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Understanding how accessibility influences health via active travel: Results from a structural equation model

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ABSTRACT

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. Research related to active travel typically either focuses on the determinants of active travel or its health effects. As far as the authors are aware, no studies have tried to include both sets of variables in a single empirical model. The goal of this study is to address this gap by developing and estimating a structural equation model including both spatial determinants of active travel and relevant physical and mental health outcomes. The model is estimated using aggregated data from all Dutch municipalities, 355 in total. The results indicate that the walking and cycling modal shares are consistently negatively associated with the prevalence of obesity and diabetes and positively correlated with overall physical activity. The effects are similar in size as those of sport participation. The results provide insights as to which spatial characteristics municipalities should focus on if their aim is to increase public health via active travel.

1. Introduction

There is strong evidence 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 does 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 (Lee et al., 2012), making physical inactivity the fourth leading health risk factor in Western countries (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; Van Wee and Ettema, 2016). Active travel can typically easily be incorporated in the daily routine and provides much potential to help people meet recommended physical activity levels. Even in a country like the Netherlands, which can be considered a country oriented towards active travel, as much as 30% of the trips with a distance shorter than five ilometer are made by car (CBS, 2019), which are trips that can be made by foot or bicycle.

Research related to active travel and health is largely driven by two questions: (1) what are the health benefits of active travel? and (2) what are the determinants of active travel? Multiple disciplines are involved in answering these two questions and the resulting literatures are vast. Regarding the health effects, relevant potential physical outcomes include increased total physical activity, increased fitness, reduced obesity and lower risk of heart diseases (see Oja et al., 2011, Wanner et al., 2012 and Saunders et al., 2013 for relevant reviews). Recently, there is also much interest related to the benefits of active travel in improving mental health (Humphreys et al., 2013; Martin et al., 2014; Rybarczyk et al., 2018; Song et al., 2013; St-Louis et al., 2014). With respect to the determinants of active travel much research has focused on role of the built environment (e.g. residential density, connectivity) and available bicycle and pedestrian infrastructure (Ding & Gebel, 2012). In addition, also the role psychological factors (perceived environmental characteristics, attitudes and preferences) have been explored, albeit to a lesser extent (Panter and Jones, 2010; Heinen et al., 2011).

Up till now, empirical studies either focus on the health benefits or the determinants of active travel. As far as the authors are aware, no studies have tried to include both sets of variables in a single empirical model. Such a model could reveal to what extent policy efforts (and non-policy induced changes in determinants of active travel) would

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influence relevant health outcomes via active travel. This knowledge could, for example, be used to assess the cost-effectiveness (health gains per unit of currency) of measures to stimulate the uptake of active travel. In addition, a model including both determinants and effects of active travel can reveal whether active travel is indeed the most relevant mediating factor and/or whether other forms of travel (car and public transport use) and/or behaviours that are associated with health (e.g. leisure physical activity) mainly or additionally function as such. Hence, by including both determinants and health effects of active travel and other relevant behavioural factors a more holistic 'system-level' perspective may be gained. Obviously such a perspective is relevant from a policy perspective.

The goal of this study is to address this gap by developing and estimating a structural equation model including both determinants of active travel and relevant health outcomes. The levels of active travel in terms of walking and cycling are considered as relevant mediating factors. In addition, other behavioural variables are also taken into account as mediating factors, namely the use of other travel modes (car and public transport) and health-related behaviours (e.g. smoking, leisure physical activity and total physical activity). To estimate the model aggregated data are used from all Dutch municipalities, 355 in total. As shown by the study of Rietveld and Daniel (2004) this unit of analysis is well suited to assess the influences of policy efforts (by local authorities) to stimulate active travel, in particular the use of the bicycle.

In the next section we briefly review relevant previous studies and develop a straightforward conceptual model, after which we will present the methods (Section 3) and discuss the empirical results (Section 4). Section 5 summarizes the conclusions and discusses the limitations.

2. Background and conceptual model

Much empirical research has been devoted to determining the health benefits of active travel. From 2008 onwards, we were able to identify six systematic review studies in the literature (Hamer and Chida (2008), Oja et al. (2011), Wanner et al. (2012) and Saunders et al. (2013), Kelly et al. (2014) and Dinu et al. (2019)). Overall, the conclusions reached by these review studies converge on some points, but diverge on others. Hamer and Chida (2008) conclude that active commuting is associated with an overall 11% reduction in cardiovascular risk. Oja et al. (2011), on the other hand, conclude that the evidence that active commuting leads to fitness benefits is strong, but moderate for benefits in cardiovascular risk factors, and inconclusive for all-cause mortality, coronary heart disease morbidity and mortality. More recently, the review of Kelly et al. (2014) does conclude that walking and cycling reduces all-cause mortality. In line with this, Dinu et al. (2019) also report that people engaged in active commuting had a significantly reduced risk of cardiovascular disease incidence, all-cause mortality and diabetes. Regarding effects on obesity, the evidence is weaker. Both Saunders et al. (2013) and Wanner et al. (2012) conclude that there is little evidence of the effectiveness of active transport interventions for reducing obesity.

Looking at studies that employed aggregate data, probably the most frequently cited study is the one of Bassett et al. (2008). These researchers examined the relationship between active transportation (defined as the percentage of trips taken by walking, bicycling, and public transit) and obesity rates across different countries (including USA and European countries) and found a strong inverse relationship between these variables. The relationships were not controlled, however, for possible confounding factors (e.g. leisure physical activity). Pucher et al. (2010) performed a similar analysis using city and state-level data to assess the relationships between active transportation and three health outcomes, namely the proportion of the population that satisfies the recommended norm for physical activity, the obesity rate and the diabetes rate. For all three outcomes they established significant positive relationships with active transportation: higher levels of active transportation are associated with better health. Also in this study relevant control variables were not considered though.

Turning to ecological studies of the determinants of active travel, Rietveld and Daniel (2004) developed an explanatory model to predict the share of the bicycle (of all trips taken) at the level of Dutch municipalities. In total, they consider 38 possible explanatory factors, including demographic and infrastructure-related factors. To estimate the statistical (semi-log linear) model, they used data from 103 Dutch municipalities. In general, the model showed that the bicycle share could be explained by factors that increase the attractiveness of using the bicycle (e.g. the directness of cycling routes) and factors that make the use of alternative modes of transport less attractive (e.g. parking fees). Demographic characteristics also played a role, such as the share of the population with a non-western migration background and the percentage that voted on a liberal party, both were found to negatively influence the bicycle share.

A second study, performed by Ververs and Ziegelaar (2006), showed comparable results. These researchers also specified an explanatory model to predict the mode share of the bicycle, which they estimated using data from 116 Dutch municipalities. In addition, they considered an even broader range of possible explanatory factors, distinguishing 61 factors in total, which they classified into bicycle policy indicators, traffic policy indicators, spatial and demographic characteristics and physical conditions (relief and weather conditions). The results of the (linear) regression model showed that parking costs (positive), the percentage of residents with a non-Western background and the degree of relief (both negative) had the strongest effects on bicycle use.

Given this background, the main contribution of the current study is that we simultaneously consider the spatial determinants of active transport (related to cycling infrastructure and access to destinations) as well as the relevant health effects in a single empirical model. In this model, we consider a broad set of behavioural factors as well as a broad set of health outcomes. Regarding the behavioural variables, we do not only consider bicycle use but also the use of other modes of transport and other behaviours that are related to health (e.g. tobacco use). And regarding the health outcomes, we do not only consider obesity (which is typically the focus of empirical studies, see e.g. Bassett et al., 2008) but also asthma (COPD), diabetes, heart failure, cancer and two mental health outcomes. Following this approach the integrated model allows us to distinguish the various pathways through which demographic and spatial characteristics influence relevant health outcomes via different behavioural factors. For example, there may be certain spatial or demographic characteristics that positively influence active travel, but have a negative direct effect on certain health outcomes. To the best of our knowledge previous studies did not allow an exploration of such direct and indirect effects.

