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Natural and built environmental exposures on children's active school travel: A Dutch global positioning system-based cross-sectional study

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ABSTRACT

Physical inactivity among children is on the rise. Active transport to school (ATS), namely walking and cycling there, adds to children's activity level. Little is known about how exposures along actual routes influence children's transport behavior. This study examined how natural and built environments influence mode choice among Dutch children aged 6–11 years. 623 school trips were tracked with global positioning system. Natural and built environmental exposures were determined by means of a geographic information system and their associations with children's active/passive mode choice were analyzed using mixed models. The actual commuted distance is inversely associated with ATS when only personal, traffic safety, and weather features are considered. When the model is adjusted for urban environments, the results are reversed and distance is no longer significant, whereas well-connected streets and cycling lanes are positively associated with ATS. Neither green space nor weather is significant. As distance is not apparent as a constraining travel determinant when moving through urban landscapes, planning authorities should support children's ATS by providing well-designed cities.

1. Background

Physical activity is a major public health asset decreasing the risk of adverse health effects (Lee et al., 2012). For children, the World Health Organization (WHO, 2015) recommends 60 min of moderate to vigorous physical activity every day to prevent disease in later life (Faulkner et al., 2009; Janssen and Leblanc, 2010). However, as a consequence of sedentary lifestyles, the number of children following this recommendation is constantly decreasing across Europe (Fyhri et al., 2011). Only 18% of Dutch children currently do so (Hildebrandt et al., 2013).

In that respect, active transport to school (ATS) – that is, walking or cycling to school – seems to be a valuable source for energy expenditure in children's daily lives (Steinbach et al., 2012; Schoeppe et al., 2013; Dessing et al., 2014). This is particularly true for Europe, where schools are well integrated in residential neighborhoods (Aarts et al., 2013). There is empirical evidence that ATS results in increased physical activity levels in children compared to those who are chauffeured by their parents (Van Sluijs et al., 2009; Cooper et al., 2010; Owen et al., 2012). ATS also mitigates adverse environmental effects around schools, such as greenhouse gas emissions and traffic congestion during peak times (Maibach et al., 2009).

A crucial first step toward comprehensive policy strategies promoting ATS is to understand the factors that stimulate and hinder ATS. Children's travel decisions are highly complex; they are driven by, for example, personal characteristics, distance between home and school, safety issues due to traffic, and stranger-danger (Sirard and Slater, 2008; Schoeppe et al., 2013; Mitra, 2013). In addition, natural and urban environmental determinants are suggested to be influential (Pont et al., 2009; Panter et al.,

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2010; Wong et al., 2011a; Sallis et al., 2015). Despite the significance of greenness and weather conditions for active transport among adults (Helbich et al., 2014; Fishman et al., 2015; Böcker et al., 2016), little is known about how these natural environmental factors shape children's mobility. Most studies either regard weather as non-modifiable or consider weather conditions (e.g., precipitation) only on a daily (or even seasonal) basis (Børrestad et al., 2011; Van Goeverden and de Boer, 2013), inappropriately reflecting their instant effects on mode choice.

More research has been conducted on urban environmental effects on children's ATS (Ewing and Cervero, 2010; Van Loon and Frank, 2011). The built environment – subsuming urban morphology, land-use, and street layout – is frequently operationalized by means of density, diversity, and design measures (Saelens and Handy, 2008; Ewing and Cervero, 2010). It is assumed that neighborhoods with, for example, a higher density and a more mixed land-use bring destinations (e.g., shops) closer together, thereby shortening trip distances (Van Loon and Frank, 2011). This increases the destination accessibility and promotes walking and cycling. Neighborhoods with pronounced land-use diversity make trip chaining via active transport modes more convenient (Saelens and Handy, 2008). Regarding the design of the street layout, more intersections yield a higher street connectivity, which increases route opportunities (Giles-Corti et al., 2011). In contrast, well-connected streets potentially attract more traffic which raises the risk of pedestrian injury (Sirard and Slater, 2008). Even though there is considerable knowledge about the impacts of built environmental features on adults, knowledge about the ATS of children is still fragmented and inconclusive (Pont et al., 2009; Wong et al., 2011a).

