Does active travel make people healthier, or are healthy people more inclined to travel actively?

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A B S T R A C T

Introduction: Active travel (walking and cycling) is increasingly being recognised as a potentially effective means of increasing physical activity levels and thereby contribute to physical and mental health. To date, however, much of the empirical evidence related to the health benefits of active travel is based on cross-sectional data. As such, the direction of causation remains uncertain, i.e. does active travel lead to improved health or vice-versa, are healthier individuals more inclined to participate in active travel? This study aims to systematically assess the bidirectional relationships between active travel, on the one hand, and two relevant health outcomes on the other, namely body-mass index (BMI) and mental health.
Method: To this end, random-intercept cross-lagged panel models are estimated using data from 10 waves (years) of the Longitudinal Internet Studies for the Social sciences panel, a panel that is representative for the Dutch population. Active travel was assessed using a measure of walking frequency and mental health was measured using the 5-item mental health inventory (MHI-5).
Results: The results indicate that active travel does not affect later BMI levels, but, vice versa, BMI does negatively influence later levels of active travel, a pattern that is in line with earlier research related to general physical activity and BMI. Regarding mental health, the pattern is exactly opposite. In this case, the effect of active travel on mental health is significant, while the reverse effect is not (at the 5% level of statistical significance).
Conclusion: Overall, the results underline the notion that cross-sectional estimates of the effects between active travel and health outcomes should be interpreted with care, as they can be the result of effects in either direction. In addition, the results suggest that the uptake of active travel may be increased by decreasing BMI levels in the population, e.g. via dietary programs.

1. Introduction

An abundant stream of research indicates that physical activity positively influences health; regular physical activity reduces the risk of cardiovascular disease, diabetes, cancer, hypertension, depression, osteoporosis and premature death (Warburton et al., 2006). Worldwide, around a third of all adults do not reach public health guidelines for recommended levels of physical activity (Hallal et al., 2012). Based on such prevalence rates, it has been estimated that inactivity causes 9% of premature mortality globally, which, in 2008, accounted for 5.3 million of the 57 million deaths in that year (Lee et al., 2012). In Western countries, physical inactivity is the fourth

leading health risk factor (after high blood pressure, tobacco use, and high body-mass index) (Lim et al., 2013).

Active travel (walking and cycling) is increasingly being recognised as a potentially effective means of increasing physical activity levels and thereby contribute to physical and mental health (Sallis et al., 2004; Frank et al., 2006; Pucher et al., 2010). Although some studies found that people frequently walking and cycling might possibly compensate by engaging less in other forms of physical activity (e.g., Voulgaris et al., 2019), other studies found that the time spent exercising is not associated with time spent travelling by active modes, and that active travel consequently adds to the total amount of daily physical activity (Cooper et al., 2003; Panik et al., 2019; Panter et al., 2008). Much empirical research has been devoted to determining the health benefits of active travel. In this regard, relevant potential outcomes include increased total physical activity, reduced obesity, increased fitness and increased psychological well-being (see Oja et al. (2011), Wanner et al. (2012) and Saunders et al. (2013) for relevant reviews). Once incorporated in the daily routine, active travel can easily become a habitual behaviour (because it is executed on a frequent basis) and there is generally much potential for active travel to help people meet recommended physical activity levels. In the US, for example, 27% of all trips in 2009 were shorter than 1 mile, but only 36% of those short trips were made by walking or cycling (Buehler et al., 2011). Also in cycling-oriented countries, like The Netherlands or Denmark, there is still considerable potential to increase active travel.

To date, however, much of the empirical evidence related to the health benefits of active travel is based on cross-sectional data. As such, the direction of causation remains uncertain, i.e. does active travel lead to improved health or vice-versa, are healthier individuals more inclined to participate in active travel? Theoretically, effects in both ways can be expected. For example, considering the body-mass index (BMI) as a potential health outcome, the biological energy-balance explains why active travel may decrease overweight (or help maintain weight). Yet, since physical activity is more strenuous for obese individuals than for normal-weight individuals, a reverse effect may also exist. Regarding general physical (in)activity, evidence indeed suggests that this reverse effect is actually greater than the original -more intuitive-effect from physical activity to obesity (Ekelund et al., 2008; Pulsford et al., 2013).

Given this background, this study aims to systematically assess the bidirectional relationships between active travel, on the one hand, and two relevant health outcomes on the other, namely body-mass index and mental health, as relevant indicators of the physical and psychological well-being of humans respectively. To achieve this aim, a series of Random-Intercept Cross-Lagged Panel Models (RI-CLPM) are specified and estimated, a model which is ideally suited to explore reciprocal relationships at the within-person level, while controlling for stable individual characteristics (Hamaker et al., 2015). Data to estimate the models are drawn from 10 waves of the Longitudinal Internet Studies for the Social sciences (LISS) panel. In the following, previous research findings will be discussed, after which the empirical study will be presented.

2. Previous longitudinal research

2.1. Active travel, general physical activity and BMI

Cross-sectional studies have generally found that active travel is inversely associated with obesity (Flint and Cummins, 2016; Flint et al., 2014; Laverty et al., 2013, 2015; Lindström, 2008; Millett et al., 2013). Evidence from longitudinal studies, however, is limited. Only three studies could be identified in the existing literature, namely the ones of Martin et al. (2015), Mytton et al. (2016a) and Flint et al. (2016). All three were focused on the prospective effects of active commuting (walking and cycling to work) on BMI, and all three concluded that active commuting reduced obesity at follow-up. However, none of these focused on possible reverse effects of BMI on active commuting.

