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DOI

[10.1016/j.jth.2021.101113](https://doi.org/10.1016/j.jth.2021.101113)

Publication date

2021

Document Version

Final published version

Published in

Journal of Transport and Health

Citation (APA)

de Haas, M., Kroesen, M., Chorus, C., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2021). Causal relations between body-mass index, self-rated health and active travel: An empirical study based on longitudinal data. *Journal of Transport and Health*, 22, Article 101113.

<https://doi.org/10.1016/j.jth.2021.101113>

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Causal relations between body-mass index, self-rated health and active travel: An empirical study based on longitudinal data

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ARTICLE INFO

Keywords:

Active travel

Body-mass index (BMI)

Self-rated health (SRH)

Random intercept cross-lagged panel model

(RI-CLPM)

Panel data

ABSTRACT

Introduction: It has been estimated that physical inactivity accounts for roughly 10% of premature mortality globally in any given year. Active travel (walking and cycling) has been promoted as an effective means to stimulate physical activity. However, many of the available studies on the relation between active travel and health are based on cross-sectional data and are therefore unable to determine the direction of causation. This study aims to unravel the bidirectional relationships between active travel measured by the active modes bicycle, e-bike and walking, on the one hand, and two health outcomes, namely body-mass index (BMI) and self-rated health (SRH), on the other.

Methods: To provide an initial assessment of the relationship between active travel and the two health outcomes, multivariate regression models are estimated. To study the direction of causation, Random-Intercept Cross-Lagged Panel Models (RI-CLPM) are estimated using three waves of the Netherlands Mobility Panel (MPN). Active travel is measured as travelled distances and trips with the bicycle, e-bike and walking. BMI is calculated based on weight and height, SRH is measured with a single question.

Results: The regression models show that a higher BMI and lower SRH are associated with less walking and cycling, while being obese is associated with more e-bike use. The results of the RI-CLPM indicate that cycling distance has a positive effect on SRH. Furthermore, walking distance has a negative effect on BMI and BMI has a negative effect on bicycle use among people without obesity. No relationships between BMI and active travel are found for people with obesity.

Conclusion: The results highlight the importance of longitudinal analyses when estimating the relationship between active travel and health. In addition, the results suggest that, relatively speaking, the increasing overweight and obesity rates may result in a decrease of bicycle use.

1. Introduction

It has been estimated that physical inactivity accounts for roughly 10% of premature mortality globally in any given year, making it one of the leading health risk factors (more important than obesity and smoking) (Lee et al., 2012). Globally, around a third of the adult

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population does not meet public health guidelines for recommended levels of physical activity (Hallal et al., 2012), but in Western societies this is typically even higher (e.g. in the Netherlands half of the population does not satisfy the norm). Given the strong impacts of physical (in)activity on our health it must be seen as one of the corner stones of preventive medicine.

For various reasons, active travel (walking and cycling) can be identified as a potentially effective means to stimulate physical activity. For one, this form of behaviour can easily be incorporated in the daily routine and, as such, become a habitual form of behaviour. Secondly, it is a 'proven' way to stimulate physical activity; recent research in the Netherlands has shown that 30% of the adult population already reaches the physical activity norm just by travelling actively (de Haas & van den Berg, 2019). And thirdly, there is still much scope to increase levels of active travel, considering that a substantial share of the short distance trips (<5 km) is already made by car.

While there are many studies available on the relation between active travel and health, most are based on cross-sectional data and are therefore unable to determine the direction of causation. Only a limited number of longitudinal studies are available. Most of these longitudinal studies did not consider a bidirectional effect between health and active travel, but only an effect of active travel on health. While studies have shown that active travel may lead to a better health (e.g. a lower body-mass index (BMI)), the reverse effect may also be present. People with a lower BMI may be more inclined to travel actively because this takes less effort for individuals with a healthy weight compared to obese individuals.

Compared to conventional active travel modes, the e-bike, having been introduced rather recently, occupies a special place. Due to the recent uptake of the e-bike in Western countries, the e-bike now plays a significant role in active travel in many countries. For instance, in 2019, the e-bike accounted for 18% of all bicycle trips and 26% of the total distance cycled in the Netherlands. While less effort is required to ride an e-bike to a regular bicycle, a systematic review showed that the needed physical activity intensity to ride an e-bike is high enough for the e-bike to be considered an active mode (Bourne et al., 2018). However, given that less effort is needed to ride an e-bike, it may be that the relation with health is different. For example, it may be that the potential health benefits are lower due to the lower physical activity intensity. On the other hand, the e-bike may offer a good alternative to the regular bicycle for people who are limited to cycle by their health. The relation between e-bike use and health has not been studied adequately yet.

This paper contributes to the scientific literature by empirically identifying the causal bidirectional relations between active travel (use of bicycle, e-bike and walking) and Body Mass Index (BMI) and self-rated health (SRH), based on longitudinal data. More specifically, we base our empirical analyses on three waves of panel data from the Netherlands Mobility Panel (MPN). In the remainder of the paper, findings from previous studies are discussed first, followed by a description of the applied methods and data and the results of the analyses.

2. Literature

In this section, relevant studies on the relation between active travel and BMI are discussed first, followed by studies on the relation between active travel and self-rated health. Due to the limited availability of longitudinal studies between the two health indicators and active travel, studies that focus on the relation between general physical activity and the health indicators are also included in the discussion.