Inconsistent findings in past research may be due to the various ways in which environmental context is delineated and contextual variables are derived (Kwan, 2012). Contextual areas for deriving environmental exposures (e.g., street intersection density) are often modeled with geographic information systems (GIS) as static areas around residential/school location (Larsen et al., 2009; Su et al., 2013), even though it is increasingly argued that not only the conditions of the origin and/or the destination, but also the traversed features of the taken route, are key (Badland et al., 2008; Duncan et al., 2009; Kwan, 2012). To substitute actual routes, Euclidean (Owen et al., 2012) or GIS-based shortest path analyses (Schlossberg et al., 2006) are employed. However, children rarely aim to minimize travel distance, and their route decisions are determined by safety issues, route attractiveness, and opportunities to meet classmates (Harrison et al., 2014). More importantly, Harrison et al. (2014) highlight significant differences in environmental exposures between the shortest and the actual paths. A promising solution is to track children with a global positioning system (GPS; Kerr et al., 2011), which is increasingly accepted as a reliable method to collect data on children's space–time mobility (Bohte and Maat, 2009; Dessing et al., 2014).

In addition to these exposure operationalization challenges, extra uncertainty about the validity of environmental correlates arises due to a North American and Australian centric research focus (McMillan, 2005; Pont et al., 2009; Su et al., 2013). Because of substantial differences in urban geographies, findings based on these regions may not be easily transferred and generalized to European areas (Panter et al., 2010; Lu et al., 2015). European cities have higher densities, distinctive land-use diversities, and lower levels of reliance on automobiles. Even within Europe, the Netherlands needs special attention as it has the world's highest level of bicycle usage (Pucher and Dijkstra, 2003) and cycling is embedded in people's daily lives not only for leisure but also for utilitarian trips (De Vries et al., 2010a).

Although there is a limited number of European studies (Bringolf-Isler et al., 2008; D'Haese et al., 2011; Broberg and Sarjala, 2015) and Dutch studies (De Vries et al., 2010a; Aarts et al., 2013; Van Goeverden and de Boer, 2013; Dessing et al., 2014), the present research addressed the aforementioned shortcomings and is among a few studies to consider the impact of not only built environmental exposures, but also natural environments (i.e., weather, green space) on children's actual commuting paths to and from school. The two research questions were:

a) Are weather conditions at the trip departure time a significant behavioral determinant influencing ATS?
b) Are the exposed natural and built environmental features en route significant determinates of ATS?

To answer these questions, we monitored children's commuting behavior by means of GPS and transport mode choice to and from six schools located in the Netherlands. The research outcomes dealing with the built environment are of fundamental importance for both urban planners and health policymakers who wish to develop strategies and interventions that will systematically promote active transport and thus a healthier urban living (Sallis et al., 2015).

2. Methods

2.1. Study design

This study was part of a project titled "SPACE: Spatial Planning and Children's Exercise" (De Vries et al., 2010a, 2010b) and focused on a subset of 97 children aged 6–11 years in six elementary schools located in five neighborhoods in mid- to large-sized Dutch cities (Amersfoort, Haarlem, Hengelo, Rotterdam, and Vlaardingen) for which GPS data was available. Children were only included when living in the neighborhood where the school was located. The schools are located in neighborhoods with similar demographic profiles (e.g., ethnicity, social status) but they varied in size and population density. Teachers invited children to participate, and their parents or legal guardians were asked for written consent.

The children's daily movements were monitored between December 2008 and April 2009 for eight consecutive days during a regular school week. To record their spatiotemporal trajectories, each child was equipped with a GPS unit (Travel recorder X, BT-Q1000X, QStarz International Co) with a sampling interval of 5 s (Kerr et al., 2011). After distributing the GPS receivers during school hours, the children were briefed by a skilled researcher on how to wear and operate the device. A manual was handed to their parents/guardians. To guarantee uniform data collection, all children carried the GPS on an elasticated belt around their hips from the morning till bedtime. They removed the device temporarily only to perform activities that would otherwise damage the receiver (e.g., showering). The ethics committee of the Leiden University Medical Center has approved the present study.

