however determine that the positive effect cycling distance has on BMI is nearly significant ($p = 0.064$), although this is not convincing evidence that, for obese people, effects exist between their BMIs and bicycle trips, yet nevertheless such relationships are interesting to explore. The effect's direction is not as expected. The parameter is positive, meaning when obese people start cycling longer distances their BMIs increase as a result.

There are several possible explanations for the effect's unexpected direction. The first is that we estimated many models, thereby increasing the likelihood the found effect is coincidental, which, in statistics, is called 'capitalising on chance' and means the positive effect found does not actually exist, but was instead discovered by chance. The finding could however also pertain to the BMI's stability over the years: in the literature, body weight fluctuations are generally greater in people of heavier body weights than of lighter ones (Bangalore et al., 2017; Stevens et al., 2006), and our sample also reflected this. Non-obese people's BMIs more strongly correlate in successive years than those of obese people (see Table 6). Obese people's BMIs therefore exhibit a greater propensity to change over the years. Such changes may well have impacted our model estimation and hence we arrived at this finding by chance.

If this unexpected effect does in fact exist for obese people, it may relate to a psychological phenomenon known as 'moral licensing', whereby moral behaviour unconsciously leads to immoral behaviour (Merritt et al., 2010), which, in the context of this research, would mean increased cycling (moral behaviour) results in immoral behaviour (overcompensating via higher energy intakes, for example, or decreasing another physical activity). Although previous research found that increased exertion due to physical activity is generally (partly) compensated for by higher energy intakes (Westerterp, 2010), the literature did not reveal whether this effect is stronger in obese people than non-obese people. Based on the available data, we cannot provide an explanation for this unexpected effect.

Table 6 Correlation between BMI in various years

		BMI 2018	BMI 2019
Non-obese	**BMI 2017**	0.907	0.876
	BMI 2018	1	0.906
Obese	**BMI 2017**	0.738	0.662
	BMI 2018	1	0.802

4.1.2 BMI and trips by bicycle, e-bike and walking

Regarding the relationship between BMI and number of trips via active transport modes, we found that for non-obese people BMI affects the number of bicycle trips. As with distance travelled, the effect is negative, meaning increased BMI results in decreased numbers of bicycle trips, while decreased BMI results in increased numbers of bicycle trips. According to our research, the number of trips via any of the active transport modes did not significantly impact BMI. Hence, making more or fewer trips via active transport modes does not change BMI. Figure 2 presents all relevant parameters.

For distance travelled, we found that walking distance impacted BMI; however, we found no significant effects (in both directions) between walking and BMI when walking was expressed in number of trips. In their study, Kroesen and De Vos (2020) did however find BMI effecting frequency of walking; however, this discrepancy can perhaps be explained by how they measured walking, as they only knew on how many days during the 7-day period their respondents walked for at least 10 minutes, while in this current study we are privy to much more detailed information about the extent of active travel. We found no significant relationships between BMI and e-bike use.

For obese people, we found no significant effects between BMI and number of trips via active transport modes. We did however find two positive relationships that were nearly significant: both BMI's effect on numbers of bicycle trips ($p = 0.085$), and the bicycle trips' effect on BMI ($p = 0.060$), were nearly significant. Because both parameters are positive, obese people will cycle more frequently when they get higher BMIs. However, when an obese person starts cycling more, we also see this reflected in an increased BMI. Because the variables in the figure are of a different scale, we examined the standardised parameters (not shown) to determine which effect was strongest. As based on the standardised parameters (not shown), we concluded that BMI's positive effect on number of bicycle trips is stronger than the reverse effect.

This unexpected direction could, as previously cited, pertain to capitalising on chance, the stability of BMI or moral licensing (see section 4.1.1). Although moral licensing is indeed a possible explanation for number of bicycle trips' positive effect on BMI, it cannot explain BMI's positive effect on number of bicycle trips; however, one possible explanation could be 'moral cleansing', whereby people tend to exhibit moral behaviour as compensation for previously exhibited immoral behaviour (Jordan et al., 2011). In this case, the behaviour that led to increased BMI (immoral behaviour) results in increased bicycle use (moral behaviour).

Figure 4 Parameter estimates RI-CLPM relationship BMI and trips per three days via active transport modes, p-values are in brackets

4.2 Perceived health and active travel

Regarding the relationship between perceived health and active travel, we estimated models for the entire sample only. We therefore did not distinguish between groups of obese and non-obese people in the model estimates, as there was no reason to assume that the relationship between perceived health and active travel differs in these groups.

4.2.1 Perceived health and distance travelled by bicycle, e-bike and walking

For the relationship between perceived health and distance travelled, we found a significant effect for bicycles – see Figure 5. Distance cycled has a significantly positive effect on perceived health; hence, the longer the distances a person cycles, the better their perceived health. The opposite effect – of perceived health on cycling distance – is nearly significant (p = 0.064). Further, we found no significant effects between perceived health and distance travelled by e-bike or walking.

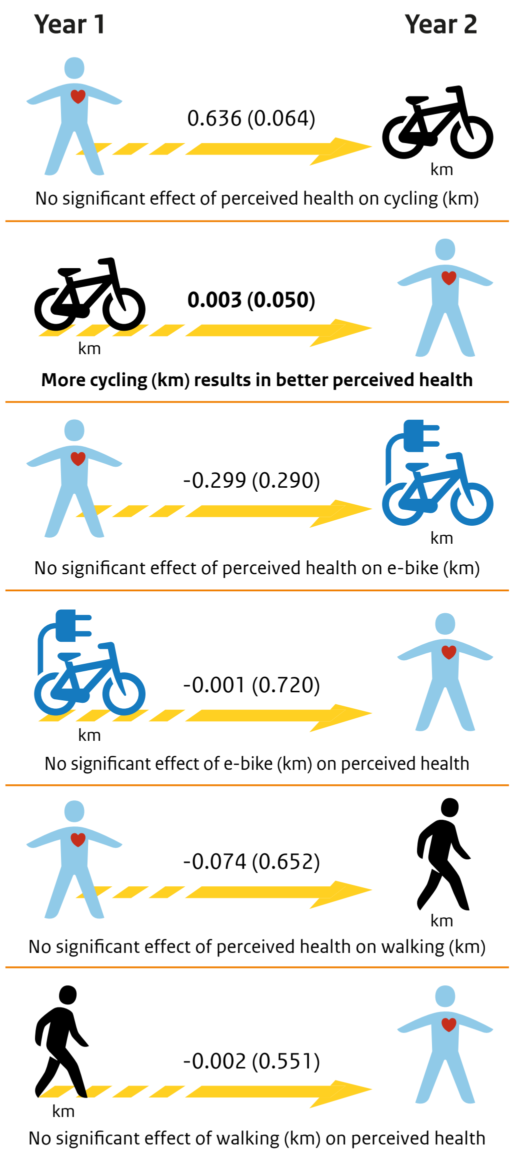

Figure 5 Parameter estimates RI-CLPM relationship perceived health and distance travelled per three days with active transport modes (in km), p-values are in brackets

4.2.2 Perceived health and trips by bicycle, e-bike and walking

We found no significant effects for the relationship between perceived health and number of trips via active transport modes. The only effects we found were nearly significant, hence, no convincing evidence. There are nearly significant relationships between perceived health and bicycle use, pertaining to perceived health's positive effect on number of bicycle trips, and number of bicycle trips' positive effect on perceived health, which implies that people who cycle more have greater perceived health. Concurrently, bicycle use increases because perceived health increases.