This reverse relation has been considered in research focusing on the relationship between *general* physical (in)activity and BMI. In this area, Petersen et al. (2004) were among the first to suggest and investigate the bidirectional effects between a physical activity and BMI. Among a random sample of the population residing in Copenhagen (Denmark) they found that leisure time physical activity -over the course of 15 years-predicted obesity, but found no evidence for a reverse relationship. Adopting similar prospective study designs, Bak et al. (2004) and Mortensen et al. (2006) replicated this finding in a sample of Danish juveniles and a sample of middle-aged white Americans respectively. Focusing on sitting behaviours in particular, Pulsford et al. (2013) found that prior obesity was prospectively associated with time spent watching TV per week, but, in line with earlier findings, they found no relationship the other way around.

While the above-mentioned studies were based on self-report measures of physical activity and obesity, which may be unreliable and therefore attenuate effects downwards, Ekelund et al. (2008) were among the first to use objective measures for both physical activity and obesity. In the study, physical activity was assessed using heart monitors, while obesity was operationalised by (objective) measurements of BMI, waist circumference and percentage body fat. Still, the pattern of findings was the same; BMI, fat mass, and waist circumference were found to predict future sedentary time (5 years later), but sedentary time did not predict future obesity. Another study using objective measurements was conducted by Golubic et al. (2015) who used accelerometers to measure physical activity. In line with the findings above, they found an effect of body fat on later physical activity, but they also found a significant, yet smaller, effect in the other direction. Hence, in line with common intuition, physical activity in this study was found to decrease body fat.

In sum, studies focusing on the health benefits of active travel have focused on active commuting in particular and consistently found negative effects of active commuting on obesity, but have not explicitly considered a reverse effect. Bidirectional effects have been explored with respect to the relationship between general physical activity and BMI and have (with one exception) concluded that BMI influences physical activity but not vice versa. This study aims to add to the available evidence base regarding the relation between active travel and BMI, focusing on general active travel and explicitly taking into account bidirectional effects.

2.2. Active travel, general physical activity and mental health

Regarding the relation between active travel and mental well-being, several cross-sectional studies, which were focused on adolescents and children, have found positive effects of active modes on mental well-being (Humphreys et al., 2013; Roberts et al., 2011; St-Louis et al., 2014; Sun et al., 2015). Other cross-sectional studies focusing on travel satisfaction – i.e., the experience of emotions during travel and a cognitive evaluation of travel – found that active trips are being experienced more positively compared to trips with motorised modes (De Vos et al., 2016; Morris and Guerra, 2015; St-Louis et al., 2014). Although it remains rather unclear why travel satisfaction levels differ according to various travel modes, the high levels of satisfaction of cyclists and pedestrians could be explained by the release of dopamine during physical activity, which affects arousal and attention, and can improve mood and reduce anxiety (Paluska and Schwenk, 2000; Penedo and Dahn, 2005). On the other hand, the high satisfaction levels might be explained by relatively positive attitudes towards active travel (compared to attitudes towards motorised travel), or short travel durations of active trips, which both can positively affect how people experience active travel (Anable and Gatersleben, 2005; De Vos, 2018).

Satisfying walking and cycling trips might directly contribute to subjectively experienced well-being since experiencing positive emotions stimulates elements such as original thinking, fostering skills, and liking of self and others (Lyubomirsky et al., 2005). Furthermore, satisfying (active) trips might also indirectly improve well-being as it can positively affect the satisfaction with – and performance of – activities at the destination of the trip (Bergstad et al., 2011; De Vos, 2019; Loong et al., 2017). Although some studies have suggested that people with a good mental health are more likely to experience positive emotions during travel (De Vos, 2019), a positive effect of mental health on choosing to travel actively has never been analysed.

Evidence from longitudinal research regarding the effects of active travel on mental well-being is again limited. Here, two studies could be found, namely the ones of Mytton et al. (2016b) and Martin et al. (2014). Based on a two-wave panel analysis of British commuters, Mytton et al. (2016b) found that the maintenance of cycling to work was also associated with better mental health over time. Similar results were obtained by Martin et al. (2014), who – using 18 waves from the British Household Panel Survey – found that commuting mode influenced psychological well-being over time; compared to use of the car, active travel and public transport were found to increase well-being. In addition, wellbeing was found to increase significantly after a switch from car (or public transport) to active travel. In both these studies, however, a possible reverse effect (from mental wellbeing to mode choice) was not investigated.

Zooming out to the relationship between general physical activity and mental health, cross-sectional research indicates a positive association between the two and intervention studies generally indicate that increasing physical activity lowers the likelihood of depression (Teychenne et al., 2008). Similar to the relation between active travel and BMI, several observational studies have examined bi-directional effects between the two outcomes. Based on a large British cohort study, Da Silva et al. (2012) found that physical activity was associated with reduced likelihood of depressive symptoms at follow-up, yet participants with anxiety and depression symptoms at baseline also had higher odds of not meeting the recommended levels of physical activity at follow-up, suggesting that the association between physical activity and symptoms of anxiety and/or depression is bidirectional. The same conclusions were reached by the studies of Stavrakakis et al. (2012) and Pereira et al. (2014), who also relied on prospective cohort data.

In sum, similar to the relation between active travel and BMI, cross-sectional evidence indicates a positive association between the two which may be explained by various causal mechanisms. Moreover, longitudinal studies have found that active travel positively influences mental health, yet reverse effects have not explicitly been considered in these studies. Reciprocal effects have been considered in research focusing on general physical activity and mental health and these studies have consistently reported positive bidirectional influences between the two.

2.3. Research contributions

As stated before, the main contribution of the present study is that we assess the bidirectional influences between active travel, on the one hand, and BMI and mental health, on the other. In addition to this, a second contribution is that we apply a model to assess these reciprocal effects at the *within-person level*, namely the so-called random intercept cross-lagged panel model (RI-CLPM). This model is recently developed by Hamaker et al. (2015). Basically, the RI-CLPM extends the traditional cross-lagged panel model (CLPM) (Finkel, 1995), which has been a popular model to assess the lagged bidirectional influences between variables. For example, as referred to above, Stavrakakis et al. (2012) have also used this model to examine the bidirectional influences between physical activity and depressive symptoms.