2.2. GPS-based trip detection, transport mode classification

GPS loggers collect time–location data under free living conditions (Kerr et al., 2011). Neither individual trips nor selected modes are gathered directly and require data processing. As Wu et al. (2011) report no striking differences between rule-based and computational approaches, we applied the former (Sterkenburg et al., 2012), as it is more intuitive. First, we used the cluster detection algorithm of Maas et al. (2013) to distinguish between stationary activity places (e.g., residential and school locations) and conducted trips. For trip detection from home to school, we identified the first GPS data point within a 40 m radius of the known residential address. The procedure queried consecutive locations chronologically until the first data point within 40 m of the known school location was reached, at which point it was fine-tuned. If the search detected the home instead of the school location first, the trip was labeled non-educational and the algorithm was restarted. To identify trips back home, the procedure was repeated from the opposite direction (i.e., from school). Trips with other destinations were not included unless this destination was a stop-over between home and school or vice versa.

Secondly, the transport mode of each trip was classified. As urban traffic flows show stop-and-go patterns, the following combinations of average and maximum speeds were utilized (Dessing et al., 2014):

a) A walking trip has an average speed of < 10 km/h and a maximum of < 14 km/h.
b) A cycling trip has an average speed of < 25 km/h and a top speed of < 35 km/h.
c) Motorized trips have a maximum speed of < 150 km/h.

In a field experiment the approach classified, on average, 90% of the transport modes correctly (Sterkenburg et al., 2012). Finally, walking and cycling trips were re-coded as active modes and motorized trips as passive modes, serving as a response variable in subsequent analyses. In addition, each trip[1] was enriched with its length in meters, time at day, and duration in minutes.

To capture exposures along each trip and around the residental and the school location, we conducted GIS-based buffer analyses. Although buffer sizes are arbitrary, we followed Panter et al. (2010) and Wiehe et al. (2013) in using a 100 m buffer width. This buffer size also represents building blocks in the study areas satisfactorily (Fig. 1). The buffered trips were then overlaid and intersected with built environmental features computed on a 100×100 m grid superimposed on the study sites. Such cell resolution is detailed enough to retain urban form (e.g., squares) while providing a large enough sample size to derive exposure variables. Because some cells were only partially included in the buffers and are thus less influential, an extra (down-)weighting was incorporated (Badland et al., 2008) before the average individual exposures were determined. To illustrate this approach, Fig. 1 shows the weighted accident risk as an example.

2.3. Natural environmental variables

Hourly meteorological data at the start of each trip was obtained from the Royal Dutch Meteorological Institute (2013). For each city, weather data of the closest station was matched with each trip date and time. We considered on an hourly basis four weather conditions that are frequently used in transport studies (Helbich et al., 2014), namely a) temperature in 0.1 °C, b) global radiation in J/cm^2, c) mean wind speed in 0.1 m/s, and d) precipitation in mm re-coded as dummy variable.

Logarithmically transformed proportion of green space was determined for each 100 m cell. Data on greenery with a spatial resolution of 25 m were taken from the Landelijk Grondgebruiksbestand Nederland 6 (LGN; Hazeu et al., 2010) for the year 2007/08. We comprehended green space not only as natural (e.g., woods, grasslands) but also as artificially installed greenery (e.g., parks), which is of particular importance in urban neighborhoods.

[1] Note that trips other than to/from school and home, outliers with a trip distance longer than 15 km or less than 50 m (e.g., due to GPS signal inaccuracies when leaving indoor), as well as weekend trips, were not further considered.

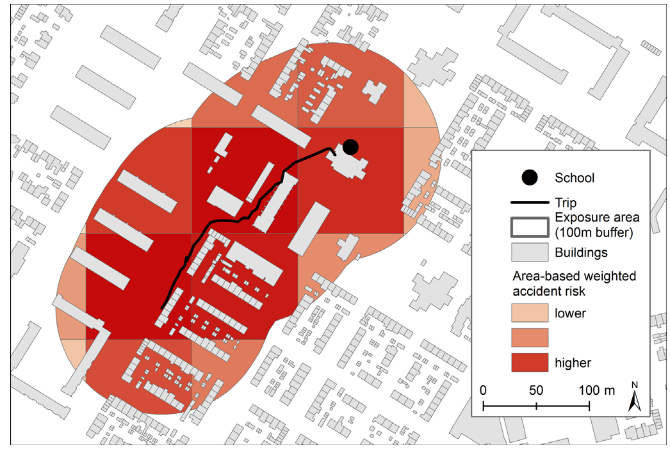

Fig. 1. Accident risk exposure along a walking trip (brighter cells receive a lower weight).