Most of the available studies on the relationship between active travel and BMI are based on cross-sectional data. These studies generally found that active travel is inversely related to a person's weight (gain), i.e. higher levels of active travel are associated with lower levels of BMI or lower overweight and obesity rates and vice versa (Bassett et al., 2008; Berglund et al., 2016; Flint et al., 2014; Lavery et al., 2013; Millett et al., 2013). Only a limited number of longitudinal studies that focus on the relationship between active travel and BMI can be identified. Martin et al. (2015) and Flint et al. (2016) found that switching from car to active travel for commuting results in a decrease in the BMI, while a shift from active travel to car resulted in an increase in BMI. Mytton et al. (2016) found that maintaining cycling levels for commuting resulted in a lower BMI and that an increase in walking is associated with a reduction in BMI. None of these three longitudinal studies distinguished between using a regular bicycle or an e-bike. Littman et al. (2005), in a study on the association between physical activity and weight gain, found that the inverse relationship between walking (but also other forms of physical activity) and weight gain is stronger among obese people than among non-obese people.

While the aforementioned longitudinal studies found effects of active travel on BMI, they did not consider a reverse effect of BMI on active travel. Several studies on the relationship between general physical activity and BMI did consider the existence of a bidirectional relationship. A longitudinal study on the long-term relationship between physical activity and obesity in adults did not find any significant effects of physical activity on later BMI levels, but found that a high BMI increased the odds of later physical inactivity (Petersen et al., 2004). Similarly, Bak et al. (2004) and Mortensen et al. (2006) found that a higher BMI is a determinant for physical inactivity or becoming sedentary, while reverse effects were not found.

Since all the studies discussed above are based on self-reported measures of active travel or physical activity and BMI, they might be subject to a reporting bias (e.g. a recall bias or social-desirability bias). However, similar results have been found in studies that objectively measured physical activity and BMI. Ekelund et al. (2008) measured sedentary behaviour with heart rate monitors, fat mass with bio-impedance and assessed body weight, BMI and waist circumference by standard clinical procedures. After a 5.6-year follow-up they concluded that sedentary time did not predict any of the obesity indicators. However, body weight, BMI and waist circumference were found to predict sedentary time. Similarly, Golubic et al. (2015) found that, after a 7-year follow-up, higher fat indices (total fat mass, percentage body fat and waist circumference) were associated with a reduction in moderate-to-vigorous physical activity and longer sedentary times. In addition, they found evidence that physical activity and longer sedentary times were associated with an increase on the fat indices.

Self-rated health (SRH), which can be assessed with a single question, is found to be strongly associated with all-cause mortality

(DeSalvo et al., 2006; Idler and Benyamini, 1997). Similar to studies on the relationship between BMI and active travel, studies on the relationship between SRH and active travel are mainly based on cross-sectional data. These studies generally find that active travel is positively associated with SRH, either in general (Avila-Palencia et al., 2018; Berglund et al., 2016; Scheepers et al., 2015) or specifically for commuting (Bopp et al., 2013; Humphreys et al., 2013).

When focusing on physical activity in general rather than on active travel alone, a number of longitudinal studies are available. In a study on patterns in physical activity and sedentary behaviour from mid-life to early old age it was found that SRH was positively associated with physical activity at follow-up (Hamer et al., 2012). Similar results were found in a study on 10-year changes in health status among older Europeans which showed that physical inactivity increased the risk of a decline in SRH (Haveman-Nies et al., 2003). Sargent-Cox et al. (2014) found, in a sample of three adult age cohorts, that overall SRH decreased over an 8-year period, but that maintaining or increasing levels of physical activity was associated with less decline in SRH.

While the discussed cross-sectional and the longitudinal studies indicate that active travel or physical activity are positively related to SRH, no studies were found that considered a bidirectional relationship. The direction of causation between SRH and active travel therefore remains uncertain. Studies on the relationship between BMI and physical activity that considered reciprocal effects indicate that the effect of BMI on physical activity may be stronger than the reverse effect (e.g. Petersen et al. (2004) and Ekelund et al. (2008)). However, only the latter effect is usually considered in studies on the relationship between active travel and BMI (e.g. Martin et al. (2015), Flint et al. (2016) and Mytton et al. (2016)). Therefore, this study aims to assess the reciprocal effects between active travel, on the one hand, and BMI and SRH on the other.

A recent study by Kroesen and De Vos (2020) assessed the bidirectional relationship between BMI and mental health, on the one hand, and walking on the other, based on longitudinal Dutch data. Results showed that walking does not influence BMI, but that the reverse effect is present. For the relationship between mental health and walking the opposite was concluded. While SRH and mental health are two different measures of health, the two are positively associated (Mavaddat et al., 2011; Meyer et al., 2014). One added value of the present study is that active travel is measured with a higher level of detail. Kroesen and De Vos (2020) only had