Hamaker et al. (2015) show, however, that the CLPM confounds between-person and within-person co-variation, which is problematic since the between-person relationship between two variables is not necessarily equivalent to the within-person relationship (Hamaker, 2012). Yet, it is at the within-person level that the assumed causal processes actually operate. For this reason it is important to also empirically establish the effects at this level. This is achieved by the RI-CLPM through specification of random intercepts which capture the trait-like stability in the variables of interest. Consequently, the estimated cross-lagged effects only capture within-person effects. The statistical model will be more elaborately discussed in section 3.2.

3. Method

3.1. Data and measures

To assess the bidirectional relationships between active travel and the two health outcomes, data are drawn from the LISS

(Longitudinal Internet Studies for the Social sciences) panel,[1] which is based on a true probability sample of Dutch households. Within this panel an annual health survey is performed, which includes measures on active travel and the two considered health outcomes. In total, 1548 respondents completed all 10 waves and are included in the present analysis. Table 1 presents an overview of the sample distributions of socio-demographic characteristics at the first measurement occasion (in 2007).

Overall, the sample distributions match the population distributions, with age being a notable exception. In addition, the fact that a pure stayer sample is selected might introduce biases in other variables including those considered in the present analysis. For example, it might be that less healthy individuals have a higher chance of dropping out over time. To assess the effects of these potential biases, the analyses presented below were also run for the complete sample, i.e. based on all individual who completed at least one wave (N = 15,219). To handle the missing values in these models, the Full Information Maximum Likelihood (FIML) estimator was used which imputes probable values for the missing data based on the model structure. This method has been shown to be least biased compared to other methods to handle missing data (Enders and Bandalos, 2001). A comparison of the estimates of these models with those presented in this study (Table 5) indicated that the deviations were generally small and did not lead to substantively different conclusions.

To measure active travel, the following question was used: 'If you look back on the last 7 days, on how many of those days did you spend at least 10 min walking?' (ranging from 0 to 7 days).[2] Although straightforward, the measure is rather crude. For example, it does not differentiate between utilitarian and leisure travel. In addition, it might be possible that people who walk infrequently in terms of walking days, walk (on average) longer on the days they do walk compared to people who walk frequently (resulting in similar overall physical activity levels). To provide some context and validation of this measure, we performed two additional analyses.

First, to assess the relative amount of utilitarian travel versus recreational travel, we used data from the Dutch national travel survey. This is a nation-wide annual travel survey in which respondents (randomly selected from the population register) record all their trips and activities for a single day. Using data from 2017 (38,127 respondents) we calculated that 75% of all walking trips had a utilitarian purpose (and thus 25% a recreational one). Hence, most walking trips (indeed) relate to active transportation.

Secondly, we analysed the relation between walking frequency (in days) and average walking time using data from the Dutch time-use survey. For this analysis, we made use of the survey conducted in 2006 which included 1875 respondents. The results indicated that the average daily walking time (calculated by dividing the total walking time over the seven days by the number of days that at least walking trip was made) increased with the number of days that at least one walking trip has been made. Hence, people who spend more days walking, walk longer on any particular day, while people who walk less frequently also spend less time walking on the days they do walk. This result shows that a higher score on our measure of walking frequency (in days) generally indicates that a respondent actually spent more time walking, which of course is a desirable outcome.

The body-mass index was calculated using respondents' self-reported height and weight. Compared to active travel and BMI, mental health was more difficult to define and operationalise. Indeed, mental health can be defined broadly, as for example, in the WHO's definition of mental health as "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community" (WHO, 2004) or more narrowly focusing on specific aspects such as subjective well-being and/or specific mental disorders, such as general anxiety disorder or depression. In this research, we used a narrow definition focused on subjective well-being and depression. In particular, we used the 5-item Mental Health Inventory (MHI-5) (Berwick et al., 1991), a scale which has previously been validated as a measure for depression using clinical interviews as the gold standard (Rumpf et al., 2001). The MHI-5 scale consists of five items related to respondents' feelings over the past month to which they could respond using a 6-point scale ranging from never (1) to continuously (6):

1. I felt very anxious
2. I felt so down that nothing could cheer me up
3. I felt calm and peaceful
4. I felt depressed and gloomy
5. I felt happy

While only consisting of 5 items this scale has been shown to have the same psychometric performance as the extensively validated 12 item General Health Questionnaire (GHQ-12) and can, as such, be used to measure and compare mental health in defined populations (McCabe et al., 1996; Hoeymans et al., 2004). In line with common practice, the items were recoded so that higher scores indicated higher mental well-being and then summed, resulting in a scale which (theoretically) ranges from 5 to 30.

Table 2 presents the means and standard deviations for the three variables considered in the analysis. The results indicate that active travel decreases over the period of 10 years (from 4.7 to 4.0 days per week), while BMI increases (from 25.2 to 25.9). These trends are consistent with the known cross-sectional effects of age on these outcomes (see e.g. Martin et al., 1997). Regarding mental health, no strong trend could be identified although it seems to be slightly increasing. It should be noted that the estimated models takes the structural trends in the means over time into account. Finally, the 5-item mental health scale was found to be sufficiently reliable across all waves (Cronbach's alpha >0.8).

To obtain some initial insights into the extent the considered variables are interrelated Table 3 presents the correlations between

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[1] All data are freely available at www.lissdata.nl.

[2] Unfortunately, no information was available regarding respondents' cycling frequency. For this reason we used the number of days respondents walked (for more than 10 min) as a proxy for active travel levels.

Table 1
Sample distributions of socio-demographic characteristics (N = 1548).