2.4. Built environmental variables

To capture the complexity of the built environment, 10 urban form measures were derived for each grid cell (Table 1). Following Larsen et al. (2009), we represented land-use mix through the (not-normalized) Shannon entropy index utilizing LGN data. Interpretatively, a cell with an index value of 0 refers to only one land-use class, while higher index values refer to a richer set of land-use classes per cell (Turner, 1990). A similar entropy index was calculated for the usage of buildings per cell (Broberg and Sarjala, 2015). Data describing the building usage was collected from the Dutch Basisregistratie Adressen en Gebouwen (BAG, 2013).

Density was reflected through the total length of street centerlines. The design of the street layout was measured as the proportion of cul-de-sacs, 3-way, 4-way, and >4-way intersections relative to all intersections within a cell (Schlossberg et al., 2006). Since these measures are descriptive, they do not provide insights into the local connectivity (accessibility) of street segments in regard to the surrounding street network (Cooper et al., 2014). Thus, we used the following two space syntax-based indices (Chiaradia et al., 2013): a) The closeness index, which describes the nearness/farness by measuring how difficult it is to go from location i to all other locations on the street network (less accessible street segments should lower ATS); and b) the betweenness index, which quantifies which street segment will be busiest to move from location i to all other locations along the shortest path (well-connected street segments have a higher index value and should increase ATS). These analytics were set up with catchment radii of 200 m, reflecting building block structures while avoiding overgeneralization. As both statistics were computed for street segments, they were aggregated to the 100 m cells by taking the mean. Street indicators utilize Navteq 2012 street data.

The aforementioned built environmental measures focus on the horizontal dimension, and fail to describe the vertical dimension of the urban morphology. We therefore developed a morphometric measure called the building-roughness index, which reflects height differences between a building and its neighbors. For input data we used the Actueel Hoogtebestand Nederland (AHN, 2008), which provides a surface model describing the topography of the built environment gathered through airborne laser scanning (Helbich et al., 2013). For realization, GIS-based focal map algebra functions are applied (Riley et al., 1999). High index values point to a pronounced building height difference, which hypothetically stimulates ATS more than uniformly high buildings (Aarts et al., 2013).

Table 1
Descriptive statistics stratified by active and passive modes on a trip level.

Variable description	Passive mode		Active mode		*P*-val.
n	53		570		
Personal char.					
Age (years) (median (SD), IQR)	7 (1.7)	6/9	9 (1.4)	8/10	< 0.001
Sex (female = 0, male = 1) (%)	21/32	39.6/60.4	356/214	62.5/37.5	0.002
BMI categories (%)					0.013
Normal	47	88.7	397	69.6	
Overweight	2	3.8	76	13.3	
Obesity	4	7.5	97	17.0	
Trip char.					
Trip direction (home to school = 1, school to home = 2) (%)	28/25	52.8/47.2	279/291	48.9/51.1	0.691
Logged trip distance (median (SD), IQR)	6.8 (0.9)	6.5/7.1	5.6 (1.4)	4.3/6.1	< 0.001
Weekday (%)					0.036
Monday	8	15.1	103	18.1	
Tuesday	5	9.4	109	19.1	
Wednesday	8	15.1	63	11.1	
Thursday	20	37.7	121	21.2	
Friday	12	22.6	174	30.5	
Traffic safety					
Availability of a major road or highway within a 100 m cell (1 = yes, 0 = no)	0.0	0.0/0.1	0.0	0.0/0.01	0.014
Euclidean distance to major roads/highways per 100 m cell (meters) (median (SD), IQR)	182 (121)	100/231	154 (116)	87/243	0.602
Proportion of cycling paths length per street length per 100 m cell (median (SD), IQR)	1.1 (16.4)	0.0/10.8	1.0 (16.0)	0.0/13.3	0.760
Probability of fatal/no-fatal accidents per 100 m cell (normalized kernel density estimation) (median (SD), IQR)	0.2 (0.2)	0.1/0.3	0.1 (0.2)	0.1/0.2	0.003
Weather and natural environment					
Hourly mean wind speed (0.1 m/s) (median (SD), IQR)	40 (20)	30/60	50 (21)	30/60	0.003
Temperature (0.1 °C)	47 (57)	13/89	63 (41)	41/87	0.017
Global radiation (J/cm²) during the hourly division (median (SD), IQR)	28 (66)	11/112	32 (69)	8/108	0.861
Hourly precipitation (1 = yes, 0 = no) (%)	41/12	77.4/22.6	447/123	78.4/21.6	0.996
Logged proportion of green space per 100 m cell (median (SD), IQR)	0.6 (1.1)	0.3/1.6	0.8 (3.9)	−6.9/1.7	0.022
Built environment					
Proportion of cul-de-sacs per 100 m cell (median (SD), IQR)	7.1 (5.7)	2.5/10.2	3.7 (8.0)	0.0/7.5	< 0.001
Proportion of 3-way intersections per 100 m cell (median (SD), IQR)	34 (7.2)	26.5/36.3	30.6 (8.7)	21.2/35.1	0.049
Proportion of 4-way intersections per 100 m cell (median (SD), IQR)	5.2 (3.2)	2.7/8.0	5.0 (3.5)	3.7/8.4	0.404
Proportion of > 4-way intersections per 100 m cell (median (SD), IQR)	0.0 (0.9)	0.0/0.9	0.0 (1.3)	0.0/1.3	0.127
Shannon land-use diversity index per 100 m cell (median (SD), IQR)	0.2 (0.1)	0.0/0.2	0.1 (0.1)	0.0/0.2	< 0.001
Shannon building usage mix per 100 m cell (median (SD), IQR)	0.1 (0.1)	0.1/0.2	0.1 (0.1)	0.0/0.2	0.946
Building-roughness index (normalized) per 100 m cell (median (SD), IQR)	0.3 (0.2)	0.2/0.3	0.2 (0.1)	0.1/0.2	< 0.001
Closeness index per 100 m cell (median (SD), IQR)	74.7 (23.2)	70.9/78.4	63.1 (9.0)	56.0/70.2	< 0.001
Betweenness index per 100 m cell (median (SD), IQR)	15.4 (5.7)	13.8/17.5	23.8 (6.8)	15.1/27.0	< 0.001
Street density per 100 m cell (median (SD), IQR)	116.0 (12.6)	105.0/125.0	107.0 (24.5)	89.1/122.0	0.005