Figure 6 presents only non-standardised parameter estimations. Because the variables are of a different scale, we examined the standardised parameters (not shown) to determine which effect was strongest. It is apparent – as based on the standardised parameters (not shown) – that number of bicycle trips has a stronger effect on perceived health than vice versa.

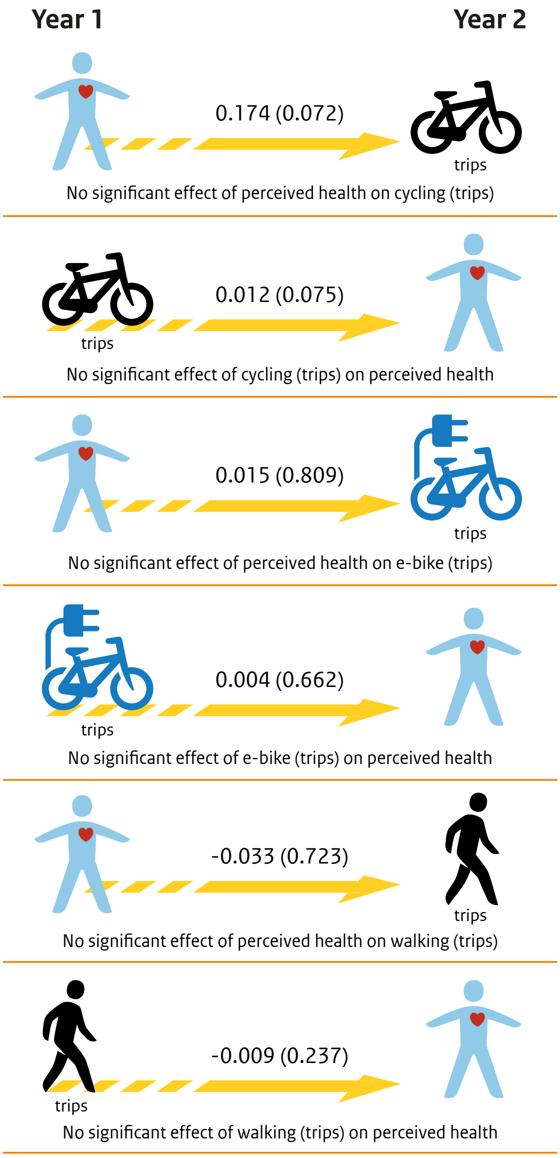

Figure 6 Parameter estimates RI-CLPM relationship perceived health and trips per three days with active transport modes, p-values are in brackets

5 Conclusions and follow-up research

According to KiM's 2019 study of the relationship between health and travel behaviour, travel behaviour is clearly related to BMI and perceived health (De Haas and Van Den Berg, 2019). People of healthy body weights cycle more and travel by car less than overweight or obese people, for example. Moreover, active travel is a key factor in terms of people getting enough physical exercise. In this follow-up research we examined the causal relationships existing between active travel and BMI and perceived health, respectively. In this chapter we present various conclusions and make recommendations for further research.

5.1 Conclusions

The relationship between BMI and active travel has certain significant effects, but only for non-obese people (BMI < 30) – see Figure 7. For example, active travel has an effect on BMI, albeit only for walking. If a person walks a longer distance, the effect on BMI is negative, with BMI decreasing. We found no such effects for bicycle and e-bike use. For non-obese people, BMI also has a seemingly negative effect on bicycle use. Increased BMI results in decreased numbers of bicycle trips and distance cycled, while decreased BMI results in increased bicycle use. These effects do not occur for obese people (BMI ≥ 30).

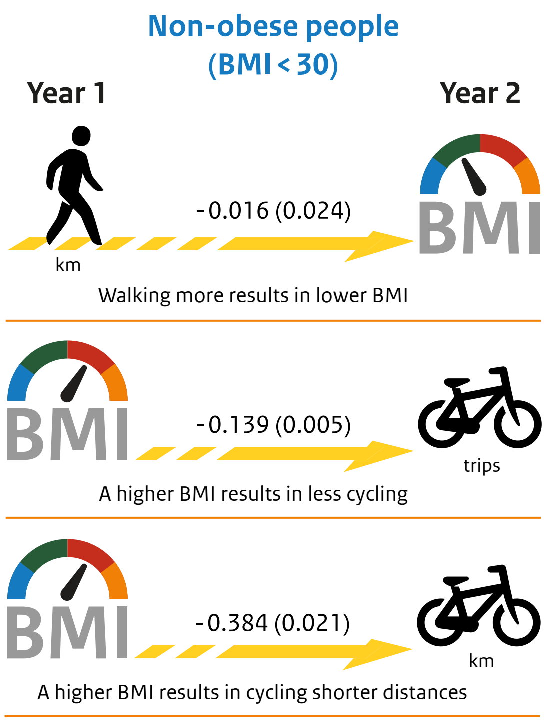

Figure 7 Significant effects between BMI and active travel for non-obese people, p-values are in brackets

The effects we found imply that overweightness, and policies aimed at healthy body weights, have an impact on bicycle use in the Netherlands. According to the Dutch government's '2018 Public Health Foresight Report' (Volksgezondheid Toekomst Verkenning), the proportion of overweight people in the Netherlands is set to rise in future (Rivm, 2018). The negative relationship between cycling and BMI implies that, in relative terms, the expected increase in overweightness will cause bicycle use to decrease in future. The fact that we found bicycle use having no effect on BMI implies that promoting bicycle use in the Netherlands will not translate into decreased average BMI. As part of the 'National Prevention Agreement, various measures were instituted to help prevent overweightness and obesity (Dutch Ministry of Public Health, 2018), with the aim being to lower the percentage of overweight and obese people by focusing on healthy diets, more sports and exercise, and a healthy and caring environment. If this policy effectively lowers BMI, the effect on bicycle use will be positive.