To assess the direct and indirect effects of the spatial and demographic factors a straightforward conceptual model - shown in Fig. 1 - is developed. The model consists of three layers; the first captures the demographic and spatial characteristics of the municipalities. The second layer captures behavioural characteristics: the use of active modes (walking and cycling), the use of other modes (car and public transport) and other behavioural factors that influence health. And the third layer captures relevant physical and mental health outcomes. The model is based on the assumption that the spatial and demographic factors influence the behavioural factors, which, in turn, are assumed to influence the health outcomes. In addition, the demographic and spatial factors are also allowed to directly influence the considered health outcomes. In this way, both direct and indirect influences of the spatial and

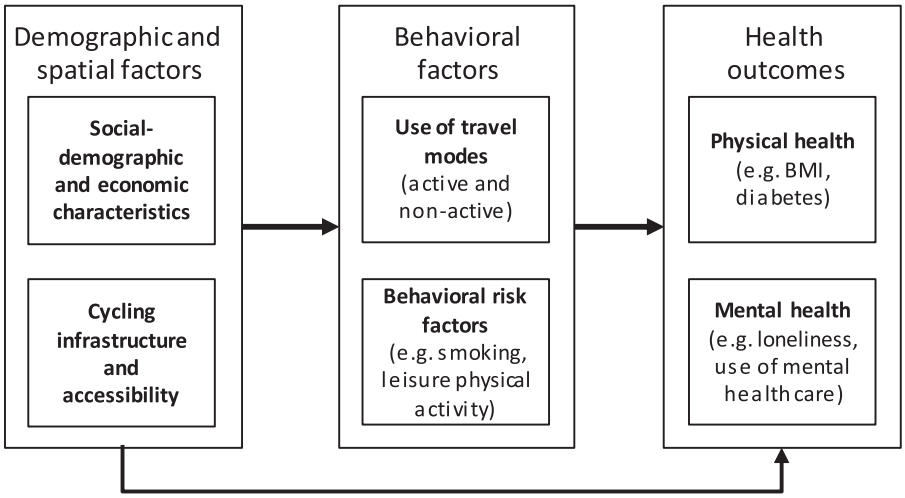

Fig. 1. A structural equation model of the effects of demographic and spatial factors on health outcomes via behavioural factors.

demographic factors can be explored and it can be assessed to what extent their effects are mediated by the included behavioural factors.

Before moving to the method, it should be noted that the present conceptualization is grafted on the data that are available and that there are obviously many other factors that influence the specified behavioural factors (e.g. meteorological/geographic conditions, psychological factors, social norms) and the health outcomes (e.g. air quality, genetic factors), which are not explicitly taken into account here. In addition the model is based on assumption that the behavioural factors influence the health outcomes and not vice versa. Recently, such reverse pathways have been shown to exist by Kroesen and De Vos (2020) who used multi-year panel. Since the present study is based on cross-sectional data, such bidirectional effects cannot be separately identified and estimated. This is an important caveat that we return to in the discussion section. Thirdly, it should be noted that the present study is based on ecological correlations, which cannot provide proof of causal relationships at the individual level. In this regard, intervention studies can provide more rigorous proof of causal relationships (Smith et al., 2017; Kärmeniemi et al., 2018; Mölenberg et al., 2019; Panter et al., 2019; Stappers et al., 2018). That being said, we believe our (correlational) study has three contributions vis-à-vis such type of studies. Firstly, intervention studies are typically focused on the effects of a single change in the built environment, e.g. a new cycling path, whereas our study captures a range of explanatory variables (related to accessibility and the cycling infrastructure). Secondly, intervention study typically focus on behavioural outcomes, i.e. changes in walking and cycling (and total physical activity), whereas our study also include the -more distant- health variables. This also allows us to compare the effects of walking/cycling (on health outcomes) with other behavioural variables (e.g. sport participation) which can yield relevant insights regarding the relative contributions. Thirdly, by including both determinants of walking/cycling and the health outcomes, both direct and indirect effects may be explored between the spatial explanatory variables and the health outcomes. For example, it may be that certain built environment characteristics have positive effects on active travel (leading to health benefits) but direct negative effects on health. By revealing these indirect and direct effects, a more holistic 'system-level' perspective may be gained as to how the built environment influences our health.

3. Method

3.1. Data and operationalization

To operationalise and test the conceptual model aggregated data are used from all Dutch municipalities, 355 in total. The Netherlands has 17.3 million residents leading to an average of 48.6 thousand inhabitants per municipality. The data related to the behavioural and health outcomes originate from large-scale nation-wide surveys, in particular the national travel survey (2017) and the national health survey (2016), with 38,127 and 457,153 respondents, respectively. This allows the calculation of reliable estimates at the municipality level. Table 1 presents an overview of the variables used to operationalise the concepts in Fig. 1, including their descriptive statistics and the sources from which the respective data originate.

In the analysis, the (average) age, immigrant background, household income and unemployment rate are used as relevant demographic and economic characteristics. As policy-related determinants of active travel (and cycling in particular) three variables related to the cycling infrastructure are considered, namely the directness of cycling routes, the right of way for cyclists at roundabouts and the relative amount of dedicated cycling lanes. The values of these variables were calculated by the Dutch cycling association at the level of municipalities. Next to the these variables, several land use and accessibility measures were included, namely the density, diversity of land use, and the (mean) distance to four relevant locations, namely primary schools, secondary schools, grocery stores and railway stations. These variables are measured by computing the average distance (by road) of all residents of a municipality to the nearest location in question.

Mode use was measured by calculating the relative trip frequency that each mode is used. Regarding active travel it can be observed that levels are generally high, on average, 27.2% of all trips are made by bicycle and 17.0% on foot. Yet, there is also considerable variation across municipalities, especially regarding bicycle use which ranges from 8.1% to 54.4% in the dataset. Next to mode use, two additional behavioural variables are considered, namely sport participation and smoking behaviour (tobacco use). Sport participation is operationalised as the percentage of the adult population (aged 19 and older) that

Table 1
Descriptive statistics of the Dutch municipalities ($N = 355$).

Factor group	Variables	Mean	SD	Source
Demographic and economic characteristics	Age (years)	43.2	2.3	a
	People with a non-Western immigrant background (%)	7.4	5.9	a
	Disposable household income (K euro)	45.1	5.7	a
	Unemployment rate (%)	3.4	0.6	a
Cycling infrastructure, diversity and accessibility	Directness of cycling routes (compared to route by car) (normalised score on 1–5 scale)	2.4	0.7	b
	Right of way for cyclists on roundabouts (normalised score on 1–5 scale)	4.0	1.6	b
	Dedicated cycling lanes in urban areas (normalised score on 1–5 scale)	2.0	1.0	b
	Density (average address density per km^2) (normalised score on 1–5 scale)	2.6	1.1	a
	Diversity (relative amount of jobs compared to residences) (%)	49.2	6.9	c
	Distance to primary school (km)	0.8	0.2	a
	Distance to high school (km)	3.2	2.0	a
	Distance to grocery store (km)	0.9	0.3	a
	Distance to railway station (km)	7.0	7.1	a
Modal split	Cycling trips (%)	27.2	6.0	d
	Walking trips (%)	17.0	3.2	d
	Car driver trips (%)	35.2	5.2	d
	Train trips (%)	1.5	1.2	d
	Bus, tram or metro (BTM) trips (%)	1.4	1.5	d
Behavioural risk factors	People engaged in sports (%)	50.8	6.0	e
	People who smoke tobacco (%)	18.7	3.2	f
	People who satisfy physical activity norm of Dutch health council (%)	63.7	4.7	f
Physical health outcomes	People who are overweight (BMI > 25) (%)	50.2	4.6	f
	People diagnosed with COPD or asthma (%)	4.3	0.7	g
	People diagnosed with heart failure (%)	3.7	0.7	g
	People diagnosed with diabetes (%)	2.3	0.5	g
	People diagnosed with cancer (%)	3.5	0.6	g
Mental health outcomes	People treated for mental health problems (%)	8.6	1.4	g
	People with high score on the loneliness scale (%)	41.0	4.4	f