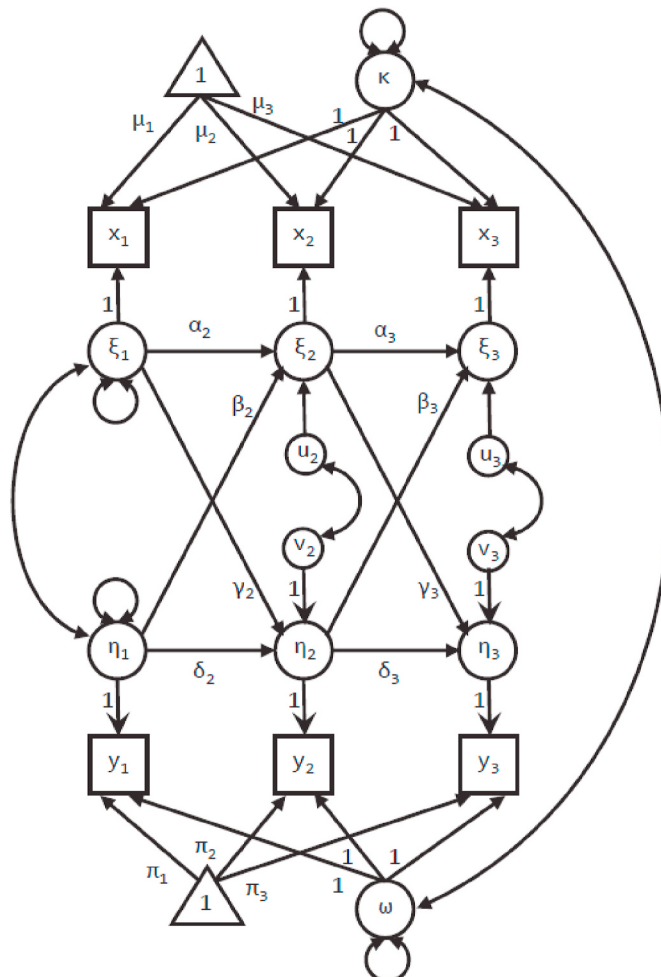


Fig. 1. Model structure three-wave Random Intercept Cross-Lagged Panel Model (Hamaker et al., 2015).

information on how many days respondents walked for at least 10 min in the past seven days. In the present study, also cycling and e-bike are considered, and active travel is measured in terms of trips and travelled distances. With these detailed indicators of active travel it is expected that the present study will provide more valid results.

3. Methods and data

To provide an initial assessment of the relationships between active travel and the two health outcomes, multivariate linear regression models are estimated for travelled distances and number of trips with active modes. Based on the evidence that we find from literature that BMI may be a stronger predictor of active travel than vice versa, we are treating the health outcomes as independent variables in the regression models. The advantage of using multivariate regression models instead of simply comparing mode use in groups with different values on the health outcomes, is that it allows controlling for factors that might influence mode use or the health outcomes. Besides BMI and SRH, the regression will be controlled for age, gender, education level, level of urbanisation of the residential location, income and origin of the respondent (native or immigrant).

The regression models will show how active mode use is different between people with different BMIs and SRH while controlling for relevant variables. However, these models cannot be used to draw conclusions about the direction of causation between active mode use and the health outcomes. To test the relationship between active travel and the health outcomes over time, a structural equation model (SEM) will be used. More specifically the Random Intercept Cross-Lagged Panel Model (RI-CLPM) is used. In a traditional Cross-Lagged Panel Model (CLPM), after controlling for stability by including autoregressive relationships, the cross-lagged relationships are assumed to represent causal influences. However, [Hamaker et al. \(2015\)](#) argued that, if the stability of the constructs is to some extent of a trait-like, time-invariant nature, the autoregressive parameters are not able to correctly control for this. In that case, the traditional CLPM is not able to fully account for time-invariant between-person differences. Both for active travel, as well as for the health outcomes it may be assumed that there exist stable individual differences over time. To cope with this limitation of the CLPM, [Hamaker et al. \(2015\)](#) proposed the RI-CLPM.

[Fig. 1](#) shows the model structure of the RI-CLPM. For each of the observed variables (x_t and y_t , representing active travel and the health outcomes in the present study) a latent variable is estimated (ξ_t and η_t) with the paths linking the observed and latent variables set to 1. Temporal group means are represented by μ_t and π_t . The random intercepts ω and κ capture the individual's stable score over all measurements and represents between-person differences. In other words, these random intercepts capture the individual's trait-like, time invariant deviations from the temporal means. With these temporal means and random intercepts, the latent variables ξ_t and η_t represent an individual's deviation from his expected score based on the combination of the temporal group mean and the random intercept. If the variance and covariance of the random intercepts would be fixed to zero, the model would collapse into a traditional CLPM.

In a traditional CLPM, the autoregressive parameters α_t and δ_t are included to account for stability of the constructs. In a RI-CLPM, the autoregressive parameters no longer represent the stability of the constructs, but rather a within-person carry-over effect. A positive autoregressive parameter indicates that occasions on which an individual scored higher than his expected score (based on the temporal mean and random intercept), this is likely followed by an occasion on which this individual also scores higher than his expected score and vice versa. The main interest is on the cross-lagged effects, represented by the parameters β_t and γ_t . These parameters indicate to which extent the variables influence each other on the within-person level. The within-person level is of interest in this study, as this is the level where the presumed causal effects actually occur.

3.1. Data

To assess the causal relationships between active travel and the two health outcomes, longitudinal data are required. In the present study, panel data from the Netherlands Mobility Panel (MPN) are used. The MPN is an annual household panel that started in 2013 and consists of approximately 2000 complete households. The MPN was set up with the goal to study the short-run and long-run dynamics in travel behaviour of Dutch individuals and households and to assess how changes in personal- and household characteristics correlate with changes in travel behaviour. To this end, household members of at least 12 years old are asked to complete a three-day travel diary each year and fill in an extensive questionnaire that includes questions on topics such as occupational status, use of different modes of transport and life events in the past year. Respondents are equally distributed over weekdays and have the same starting weekday each year. Furthermore, every household is asked to fill in a questionnaire about household related characteristics, such as information about household composition and ownership of means of transport. A more extensive description of the MPN can be found in [Hoogendoorn-Lanser et al. \(2015\)](#).

Starting from the fifth wave in 2017, a number of health-related questions are part of the individual questionnaire. The respondents' BMI is determined based on self-reported height and length (with the formula $BMI = \text{weight (kg)}/\text{length (m)}^2$). SRH is measured with the question 'How would you rate your health in general?'. The five possible answers are excellent, very good, good, moderate or bad. Data from 2017, 2018 and 2019 are used in this study.