Variable	Categories	Sample (%)	Population (%)[a]
Gender	Male	51	50
	Female	49	50
Age	15–34 years	13	29
	35–44 years	17	17
	45–54 years	26	18
	55–64 years	30	16
	65 years and older	14	20
Level of education	Primary school	8	10
	Intermediate secondary education	28	20
	Higher secondary education	10	10
	Intermediate vocational education	23	28
	Higher vocational education (college)	24	20
	University	7	11
Occupational status	Paid employment	52	53
	Freelancer or self-employed	6	6
	Attends school or is studying	4	11
	Takes care of the housekeeping	12	10
	Pensioner	18	13
	Other	8	7
Personal net monthly income	No income	9	12
	EUR 500 or less	7	9
	EUR 501 to EUR 1000	16	17
	EUR 1001 to EUR 1500	19	21
	EUR 1501 to EUR 2000	22	21
	EUR 2001 to EUR 2500	12	10
	More than EUR 2500	10	10
	Missing	4	

[a] The population figures were retrieved from Statistics Netherlands (www.statline.nl).

Table 2
Means and standard deviations of the four dependent variables (N = 1548).

Wave	Active travel (#days with >10 min walking)		BMI		Mental health		
	Mean	SD	Mean	SD	Mean	SD	Alpha
1	4.7	2.4	25.2	3.8	23.7	3.8	0.82
2	4.4	2.5	25.3	3.8	23.9	3.9	0.83
3	4.2	2.6	25.5	3.8	24.1	3.8	0.84
4	4.1	2.6	25.6	3.8	24.1	4.1	0.85
5	4.2	2.6	25.6	3.9	24.2	3.9	0.85
6	4.0	2.6	25.6	3.9	24.3	4.0	0.86
7	3.9	2.6	25.7	3.9	24.4	4.0	0.84
8	4.0	2.7	25.8	4.0	24.4	4.0	0.87
9	4.0	2.6	25.9	4.0	24.4	3.9	0.86
10	4.0	2.6	25.9	4.0	24.4	4.1	0.86

Table 3
Correlations between dependent variables.

	AT	BMI	MHI	Sport
Active travel	1			
BMI	-0.091*	1		
Mental health	0.058*	-0.010	1	

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

the three variables based on a pooled dataset (all person-waves stacked). These indicate that, as expected, active travel is negatively correlated with BMI, while positively correlated with mental health. The correlation with BMI is stronger than the one with mental health, yet both correlations can be classified as rather small. In addition, no association was found between BMI and mental health.

Table 4
Model fit.

Model	χ^2	df	p-value	RMSEA[a]	CFI[b]	SRMR[c]
1a	3144.5	160	0.00	0.110	0.924	0.136
1b	480.6	157	0.00	0.037	0.992	0.037
2a	3997.9	160	0.00	0.125	0.741	0.198
2b	498.5	157	0.00	0.037	0.977	0.029
3a	3612.5	160	0.00	0.118	0.921	0.155
3b	628.6	157	0.00	0.044	0.989	0.023

[a] Root Mean Square Error of Approximation (<0.06 indicates good fit, Hu and Bentler (1999)).
[b] Comparative Fit Index (>0.95 indicates good fit, Hu and Bentler (1999)).
[c] Standardized Root Mean squared Residual (<0.08 indicates good fit, Hu and Bentler (1999)).

Table 5
Standardized parameter estimates.[a]

Model	Direction	CLPM (a)		RI-CLPM (b)			
		Cross-lagged effect		Cross-lagged effect		Correlation RIs	
		Est.	t-value	Est.	t-value	Est.	t-value
1	AT → BMI	-0.002	-0.65	-0.007	-0.94	-0.130	-4.59
	BMI → AT	-0.051	-6.84	-0.021	-2.10		
2	AT → MHI	0.018	2.85	0.020	2.26	0.086	2.89
	MHI → AT	0.022	2.97	0.016	1.69		
3	BMI → MHI	-0.009	-1.47	0.001	0.07	-0.023	-0.85
	MHI → BMI	-0.006	-2.47	0.001	0.11		

[a] The presented figures present the means of the standardized estimates across all waves. Note that, while the unstandardized estimates are equal across all waves, the standardized estimates differ slightly from wave to wave, due to the time-varying variances of the variables.

3.2. Statistical model

To test the bidirectional relationships between active travel and the two health outcomes, the Random Intercept Cross-lagged Panel Model (RI-CLPM) is used. In the following, the model will be briefly introduced (for a full description we refer to Hamaker et al. (2015)).

Fig. 1 presents the structure of the RI-CLPM for three waves of data. Note that in the present application the model will be extended to 10 waves. In the model, x_t and y_t are the observed variables which in the present case relate to active travel and the health outcomes. These variables are assumed to exert bidirectional influences on each other. For each observed variable a respective latent variable is specified, namely p_t and q_t for x_t and y_t. The paths linking these latent variables to the observed ones are set to 1. In addition, temporal means are included for each respective point in time (μ_t and π_t). As such, the variables p_t and q_t effectively capture respondents' temporal deviations from the time-varying group means, thereby accounting for population-wide structural change in the variables of interest. Such structural changes are indeed present (Table 2).

Next, it is assumed that p_t and q_t have lagged relationships on their own respective versions over time. These influences are captured by parameters α_t and δ_t. In addition, in line with the main aim of the RI-CLPM, the variables p_t and q_t may influence each other over time, as captured by parameters β_t and γ_t. These 'cross-lagged' effects are of main interest as they indicate to which extent causal effects exist in either direction. Finally, the error terms of p_t and q_t, u_t and v_t respectively, are allowed to be correlated as well as p_t and q_t for the first point in time. These (dynamic) correlations account for possible synchronous effects between both variables as well as the effects of (unmodelled) time-varying factors between the two variables (p_t and q_t).

The above description applies to the CLPM. An important limitation of the model, as argued by Hamaker et al. (2015), is that, while the CLPM is able to capture temporal stability (through the parameters α_t and δ_t), it does not account for stable trait-like individual differences that endure over time (at least for the periods typically considered in panel studies). Indeed, this is a problematic assumption, since physical and psychological variables are generally characterized by stable individual differences (Hamaker et al., 2015).