Note: SD = standard deviation. IQR = interquartile range.
P-values for categorical variables are based on Chi^2 tests, while for continuous ones Wilcox tests were used. Some variables were log transformed to receive more Gaussian-like distributions. To save degrees of freedoms, BMI classes are modeled as numeric variable. Other variables (e.g., ethnicity) are not considered due to several missing values.

2.5. Personal characteristics and traffic safety control variables

The parents/guardians of the school children who participated in the study completed a survey, which provided the gender, age, and ethnicity of each subject. The children's height and weight were registered with a digital scale (Seca 812, Vogel & Halke GmbH & Co) and a microtoise (Stanley 04–116). These data were used to determine an independent variable reflecting sex- and age-specific body mass index (BMI, kg/m^2) classes, namely normal weight, overweight, and obesity (Cole et al., 2000).

The traffic safety control variables were a compromise between data availability and literature suggestions (Pont et al., 2009; Wong et al., 2011a; Yeung et al., 2008). Firstly, a dummy variable indicated whether a cell was traversed by a major road or highway (extracted from Navteq data). Secondly, we determined the Euclidean proximity to major roads. Thirdly, as traffic accidents are perceived as strong barriers to walking or cycling (Panter et al., 2010), data on registered fatal and non-fatal road accidents for 2009 were obtained from the Basisregister Onderwijs (Ministry of Infrastructure and the Environment). To model accident risk, kernel density estimation (Bailey and Gatrell, 1995) with an adaptive Gaussian kernel was applied. Higher values refer to a more pronounced accident probability (Fig. 1). Fourthly, the proportion of cycling path (extracted from OpenStreetMap 2014; Jokar Arsanjani et al., 2015) relative to the overall street length per cell was determined. Sidewalks are ubiquitous in the investigated neighborhoods and were thus excluded from further consideration. No reliable geodata on pedestrian crossings (with traffic lights) were available.

2.6. Statistical analyses

Initially, to investigate differences between active and passive modes, we employed Chi^2 tests for categorical variables and Wilcox tests for continuous variables. As highlighted by Oliver et al. (2014), the joint consideration of multiple built environmental variables provokes multicollinearity problems in regressions (Lu et al., 2015). This makes individual exposure effects hardly assignable. To circumvent this, one could remove correlated variables – resulting in a loss of information – or derive latent variables, using principle component analysis. However, individual variable effects remain unidentifiable. We therefore followed an alternative strategy (Berrigan et al., 2014) by pre-screening the associations between the response (i.e., ATS yes/no) and the predictor variables with a binomial elastic net (Zou and Hastie, 2005). This approach is robust against highly correlated variables and allows selection of the relevant exposures.