Earlier research has shown that people tend to report a greater body height and lower body weight when working with self-reported measures ([Gorber et al., 2007](#)). This would result in an underestimation of the BMI. Since the same respondents participate yearly in the MPN, it is likely that, if this bias is also present in the MPN, the measurement error will be the same each year. If the measurement error is indeed constant over the years, this measurement error would be captured by the random intercept in the RI-CLPM. Therefore, it is likely that this has little influence on the results. As there is no possibility to validate the reported height and weight, only extreme values are removed from the sample. Eight respondents with a BMI below 15 (very severely underweight) or above 50 (super obese)

are removed from the sample. From Table 1 it is evident that the distribution of BMI in the MPN is representative of distribution of the Dutch population, with a very slight overrepresentation of overweight and obese people.

In the three-day travel diary, respondents report all their trips for three consecutive days. Several possible indicators to describe a person's travel behaviour are available, such as trip count, travel distances and travel times. It is known that distance and duration might be biased due to round-off errors when working with self-reported travel diaries (Rietveld, 2001). However, it can be assumed that round-off errors are not dependent on health status. Therefore, as round-off errors may be considered to be random it is not expected that the results will be biased because of them. In this study, both trip counts and travel distances are used to measure active travel.

In this study, only the main mode of transport is considered. When a multi-modal trip is reported, access and egress modes are not included in the analyses. Travel distances and times are only known for the total trip in the MPN. As a result, it cannot be determined how long and how far respondents travelled with the access and egress mode. A downside of not being able to include access and egress mode is that especially for public transport users the amount of active travel is somewhat underrepresented as it is known that a considerable share of public transport trips in the Netherlands are combined with cycling or walking as access or egress modes (Jonkeren et al., 2018).

Although children between the ages of 12 and 18 also participate in the MPN, only adult respondents of 18 years and older are included in this study. Children are still developing physically and as a result especially the BMI of children will show relatively strong changes. As this would bias the results, children are not included in this study. This results in a sample of 6745 respondents. Table 1 shows the composition of the 2019 sample and the composition of the Dutch population based on the so-called 'Gold Standard' (MOA, 2019). The Gold Standard is a calibration tool for sampling in the Netherlands. The table shows that the sample is representative for the Dutch population for most variables. Young adults between 18 and 30 years old are somewhat underrepresented, while people with a high education level and adult households are overrepresented. Since the regression models are controlled for several sociodemographic variables and the RI-CLPM automatically controls the estimated (within-person) effects for all (unobserved) time-invariant variables it is not expected that the results are biased due to these small deviations from the Dutch population.

Table 2 shows the correlation between the dependent variables in the RI-CLPM in the pooled MPN sample. While cycling and walking are negatively correlated with BMI, e-bike use is positively correlated with BMI. The correlation between e-bike and

Table 1
Sample (MPN wave 2019, n = 4511) and Gold standard distributions.

Variable	MPN (2019) (%)	Gold Standard (2019) (%)
Gender		
Male	47.9	49.3
Female	52.1	50.7
Age		
18–30	14.5	20.4
31–40	17.1	15.0
41–50	14.9	17.3
51–64	27.0	24.4
65+	26.4	22.9
Education level		
Low	27.0	28.5
Medium	38.9	42.9
High	33.9	28.6
Work status		
Working	54.5	54.6
Not working	11.1	12.0
Incapacitated	6.3	3.9
Student	4.9	6.8
Retired	23.1	22.6
Household situation		
Single household	22.2	22.0
Adult household	54.1	49.6
Household with child ≤ 12 years old	17.6	20.3
Household with child between 13 and 17 years old	6.1	8.1
Level of urbanization ^a		
Non-urbanised (<500 addresses/km ²)	8.0	7.8
Slightly urbanised (500–1000 addresses/km ²)	21.5	21.6
Moderately urbanised (1000 to 1500 addresses/km ²)	18.8	15.6
Highly urbanised (1500 to 2500 addresses/km ²)	31.8	30.3
Very highly urbanised (≥ 2500 addresses/km ²)	19.8	24.6
Weight class ^b		
Healthy weight (BMI < 25)	47.3	49.9
Overweight (BMI 25–30)	36.2	35.4
Obese (BMI ≥ 30)	16.5	14.7
Experienced health ^c		
Excellent	11.2	–
Very good	23.7	–
Good	49.1	–
Moderate	13.7	–
Bad	2.2	–

^a Distribution of level of urbanization based on the Gold Standard shows the distribution for all Dutch inhabitants of 13 years and older. A distribution for Dutch inhabitation of 18 years and older is not available.

^b Distribution of weight classes in the Dutch population is based on (CBS & RIVM, 2019).

^c No information on the distribution of experienced health in the Netherlands is available.

experience health is also in another direction than the correlation between experienced health and bicycle and walking. There are also some significant correlations between the use of the different active modes. All correlations are relatively small.

3.2. Model estimation and coding

The RI-CLPM is estimated with the statistical software package Mplus (Muthén & Muthén, 1998–2017). Due to attrition and recruitment of new respondents, not all respondents participated in all three used MPN waves. Table 3 shows the participation patterns of respondents in the fifth through seventh wave of the MPN (e.g. pattern 001 indicates respondents who only participated in 2019, while pattern 111 represents respondents who participated in all three waves). All respondents that participated in at least one wave are included in the RI-CLPM. To handle this missing data, the RI-CLPM is estimated using the Full Information Maximum Likelihood (FIML) estimator, which has been shown to effectively handle missing data by Enders and Bandalos (2001). To estimate the regression models, only a single year of data is required. The most recent data from 2019 is used for the regression models.