These stable individual differences may be accounted for by including two additional latent variables, k and w for x and y respectively, which can be interpreted as random intercepts. To capture the notion that they have a constant (time-independent) 'trait-like' influence on the observed outcomes, the paths linking these variables to the observed variables are set to 1. Essentially, since the random intercepts capture variation between persons, stable 'between-person' variation is 'factored out'. This has two benefits, namely (1) the stability/cross-lagged relations (α_t, δ_t, β_t and γ_t) now capture 'within-person' carry-over effects from one occasion to the next, i. e. the level at which the causal processes are actually assumed to operate, and (2) all time-constant variables that may influence both variables (x_t and y_t) are controlled for. This also means that it is not vital to include socio-demographic variables, which are generally (very) inert, as confounders in the model. Again, similar to the error terms of p_t and q_t, k and w are allowed to be correlated. This
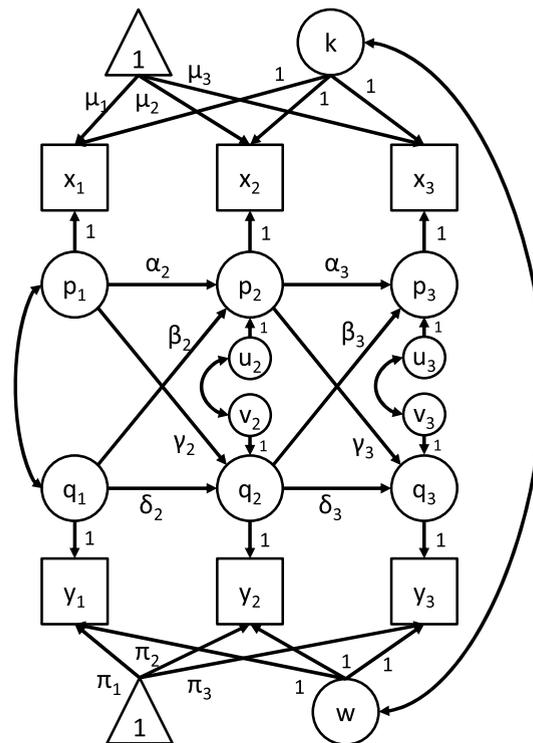
Fig. 1. A 3-wave random intercept cross-lagged panel model (Hamaker et al., 2015).

correlation then indicates the extent in which the variables of interest are correlated at the 'between-person' level due to other factors than the assumed causal effects that operate between the two variables at the 'within-person' level.

4. Results

Separate models were estimated for relationships between active travel and BMI (model 1), active travel and mental health (model 2) and mental health and BMI (model 3). For each relation a CLPM and a RI-CLPM was estimated (version a and b respectively). The models were estimated using AMOS 25 using the maximum likelihood (ML) estimator.[3]

Table 4 presents the model fit of the 6 models. While the CLPMs do not fit according to conventionally used fit criteria, the RI-CLPMs all fit the data well. This indicates that the additionally added random intercepts indeed capture stable between-person individual differences.

Table 5 presents the (standardized) parameter estimates of all six models. Although the CLMPs did not fit the data well, the results of these models are still interesting for reasons of comparison. With two exceptions, the parameters of the CLPMs are all smaller than those of the respective RI-CLPMs. This indicates that the CLPMs generally over-estimate the (within-person) effects, which is due to the confounding of between-person and within-person co-variation. This illustrates the importance of discriminating and separately identifying the between-person and within-person effects.

The results of the RI-CLPM for active travel and BMI indicates that the level of active travel in one year does not influence the level of BMI in the next ($\beta = -0.007$, $p = 0.348$), yet, the reverse effect from BMI to active travel is significant ($\beta = -0.021$, $p = 0.036$). In line with studies focusing on general physical activity and weight (Ekelund et al., 2008; Pulsford et al., 2013), this indicates that – over time – more obese individuals tend to decrease their walking frequency, but walking does not lead to lower BMI over time. With respect to the relation between active and mental health, the results of the RI-CLPM indicate that the level of active travel in one year has a positive influence on the level of mental health in the next ($\beta = 0.020$, $p = 0.024$). Mental health also has a positive influence on active travel in the next year, yet this effect was only significant at the 10% level ($\beta = 0.016$, $p = 0.091$). Despite contrasting research showing positive bidirectional influences between the two (which would also be the conclusion when using the results of the CLPM), the present study indicates that the effect of active travel on mental health is stronger than vice versa. Finally, with respect to BMI and mental

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[3] The ML estimator assumes that the variables in the model are continuous and follow a multivariate normal distribution, while, in our application, (some) variables are (non-normally distributed) ordinal measures. In such cases the use of an alternative estimator (instead of the usual maximum likelihood estimator) is more appropriate. In AMOS, Bayesian estimation is a feasible alternative (although not widely known or used, see e.g. Taylor, 2019). Using this estimation method we found nearly exactly the same estimates as with the use of the maximum likelihood estimator.

health no effects -in either direction-were found, although the effect of mental health on BMI was significant in the CLPM. Note that, as indicated by the results of the RI-CLPM, BMI and mental health are indirectly linked via active travel, i.e. BMI influences active travel which in turn influences mental health.

In addition to the 'within-person' cross-lagged effects the RI-CLPM provides estimates of the correlations between the random intercepts, which reflect the associations between the variables at the between-person level. The correlations show that, at this level, active travel is associated with both BMI (negative) and mental health (positive). These correlations are likely due to unmodelled 'third' variables that influence the outcomes, such as unhealthy lifestyles (e.g. a high intake of energy-dense foods or frequent smoking and alcohol use, see for instance Kroesen (2019)). The nature of the RI-CLPM does not require these variables (insofar as they are stable) to be measured to account for them in the model.