Subsequently, the impact of pre-screened exposures on the probability of children's ATS was determined by means of generalized linear mixed models with a logit link function (GLMM; Gelman and Hill, 2007). GLMMs account for the complex correlation structures arising as trips are taken repeatedly by the same child and are nested within schools, otherwise having serious consequences for statistical validity. We first determined an appropriate random effect structure through model comparisons of the full models utilizing the Akaike information criterion (AIC; Gelman and Hill, 2007) score. The following correlations were tested: a) trips nested in children, b) children nested in schools, and c) trips clustered in children and within cities. Variables were retained in the regression, being significant at the 0.1 level. To determine the goodness-of-fit, marginal and conditional pseudo-R^2s were investigated. The former refers to the variance explained by the fixed effects while the latter comprises both the fixed and the random effects.

3. Results

The median age of the 97 participating children was 9 years. Roughly 60% of the subjects were girls. The majority (71%) of the children had a normal BMI score; 13% were overweight and 16% were obese. Approximately a tenth of all trips were made by automobile or public transport. The trip distances were rather unevenly distributed, with more shorter trips. The overall median trip distance was 284 m with a standard deviation (SD) of 2221 m, while the median ATS distance was 264 m (SD=923 m) and the motorized travel distance 908 m (SD=6771 m). With $p<0.001$, the Wilcoxon test refers to significant distance differences between active and passive modes. No differences in trip length were found for trip direction (from or to school) pointing to a well-balanced sample (51% vs. 49%). More detailed descriptive statistics are shown in Table 1.

Bivariate relationships between the environmental variables were tested in advance. Spearman's correlation coefficients show some pronounced associations not only between the built environment variables, but also between a few weather variables. In order to reduce multicollinearity and remove predictors not related to the response (i.e., ATS yes/no), we employed an elastic net. We used a penalty of 0.5, being a compromise between ridge ($\alpha=0$) and lasso penalty ($\alpha=1$). Other hyperparameters of the elastic net were optimized via 10-fold cross-validation. The elastic net suggested that 13 out of 25 variables are associated with ATS. Variables such as day of the trip, trip direction, precipitation, green space, building usage mix, and land-use diversity were dropped at this stage. Re-running Spearman's coefficients confirmed a marked reduction of correlations between the remaining predictors. These 13 variables served as input for GLMMs.

To determine the relative impact of different exposure groups, the GLMMs were adjusted iteratively by adding variables groupwise. Model 1 is based on personal characteristics, trip characteristics, and traffic safety variables. Model 2 also considers weather characteristics,[2] while Model 3 extends Model 2 through built environmental variables. After testing different random effect structures using AIC scores, all GLMMs were estimated with a subject-specific random effect (i.e., trips nested within persons). To receive the most parsimonious models, insignificant factors at the 0.1 level were eliminated sequentially (De Vries et al., 2010a; Oliver et al., 2014). Table 2 depicts the model results.

The base model (Model 1) comprises two predictors. With an estimated parameter of 0.761, age is significantly positively associated with ATS ($p=0.022$). Logged trip distance shows a weak but significant negative association ($\beta=-0.512$, $p=0.062$): As distance increases, the likelihood of ATS decreases. A weak negative association is found for major roads ($\beta=-9.855$, $p=0.099$). After variable selection, no weather variable seems to be related with ATS and the reduced Model 2 is similar to Model 1. In Model 3, age remains an important variable, although the correlation ($\beta=0.652$, $p=0.029$) is slightly reduced. In contrast to Model 2, trip distance loses its significance and cycling path availability ($\beta=0.046$, $p=0.053$) replaces the variable major roads in Model 2. Furthermore, while the closeness index shows a strong negative association ($\beta=-0.118$, $p=0.001$), the betweenness index shows a weak positive one with ATS ($\beta=0.116$, $p=0.092$). However, both measures indicate that a less accessible network decreases ATS, and that well-connected streets increase ATS. The marginal R^2 increases in Model 3 compared to Model 2 from 0.234 to 0.364, which is a marked increase (35%). In addition, the AIC score drops from 222 to 211. Both measures refer to better model fits when built environmental features are included. Still in Model 3, no effects are found for the weather conditions on ATS.