The Maximum Likelihood estimator assumes that all variables in the model are continuous and are normally distributed. In our model, self-rated health is measured on a five point ordinal scale. In that case, using an alternative estimator (e.g. a least squares estimator) may be preferable. However, it is (currently) not possible to estimate the RI-CLPM in Mplus using a least squares estimator. Therefore, also the models including self-rated health are estimated using the ML estimator. It is expected this has little influence on the results, as Rhemtulla et al. (2012) showed that with ordinal variables with at least five categories, the ML estimator results in equal or even better results compared to least squares.

Since our main interest is in the relation between active travel and the two health outcomes, separate RI-CLPMs are estimated for the bicycle, e-bike and walking. Modelling the three active modes in an integrated model would result in a much more complex model, while the estimated relationships between the active modes and the health outcomes would be the same. An advantage of estimating a single model (including all modes) would be that the extent to which active modes substitute each other over the years would also become clear from the analysis. However, assessing such substitution effects has already been done by de Haas et al. (2021) and is outside the scope of the current study.

Furthermore, earlier research suggests that the relationship between BMI and physical activity may be different among obese people compared to non-obese. Littman et al. (2005) showed that the inverse relationship between physical activity and weight gain is stronger among obese people. Therefore, to study the relationship between BMI and active travel, a multi-group RI-CLPM is estimated in which obese people are distinguished from non-obese people.

4. Results

4.1. Regression models

As described in the previous section, multivariate regression models are used to assess whether the two health outcomes (BMI and self-rated health (SRH)) and the use of active modes are related. This allows controlling for confounding variables. The use of active modes is used as the dependent variable with the health indicators as independent explanatory variables. Separate models are estimated for the number of trips and for the travelled distances. Table 4 shows the parameter estimated for the health related variables. The parameter estimates of the control variables are not shown to limit the table size.

To ease interpretation, BMI is included as a categorical variable (BMI < 25, BMI 25–30 and BMI ≥ 30) and SRH is included as a binary variable. People who rate their health as excellent, very good or good are included as having a good self-rated health, while people who rate their health as moderate or bad are the reference. There is a clear relation between the two health outcomes and active travel. People who are overweight or obese make fewer trips and travel less distance by bicycle. As these are unstandardized parameters, they can be directly interpreted as differences in number of trips or travelled distances. For instance, while people in our sample make 1.4 cycling trips over a distance of 3.9 km in three days on average, obese people make on average 0.56 fewer trips and cycle 1.47 km less compared to people with a healthy weight. Similar relationships are found between the BMI and walking, with the only difference that overweight people do not make significantly fewer trips on foot compared to people with a healthy weight.

While the results suggest that, in line with literature, people with a higher BMI make less use of active modes, this does not hold for the e-bike. Obese people make more trips by e-bike compared to people with a healthy weight. The difference in travelled distances is not statistically significant, indicating that the extra trips on e-bike by obese people are likely to be relatively short trips. This difference

Table 2

Correlation between dependent variables RI-CLPM, pooled MPN sample 2017–2019 (lower left triangle represents trips, upper right triangle distance).

	B	E	W	BMI	EH	B
Bicycle (B)	1	−0.045 ^b	0.016 ^a	−0.092 ^b	0.100 ^b	1
E-bike (E)	−0.116 ^b	1	−0.016	0.019 ^a	−0.009	−0.045 ^b
Walking (W)	0.023 ^b	−0.015	1	−0.053 ^b	0.016	0.016 ^a
BMI	−0.117 ^b	0.059 ^b	−0.031 ^b	1	−0.255 ^b	−0.092 ^b
Experienced health (EH)	0.117 ^b	−0.051 ^b	0.016 ^a	−0.255 ^b	1	0.100 ^b

^a Correlation is significant at the 0.05 level (2-tailed).

^b Correlation is significant at the 0.01 level (2-tailed).

Table 3

Participation patterns of MPN respondents, wave 5 through 7 (2017–2019).

Pattern	#	%	Pattern	#	%
001	443	6.6	101	314	4.7
010	669	9.9	110	743	11.0
011	923	13.7	111	2831	42.0
100	822	12.2	Total	6745	100

Table 4

Parameter estimates of the health outcomes multiple regression models without distinction between trip motives.

	Trips (# per three days)			Distance (kilometres per three days)		
	Bicycle	E-bike	Walking	Bicycle	E-bike	Walking
Overweight (ref. healthy weight)	−0.30 (−3.22)	0.04 (0.72)	−0.08 (−0.87)	−1.13 (−3.23)	0.59 (1.12)	−0.36 (−2.25)
Obese (ref. healthy weight)	−0.56 (−4.66)	0.21 (2.60)	−0.35 (−3.02)	−1.47 (−3.26)	0.33 (0.49)	−0.88 (−4.24)
Good self-rated health	0.61 (4.97)	0.11 (1.34)	0.52 (4.36)	1.99 (4.30)	1.12 (1.60)	0.81 (3.82)
R-squared	0.049	0.039	0.034	0.035	0.009	0.029
Average in sample	1.40	0.57	1.51	3.9	2.4	2.1

t-values are presented in parentheses, parameters with $|t| > 1.96$ are bold.

in e-bike use raises the question whether obese people make more use of the e-bike because of their weight (since the e-bike provides them with a relatively easy method of active travel) or that the e-bike use contributes to a higher weight (because the physical intensity might be lower compared to a non-electric bicycle).