5. Conclusion and discussion

The present study clearly illustrates the need for a longitudinal approach to study the health benefits of active travel. Results of this study, using Random Intercept Cross-Lagged Panel Models of 1548 Dutch residents, indicate that especially BMI affects active travel levels, while active travel mainly influences mental health. The results also show that cross-sectional estimates of the effects between active travel and health outcomes should be interpreted with care, as they can be the result of effects in either direction. Given the results it is likely that the effect from active travel to BMI has been overestimated in previous (cross-sectional) studies. Overall, it seems that the role of active travel in creating desired levels of BMI is limited and might be more affected by, for instance, food intake or genetic factors. Or alternatively, it might be possible that the effect of active travel on BMI is limited because high levels of active travel might substitute - rather than compensate - other forms of physical activity (in line with Voulgaris et al., 2019). Since BMI significantly affects active travel levels, more walking and cycling – which might not have direct positive effects on BMI but can improve air pollution, congestion levels, etc. – could be realized by stimulating populations to have more healthy diets or non-transport related forms of physical activity.

The strong effect of active travel on mental health is in line with studies indicating that walking and cycling result in the experience of positive emotions (e.g., De Vos et al., 2016; Morris and Guerra, 2015; St-Louis et al., 2014). We also found a positive – though less strong – effect of mental health on active travel levels, i.e., people who felt positive emotions over the past months are more likely to walk in the future compared to those who did not. Although the effect of mental health on active travel seems somewhat hard to explain, it might be possible that mental health and active travel positively reinforce each other. In particular, the increase in well-being due to active travel may be hypothesized to function as a 'reward' for active travellers, which, in turn, shapes their (intrinsic) motivations to obtain this outcome again in the future.

Although previous studies have found that health is often regarded as an important determinant of subjective well-being (e.g., Diener et al., 1999), and that high levels of satisfaction with life and good mood are beneficial to one's physical health (Diener and Wang, 2011), we did not find significant effect between BMI and mental health. Yet, the results do suggest the presence of an indirect (spill-over) effect between BMI and mental health *through* active travel.

From a policy perspective, the fact that active travel does not seem to have an effect on (later levels of) BMI should not be taken as evidence that active travel should not be stimulated for health-related reasons. The increase in physical activity as a result of active travel is already an important health benefit, irrespective of any effect on body weight. Moreover, active travel does seem to have an effect on (later levels of) mental well-being, so for that reason alone it seems wise to try and stimulate high levels of active travel in the population. In this respect, it may even be considered as part of therapies to treat depression or other mental health diseases, in which (leisure) physical activity typically already plays a role (Martinsen, 2008).

Since we used self-reported measures of active travel, BMI and mental health, the measures may not be entirely valid (e.g. due to social desirable answering) and/or reliable (e.g. due to recall bias) (Newell et al., 1999). In addition, they do not cover all relevant aspects of active travel, physical and mental health. For example, BMI is just one indicator of physical health. Other relevant aspects include blood pressure, asthma, or diabetes. In addition, percentage body fat (and especially abdominal fat) is more relevant as a measure of health, since it is more predictive of diseases than body weight (Shah and Braverman, 2012). In a similar fashion, it would relevant to consider other aspects of mental well-being, e.g. focusing on other mental health problems (e.g. anxiety) or eudaimonic aspects of well-being such as self-actualization or vitality. Regarding active travel, it should be noted that the measure covers a relatively short time frame (seven days) and does not capture the use of the bicycle. Future studies should – in order to precisely and objectively measure physical activity associated with active travel – use accelerometers along with travel behaviour diaries to enable the registration of both walking and cycling trips and their exact durations. Nevertheless, even with the present crude measurements, the analysis did reveal significant lagged (within-person) effects. Considering the potential unreliability in the measures, the reported effects should be regarded as conservative estimates of the true effects, i.e. they are more likely underestimated than overestimated.

Finally, it should be emphasized that although the longitudinal approach used in this study provides valuable insights into the extent and causality of links between active travel, physical health and subjective well-being, qualitative studies – performing in-depth interviews or focus groups – can further disentangle these relationships and potentially uncover the assumed mechanisms underlying the relationships. For example, it may be assessed to what extent physical activity, including active travel, is indeed more difficult or strenuous for individuals suffering from obesity. Perhaps other mechanisms (e.g. social stigma) also play a role in this regard. Similarly, qualitative research may potentially shed light on the mechanisms underlying the reciprocal relation between active travel and mental health.

Author statement

We hereby confirm that the work has not been previously been published or submitted elsewhere.

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Declaration of competing interest

A conflict of interest may exist when an author or the author's institution has a financial or other relationship with other people or organizations that may inappropriately influence the author's work. A conflict can be actual or potential. At the end of the text, under a subheading 'Disclosure Statement', all authors must disclose any actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations within three (3) years of beginning the work submitted that could inappropriately influence (bias) their work. Examples of potential conflicts of interest which should be disclosed include employment, consultancies, stock ownership, honoraria, paid expert testimony, patent applications/registrations, and grants or other funding.

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References

Anable, J., Gatersleben, B., 2005. All work and no play? The role of instrumental and affective factors in work and leisure journeys by different travel modes. Transport. Res. Part A 39 (2–3), 163–181.

Bak, H., Petersen, L., Sørensen, T.I.A., 2004. Physical activity in relation to development and maintenance of obesity in men with and without juvenile onset obesity. Int. J. Obes. 28 (1), 99.

Bergstad, C.J., Gamble, A., Gärling, T., Hagman, O., Polk, M., Ettema, D., Friman, M., Olsson, L.E., 2011. Subjective well-being related to satisfaction with daily travel. Transportation 38 (1), 1–15.

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. Med. Care 169–176.

Buehler, R., Pucher, J., Merom, D., Bauman, A., 2011. Active travel in Germany and the US: contributions of daily walking and cycling to physical activity. Am. J. Prev. Med. 41 (3), 241–250.