a: Municipality data (2017) - Statistics Netherlands (CBS).
b: Election of cycling municipality (2018) - Cyclists' association (Fietsersbond).
c: Municipality data (2017) - Statistics Netherlands (CBS), measure developed by ABF Research.
d: National Travel Survey (2017) - Statistics Netherlands (CBS).
e: Knowledge and Information System Sport (KISS) (2017) - Sport Unions and NOC*NSF.
f: National Health Monitor (2016) - National Institute for Public Health and the Environment (RIVM).
g: Medical diagnoses based on medicine use (2017) - Vektis (private company handling health care data).

engages in sports at least once a week and tobacco use as the percentage of the population that uses tobacco at least sometimes. Unfortunately, no data was available related to diet (e.g. fruit and vegetable intake).[1]

The physical health outcomes include the percentages of the population in the respective municipalities that meet the (WHO's) physical activity norm (150 min moderate to vigorous physical activity per week) (WHO, 2010), that are overweight (i.e. have a body-mass index over 25), and are diagnosed with COPD/asthma, heart failure, diabetes and cancer. The mental health outcomes include the percentage of the population that receives treatment for mental health problems and the percentage of the population that has a high score on a (11-item) scale measuring emotional/social loneliness developed by De Jong-Gierveld and Kamphuls (1985).

3.2. Motivation of the research unit (municipalities)

To empirically assess the relationships as specified in the conceptual model in Fig. 1 ideally individual level data should be used to prevent the so-called ecological fallacy, which refers to the problem that correlations at the aggregate level are not necessarily reflective of (and typically larger than) those at the disaggregate level (we will also discuss this issue in the concluding section). Related to this, two other problems associated with the use of an aggregate unit of analysis are the modifiable areal unit problem (MAUP) and the uncertain geographic context problem (UGCoP) (Kwan, 2012). The first problem (MAUP), which has received a lot of attention in geographic research, refers to the notion that the (arbitrary defined) zoning scheme and/or geographic scale of the areal units used can result in different estimates between the variables involved in the analysis. The second problem (UGCoP), put forward by Kwan (2012), is related but distinct from this problem and refers to the notion that the chosen geographic delineations (e.g. neighbourhoods) deviate from the true geographic context which give rise to the effects on the outcomes under investigation.

Against this background, the following considerations have played a role in selecting the municipal level as the research unit. Obviously, the main reason is that data at the municipality level are readily available (or can be calculated easily), which would not be the case for other zoning schemes. Adding to this in our particular case, the use of municipalities as research units has allowed us to integrate two large national datasets (related to mobility and health), which otherwise could not have been linked (because different participants were involved). Secondly, related to the UGCoP, the municipality level arguably overlaps strongly with the 'true' geographical context at which causal effects may be expected to occur. Regarding the main explanatory variables of interest, the relative shares of walking and cycling, an analysis of the disaggregate data of the national travel survey (of the respective year, i.e. 2017) reveals that 82% of the cycling trips (with an average distance of 3.4 km) and 86% of the walking trips (with an average distance 1.5 km) have an origin and destination within the boundaries of the municipality. Hence, most of the active travel occurs within municipalities, which is also logical considering the average size of a municipality, which is 9.5 km^2 (roughly 10*10 km), whereas the built-up area is even smaller, making active modes an attractive option for many local trips. Finally, while municipalities are sufficiently large to capture the active travel patterns, the areas are still small enough to retain much of the variance in the (independent) variables (compared to e.g. Bassett et al., 2008 who performed their analysis at the country level). Fig. 2 provide the shares of walking and cycling across the (355) municipalities, which

[1] Obviously dietary intake is an important variable to consider in explaining health outcomes (e.g. obesity). It should be noted, however, that the effects of active travel on health are only biased insofar the dietary intake is also associated with levels of active travel. Hence, its exclusion does not necessarily lead to biased parameter estimates, but ideally this should be explored in future research.

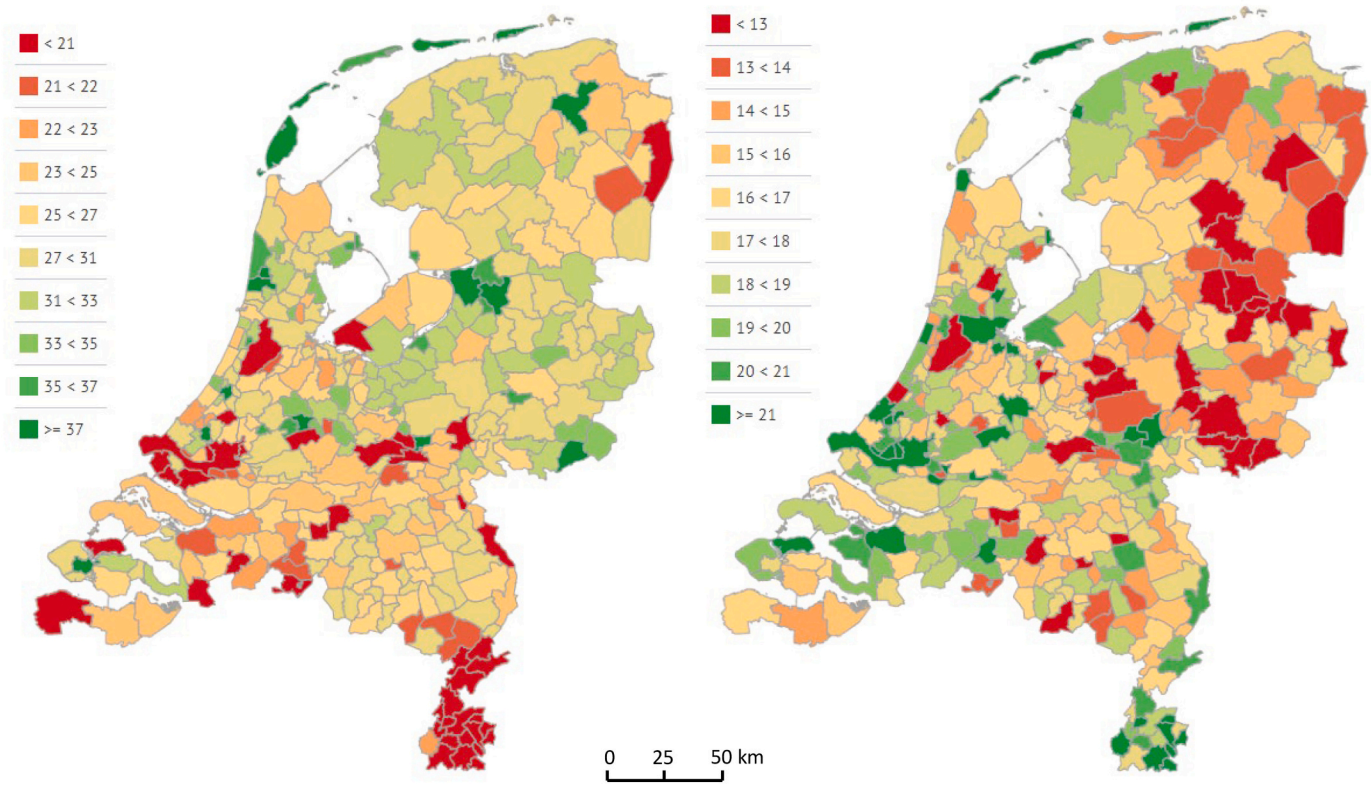

Fig. 2. Modal shares (% of trips by the respective mode) of cycling (left) and walking (right) across the 355 Dutch municipalities.

shows there is indeed quite some variation. This variation is required to assess effects on the considered health outcomes.