For the relationship between BMI and active travel, we specifically distinguished between obese and non-obese people. Based on the literature, we expected that there would be a stronger relationship between BMI and active travel among obese people than non-obese people; however, our findings failed to reflect this, as we only found significant effects for non-obese people. We did however find some nearly significant effects for obese people ($p < 0.10$), all relating to bicycles and going in unexpected directions, and implying that increased BMI results in increased numbers of bicycle trips, and increased bicycle use (in terms of trips and distance travelled) results in increased BMI, for which there are several possible explanations (see section 4.1). However, based on the available data, we cannot provide a satisfactory explanation and hence further research is required.

We found few significant effects for the relationship between perceived health and active travel: only cycling distance has a slight, significantly positive effect on perceived health; hence, if people cycle greater distances they feel healthier. For e-bikes and walking, we found no significant relationships to perceived health.

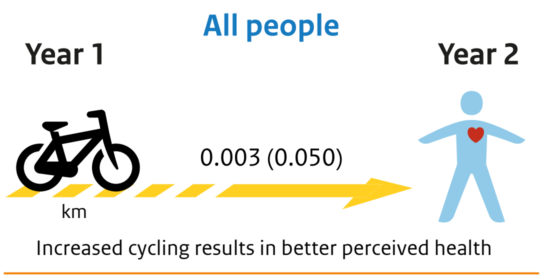

Figure 8 Significant effects between perceived health and active travel, p-values are in brackets

The fact that we only found walking to result in decreased BMI, and cycling in increased perceived health, does not mean these are the only health benefits of active travel. There is a great deal of available literature showing how active travel or exercise generally have positive effects on subjective health, disease burden and life expectancy. Cycling and walking to work for example lowers risks of premature death and cardiovascular disease. Concurrently, higher risks of accidents, and of inhaling polluted air during active travel, have negative effects on health. Nevertheless, multiple studies have shown that the positive effects greatly outweigh the negative ones.

5.2 Follow-up research

This study's findings give rise to further research. KiM had also made some of these recommendations for follow-up research at the time of its 2019 study of the relationship between health and travel behaviour.

For this current study we used data from the MPN, which offers detailed insights into the respondents' travel behaviour over a period of several years. The health information in the MPN is however limited to BMI and perceived health, yet the literature also associates active travel with other health effects; for example, international literature revealed that active travel affects psychological well-being, which is not found in the Dutch context. Concurrently, recent Dutch research found that frequency of walking significantly impacts subjective well-being. The exact relationship between mental health and active travel in the Netherlands is therefore not yet clearly understood. In 2020, the MPN started collecting information about mental health (measured according to the Mental Health Inventory (MHI-5); Berwick et al. (1991)), and consequently we will be able to further examine that relationship in future. However, we need at least three years to collect sufficient MPN data for studying the causal relationship between mental health and active travel in the Netherlands.

The Dutch Ministry of Infrastructure and Water Management is actively committed to increasing the number of commuters cycling to work. The Ministry, in taking an employer's approach, aims to achieve this goal in conjunction with employers. If cycling to work makes employees demonstrably healthier, this is the extra motivation that employers need to encourage them to cycle to work. Researching this subject would require a multi-year study in collaboration with companies. Such a study would also allow researchers to examine the impact that walking and cycling to work have on aspects like employee absenteeism or vitality.

In this study we found unexpected effects between BMI and bicycle use for obese people. Our findings, although nearly significant, imply that increased BMI in obese people results in increased bicycle use, and increased bicycle use results in increased BMI, for which there are several possible explanations. Further research is required to arrive at the correct explanation. If bicycle use among obese people does indeed positively impact BMI, then it is important to understand the underlying causes. With such insight, policy could potentially influence the effect.

Summary KiM study ‘The relationship between health and the use of active transport modes’

In 2019, the KiM Netherlands Institute for Transport Policy Analysis published a research study titled, ‘The relationship between health and use of active transport modes’. The present study is a follow-up study to the 2019 study. Below is the summary of the 2019 study.

Although the Netherlands is renowned as the cycling country, half of all car trips in the Netherlands are shorter than 7.5 kilometres, and a third less than 5 kilometres. Such distances could easily be covered by bicycle as well. One option for improving accessibility and sustainability is to focus on a switch from cars to bicycles or walking. The Netherlands Ministry of Infrastructure and Water Management aspires to gain an additional 200,000 bicycle commuters within the government’s current term. Various studies have revealed that, in addition to improving accessibility, cycling and walking have positive effects on health and the environment.

This research study examined the relationship between people’s health and travel behaviour in the Netherlands. The focus was not only on the health differences between people of varying travel behaviour. We also examined the physical activity people derive from their daily mobility, as the literature had shown that physical activity benefits people’s health.

This study includes both objective and subjective aspects of health. The Body Mass Index (BMI) measures a person’s objective health, while subjective health is how healthy people find themselves to be. The amount of physical activity that can be derived from daily mobility is determined by how long a person travels by bicycle, e-bike or on foot. This study used data from the Netherlands Mobility Panel (MPN).

Previous studies revealed a significant relationship between the use of active transport modes and health. A limited number of studies found that switching to active transport modes impacted people’s health; however, it was often unclear whether a change in travel behaviour led to a change in health or vice versa. Moreover, most relevant literature did not pertain to the situation in the Netherlands; consequently, determining whether such effects would have also occurred in the Netherlands was difficult. Studies focusing on the health benefits of physical activity concluded that extra physical activity lowered the risks of premature death and disease, including cardiovascular disease, diabetes and depression.

Quantitative analyses, as based on MPN data, established a clear correlation between people's health and travel behaviour in the Netherlands. The relationship between transport mode use and health was also studied, as was the relationship between people’s entire travel patterns and health. People of healthy body weights seemingly cycle more frequently and use cars less often than heavier people. Moreover, obese people use e-bikes more and walk less than people of healthy weights. The fact that many people use various transports modes for their daily mobility was accounted for when examining the entire travel pattern.

Health differences also clearly emerged among people of varying travel patterns: those whose travel patterns featured active transport modes were on average in better subjective health and had healthier BMIs than those whose travel patterns primarily involved car travel. The travel pattern featuring e-bikes was the sole exception: the group of people in this travel pattern had the highest average BMIs and highest proportion of obese people, which is perhaps largely attributed to the fact that people in this travel pattern have a relatively high average age. Determining whether e-bikes contribute to high BMIs is beyond the scope of this study, however.