Positive relationships between SRH and cycling and walking are found. This indicates that people with a good SRH walk and cycle more compared to people who do not rate their health as good. It was found that SRH is correlated with the weight classes, as shown in Table 5. People in a lower weight class more often have a more positive SRH (χ^2 (8, N = 4511) = 314.501, $p = 0.000$). Considering this association, the difference in cycling and walking between people with a healthy weight and people with a higher weight is even larger than indicated by the negative parameters for the weight classes. The more positive SRH by people with a healthy weight results in an additive effect of SRH on the effect of BMI on walking and cycling.

It should be stressed again, that based on the multivariate regression models, no conclusions can be drawn about causality between the two health outcomes and active travel. The health indicators could also be used as dependent variables and the trips or distances with the different active modes as predictors. This would lead to similar conclusions.

4.2. Random Intercept Cross-Lagged Panel Models

Twelve separate RI-CLPMs are estimated resulting from the combination of two indicators of active travel (distances and trips) with three active modes (bicycle, e-bike and walking) and two health outcomes. All models show a good to excellent model fit, as based on the model fit indices shown in Table 6.

Table 7 presents the cross-lagged parameter estimates of the multi-group RI-CLPMs concerning the relation between active travel and BMI. RI-CLPMs focusing on the relation between BMI and active travel were also estimated without distinguishing between weight class. These models also showed a good model fit, but no significant relationships were found. Since we make use of the three day travel diary of the MPN, the parameters refer to distances or trips per three days. The results show that there is a small, but significant negative effect of walking distance on BMI among non-obese people ($\beta = -0.016$, $p = 0.024$). This indicates that when people increase their walking distance per three days with 10 km, this results in a decrease of their BMI by 0.16 in the following year. For someone of 1.80 m tall, this translates to 0.52 kg of weight loss. A similar (negative) effect is not found for obese people.

The results show that the effect of active travel on BMI is not present for cycling. For cycling, a reverse effect is found among non-obese people. That is, an increase in the level of BMI in one year results in a decrease in bicycle use in the next year, both in travelled distances ($\beta = -0.384$, $p = 0.021$) and trips ($\beta = -0.139$, $p = 0.005$). No such effects are found in the obese group. Also between e-bike use and BMI no significant effects are found.

Several parameters relating to the relationships between bicycle use and BMI among obese people are close to being statistically significant at the 5% level with t-values close to 1.96. These parameters all have unexpected signs as they would imply that bicycle use

Table 5

Self-rated health per weight class MPN 2019.

Weight class	Self-rated health (%)					
	Excellent	Very good	Good	Moderate	Bad	Total
Healthy weight (BMI < 25)	16.4	29.1	43.8	9.2	1.5	100
Overweight (BMI 25–30)	7.7	22.4	52.9	15.0	2.0	100
Obese (BMI ≥ 30)	4.1	11.5	56.1	23.5	4.7	100

Table 6
Model fit of RI-CLPMs.

Model	Chi-square	RMSEA ^a	CFI ^a	SRMR ^a
BMI and cycling (distance)	4.000, df = 6, p = 0.677	0.000	1.000	0.005
BMI and e-bike (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
BMI and cycling (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
SRH and cycling (distance)	3.634, df = 3, p = 0.304	0.006	1.000	0.006
SRH and e-bike (distance)	3.895, df = 3, p = 0.273	0.007	1.000	0.006
SRH and walking (distance)	4.737, df = 3, p = 0.192	0.009	1.000	0.006
SRH and cycling (trips)	4.912, df = 3, p = 0.178	0.010	1.000	0.007
SRH and e-bike (trips)	4.523, df = 3, p = 0.210	0.009	1.000	0.006
SRH and walking (trips)	7.332, df = 3, p = 0.062	0.015	1.000	0.007

^a A Root Mean Square Error of Approximation (RMSEA) < 0.05, a Comparative Fit Index (CFI) > 0.95 and a Standardized Root Mean Square Residual (SRMR) < 0.08 indicate a good model fit (Brown, 2014).

Table 7
Cross-lagged parameter estimates RI-CLPM relation BMI and active travel (travelled distances in km per three days (left) and trips in three days (right)).

Direction	Distance (km per three days)				Trips (per three days)			
	Non-obese (BMI<30)		Obese (BMI≥30)		Non-obese (BMI<30)		Obese (BMI≥30)	
	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value
BMI → cycling	−0.384	−2.316	0.112	1.148	−0.139	−2.815	0.062	1.725
Cycling → BMI	−0.002	−0.649	0.029	1.854	−0.005	−0.351	0.085	1.882
BMI → E-bike	−0.045	−0.323	−0.004	−0.029	−0.017	−0.518	0.002	0.062
E-bike → BMI	−0.002	−0.614	0.000	0.006	−0.008	−0.362	−0.028	−0.432
BMI → Walking	0.081	1.005	−0.020	−0.324	−0.035	−0.737	−0.042	−0.958
Walking → BMI	−0.016	−2.258	0.010	0.354	−0.011	−0.755	−0.035	−0.522

leads to an increase in the BMI and an increase in the BMI leads to higher bicycle use.

Table 8 presents the cross-lagged parameter estimates of the RI-CLPMs on the relation between active travel and SRH. One statistically significant positive relationship is found between cycled distance and SRH ($\beta = 0.003$, $p = 0.050$), indicating that an increase in the travelled distance by bicycle in one year results in a more positive SRH in the next year. This is, again, a small effect. The other parameters related to cycling indicate that an improvement in SRH leads to an increase in bicycle use. These parameters are, however, not significant at the 5% level ($\beta = 0.636$, $p = 0.072$ for travelled distance and $\beta = 0.174$, $p = 0.075$ for number of trips). No significant relationships are found between SRH and the other active travel modes e-bike and walking.