3.3. Model specification and estimation

The developed conceptual model (Fig. 1) is operationalised as a structural equation model, which is a statistical modelling technique that can be used to test complex causal structures (i.e. models with direct and indirect effects between variables) including latent variables to measure psychological constructs, see Golob (2003) for an explanation of the method in transportation research and Ding and Lu (2016); Najaf et al. (2018); Van Acker et al. (2007) for applications of the method in transport geography. In the present application no latent variables are included, all model variables (Table 1) are specified as observed variables.

In line with the conceptual model the spatial and demographic factors are specified as exogenous variables and assumed to influence both the behavioural variables and the health outcomes. The behavioural variables are hypothesized to (partially) mediate the effects of the spatial and demographic factors on the health outcomes. The error terms of the endogenous variables at the same level of the causal chain (so at the level of behavioural and health outcomes respectively) are allowed to freely correlate. The model is estimated in MPlus 8.4 using the robust maximum likelihood estimator, which corrects the estimates and standard errors for possible deviations from (multivariate) normality (Bandalos, 2014).

To obtain a parsimonious model, insignificant direct effects are deleted in a stepwise fashion through a process of backward elimination. Any insignificant direct effects ($p < 0.05$) are deleted in this iterative process. All correlations between error terms are retained (even when insignificant) to ensure proper statistical control. In the end, 166 direct paths are deleted. The resulting model yields a good model fit ($\chi^2 = 249.6$, df = 166, $p = 0.00$, CFI = 0.981, RMSEA = 0.038) according for conventional criteria (see Hu and Bentler, 1999).

4. Results and discussion

4.1. Correlations

Before turning to the model estimates it is interesting to explore the bivariate relationships in the data and highlight some patterns. Table 4 in the Appendix A presents the observed correlation matrix between all variables in the model.

One consistent pattern is that income correlates strongly and negatively with all health outcomes, while unemployment rate correlates positively (albeit less strongly) with the health variables (implying negative health effects). These results are well in line with prior research on the effects of these variables on health (Fiscella and Franks, 2000; Bartley et al., 2004).

Regarding the modal shares the correlation pattern is mixed, with some modes correlating negatively, indicating substitution, and some positively, indicating complementarity. For example, the bicycle and car

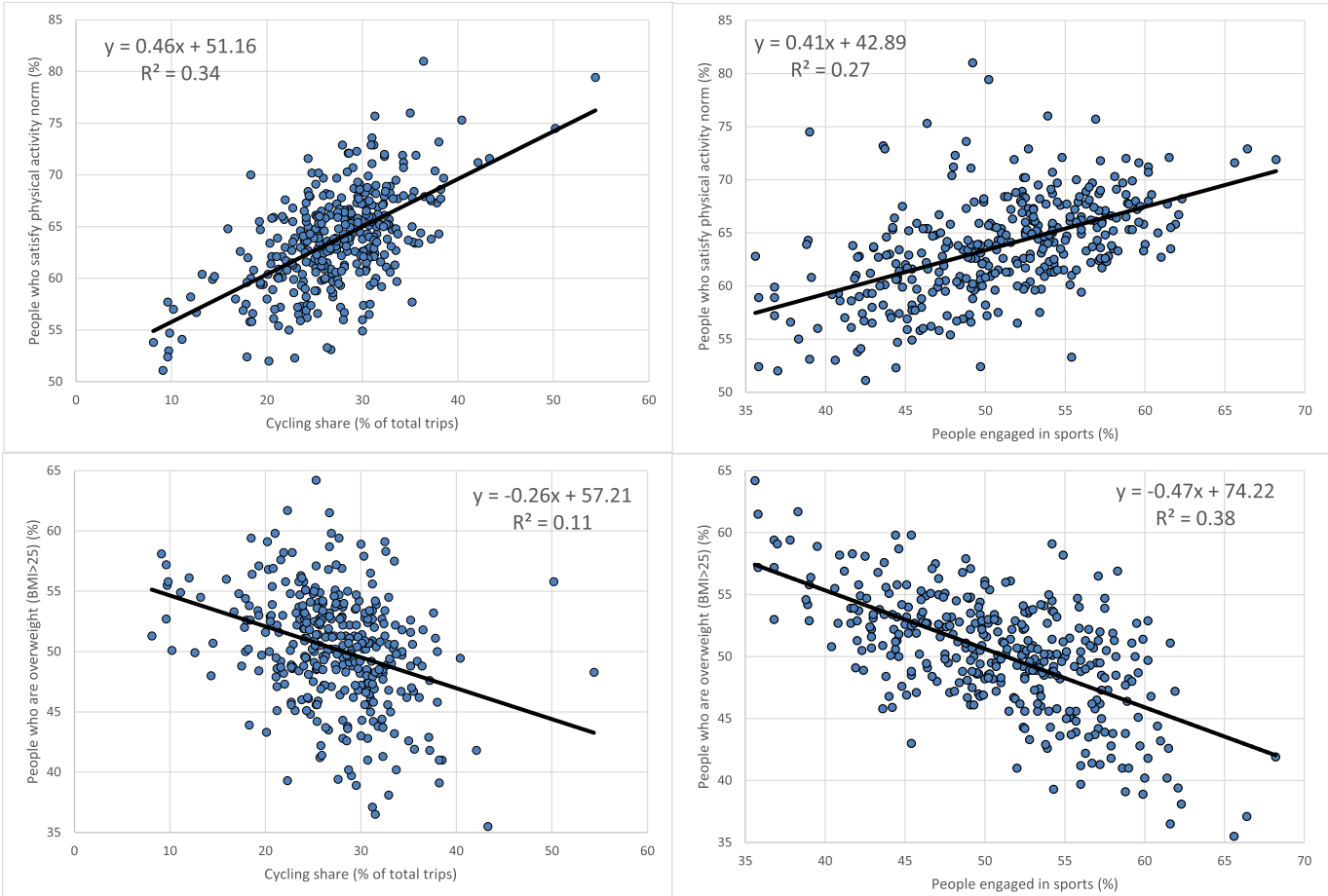

Fig. 3. Scatterplots between cycling share and sport participation and percentage that satisfies the PA norm and the obesity rate.

modal shares correlate strongly negatively (−0.69) while the walking and Bus, Tram and Metro (BTM) shares correlate positively (0.38). Hence, in the Netherlands the bicycle and car seem to act as substitutes for one another, while walking complements BTM use. This latter finding makes intuitive sense, because walking is the most important access and egress mode for BTM.