The amount of physical activity a person engages in is not a direct indicator of good health; nonetheless, the Dutch Health Council advises adults to partake in at least 150 minutes of physical activity per week, as this has proven health benefits. Approximately 54% of Dutch adults meet this physical activity standard. Analysis of people's travel behaviour revealed that approximately one in every three Dutch adults already reached that 150-minute standard simply by making trips via bicycles, e-bikes or on foot. Daily mobility therefore is a key factor for determining whether one reaches the 150-minute mark. Because people of healthy weights use active transport modes more frequently, they also more often meet the 150-minute standard than overweight and obese people.

Those who meet the standard for physical activity through their daily mobility are much more active than those who fail to reach the standard: the people meeting the standard actively travel some 50 minutes per day on average, while those failing to meet the standard actively travel for only 5 minutes a day on average. Major differences emerged when we examined the average amount of physical activity people get from their various travel patterns; people who travel virtually everywhere by car are physically active for less than 5 minutes per day during the course of their daily mobility, for example, while those regularly travelling via public transport are physically active for some 25 minutes per day on average through their daily mobility.

This study was unable to definitively answer the question of whether causality exists between BMI and active transport mode use, but our research findings did indicate that BMI is more of a determinant of travel behaviour than vice versa. In most cases the insights pointed in the expected direction: for example, people with higher BMIs use cars more frequently and cycle and walk less over successive years. However, to make definitive statements about causality, a minimum of three years of data is required, yet only two years of data were available at the time of this study.

This research was limited by the availability of health data. The MPN collects data pertaining to the height, weight and subjective health of respondents, from which insights into the relationship between health and travel behaviour were derived. It is however also important to study other aspects of health. A person’s BMI does not necessary say anything definitive about that person’s physical health. Moreover, apart from how healthy people deem themselves to be, we know virtually nothing about people’s psychological well-being, which thus serves as a compelling reason to compile additional indicators of physical health and psychological well-being in a follow-up study.

Literature

Arem, H., Moore, S. C., Patel, A., Hartge, P., De Gonzalez, A. B., Visvanathan, K., . . . Adami, H. O. (2015). Leisure time physical activity and mortality: a detailed pooled analysis of the dose-response relationship. *JAMA internal medicine, 175*(6), 959-967.

Aune, D., Norat, T., Leitzmann, M., Tonstad, S., & Vatten, L. J. (2015). Physical activity and the risk of type 2 diabetes: a systematic review and dose–response meta-analysis: Springer.

Bak, H., Petersen, L., & Sørensen, T. (2004). Physical activity in relation to development and maintenance of obesity in men with and without juvenile onset obesity. *International journal of obesity, 28*(1), 99-104.

Bangalore, S., Fayyad, R., Laskey, R., DeMicco, D. A., Messerli, F. H., & Waters, D. D. (2017). Body-weight fluctuations and outcomes in coronary disease. *N Engl J Med, 376*, 1332-1340.

Berwick, D. M., Murphy, J. M., Goldman, P. A., Ware Jr, J. E., Barsky, A. J., & Weinstein, M. C. (1991). Performance of a five-item mental health screening test. *Medical care*, 169-176.

Boogaard, H., Borgman, F., Kamminga, J., & Hoek, G. (2009). Exposure to ultrafine and fine particles and noise during cycling and driving in 11 Dutch cities. *Atmospheric Environment, 43*(27), 4234-4242.

Bourne, J. E., Sauchelli, S., Perry, R., Page, A., Leary, S., England, C., & Cooper, A. R. (2018). Health benefits of electrically-assisted cycling: a systematic review. *International journal of behavioral nutrition and physical activity, 15*(1), 116.

Brown, T. A. (2014). *Confirmatory factor analysis for applied research:* Guilford Publications.

CBS. (2020a, 7 September 2020). Bevolking; geslacht, leeftijd en burgelijke staat, 1 January. Retrieved 3 December 2020, from https://opendata.cbs.nl/statline/?dl=308BE#/CBS/nl/dataset/7461bev/table

CBS. (2020b, 15 April 2020). Meer twintigers en dertigers omgekomen in verkeer in 2019. Retrieved 2 November 2020, from https://www.cbs.nl/nl-nl/nieuws/2020/16/meer-twintigers-en-dertigers-omgekomen-in-verkeer-in-2019

CBS. (2020c, 15 April 2020). Overledenen; doden door verkeersongeval in Nederland, wijze van deelname. Retrieved 2 November 2020, from https://opendata.cbs.nl/statline/#/CBS/nl/dataset/71936ned/table?ts=1539365088669

CBS, & RIVM. (2019). Gezondheidsenquete/Leefstijlmonitor. Retrieved 14-10-2020, from https://www.rivm.nl/leefstijlmonitor/gezond-gewicht

Celis-Morales, C. A., Lyall, D. M., Welsh, P., Anderson, J., Steell, L., Guo, Y., . . . Sattar, N. (2017). Association between active commuting and incident cardiovascular disease, cancer, and mortality: prospective cohort study. *bmj, 357*, j1456.

Cloostermans, L., Wendel-Vos, W., Doornbos, G., Howard, B., Craig, C. L., Kivimäki, M., . . . Brown, W. J. (2015). Independent and combined effects of physical activity and body mass index on the development of Type 2 Diabetes–a meta-analysis of 9 prospective cohort studies. *International journal of behavioral nutrition and physical activity, 12*(1), 147.

De Haas, M. (2019). Het gebruik van de e-fiets en de effecten op andere vervoerwijzen. The Hague: KiM Netherlands Institute for Transport Policy Analysis.

De Haas, M., & Hamersma, M. (2020). Fietsfeiten: nieuwe inzichten. The Hague: KiM Netherlands Institute for Transport Policy Analysis.

De Haas, M., & van den Berg, M. (2019). De relatie tussen gezondheid en het gebruik van actieve vervoerwijzen. The Hague: KiM Netherlands Institute for Transport Policy Analysis.

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), 1109-1116.

De Nazelle, A., Bode, O., & Orjuela, J. P. (2017). Comparison of air pollution exposures in active vs. passive travel modes in European cities: a quantitative review. Environment international, 99, 151-160.

DeSalvo, K. B., Bloser, N., Reynolds, K., He, J., & Muntner, P. (2006). Mortality prediction with a single general self-rated health question. *Journal of general internal medicine, 21*(3), 267.