4. Discussion

4.1. Empirical findings

The overwhelming majority (91%) of the trips were conducted on foot or by bicycle, which can partly be explained by the fact that only children that lived in the same neighborhood as their school was located were included in this study. As anticipated, this proportion is in sharp contrast to the finding of North American studies (McDonald, 2008). Wong et al. (2011b), for instance, report only 47% school-bound and 38% home-bound ATS trips for Canadian children. Contrasting our ATS frequency with European research, the Netherlands still shows a high ATS share. For example, 78% ATS trips were found for children aged 6–14 years in Switzerland (Bringolf-Isler et al., 2008) and 59% for 11–12-year-old Belgian children (D'Haese et al., 2011). The low share of motorized trips in our study is consistent with a Dutch questionnaire-based study by Aarts et al. (2013), which showed that only 10% of the trips within a distance of 1 km from school were made by passive modes. Explanations for such a high usage of active modes are the Dutch-specific cycling mentality, whereby children start cycling at an early age, and well-supported infrastructures (e.g., cycling paths). Other external factors relevant to parental chauffeuring might be higher automobile ownership costs, and higher fuel prices in the Netherlands compared to North America (Pucher and Dijkstra, 2003). Furthermore, Dutch elementary schools are well-embedded in or near residential areas (Aarts et al., 2013), and in the present study, children were selected on the basis of having their residence in the same neighborhood as where the school was located. This also explains the short distances and transport mode choice. Thus, it is not surprising that the distance from home to school is, at 284 m, generally shorter than the 2.5 km reported by Yeung et al. (2008) for Brisbane, Australia. For such short distances, the automobile is less competitive (Van Goeverden and de Boer, 2013). Our study does not support a significant number of mode choice switchers from the morning to the afternoon (5.6% for

[2] Other variables describing the natural environment were not selected by means of the elastic net.

Table 2
Results of the fixed effects for the full and stepwise GLMMs ($n = 623$).

	Full Model 1				**Stepwise Model 1**			
	Coef.	**Std. err.**	***Z*-val.**	***P*-val.**	**Coef.**	**Std. err.**	***Z*-val.**	***P*-val.**
Intercept	−0.016	3.720	−0.004	0.997	1.239	3.211	0.387	0.670
Personal char.								
Age	0.754	0.315	2.393	0.017**	0.761	0.331	2.299	0.022**
Sex	−0.930	0.913	−1.018	0.309				
BMI	0.536	0.744	0.720	0.471				
Trip char.								
Logged distance	−0.598	0.285	−2.101	0.036**	−0.512	0.274	−1.868	0.062*
Traffic safety								
Major road	−9.117	5.698	−1.600	0.110	−9.855	5.967	−1.652	0.099*
Cycling path	0.026	0.025	1.007	0.314				
Marginal R^2	0.322				0.234			
Conditional R^2	0.737				0.741			
AIC	224				222			
Full Model 2					**Stepwise Model 2**			
	Coef.	**Std. err.**	***Z*-val.**	***P*-val.**	**Coef.**	**Std. err.**	***Z*-val.**	***P*-val.**
Intercept	−0.548	3.425	−0.160	0.873	1.239	3.211	0.387	0.670
Personal char.								
Age	0.696	0.283	2.457	0.014**	0.761	0.331	2.299	0.022**
Sex	−0.852	0.814	−1.046	0.296				
BMI	0.571	0.676	0.845	0.398				
Trip char.								
Logged distance	−0.640	0.271	−2.363	0.018**	−0.512	0.274	−1.868	0.062*
Traffic safety								
Major road	−10.365	5.285	−1.961	0.049**	−9.855	5.967	−1.652	0.099*
Cycling path	0.278	0.023	1.207	0.228				
Weather char.								
Wind	0.008	0.014	0.569	0.569				
Temperature	0.009	0.007	1.208	0.227				
Marginal R^2	0.371				0.234			
Conditional R^2	0.711				0.741			
AIC	226				222			
Full Model 3					**Stepwise Model 3**			
	Coef.	**Std. err.**	***Z*-val.**	***P*-val.**	**Coef.**	**Std. err.**	***Z*-val.**	***P*-val.**
Intercept	1.960	3.712	0.528	0.597	3.678	3.519	1.045	0.296
Personal char.								
Age	0.579	0.245	2.359	0.018**	0.652	0.298	2.188	0.029**
Sex	−0.835	0.738	−1.131	0.258				
BMI	0.654	0.691	0.946	0.344				
Trip char.								
Logged distance	0.307	0.418	0.734	0.463				
Traffic safety								
Major road	3.571	6.407	0.557	0.577				
Cycling path	0.055	0.023	2.367	0.018**	0.046	0.024	1.935	0.053*
Weather char.								
Wind	0.012	0.015	0.827	0.408				
Temp	0.008	0.006	1.217	0.224				
Built environment								
3-way intersections	−0.045	0.059	−0.765	0.444				
Roughness index	−5120	4.711	−1.087	0.277				
Closeness index	−0.097	0.057	−1.706	0.088*	−0.118	0.037	−3.176	0.001***
Betweenness index	0.132	0.075	1.757	0.079*	0.116	0.069	1.688	0.092*
Street density	−0.020	0.027	−0.718	0.473				
Marginal R^2	0.474				0.364			
Conditional R^2	0.691				0.725			
AIC	220				211			