Regarding the correlations between the behavioural factors and the health outcomes, tobacco use is, as is to be expected, positively correlated with the health variables, i.e. leading to increased incidence of especially cancer. Another interesting finding is that the pattern of correlations between sport participation and the health outcomes (generally positive) is very similar to the one of the bicycle modal share and the health outcomes. To examine these correlations in some more detail Fig. 3 presents the scatterplots between participation in sports and the bicycle modal share, on the on hand, and two of the health-related factors, on the other, namely the percentage that satisfies the physical activity norm and the obesity rate. It can be seen that both behaviours correlate strongly with the percentage that satisfies the physical activity norm (as established by the WHO). For each percentage increase in the cycling modal share, the percentage that satisfies the physical activity norm increases by 0.46%. The effect of participating in sports is similar in size, but somewhat smaller (0.41). For the obesity rate this pattern in reversed. Here participation in sports has a somewhat larger (negative) correlation than the cycling modal share. Interestingly, sport participation is positively correlated with bicycle use (0.32), indicating that these different forms of physical activity complement (rather than substitute) each other, or are both positively influenced by a third factor, such as the genetic inclination to be physically active (Pérusse et al., 1989).

Finally, the correlations among the health outcomes are all positive, with the exception of the percentage that satisfies the physical activity norm, which is, as to be expected, negatively correlated with the other health factors. Again, the existence of these correlations is intuitively plausible, as it is likely that common factors contribute to explaining them, e.g. lifestyle factors or socio-demographic characteristics like age, income and education level. In addition, the health factors may directly impact one another, for example, it is well-established that obesity is associated with increased risk of diabetes, heart failure and cancer (Carbone et al., 2017; Lazar, 2005; Wolin et al., 2010).

While these bivariate correlations already provide interesting and plausible insights, to properly estimate the unique effects of the explanatory variables on the health outcomes, they should be controlled for the correlations that exists among the factors. This is achieved by the estimated structural equation model, which is discussed in the following.

4.2. Model results and discussion

Table 2 presents the standardized direct effects between the model variables as well as the correlations between the error terms of the endogenous variables. In the following the most important findings are highlighted.

Table 2
Standardized direct effects between exogenous and endogenous variables and correlations between error terms of endogenous variables.

	Endogenous variables														
	Mode use					Health-related behaviours			Physical health					Mental health	
	Cycling	Walking	Car	Train	BTM	Sport	Smoking	PA norm	Over-weight	COPD/ Asthma	Heart failure	Diabetes	Cancer	Mental health care	Loneliness
Exogenous variables															
Age (years)	−0.374		0.353					0.229			0.318	0.509	0.295		0.260
Share of non-Western immigrant background (%)	−0.390	−0.195		0.476	0.718			−0.183		−0.319		−0.200		−0.263	0.321
Disposable household income (Keuro)		−0.187			0.126	0.544	−0.352	0.194	−0.388	−0.299	−0.270	−0.273	−0.373	−0.157	−0.150
Unemployment rate (%)					0.115		0.376			0.154	0.328		0.238	0.465	0.137
Directness of cycling routes	0.078	−0.155												−0.115	
Right of way for cyclists on roundabouts											−0.084				
Dedicated cycling lanes in urban areas												−0.083		0.079	
Density						0.208				0.257				0.196	0.138
Diversity	0.165	−0.175				0.157		0.247	−0.084						
Distance to primary school (km)		−0.178	0.147					−0.110		−0.179					
Distance to high school (km)	−0.168		0.154												
Distance to grocery store (km)		−0.144					−0.094								
Distance to railway station (km)				−0.362	0.342										
Endogenous variables															
Cycling share (%)									−0.181			−0.247			−0.165
Walking share (%)	−0.111								−0.185		−0.137	−0.126	−0.123		0.109
Car share (%)	**−0.754**	**−0.375**										−0.216			
Train share (%)	**0.165**	0.043	**−0.293**						−0.303	0.107	−0.089			0.194	
Bus, tram or metro (BTM) share (%)	**−0.200**	**0.162**	−0.100	−0.086							−0.109				
Sport participation (%)	**0.323**	0.048	**−0.242**	**0.164**	0.008				−0.291	−0.225	−0.135	−0.205			−0.231
People who smoke tobacco (%)	−0.017	0.024	−0.055	−0.038	0.017	**−0.358**									
People that satisfy the PA norm (%)	**0.681**	−0.006	**−0.573**	**0.149**	−0.068	**0.527**	−0.063				−0.176	−0.160	−0.204		
People diagnosed with COPD or Asthma (%)									0.075						
People diagnosed with heart failure (%)									**0.331**	**0.298**					
People diagnosed with diabetes (%)									0.089	0.072	**0.171**				
People diagnosed with cancer (%)									**0.377**	0.060	**0.481**	**0.371**			
People treated for mental health problems (%)									0.076	**0.570**	**0.299**	0.092	0.079		
People with high score on loneliness scale (%)									**−0.124**	**0.176**	0.031	0.024	−0.082	−0.019	
R-square	0.252	0.301	0.262	0.466	0.534	0.343	0.436	0.130	0.578	0.357	0.537	0.686	0.732	0.423	0.581

Note: All shown effects as well as correlations in bold are significant at 5% level.

Table 3
The (total) indirect effects between the socio-demographic and spatial factors and the health factors.

	Overweight	COPD/Asthma	Heart failure	Diabetes	Cancer	Mental health care	Loneliness
Age (years)	0.068		−0.040	−0.021	−0.047		0.062
Share of a non-Western immigrant background (%)	−0.111	0.051	−0.117	0.100	−0.021	0.092	0.087
Disposable household income (Keuro)	−0.122	−0.122	−0.095	−0.118	−0.165		−0.147
Unemployment rate (%)			−0.013		0.050		
Directness of cycling routes	0.015		0.021		0.019		−0.030
Right of way for cyclists on roundabouts							
Dedicated cycling lanes in urban areas							
Density	−0.061	−0.047	−0.028	−0.043	−0.039		−0.048
Diversity	−0.043	−0.035	−0.041	−0.090	−0.058		−0.083
Distance to primary school (km)	0.033		0.044	0.008	0.044		−0.019
Distance to high school (km)	0.031			0.008			0.028
Distance to grocery store (km)	0.027		0.020	0.018	0.005		−0.016
Distance to railway station (km)	0.110	−0.039	−0.005		0.025	−0.070	

Note: all shown effects are significant at 5% level.

Turning first to the determinants of active mode use, the directness of the cycling routes is found to be positively associated with the cycling rate (0.078), yet, correlates negatively with the walking share (−0.155). A similar pattern is found for the level of diversity, which is positively associated with the share of cycling trips (0.165) but negatively with the walking share (−0.175). Surprisingly, the other variables related to cycling infrastructure were not found to be significant.

Regarding the accessibility variables, the results show that the distance to primary schools correlates negatively with the walking share (−0.178), while the distance to high schools correlates negatively with the cycling share (−0.168). It may be speculated that when these distances increase parents will more likely to drop their children of by car rather than walking them to school or letting them cycle to school (when they are in high school). Significant effects are also revealed between the built environment variables and engagement in sport. For example, density is positively associated with sport participation (0.208). This may be due to the fact that dense urban environments generally offer people more opportunities at an acceptable distance to engage in (a variety of) sport activities. Interestingly, density does not have significant effects on the shares of walking and cycling. Even tough density is positively correlated with the walking share (−0.33, see Table 4 in the Appendix A) this effect is 'crowded out' by other spatial variables that are more strongly correlated with the walking share, specifically the average distance to primary schools (note that this variable is also highly correlated with density, −0.66).

Regarding the health effects of mode use, the walking and cycling shares are negatively correlated with the shares of the population that are overweight and diagnosed with diabetes. In addition, the walking share is also negatively correlated with the incidence of health failure and cancer. With respect to COPD/asthma no significant effects are found. It may be speculated that the exposure to pollutants (particular matter, nitrogen dioxide) associated with walking and cycling outside (especially in urban environments) counters the positive health benefits, although earlier studies found the positive impacts of exercise to more than compensate for this intake of pollutants effect, at least in the case of cycling (e.g. De Hartog et al., 2010). On the other hand, this interpretation fits with the finding that engagement in sport does have an expected negative effect on COPD/asthma. Overall, the effects of the active mode variable are similar in size as the effects of sport participation on the health outcomes.