Dinu, M., Pagliai, G., Macchi, C., & Sofi, F. (2019). Active Commuting and Multiple Health Outcomes: A Systematic Review and Meta-Analysis. *Sports Medicine, 49*(3), 437-452. doi: 10.1007/s40279-018-1023-0

Dobbins, M., Husson, H., DeCorby, K., & LaRocca, R. L. (2013). School-based physical activity programs for promoting physical activity and fitness in children and adolescents aged 6 to 18. *Cochrane database of systematic reviews*(2).

Ekelund, U., Ward, H. A., Norat, T., Luan, J. a., May, A. M., Weiderpass, E., . . . Tjønneland, A. (2015). Physical activity and all-cause mortality across levels of overall and abdominal adiposity in European men and women: the European Prospective Investigation into Cancer and Nutrition Study (EPIC). *The American journal of clinical nutrition, 101*(3), 613-621.

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural equation modeling, 8*(3), 430-457.

Falconer, C. L., Leary, S. D., Page, A. S., & Cooper, A. R. (2015). The tracking of active travel and its relationship with body composition in UK adolescents. *Journal of Transport & Health, 2*(4), 483-489.

Flint, E., Webb, E., & Cummins, S. (2016). Change in commute mode and body-mass index: prospective, longitudinal evidence from UK Biobank. *The lancet Public health, 1*(2), e46-e55.

Flora, D. B., & Curran, P. J. (2004). An empirical evaluation of alternative methods of estimation for confirmatory factor analysis with ordinal data. *Psychological methods, 9*(4), 466.

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. doi: 10.1111/j.1467-789X.2007.00347.x

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

Hendriksen, I., & Van Gijlswijk, R. (2010). Fietsen is groen, gezond en voordelig: Onderbouwing van 10 argumenten om te fietsen. TNO Kwaliteit van Leven: Preventie en Zorg: Leiden.

Hupin, D., Roche, F., Gremeaux, V., Chatard, J.-C., Oriol, M., Gaspoz, J.-M., . . . Edouard, P. (2015). Even a low-dose of moderate-to-vigorous physical activity reduces mortality by 22% in adults aged ≥ 60 years: a systematic review and meta-analysis. *Br J Sports Med, 49*(19), 1262-1267.

Idler, E. L., & Benyamini, Y. (1997). Self-rated health and mortality: a review of twenty-seven community studies. *Journal of health and social behavior,* 21-37.

Janssen, I., & LeBlanc, A. G. (2010). Systematic review of the health benefits of physical activity and fitness in school-aged children and youth. *International journal of behavioral nutrition and physical activity, 7*(1), 40.

Jordan, J., Mullen, E., & Murnighan, J. K. (2011). Striving for the moral self: The effects of recalling past moral actions on future moral behavior. *Personality and Social Psychology Bulletin, 37*(5), 701-713.

Kahlmeier, S., Götschi, T., Cavill, N., Castro Fernandez, A., Brand, C., Rojas Rueda, D., . . . Oja, P. (2017). Health economic assessment tool (HEAT) for walking and for cycling. Methods and user guide on physical activity, air pollution, injuries and carbon impact assessments.

Kelley, G. A., Kelley, K. S., & Tran, Z. V. (2003). The effects of exercise on resting blood pressure in children and adolescents: a meta-analysis of randomized controlled trials. *Preventive cardiology, 6*(1), 8-16.

Kelly, P., Kahlmeier, S., Götschi, T., Orsini, N., Richards, J., Roberts, N., . . . Foster, C. (2014). Systematic review and meta-analysis of reduction in all-cause mortality from walking and cycling and shape of dose response relationship. *International journal of behavioral nutrition and physical activity, 11*(1), 132.

KiM Netherlands Institute for Transport Policy Analysis. (2019). Mobiliteitsbeeld 2019. The Hague: KiM Netherlands Institute for Transport Policy Analysis.

Kroesen, M., & De Vos, J. (2020). Does active travel make people healthier, or are healthy people more inclined to travel actively? *Journal of Transport & Health, 16,* 100844.

Kuwahara, K., Noma, H., Nakagawa, T., Honda, T., Yamamoto, S., Hayashi, T., & Mizoue, T. (2019). Association of changes in commute mode with body mass index and visceral adiposity: a longitudinal study. *International journal of behavioral nutrition and physical activity, 16*(1), 101. doi: 10.1186/s12966-019-0870-x

Littman, A., Kristal, A., & White, E. (2005). Effects of physical activity intensity, frequency, and activity type on 10-y weight change in middle-aged men and women. *International journal of obesity, 29*(5), 524-533.

Liu, L., Shi, Y., Li, T., Qin, Q., Yin, J., Pang, S., . . . Wei, S. (2016). Leisure time physical activity and cancer risk: evaluation of the WHO's recommendation based on 126 high-quality epidemiological studies. *Br J Sports Med, 50*(6), 372-378.

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.

Merritt, A. C., Effron, D. A., & Monin, B. (2010). Moral self-licensing: When being good frees us to be bad. *Social and personality psychology compass, 4*(5), 344-357.

Ministry of Health, Welfare and Sport. (2018). Nationaal Preventieakkoord. The Hague: VWS.

MOA. (2019). Gold Standard: A Unique Calibration Tool for National and Regional Samples. 2020, from https://www.moa.nl/gouden-standaard-expertise-center.html

Mortensen, L. H., Siegler, I. C., Barefoot, J. C., Grønbæk, M., & Sørensen, T. I. (2006). Prospective associations between sedentary lifestyle and BMI in midlife. *Obesity, 14*(8), 1462-1471.

Murtagh, E. M., Nichols, L., Mohammed, M. A., Holder, R., Nevill, A. M., & Murphy, M. H. (2015). The effect of walking on risk factors for cardiovascular disease: an updated systematic review and meta-analysis of randomised control trials. *Preventive medicine, 72*, 34-43.

Muthén, L. K., & Muthén, B. O. (1998-2017). Mplus User's Guide. Eighth Edition., Los Angeles, CA: Muthén & Muthén.

Mytton, O. T., Panter, J., & Ogilvie, D. (2016a). Longitudinal associations of active commuting with body mass index. *Preventive medicine, 90*, 1-7.

Mytton, O. T., Panter, J., & Ogilvie, D. (2016b). Longitudinal associations of active commuting with wellbeing and sickness absence. Preventive medicine, 84, 19-26.

Panis, L. I., De Geus, B., Vandenbulcke, G., Willems, H., Degraeuwe, B., Bleux, N., . . . Meeusen, R. (2010). Exposure to particulate matter in traffic: a comparison of cyclists and car passengers. *Atmospheric Environment, 44*(19), 2263-2270.