Cooper, A.R., Page, A.S., Foster, L.J., Qahwaji, D., 2003. Commuting to school: are children who walk more physically active? Am. J. Prev. Med. 25 (4), 273–276.

Da Silva, M.A., Singh-Manoux, A., Brunner, E.J., Kaffashian, S., Shipley, M.J., Kivimäki, M., Nabi, H., 2012. Bidirectional association between physical activity and symptoms of anxiety and depression: the Whitehall II study. Eur. J. Epidemiol. 27 (7), 537–546.

De Vos, J., 2018. Do people travel with their preferred travel mode? Analysing the extent of travel mode dissonance and its effect on travel satisfaction. Transport. Res. Part A 117, 261–274.

De Vos, J., 2019. Analysing the effect of trip satisfaction on satisfaction with the leisure activity at the destination of the trip, in relationship with life satisfaction. Transportation 46, 623–645.

De Vos, J., Mokhtarian, P.L., Schwanen, T., Van Acker, V., Witlox, F., 2016. Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility. Transportation 43 (5), 771–796.

Diener, E., Suh, E., Lucas, R.E., Smith, H.L., 1999. Subjective well-being: three decades of progress. Psychol. Bull. 125 (2), 276–302.

Diener, E., Wang, M.Y., 2011. Happy people live longer: subjective well-being contributes to health and longevity. Appl. Psychol.: Health Well-Being 3 (1), 1–43.

Ekelund, U., Brage, S., Besson, H., Sharp, S., Wareham, N.J., 2008. Time spent being sedentary and weight gain in healthy adults: reverse or bidirectional causality? Am. J. Clin. Nutr. 88 (3), 612–617.

Enders, C.K., Bandalos, D.L., 2001. The relative performance of full information maximum likelihood estimation for missing data in structural equation models. Struct. Equ. Model. 8 (3), 430–457.

Finkel, S.E., 1995. Causal Analysis With Panel Data (No. 105). Sage.

Flint, E., Cummins, S., 2016. Active commuting and obesity in mid-life: cross-sectional, observational evidence from UK Biobank. Lancet Diabetes Endocrinol. 4 (5), 420–435.

Flint, E., Cummins, S., Sacker, A., 2014. Associations between active commuting, body fat, and body mass index: population based, cross sectional study in the United Kingdom. BMJ 349, g4887.

Flint, E., Webb, E., Cummins, S., 2016. Change in commute mode and body-mass index: prospective, longitudinal evidence from UK Biobank. Lancet Publ. Health 1 (2), e46–e55.

Frank, L.D., Sallis, J.F., Conway, T.L., Chapman, J.E., Saelens, B.E., Bachman, W., 2006. Many pathways from land use to health: associations between neighborhood walkability and active transportation, body mass index, and air quality. J. Am. Plann. Assoc. 72 (1), 75–87.

Golubic, R., Wijndaele, K., Sharp, S.J., Simmons, R.K., Griffin, S.J., Wareham, N.J., et al., 2015. Physical activity, sedentary time and gain in overall and central body fat: 7-year follow-up of the ProActive trial cohort. Int. J. Obes. 39 (1), 142.

Hallal, P.C., Andersen, L.B., Bull, F.C., Guthold, R., Haskell, W., Ekelund, U., Lancet Physical Activity Series Working Group, 2012. Global physical activity levels: surveillance progress, pitfalls, and prospects. Lancet 380 (9838), 247–257.

Hamaker, E.L., 2012. Why Researchers Should Think" Within-Person": A Paradigmatic Rationale.

Hamaker, E.L., Kuiper, R.M., Grasman, R.P., 2015. A critique of the cross-lagged panel model. Psychol. Methods 20 (1), 102–116.

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

Hu, L.T., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equ. Model.: Multidiscipl. J. 6 (1), 1–55.

Humphreys, D.K., Goodman, A., Ogilvie, D., 2013. Associations between active commuting and physical and mental wellbeing. Prev. Med. 57 (2), 135–139.

Kroesen, M., 2019. Is active travel part of a healthy lifestyle? Results from a latent class analysis. J. Transport Health 12, 42–49.

Laverty, A.A., Mindell, J.S., Webb, E.A., Millett, C., 2013. Active travel to work and cardiovascular risk factors in the United Kingdom. Am. J. Prev. Med. 45 (3), 282–288.

Laverty, A.A., Palladino, R., Lee, J.T., Millett, C., 2015. Associations between active travel and weight, blood pressure and diabetes in six middle income countries: a cross-sectional study in older adults. Int. J. Behav. Nutr. Phys. Activ. 12 (1), 65.

Lee, I.M., Shiroma, E.J., Lobelo, F., Puska, P., Blair, S.N., Katzmarzyk, P.T., Lancet Physical Activity Series Working Group, 2012. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. Lancet 380 (9838), 219–229.

Lim, S.S., Vos, T., Flaxman, A.D., Danaei, G., Shibuya, K., Adair-Rohani, H., et al., 2013. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. Lancet 380 (9859), 2224–2260.

Lindström, M., 2008. Means of transportation to work and overweight and obesity: a population-based study in southern Sweden. Prev. Med. 46 (1), 22–28.

Loong, C., van Lierop, D., El-Geneidy, A., 2017. On time and ready to go: an analysis of commuters' punctuality and energy levels at work or school. Transport. Res. Part F 45, 1–13.

Lyubomirsky, S., King, L., Diener, E., 2005. The benefits of frequent positive affect: does happiness lead to success? Psychol. Bull. 131 (6), 803–855.

Martin, A., Goryakin, Y., Suhrcke, M., 2014. Does active commuting improve psychological wellbeing? Longitudinal evidence from eighteen waves of the British Household Panel Survey. Prev. Med. 69, 296–303.