Regarding mental health, it can be observed that the cycling share is negatively related with the level of loneliness (−0.165). Surprisingly, however, the walking share is positively linked with loneliness (0.109). Sport participation is again negatively associated with loneliness (−0.231). It may be speculated that the effects of sport participation are due to the (often) social nature of this activity, which obviously holds to a lesser extent for walking and cycling. And it could be that lonely people more often take a walk.

The correlations between the error terms of the behavioural variables also provide relevant insights. Here, it can be observed that, while the cycling share is strongly correlated with the portion that satisfies the physical activity norm (0.681). The correlation with cycling is even stronger than the correlation with sport participation (0.527). Interestingly, the percentage that meets the physical activity norm is also negatively correlated with the share of the car (−0.573), which also makes sense given that the car and cycling shares are also negatively correlated with one another (−0.754). As mentioned above, this indicates that these modes act as substitutes of each other (rather than complements). Finally, sport participation is also positively correlated with the cycling share (0.323), indicating that cycling does not deter from other forms of leisure physical activity, which is also consistent with previous empirical evidence from longitudinal studies (Sahlqvist et al., 2012; Laeremans et al., 2017).

The results are also informative as to whether the considered behavioural variables are indeed the most relevant mediating variables in the relation between the built environment and health. In this regard, it can be observed that several direct effects remain, of which the strongest are linked to density. In particular, density is positively associated with COPD/asthma prevalence (0.257), mental health care use (0.196) and the level of loneliness (0.138). Regarding COPD/asthma, (again) a plausible explanation is that exposure to pollutants (particulate matter, nitrogen dioxide) is higher in dense urban regions compared to rural ones. The negative impact of density on mental health care used might be explained by residential self-selection: people who need such care might prefer to live in dense urban areas, so that mental health care (and other destinations) are nearby. But all these explanations are highly speculative, and need further research.

Looking at the R-square values (presented in the bottom row of Table 2), it can be observed that the spatial and demographic factors can explain substantial portions of the variance in the behavioural variables (with values ranging from 0.130–0.534), while the portions of explained variance in the health factors are even higher (with values ranging from 0.423–0.732). For example, the model can explain 68.6% of the variance in the diabetes rate and 73.2% of the variance in the cancer prevalence rate. This makes the model suited for predictive purposes (at the aggregate level).

The direct effects also allow the calculation of the (total) indirect effects between the socio-demographic and spatial factors, on the one hand, and the health factors on the other(respectively, the first and third layer of the conceptual model, see Fig. 1). Table 3 presents these effects.

Several indirect effects are sizeable and therefore noteworthy. Firstly, it is interesting to note that the indirect effects of income on the various health outcomes are sizeable. Looking at the direct effects (Table 2) it can be concluded that these indirect effects are mainly due to the positive effect of income on sport participation. Secondly, density and diversity both have negative indirect effects on the prevalence of the

various health conditions. Here as well, the effects are mainly due to the positive effect of these variables on sport participation, but also on the cycling share.

5. Conclusions and discussion

In this paper a structural equation model is estimated including spatial, demographic and behavioural factors as well as relevant physical and mental health outcomes. The model is estimated using data from an aggregated unit of analysis, namely Dutch municipalities (355 in total). The results provide insights as to which spatial characteristics (related to accessibility and cycling infrastructure) municipalities could focus on, if their aim is to increase health via active travel. The model shows that decreasing the (mean) distances to schools will sort the most effect. The importance of decreasing distances to schools goes against the current trend in the Netherlands to merge smaller schools into larger ones, which generally results in lower accessibility. We also found the directness of the cycling routes and level of diversity correlated positively with the cycling rate, and that built environment variables such as density are correlated with engagement in sport activities. Walking and cycling shares are negatively correlated with the portions of the population that are overweight and are diagnosed with heart failure, diabetes and cancer, overweight and diabetes.

Although this is not the case in the present study, density is typically found to increase active mode use, supporting policy recommendations to increase densities to stimulate active mode use. As shown by this study, however, such recommendations should be made with care, as density may also negatively influence health via other pathways. But it is too early to conclude that building in high densities therefore is not recommended. First of all, the evaluation of such policies should be based on all important effects, not only on health effects, other relevant effects being environmental impacts, land take, safety, accessibility, preferences of citizens, firms and other organizations, and costs. Limiting ourselves to health effect only, we do not yet know why a higher density is correlated with unfavourable scores on the health outcomes. For example, it may be that unhealthy people are more likely to live in compact cities, so that health care and other activity locations are relatively accessible. And it could be that higher densities itself are not the main problem, but more the way of compact building. For example, if the current way of building in high densities would result in higher noise levels and concentrations of pollutants, this could negatively influence health. But less car oriented forms of compact building could result in lower, not higher noise and pollution levels than other forms of urbanization. And it could be that municipalities with higher densities are larger cities, and that the negative effects on health are correlated with the size of the urban area, not the densities itself. It is therefore too early to recommend not to build compactly for health reasons. From a scientific perspective, it is important to better understand the underlying pathways and try and identify the variables that act as relevant mediators. A growing body of literature suggests that the impact of built environment characteristics (such as densities) on travel behaviour (and next health) is non-linear (Tao et al., 2020), and that threshold values for densities exist (e.g. Wali et al., 2021). Because densities vary strongly between, for example, USA, European and Asian cities, context probably plays a strong role in the health impacts of densities via multiple complex routes, such as via travel behaviour and exposure to pollutants.

Building upon the debate on densities in the previous paragraph a first avenue for further research we suggest is to further study the impact of densities on travel behaviour and health explicitly exploring specific geographical contexts therefore is recommended. Another relevant research direction relates to the assumed directions of causation. In line with the common conceptualization we assumed that active travel (and the other behavioural factors) influence the health outcomes and not vice versa. Recent research has shown, however, that this assumption may not be tenable and/or that bidirectional relationships may exist between active travel and health (Kroesen and De Vos, 2020). To properly explore such relationships longitudinal data should be used in combination with appropriate statistical models (e.g. cross-lagged panel models). The authors aim to explore this research direction (at the level of municipalities) in the future.

Another important limitation of the present study is that the ecological correlations presented here are suggestive of (causal) relationships at the individual level, but do not provide definitive proof of them. In fact, the correlations at the aggregate unit of analysis (here municipalities) may be very different from those that exist at the individual level, a point which is nicely illustrated by Robinson (2009). Nevertheless, the 'aggregation bias' only arises when certain conditions are met and, as noted by Hammond (1973), information about the social processes that operate may be used to assess whether these conditions are met or not. For example, regarding mental health 'selection by the dependent variable' seems likely; certain spatial characteristics (like density) may contribute to poor mental health, but the mentally ill may also be attracted by areas with those characteristics (as discussed above), resulting in a positive aggregate-level correlation. However, regarding the relationships between the behavioural factors (the modal shares and sport participation) and the health outcomes, such selection processes are less likely. People will more likely be attracted to a municipality because cycling conditions are good, not because many people actually cycle. In this respect, the observation that the direct effects of sport participation on the health outcomes, which are well supported by evidence from randomised controlled trials (Lin et al., 2015), are similar in size as those of the cycling modal share on the health outcomes, also lends support to the validity of the results. In the end, the best way to address this limitation is by studying individual-level data. In this regard, an important recommendation is to also include (several) health-related outcomes in national mobility surveys.