Petersen, L., Schnohr, P., & Sørensen, T. (2004). Longitudinal study of the long-term relation between physical activity and obesity in adults. *International journal of obesity, 28*(1), 105-112.

Pozza, C., & Isidori, A. M. (2018). What's behind the obesity epidemic *Imaging in Bariatric Surgery* (pp. 1-8): Springer.

Rabl, A., & De Nazelle, A. (2012). Benefits of shift from car to active transport. *Transport Policy, 19*(1), 121-131.

Rhemtulla, M., Brosseau-Liard, P. É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological methods, 17*(3), 354.

RIVM. (2018). Volksgezondheid Toekomst Verkenning (VTV) 2018. Bilthoven: National Institute for Public Health and the Environment (RIVM).

Scheepers, C., Wendel-Vos, G., van Wesemael, P., den Hertog, F., Stipdonk, H., Panis, L. I., . . . Schuit, A. (2015). Perceived health status associated with transport choice for short distance trips. *Preventive medicine reports, 2*, 839-844.

Schepers, P., Stipdonk, H., Methorst, R., & Olivier, J. (2017). Bicycle fatalities: trends in crashes with and without motor vehicles in The Netherlands. *Transportation Research Part F: Traffic Psychology and Behaviour, 46*, 491-499.

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.

Stevens, J., Truesdale, K. P., McClain, J. E., & Cai, J. (2006). The definition of weight maintenance. *International journal of obesity, 30*(3), 391-399.

Turrell, G., Hewitt, B. A., Rachele, J. N., Giles-Corti, B., & Brown, W. J. (2018). Prospective trends in body mass index by main transport mode, 2007–2013. *Journal of Transport & Health, 8*, 183-192.

VeiligheidNL. (2020). SEH-bezoeken als gevolg van een verkeersongeval in 2019. Amsterdam: VeiligheidNL.

Visscher, T. L., & Seidell, J. C. (2001). The Public Health Impact of Obesity. *Annual Review of Public Health, 22*(1), 355-375. doi: 10.1146/annurev.publhealth.22.1.355

Westerterp, K. R. (2010). Physical activity, food intake, and body weight regulation: insights from doubly labeled water studies. *Nutrition reviews, 68*(3), 148-154.

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

World Health Organization. (2019). Body mass index - BMI from http://www.euro.who.int/en/health-topics/disease-prevention/nutrition/a-healthy-lifestyle/body-mass-index-bmi

Wu, Y., Zhang, D., & Kang, S. (2013). Physical activity and risk of breast cancer: a meta-analysis of prospective studies. *Breast cancer research and treatment, 137*(3), 869-882.

Zuurbier, M., Hoek, G., Oldenwening, M., Lenters, V., Meliefste, K., Van Den Hazel, P., & Brunekreef, B. (2010). Commuters' exposure to particulate matter air pollution is affected by mode of transport, fuel type, and route. *Environmental health perspectives, 118*(6), 783-789.

Appendix A
Description Random Intercept Cross-Lagged Panel Model (RI-CLPM)

**In Chapter 3 we briefly described the statistical method used in this study.
In this appendix we describe the RI-CLPM in greater detail.**

Random Intercept Cross-Lagged Panel Model

We used a Random Intercept Cross-Lagged Panel Model (RI-CLPM) to study the causal relationships between BMI, perceived health and use of active transport modes (Hamaker et al., 2015). The RI-CLPM is an extension of the traditional cross-lagged panel model (CLPM). In the literature, CLPMs are often used to determine causality. In a traditional CLPM, the indicators' stability is controlled for by estimating autoregressive relationships. In this current study, for example, the control would be for the fact that BMI and transport mode use are generally relatively stable over time. However, Hamaker et al. (2015) found that when this stability differs to certain degrees among respondents, autoregressive relationships do not correct for this. In other words, the traditional CLPM fails to fully control for time-independent differences between individuals. Consequently, a traditional CLPM's cross-relationships do not represent actual effects within a person, and in some cases this leads to incorrect conclusions about the existence of a causal relationship or about which indicator is causal dominant, for example.

The difference between an RI-CLPM and traditional CLPM is that an RI-CLPM estimates a random intercept for each indicator. This random intercept represents the mean deviation from the total average of a given indicator for an individual. On average people make for example three trips by bicycle during a 3-day period (this group average could shift over time). A traditional CLPM assumes that over time the bicycle use of all individuals fluctuates around the group mean, but of course in reality this differs: some people make more than three bicycles trips on average and others make less. The random intercept shows the difference between the total average bicycle use and the average bicycle use of an individual. A random intercept is included for each indicator. In this way we correct for the fact that not everyone has the same average travel behaviour, same BMI and same perceived health, which is what is implicitly assumed in a traditional CLPM.

Figure 9 shows the RI-CLPM conceptual model for the relationship between BMI and cycling distance. Multiple models were estimated in this study. The square blocks represent the reported values for BMI and cycling distance. The random intercepts capture the individuals' time-independent deviation from the group mean, thus reflecting the stable differences between persons. Finally, the ellipses denoting BMI and cycling distance indicate the 'temporary' (at that specific measurement moment) deviation of the reported BMI and cycling distance from the sum of the group mean and the random intercept. The RI-CLPM was estimated using the statistical package, Mplus (Muthén and Muthén, 1998-2017).

Not all respondents participate in the MPN each year, and so we are missing some data. We had to contend with people who quit and with new respondents. To deal with this missing data we used the Maximum Likelihood (ML) estimation method. Enders and Bandalos (2001) showed how adept this method is at dealing with missing data. The method assumes that the variables are normally distributed; however, generally, this not the case with ordinal variables, such as perceived health. In such cases, another method, like Weighted Least Squares (WLS), could be used instead of ML (Flora and Curran, 2004). However, in Mplus, it is not (yet) possible to use the WLS method for estimating RI-CLPM; consequently, we also used the ML method to estimate the models for perceived health. Rhemtulla et al. (2012) have shown that the ML method works as well or even better than WLS when the ordinal variable has five or more categories. We therefore assume that using the ML method had no significant affect on the results.