The above-discussed cross-lagged parameter estimates indicate within-person effects. The RI-CLPM also provides estimates of the correlation between the random intercepts. These correlations indicate the association between the variables on the between-person level. Table 9 shows these estimated correlation coefficients between the random intercepts for each of the estimated models. In the multi-group models, the correlation between the random intercepts is estimated separately for each of the groups. Results are largely in line with the outcomes of the presented regression models. People with a more positive SRH make more use of the bicycle and travel more distance by foot compared to people with a more negative SRH. A higher BMI is associated with less bicycle use, both in the obese and non-obese group. For walking distance, there is only a significant negative correlation with BMI in the obese group. Interestingly, in the non-obese group, BMI is positively correlated with e-bike use, indicating that people with a higher BMI make more use of the e-bike in the non-obese group. This positive correlation is not observed in the obese group.

Table 8
Cross-lagged parameter estimates RI-CLPM relation self-rated health (SRH) and active travel (travelled distances in km per three days (left) and trips in three days (right)).

Direction	Distance (km per three days)		Trips (per three days)	
	Est.	t-value	Est.	t-value
SRH → cycling	0.636	1.852	0.174	1.800
Cycling → SRH	0.003	1.960	0.012	1.782
SRH → e-bike	−0.299	−1.058	0.015	0.241
E-bike → SRH	−0.001	−0.358	0.004	0.437
SRH → walking	−0.074	−0.452	−0.033	−0.355
Walking → SRH	−0.002	−0.597	−0.009	−1.183

Table 9
Correlation coefficients between the random intercepts

Relation	Distance		Trips	
	Est.	t-value	Est.	t-value
Perc. health - cycling	0.222	8.289	0.023	6.905
Perc. health - e-bike	-0.017	-0.676	-0.100	-4.830
Perc. health - walking	0.063	2.351	-0.017	-0.730
	Non-obese (BMI<30)		Obese (BMI≥30)	
	Est.	t-value	Est.	t-value
BMI - cycling	-0.153	-6.981	-0.285	-2.397
BMI - e-bike	0.065	3.231	-0.051	-0.523
BMI - walking	-0.033	-1.551	-0.231	-2.328

5. Discussion

From the analyses we find only limited evidence for the existence of causal effects between BMI and active travel. Contrary to previous studies, we find no significant effects in the generic models (i.e. where we do not distinguish between obese and non-obese people). Only in the multi-group models significant effects are found. Here, we find that walking has a small negative effect on BMI in a later year among non-obese people, while no evidence was found for the reverse effect. While the effect is small, this result is in line with studies concerning the relationship between active travel who did not consider reciprocal effects (e.g. [Martin et al. \(2015\)](#) and [Flint et al. \(2016\)](#)). Our results, however, contradict those obtained in the study of [Kroesen and De Vos \(2020\)](#), who found that the level of BMI does have an influence on walking, while the reverse effect was not observed. This discrepancy in results could be related to the different ways in which walking is operationalised in the two studies. In the study of [Kroesen and De Vos \(2020\)](#), walking frequency is measured as the number of days that an individual walked for at least 10 min in the past 7 days. In the present study, more detailed information on the number of trips and travelled distances is available.

Our results with regard to the relationship between cycling and BMI are more in line with those obtained in studies focusing on bidirectional effects between physical activity and BMI. Similarly to [Bak et al. \(2004\)](#), [Petersen et al. \(2004\)](#), [Mortensen et al. \(2006\)](#) and [Ekelund et al. \(2008\)](#) we find that a change in BMI has a negative effect on cycling, while no effect of cycling on the BMI is found. However, the found effect is relatively small: for every point change in BMI, an individual will change his or her bicycle usage in three days in the inverse direction of the BMI change with 0.384 km or 0.139 trips. For an individual of 1.80 m tall, a point change in BMI translates to 3.24 kg. As it is expected that the share of overweight and obese people will increase in the near future ([Pineda et al., 2018](#); [Ward et al., 2019](#)), these results do imply that, relatively speaking, bicycle usage could decrease in the future, *ceteris paribus*.

We found no significant effects between e-bike use and BMI. This implies that, contrary to the regular bicycle, e-bike use would not be affected by the expected increase in overweight and obesity rates. Although riding an e-bike requires less effort compared to a regular bicycle, several studies found that it may be considered a moderate intensive physical activity ([Bourne et al., 2018](#)). E-bike use thereby contributes to reaching physical activity guidelines. Therefore, if the use of the regular bicycle will indeed decrease in the future due to overweight and obesity rates, the e-bike may turn out to be a promising mode of transport that will allow people to maintain current 'bicycle' levels.

Based on findings from literature, we expected that the relationship between active travel and BMI would be stronger among obese people compared to non-obese people. However, we did not find any statistically significant effects among obese people. We did, however, find several parameters in an unexpected direction related to cycling and BMI among obese people that are statistically significant at the 10% (two-tailed) level with t-values greater than 1.645. These parameters imply that bicycle use among obese people leads to an increase in the BMI and an increase in the BMI leads to higher bicycle use. While not significant at the 5% level, we will discuss a number of possible explanations for these unexpected findings.

Since we are estimating many models and allowing a 5% error margin in each of these models, it is possible that we find unexpected effects by chance. The unexpected signs could also be related to the (in)stability of the BMI among obese people. Other studies report that weight is less stable among people with a high weight ([Bangalore et al., 2017](#); [Stevens et al., 2006](#)). This is also true for our sample. The correlation of the BMI between years is higher among non-obese (correlation coefficients between 0.876 and 0.907) than obese (correlation coefficients between 0.662 and 0.802) people. These fluctuations in BMI, which may be unrelated to bicycle use, may have an effect on the model estimations that causes us to find this result by chance.