Finally, while the present study included characteristics that capture the attractiveness of using active modes, future studies could focus on factors that make the use of motorised modes, and in particular the car, less attractive. For example, previous research has shown that parking costs has a strong positive effect on cycling levels (Rietveld and Daniel, 2004; Ververs and Ziegelaar, 2006). It would be relevant to consider such factors in future research and, in line with this finding, also consider more recent measures that are taken by cities around the world (and also in the Netherlands) to reduce the attractiveness of the car simply by providing less room for car, for example by closing roads, implementing car-free neighbourhoods or reducing the number of parking spots. It would be worthwhile to collect data on such measures at a city (municipality) level and assess the effects of such measures in practice, not only in terms of increased active mode use, by also in terms of increased public health.

To conclude, the present study has added to our understanding of how active travel influences various health conditions and it, in turn, how level of active travel are affected by relevant characteristics related to the built environment. A key contribution of this approach is that it allows an exploration of the direct and indirect effects of urban characteristics on various health outcomes.

Author statement

Maarten Kroesen: Data collection, study conception and design, literature search and review, analysis and interpretation of results, manuscript writing; Bert van Wee: Manuscript writing; manuscript editing; all authors read and approved the final manuscript.

Appendix A

Table 4
Observed correlation matrix of the model variables.

		s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	b1	b2	b3	b4	b5	b6	b7	b8	h1	h2	h3	h4	h5	h6	h7
s1	Age (years)	1.00																											
s2	People with a non-Western immigrant background (%)	-0.43	1.00																										
s3	Disposable household income (K euro)	-0.01	-0.18	1.00																									
s4	Unemployment rate (%)	-0.12	0.64	-0.54	1.00																								
s5	Directness of cycling routes (compared to route by car) (normalised score on 1-5 scale)	0.05	-0.19	0.08	-0.10	1.00																							
s6	Right of way for cyclists on roundabouts (normalised score on 1-5 scale)	-0.05	0.06	0.17	-0.12	0.01	1.00																						
s7	Dedicated cycling lanes in urban areas (normalised score on 1-5 scale)	-0.26	0.37	0.19	0.13	-0.09	0.13	1.00																					
s8	Density (average address density per km2) (normalised score on 1-5 scale)	-0.39	0.77	-0.12	0.54	-0.17	0.05	0.42	1.00																				
s9	Diversity (relative amount of jobs compared to residences) (%)	-0.51	0.25	-0.04	0.02	0.03	0.05	0.14	0.20	1.00																			
s10	Distance to primary school (km)	0.38	-0.48	0.03	-0.23	0.13	-0.05	-0.30	-0.66	-0.17	1.00																		
s11	Distance to high school (km)	0.27	-0.46	0.05	-0.33	0.07	-0.03	-0.23	-0.63	-0.22	0.52	1.00																	
s12	Distance to grocery store (km)	0.15	-0.43	0.05	-0.22	0.16	-0.10	-0.25	-0.59	-0.05	0.70	0.42	1.00																
s13	Distance to railway station (km)	0.19	-0.32	-0.06	-0.29	0.10	-0.15	-0.18	-0.41	-0.06	0.29	0.35	0.21	1.00															
b1	Cycling share (% of total trips)	-0.34	-0.08	0.08	-0.13	0.21	0.03	0.09	0.05	0.28	-0.15	-0.20	-0.02	0.02	1.00														
b2	Walking trips (%)	-0.03	0.38	-0.35	0.32	-0.23	-0.03	0.12	0.33	-0.11	-0.34	-0.18	-0.41	0.02	-0.20	1.00													
b3	Car driver trips (%)	0.42	-0.36	0.11	-0.21	-0.02	-0.02	-0.23	-0.39	-0.19	0.41	0.35	0.32	0.04	-0.69	-0.40	1.00												
b4	Train trips (%)	-0.29	0.60	-0.09	0.43	-0.16	0.15	0.30	0.53	0.19	-0.33	-0.37	-0.32	-0.50	0.07	0.21	-0.37	1.00											
b5	Bus, tram or metro (BTM) trips (%)	-0.19	0.66	-0.14	0.44	-0.10	0.01	0.19	0.39	0.07	-0.21	-0.15	-0.27	0.10	-0.23	0.38	-0.26	0.25	1.00										
b6	People engaged in sports (%)	-0.10	0.08	0.52	-0.22	0.10	0.20	0.24	0.19	0.16	-0.17	-0.22	-0.08	-0.21	0.32	-0.12	-0.21	0.21	-0.03	1.00									
b7	People who smoke tobacco (%)	-0.11	0.35	-0.56	0.60	-0.16	-0.16	0.03	0.29	0.06	-0.17	-0.17	-0.21	-0.02	-0.07	0.31	-0.20	0.17	0.28	-0.47	1.00								
b8	People who satisfy physical activity norm of Dutch health council (%)	0.16	-0.18	0.20	-0.20	0.16	0.04	0.07	-0.07	0.07	-0.04	-0.05	-0.02	0.06	0.59	-0.13	-0.38	0.00	-0.17	0.52	-0.20	1.00							
h1	People who are overweight (BMI>25) (%)	0.24	-0.20	-0.46	0.08	-0.02	-0.20	-0.30	-0.25	-0.21	0.19	0.20	0.15	0.20	-0.33	-0.04	0.38	-0.40	-0.08	-0.61	0.26	-0.35	1.00						
h2	People diagnosed with COPD or asthma (%)	-0.04	0.16	-0.48	0.38	-0.15	-0.05	0.04	0.27	0.02	-0.24	-0.16	-0.20	-0.14	-0.18	0.23	0.02	0.15	0.04	-0.39	0.35	-0.30	0.29	1.00					
h3	People diagnosed with heart failure (%)	0.33	-0.05	-0.50	0.38	0.01	-0.24	-0.17	-0.06	-0.20	0.17	0.04	0.10	0.00	-0.35	0.03	0.31	-0.12	-0.05	-0.51	0.33	-0.34	0.61	0.47	1.00				
h4	People diagnosed with diabetes (%)	0.61	-0.33	-0.39	0.09	0.02	-0.14	-0.39	-0.32	-0.37	0.28	0.25	0.12	0.19	-0.43	0.05	0.40	-0.30	-0.09	-0.54	0.19	-0.27	0.55	0.26	0.58	1.00			
h5	People diagnosed with cancer (%)	0.27	0.09	-0.67	0.50	-0.03	-0.21	-0.21	0.00	-0.19	0.08	-0.01	0.04	0.02	-0.35	0.15	0.21	-0.07	0.11	-0.64	0.54	-0.41	0.66	0.43	0.77	0.66	1.00		
h6	People treated for mental health problems (%)	-0.07	0.37	-0.39	0.59	-0.22	-0.04	0.19	0.42	0.00	-0.24	-0.26	-0.24	-0.30	-0.19	0.24	-0.05	0.39	0.22	-0.21	0.42	-0.26	0.11	0.67	0.41	0.14	0.38	1.00	
h7	People with high score on the loneliness scale (%)	0.13	0.46	-0.47	0.57	-0.18	-0.08	0.07	0.36	-0.13	-0.16	-0.16	-0.27	-0.07	-0.41	0.43	0.04	0.23	0.35	-0.38	0.40	-0.28	0.19	0.44	0.38	0.28	0.45	0.40	1.00

Note: all correlations smaller than −0.11 or larger than 0.11 are significant at the 5% level.

References

Bandalos, D.L., 2014. Relative performance of categorical diagonally weighted least squares and robust maximum likelihood estimation. Struct. Equ. Model. Multidiscip. J. 21 (1), 102–116.

Bartley, M., Sacker, A., Clarke, P., 2004. Employment status, employment conditions, and limiting illness: prospective evidence from the British household panel survey 1991–2001. J. Epidemiol. Community Health 58 (6), 501–506.