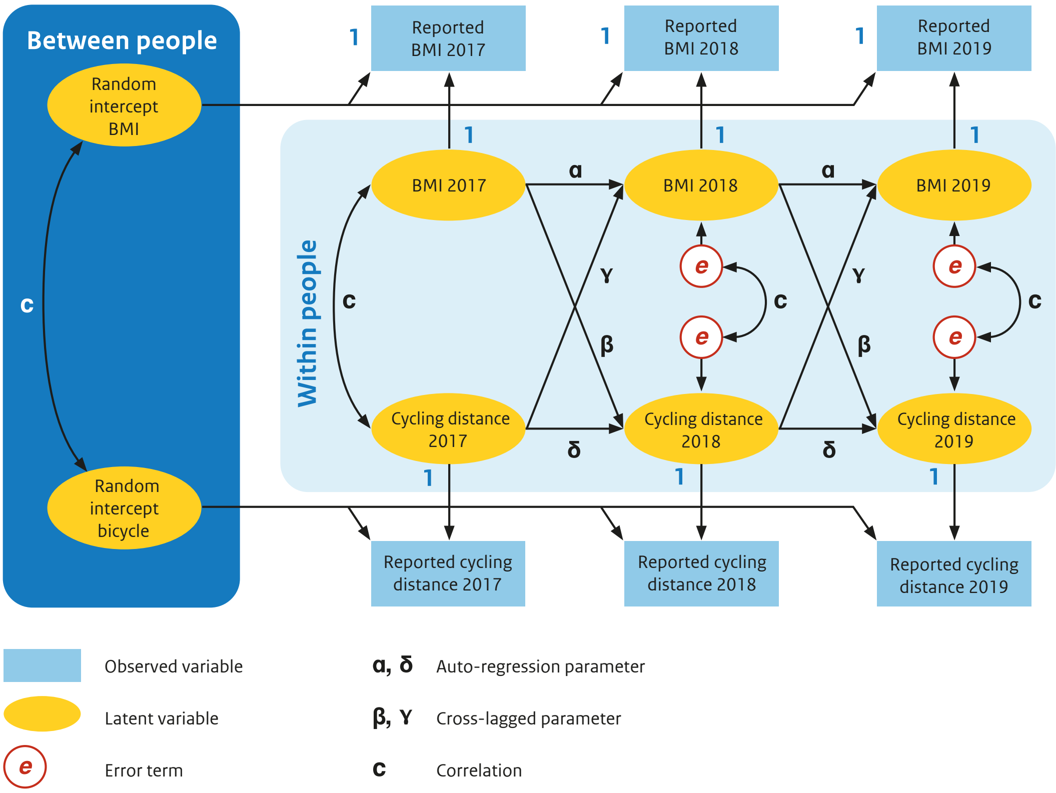

Figure 9 Conceptual model of Random Intercept Cross-Lagged Panel Model for relationship between BMI and cycling distance

Appendix B
Additional output model estimations

In Chapter 4 we depicted the key findings of the model estimations. In this appendix we provide additional information about the model fit of each model and the parameter estimates in tabular form. Additionally, we present the model outcomes for the relationship between BMI and active travel, without distinguishing by weight classification.

Model fit of models presented in Chapter 4

The model fit for all models presented in Chapter 4 can be considered good, as based on the chi-squared test, Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardised Root Mean Square Residual (SRMR) (Brown, 2014). Table 7 shows the different values of these fit indices.

Table 7 Model fit RI-CLPM models Chapter 4

Model	Chi-square	RMSEA	CFI	SRMR
BMI and bicycle trips	2.955, df = 6, p=0.815	0.000	1.000	0.005
BMI and e-bike trips	7.357, df = 6, p=0.289	0.008	1.000	0.007
BMI and walking trips	8.119, df = 6, p=0.230	0.010	1.000	0.009
BMI and cycling distance	4.000, df = 6, p=0.677	0.000	1.000	0.005
BMI and e-biking distance	5.655, df = 6, p=0.463	0.000	1.000	0.006
BMI and walking distance	3.473, df = 6, p=0.748	0.000	1.000	0.006
Perceived health and bicycle trips	4.912, df = 3, p=0.178	0.010	1.000	0.007
Perceived health and e-bike trips	4.523, df = 3, p=0.210	0.009	1.000	0.006
Perceived health and walking trips	7.332, df = 3, p=0.062	0.015	1.000	0.007
Perceived health and cycling distance	3.634, df = 3, p=0.304	0.006	1.000	0.006
Perceived health and e-biking distance	3.895, df = 3, p=0.273	0.007	1.000	0.006
Perceived health and walking distance	4.737, df = 3, p=0.192	0.009	1.000	0.006

Parameter estimation of models presented in Chapter 4

We depicted the key parameter estimations in Chapter 4. The tables below contain the same parameter estimations, supplemented with the corresponding t-value. The models are in the same order as in Chapter 4. Table 8 and Table 9 contain the parameter estimates for the relationship between BMI and active travel as pertaining to distance travelled and number of trips, respectively. Table 10 and Table 11 contain the parameter estimates for the relationship between perceived health and active travel as pertaining to distance travelled and number of trips, respectively.

Table 8 Parameter estimates RI-CLPM relationship BMI and distance travelled per three days with active transport modes (in km)

	Non-obese (BMI < 30)			Obese (BMI ≥ 30)		
Effect	**Parameter**	**t-value**	**p-value**	**Parameter**	**t-value**	**p-value**
BMI → Cycling distance (km)	**-0.384**	**-2.316**	**0.021**	0.112	1.148	0.251
Cycling distance (km) → BMI	-0.002	-0.649	0.517	0.029	1.854	0.064
BMI → E-biking distance (km)	-0.045	-0.323	0.747	-0.004	-0.029	0.977
E-biking distance (km) → BMI	-0.002	-0.614	0.539	0.000	0.006	0.995
BMI → Walking distance (km)	0.081	1.005	0.315	-0.020	-0.324	0.746
Walking distance (km) → BMI	**-0.016**	**-2.258**	**0.024**	0.010	0.354	0.723

Table 9 Parameter estimates RI-CLPM relationship BMI and trips per three days with active transport modes

	Non-obese (BMI < 30)			Obese (BMI ≥ 30)		
Direction of effect	**Parameter**	**t-value**	**p-value**	**Parameter**	**t-value**	**p-value**
BMI → Bicycle trips	**-0.139**	**-2.815**	**0.005**	0.062	1.725	0.085
Bicycle trips → BMI	-0.005	-0.351	0.726	0.085	1.882	0.060
BMI → E-bike trips	-0.017	-0.518	0.605	0.002	0.062	0.951
E-bike trips → BMI	-0.008	-0.362	0.717	-0.028	-0.432	0.666
BMI → Walking trips	-0.035	-0.737	0.461	-0.042	-0.958	0.338
Walking trips → BMI	-0.011	-0.755	0.450	-0.035	-0.522	0.602

Table 10 Parameter estimates RI-CLPM relationship perceived health and distance travelled per three days with active transport modes (in km)