However, it is also possible that these unexpected effects actually do exist among obese people. The notions of moral licensing and moral cleansing can be identified as possible behavioural mechanisms that underlie the effects. Moral licensing is the subconscious phenomenon that moral behaviour can lead to engaging in immoral behaviour ([Merritt et al., 2010](#)), driven by mental accounting or 'book-keeping' processes. This may explain why an increase in cycling would result in an increase in the level of BMI. It is known that an increase in energy expenditure due to physical activity is compensated to a certain extent by, for instance, a higher energy intake ([Westertorp, 2010](#)). It may be that the increase in cycling among obese people leads to overcompensating, i.e. increasing the subsequent energy intake more than would be justified by the increase in energy expenditure. Moral cleansing refers to the phenomenon that people tend to show moral behaviour when an individual's self-perception has been compensated due to immoral behaviour ([Jordan et al., 2011](#)). Behaviour that led to an increase in the BMI (immoral behaviour) may lead to an increase in bicycle use (moral

behaviour), explaining the positive effect of BMI on cycling.

For the relationship between active travel and SRH, we only found a significant positive effect of cycling distance on SRH. In other words, when people increase their travelled cycling distance in one year, they will rate their health more positively in the following year. This result is in line with studies that assessed the relationship between SRH and general physical activity (e.g. [Hamer et al. \(2012\)](#) and [Haveman-Nies et al. \(2003\)](#)). Although only significant at the 10% level, we also found a positive effect of SRH on both cycling distance and cycling trips. This is an interesting finding, as we found no previous studies considering this effect. The standardized parameters ($\beta = 0.047$ for cycling distance on SRH, $\beta = 0.039$ for SRH on cycling distance) indicate that the effect of cycling on SRH is stronger than the reverse effect. In line with [Avila-Palencia et al. \(2018\)](#), no relations between e-bike and SRH were found.

6. Conclusion

In this study, we assessed the bi-directional relationship between active travel, measured by both trips and distances with the bicycle, e-bike or walking, on the one hand, and two health outcomes, namely BMI and self-rated health (SRH), on the other hand. The results of the RI-CLPMs, based on three waves of data from the Netherlands Mobility Panel (MPN), highlight the importance of longitudinal analyses when estimating the relationship between active travel and health. While the cross-sectional regression models showed relatively strong relationships between active travel and the two health outcomes considered in this paper, most of the relationships do not appear to be present on the within-person level. We only find a small negative effect for walking distance on BMI for non-obese people. Furthermore, while most previous longitudinal studies only considered an effect of active travel on BMI, we found evidence for a negative reverse effect of BMI on cycling distance. For the relation between active travel and SRH we find a significant positive effect of cycling distance on SRH.

From a policy perspective, our results indicate that promoting active travel may only result in a slight decrease of BMI through an increase in walking. The reverse negative effect of BMI on cycling implies that policies aimed at decreasing overweight and obesity may have an effect on cycling levels. In light of increasing overweight and obesity rates, policies aimed at reducing the consumption of unhealthy foods and increasing physical activity levels are already in place ([Ministry of Health, Welfare and Sport, 2019](#); [World Health Organization, 2016](#)). If these policies are effective in realizing a decrease in BMI, this may result in an increase of cycling rates.

A limitation of this study is that we used self-reported measures of active travel and health. The measures may therefore be biased, for instance due to rounding of travel times or under- and over-reporting weight and height ([Rietveld, 2001](#); [Stommel and Schoenborn, 2009](#)). As explained before, such biased measurements are unlikely to lead to biased results in our study. However, objectively measuring active travel (e.g. with accelerometers) and BMI (e.g. with physical measurements of weight and height) may still result in more valid results. As we used data from the Netherlands Mobility Panel (MPN), three days of travel behaviour per wave are available. Three days may be too short to capture active travel. For instance, there may be respondents who primarily use active modes during weekends but were asked to report three weekdays.

Furthermore, the available measures of health (BMI and SRH) only give a limited reflection of one's health. For instance, while the amount and distribution of body fat are important health outcomes, BMI does not account for body composition ([Wells and Fewtrell, 2006](#)). Future research could include more objective measures of physical health, such as blood pressure, diabetes and amount of body fat. Besides physical health, including other health outcomes such as mental health, psychological well-being, vitality or sick days would be helpful understanding the relation between active travel and health.

Finally, the dataset that we used in this study was collected before the COVID-19 pandemic. The pandemic and all measures taken to reduce the spread of the virus greatly impacted people's lives. Insights from the Netherlands showed that while the total amount of trips and travelled distances dropped due to the coronavirus crisis, the popularity of roundtrips (e.g. a walking or cycling tour) gained in popularity ([de Haas et al., 2020](#)). It may be that the role of active travel in reaching physical activity guidelines may have changed during the coronavirus crisis (e.g. because people could not perform their usual physical activity as a result of measures taken to reduce the spread of the virus). It may therefore be that the relation between active travel and health has changed due to the coronavirus crisis (e.g. it may be that active travel became more important in weight maintenance if it became the primary source of physical activity). Such effects would be an interesting subject of future research.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRedit authorship contribution statement

Mathijs de Haas: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Maarten Kroesen:** Conceptualization, Methodology, Writing – review & editing. **Caspar Chorus:** Conceptualization, Writing – review & editing. **Sascha Hoogendoorn-Lanser:** Conceptualization, Writing – review & editing. **Serge Hoogendoorn:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare no competing interests.

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