Martin, A., Panter, J., Suhrcke, M., Ogilvie, D., 2015. Impact of changes in mode of travel to work on changes in body mass index: evidence from the British Household Panel Survey. J. Epidemiol. Community Health 69 (8), 753–761.

Martin, S.E., Mathur, R., Marshall, I., Douglas, N.J., 1997. The effect of age, sex, obesity and posture on upper airway size. Eur. Respir. J. 10 (9), 2087–2090.

Martinsen, E.W., 2008. Physical activity in the prevention and treatment of anxiety and depression. Nord. J. Psychiatr. 62 (Suppl. 47), 25–29.

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

Millett, C., Agrawal, S., Sullivan, R., Vaz, M., Kurpad, A., Bharathi, A.V., et al., 2013. Associations between active travel to work and overweight, hypertension, and diabetes in India: a cross-sectional study. PLoS Med. 10 (6), e1001459.

Morris, E.A., Guerra, E., 2015. Mood and mode: does how we travel affect how we feel? Transportation 42 (1), 25–43.

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.

Mytton, O.T., Panter, J., Ogilvie, D., 2016a. Longitudinal associations of active commuting with body mass index. Prev. Med. 90, 1–7.

Mytton, O.T., Panter, J., Ogilvie, D., 2016b. Longitudinal associations of active commuting with wellbeing and sickness absence. Prev. Med. 84, 19–26.

Newell, S.A., Girgis, A., Sanson-Fisher, R.W., Savolainen, N.J., 1999. The accuracy of self-reported health behaviors and risk factors relating to cancer and cardiovascular disease in the general population: a critical review. Am. J. Prev. Med. 17 (3), 211–229.

Oja, P., Titze, S., Bauman, A., de Geus, B., Krenn, P., Reger-Nash, B., Kohlberger, T., 2011. Health benefits of cycling: a systematic review. Scand. J. Med. Sci. Sports 21 (4), 496–509.

Paluska, S.A., Schwenk, T.L., 2000. Physical activity and mental health. Sports Med. 29 (3), 167–180.

Panik, R.T., Morris, E.A., Voulgaris, C.T., 2019. Does walking and bicycling more mean exercising less? Evidence from the U.S. and The Netherlands. J. Transport Health 15, 100590.

Panter, J.R., Jones, A.P., van Sluijs, E.M.F., 2008. Environmental determinants of active travel in youth: a review and framework for future research. Int. J. Behav. Nutr. Phys. Activ. 5 (34).

Penedo, F.J., Dahn, J.R., 2005. Exercise and well-being: a review of mental and physical health benefits associated with physical activity. Curr. Opin. Psychiatr. 18 (2), 189–193.

Pereira, S.M.P., Geoffroy, M.C., Power, C., 2014. Depressive symptoms and physical activity during 3 decades in adult life: bidirectional associations in a prospective cohort study. JAMA Psychiatr. 71 (12), 1373–1380.

Petersen, L., Schnohr, P., Sørensen, T.I.A., 2004. Longitudinal study of the long-term relation between physical activity and obesity in adults. Int. J. Obes. 28 (1), 105–112.

Pucher, J., Buehler, R., Bassett, D.R., Dannenberg, A.L., 2010. Walking and cycling to health: a comparative analysis of city, state, and international data. Am. J. Publ. Health 100 (10), 1986–1992.

Pulsford, R.M., Stamatakis, E., Britton, A.R., Brunner, E.J., Hillsdon, M.M., 2013. Sitting behavior and obesity: evidence from the Whitehall II study. Am. J. Prev. Med. 44 (2), 132–138.

Roberts, J., Hodgson, R., Dolan, P., 2011. "It's driving her mad": gender differences in the effects of commuting on psychological health. J. Health Econ. 30 (5), 1064–1076.

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

Sallis, J.F., Frank, L.D., Saelens, B.E., Kraft, M.K., 2004. Active transportation and physical activity: opportunities for collaboration on transportation and public health research. Transport. Res. Pol. Pract. 38 (4), 249–268.

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

Shah, N.R., Braverman, E.R., 2012. Measuring adiposity in patients: the utility of body mass index (BMI), percent body fat, and leptin. PloS One 7 (4), e33308.

Stavrakakis, N., de Jonge, P., Ormel, J., Oldehinkel, A.J., 2012. Bidirectional prospective associations between physical activity and depressive symptoms. The TRAILS Study. J. Adolesc. Health 50 (5), 503–508.

St-Louis, E., Manaugh, K., van Lierop, D., El-Geneidy, A., 2014. The happy commuter: a comparison of commuter satisfaction across modes. Transport. Res. Part F 26, 160–170.

Sun, Y., Liu, Y., Tao, F.B., 2015. Associations between active commuting to school, body fat, and mental well-being: population-based, cross-sectional study in China. J. Adolesc. Health 57 (6), 679–685.

Taylor, J.M., 2019. Overview and illustration of Bayesian confirmatory factor Analysis with ordinal indicators. Practical Assess. Res. Eval. 24 (4).

Teychenne, M., Ball, K., Salmon, J., 2008. Physical activity and likelihood of depression in adults: a review. Prev. Med. 46 (5), 397–411.

Voulgaris, C.T., Smart, M.J., Taylor, B.D., 2019. Tired of commuting? Relationships among journeys to school, sleep, and exercise among American teenagers. J. Plann. Educ. Res. 39 (2), 142–154.

Wanner, M., Götschi, T., Martin-Diener, E., Kahlmeier, S., Martin, B.W., 2012. Active transport, physical activity, and body weight in adults: a systematic review. Am. J. Prev. Med. 42 (5), 493–502.

Warburton, D.E., Nicol, C.W., Bredin, S.S., 2006. Health benefits of physical activity: the evidence. Can. Med. Assoc. J. 174 (6), 801–809.

World Health Organization, 2004. Promoting Mental Health: Concepts, Emerging Evidence, Practice: Summary Report.