Direction of effect	Parameter	t-value	p-value
Perceived health → Cycling distance (km)	0.636	1.852	0.064
Cycling distance (km) → Perceived health	**0.003**	**1.960**	**0.050**
Perceived health → E-biking distance (km)	-0.299	-1.058	0.290
E-biking distance (km) → Perceived health	-0.001	-0.358	0.720
Perceived health → Walking distance (km)	-0.074	-0.452	0.652
Walking distance (km) → Perceived health	-0.002	-0.597	0.551

Table 11 Parameter estimates RI-CLPM relationship perceived health and trips per three days with active transport modes

Direction of effect	Parameter	t-value	p-value
Perceived health → Bicycle trips	0.174	1.800	0.072
Bicycle trips → Perceived health	0.012	1.782	0.075
Perceived health → E-biking trips	0.015	0.241	0.809
E-biking trips → Perceived health	0.004	0.437	0.662
Perceived health → Walking distance	-0.033	-0.355	0.723
Walking distance → Perceived health	-0.009	-1.183	0.237

The previous tables present only part of the model output; another part is the correlation between random intercepts, as shown in Table 12. The correlation between random intercepts indicates whether significant differences do indeed exist between persons on the dependent variables. We consider the correlation significant at a t-value greater than 1.960 or less than -1.960, and this holds for most correlations. A positive correlation means a higher value health indicator is associated with a higher degree of active travel and vice versa. A negative parameter means a higher value health indicator is associated with a lower degree of active travel and vice versa. Better perceived health is associated with higher rates of bicycle use and shorter walking distances, for example. Concurrently, better perceived health is associated with fewer trips by e-bike.

We observed a distinctly negative relationship between BMI and bicycle use: people with higher BMIs cycle less and for shorter distances, which applies to both obese and non-obese people. We observed less cohesion for walking: only among the obese is higher BMI significantly associated with shorter walking distances. For e-bikes, higher BMI is associated with greater e-bike use for non-obese people, while for obese people we found no significant association with e-bike use.

Table 12 Correlation between the random intercepts

	Distance		Trips	
Relationship	**Parameter**	**t-value**	**Parameter**	**t-value**
Perceived health – Bicycle	0.222	8.289	0.023	6.905
Perceived health – E-bike	-0.017	-0.676	-0.100	-4.830
Perceived health – Walking	0.063	2.351	-0.017	-0.730

	Non-obese (BMI < 30)		Obese (BMI ≥ 30)		Non-obese (BMI < 30)		Obese (BMI ≥ 30)	
	Parameter	**t-value**	**Parameter**	**t-value**	**Parameter**	**t-value**	**Parameter**	**t-value**
BMI – Bicycle	-0.153	-6.981	-0.285	-2.397	-0.118	-6.408	-0.323	-2.126
BMI – E-bike	0.065	3.231	-0.051	-0.523	0.083	4.789	-0.069	-0.969
BMI – Walking	-0.033	-1.551	-0.231	-2.328	0.006	0.323	-0.092	-1.504

Model estimations BMI and active travel without distinction according to weight classifications

In section 4.1 we presented the RI-CLPM outcomes with a distinction made between obese and non-obese people. The models that made no such distinction failed to yield significant results; the relevant model output is presented in Table 13 and Table 14. Table 15 shows the model fit for each model. Again, the model fit of each model is considered good.

Table 13 Parameter estimates RI-CLPM relationship BMI and trips per three days with active transport modes without distinction according to weight classification

Direction of effect	Parameter	t-value	p-value
BMI → Bicycle trips	0.008	0.483	0.629
Bicycle trips → BMI	-0.039	-0.930	0.352
BMI → E-biking trips	-0.041	-1.495	0.135
E-biking trips → BMI	-0.038	-1.321	0.187
BMI → Walking trips	-0.013	-0.713	0.476
Walking trips → BMI	-0.029	-0.714	0.475

Table 14 Parameter estimates RI-CLPM relationship BMI and distance travelled per three days with active transport modes (in km)

Direction of effect	Parameter	t-value	p-value
BMI → Cycling distance (km)	-0.129	-0.925	0.355
Cycling distance (km) → BMI	0.00	0.059	0.953
BMI → E-biking distance (km)	-0.085	-0.680	0.496
E-biking distance (km) → BMI	-0.003	-0.624	0.533
BMI → Walking distance (km)	0.084	1.227	0.220
Walking distance (km) → BMI	-0.006	-0.653	0.514

Table 15 Model fit RI-CLPM BMI and active travel without distinction according to weight classification

Model	Chi-square	RMSEA	CFI	SRMR
BMI and bicycle trips	0.987, df = 3, p = 0.804	0.000	1.000	0.003
BMI and e-bike trips	3.424, df = 3, p = 0.331	0.005	1.000	0.006
BMI and walking trips	1.619, df = 3, p = 0.655	0.000	1.000	0.004
BMI and cycling distance	1.218, df = 3, p = 0.749	0.000	1.000	0.004
BMI and e-biking distance	2.099, df = 3, p = 0.552	0.000	1.000	0.004
BMI and walking distance	0.377, df = 3, p = 0.945	0.000	1.000	0.002

Colophon

This is a publication of the Ministry of Infrastructure and Water Management
KiM Netherlands Institute for Transport Policy Analysis

March 2021

ISBN/EAN: 978-90-8902-243-1
KiM-21-A003

Author
Mathijs de Haas

Design and layout
KiM Netherlands Institute for Transport Policy Analysis

This report is a translation of a research report previously published in Dutch.
The original name is ‘Het verband tussen gezondheid en actief reizen’.

KiM is responsible for the content and conclusions of this publication.

KiM Netherlands Institute for Transport Policy Analysis
P.O. Box 20901
2500 EX The Hague
Telephone: +31 (0)70 456 19 65

Website: www.kimnet.nl
E-mail: info@kimnet.nl

KiM publications can be downloaded from our website: www.kimnet.nl
Please feel free to also contact one of our staff members.

The Netherlands Institute for Transport Policy Analysis (KiM) conducts mobility analyses that are subsequently incorporated in national transportation policy. As an independent institute within the Dutch Ministry of Infrastructure and Water Management, KiM provides strategic research and policy analysis. The content of KiM publications is independent and does not need to reflect the views held by the minister and/or state secretary of Infrastructure and Water Management.

The Netherlands Institute for
Transport Policy Analysis (KiM)

This is a publication by the

Ministry of Infrastructure and Water Management

P.O. Box 20901 | 2500 EX The Hague
www.rijksoverheid.nl/ienw

english.kimnet.nl

ISBN 978-90-8902-243-1
March 2021 | KiM-21-A003