Bassett, D.R., Pucher, J., Buehler, R., Thompson, D.L., Crouter, S.E., 2008. Walking, cycling, and obesity rates in Europe, North America, and Australia. J. Phys. Act. Health 5 (6), 795–814.

Carbone, S., Lavie, C.J., Arena, R., 2017. Obesity and heart failure: focus on the obesity paradox. In: Mayo Clinic Proceedings, Vol. 92. Elsevier, pp. 266–279. No. 2.

CBS, 2019. Onderzoek Verplaatsingsgedrag in Nederland (OViN) 2018. Statistics Netherlands.

De Hartog, J.J., Boogaard, H., Nijland, H., Hoek, G., 2010. Do the health benefits of cycling outweigh the risks? Environ. Health Perspect. 118 (8), 1109–1116.

De Jong-Gierveld, J., Kamphuls, F., 1985. The development of a Rasch-type loneliness scale. Appl. Psychol. Meas. 9 (3), 289–299.

Ding, Y., Lu, H., 2016. Activity participation as a mediating variable to analyze the effect of land use on travel behavior: A structural equation modeling approach. J. Transp. Geogr. 52, 23–28.

Dinu, M., Pagliai, G., Macchi, C., Sofi, F., 2019. Active commuting and multiple health outcomes: a systematic review and meta-analysis. Sports Med. 49 (3), 437–452.

Fiscella, K., Franks, P., 2000. Individual income, income inequality, health, and mortality: what are the relationships? Health Serv. Res. 35 (1 Pt 2), 307.

Golob, T.F., 2003. Structural equation modeling for travel behavior research. Transp. Res. B Methodol. 37 (1), 1–25.

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.

Hamer, M., Chida, Y., 2008. Active commuting and cardiovascular risk: a meta-analytic review. Prev. Med. 46 (1), 9–13.

Hammond, J.L., 1973. Two sources of error in ecological correlations. Am. Sociol. Rev. 764–777.

Heinen, E., Maat, K., Van Wee, B., 2011. The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. Transp. Res. Part D: Transp. Environ. 16 (2), 102–109.

Hu, L.T., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equ. Model. Multidiscip. 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.

Kärmeniemi, M., Lankila, T., Ikäheimo, T., Koivumaa-Honkanen, H., Korpelainen, R., 2018. The built environment as a determinant of physical activity: a systematic review of longitudinal studies and natural experiments. Ann. Behav. Med. 52 (3), 239–251.

Kelly, P., Kahlmeier, S., Götschi, T., Orsini, N., Richards, J., Roberts, N., Foster, C., 2014. Systematic review and meta-analysis of reduction in all-cause mortality from walking and cycling and shape of dose response relationship. Int. J. Behav. Nutr. Phys. Act. 11 (1), 1–15.

Kroesen, M., De Vos, J., 2020. Does active travel make people healthier, or are healthy people more inclined to travel actively? J. Transp. Health 16, 100844.

Kwan, M.P., 2012. The uncertain geographic context problem. Ann. Assoc. Am. Geogr. 102 (5), 958–968.

Laeremans, M., Gotschi, T., Dons, E., Kahlmeier, S., Brand, C., de Nazelle, A., Panis, L.I., 2017. Does an increase in walking and cycling translate into a higher overall physical activity level? J. Transp. Health 5, S20.

Lazar, M.A., 2005. How obesity causes diabetes: not a tall tale. Science 307 (5708), 373–375.

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., Aryee, M., 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.

Lin, X., Zhang, X., Guo, J., Roberts, C.K., McKenzie, S., Wu, W.C., Song, Y., 2015. Effects of exercise training on cardiorespiratory fitness and biomarkers of cardiometabolic health: a systematic review and meta-analysis of randomized controlled trials. J. Am. Heart Assoc. 4 (7), e002014.

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.

Mölenberg, F.J., Panter, J., Burdorf, A., van Lenthe, F.J., 2019. A systematic review of the effect of infrastructural interventions to promote cycling: strengthening causal inference from observational data. Int. J. Behav. Nutr. Phys. Act. 16 (1), 1–31.

Najaf, P., Thill, J.C., Zhang, W., Fields, M.G., 2018. City-level urban form and traffic safety: a structural equation modeling analysis of direct and indirect effects. J. Transp. Geogr. 69, 257–270.

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.

Panter, J.R., Jones, A., 2010. Attitudes and the environment as determinants of active travel in adults: what do and don't we know? J. Phys. Act. Health 7 (4), 551–561.

Panter, J., Guell, C., Humphreys, D., Ogilvie, D., 2019. Can changing the physical environment promote walking and cycling? A systematic review of what works and how. Health Place 58, 102161.

Pérusse, L., Tremblay, A., Leblanc, C., Bouchard, C., 1989. Genetic and environmental influences on level of habitual physical activity and exercise participation. Am. J. Epidemiol. 129 (5), 1012–1022.

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. Public Health 100 (10), 1986–1992.

Rietveld, P., Daniel, V., 2004. Determinants of bicycle use: do municipal policies matter? Transp. Res. A Policy Pract. 38 (7), 531–550.

Robinson, W.S., 2009. Ecological correlations and the behavior of individuals. Int. J. Epidemiol. 38 (2), 337–341.

Rybarczyk, G., Banerjee, S., Starking-Szymanski, M.D., Shaker, R.R., 2018. Travel and us: the impact of mode share on sentiment using geo-social media and GIS. Journal of Location Based Services 12 (1), 40–62.

Sahlqvist, S., Song, Y., Ogilvie, D., 2012. Is active travel associated with greater physical activity? The contribution of commuting and non-commuting active travel to total physical activity in adults. Prev. Med. 55 (3), 206–211.

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. Transp. Res. A Policy 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.

Smith, M., Hosking, J., Woodward, A., Witten, K., MacMillan, A., Field, A., Mackie, H., 2017. Systematic literature review of built environment effects on physical activity and active transport–an update and new findings on health equity. Int. J. Behav. Nutr. Phys. Act. 14 (1), 1–27.

Song, C., Joung, D., Ikei, H., Igarashi, M., Aga, M., Park, B.-J., Miyazaki, Y., 2013. Physiological and psychological effects of walking on young males in urban parks in winter. J. Physiol. Anthropol. 32 (1), 18.

Stappers, N.E.H., Van Kann, D.H.H., Ettema, D., De Vries, N.K., Kremers, S.P., 2018. The effect of infrastructural changes in the built environment on physical activity, active transportation and sedentary behavior–a systematic review. Health Place 53, 135–149.

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

Tao, T., Wu, X., Cao, J., Fan, Y., Das, K., Ramaswami, A., 2020. Exploring the nonlinear relationship between the built environment and active travel in the twin cities. J. Plan. Educ. Res.

Van Acker, V., Witlox, F., Van Wee, B., 2007. The effects of the land use system on travel behavior: a structural equation modeling approach. Transp. Plan. Technol. 30 (4), 331–353.

Van Wee, B., Ettema, D., 2016. Travel behaviour and health: A conceptual model and research agenda. J. Transp. Health 3 (3), 240–248.

Ververs, R., Ziegelaar, A., 2006. Verklaringsmodel voor fietsgebruik gemeenten. Een onderzoek in opdracht van Fietsberaad, Leiden.

Wali, B., Frank, L.D., Chapman, J.E., Fox, E.H., 2021. Developing policy thresholds for objectively measured environmental features to support active travel. Transp. Res. Part D: Transp. Environ. 90, 102678.

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.

Wolin, K.Y., Carson, K., Colditz, G.A., 2010. Obesity and cancer. Oncologist 15 (6), 556.

World Health Organization, 2010. Global Recommendations on Physical Activity for Health. World Health Organization.