Signif. codes:

* < 0.1.

** < 0.05.

*** < 0.01.

passive and 2.2% for active transport modes); this is in line with Broberg and Sarjala (2015) study for Helsinki (Finland). This implies that chauffeuring children to school one-way is less attractive, and that mode decisions are made for both directions in the Netherlands.

With respect to the multivariate models, Table 2 shows that only a limited number of variables are significantly related to ATS, replicating Oliver et al. (2014). When further adjusted with natural environmental exposures, both Model 1 and Model 2 show that trip distance is a significant predictor, as previously found by, for example, Bringolf-Isler et al. (2008), Larsen et al. (2009), Aarts et al. (2013) and Dessing et al. (2014). This result intuitively makes sense, in that with an increasing distance, the probability of ATS decreases and the attractiveness of motorized transport increases. From a planning point of view, home-school distance is a factor that needs particular attention since it can be directly influenced by school locational policies. However, once the built environment is taken into account (Model 3), distance is no longer a significant determinant. This might be because built environmental characteristics absorb distance effects through increased architectural diversification, causing longer distances to be perceived as less discouraging.

The personal characteristics indicate that gender is insignificant. However, in general, the findings about sex are inconsistent across the litrature (Faulkner et al., 2009). For example, whereas van Goeverden and de Boer (2013) argue that girls have a higher security risk than boys and are less likely to use ATS, others disagree. Moreover, we cannot confirm that children who actively commute have lower BMI scores than inactive children (Faulkner et al., 2009). There are two reasons for this: Firstly, our sample has an insufficiently low variance to detect differences (Table 1), and secondly, the BMI effect might be moderated by distance, meaning that active commuters tend to live closer to school. In contrast to gender and BMI, the variable age is persistently positively associated with ATS across all models, which is in line with a review by Mitra (2013) consistently reporting a positive association. Faulkner et al. (2009) state that older children have an increasingly autonomous mobility behavior and are less dependent on their parents. Such an increase in independent travelling is also related to children's developing ability to perceive and cope with risky traffic situations along their school route (Mitra, 2013).

Our models show that traffic safety is of importance. The variables operationalizing the exposure to major roads/highways (Model 2) and cycling path availability (Model 3) within a buffered trip, have a significantly negative and positive correlation, respectively, with ATS (Pont et al., 2009). The explanations for both variables are clear: Being separated from busy roads reduces the risk of being injured when crossing busy streets, and cycling infrastructure reduces parental concerns about traffic safety (Pucher and Dijkstra, 2003; Pont et al., 2009). This is in line with van Kann et al. (2015). Even though traffic safety is essential for ATS (De Vries et al., 2010a), Aarts et al. (2013) found no significant association for the Netherlands. Although Larsen et al. (2009) used the perceived quality of sidewalks and cycling lanes instead of objective measures, they report a supporting effect for the USA.

In this study weather variables are not related to children's ATS. This finding contradicts not only transport studies that argue that, for adults, active transport is highly sensitive with respect to poor weather conditions (Helbich et al., 2014; Böcker et al., 2016), but also a few school travel studies (Oliver et al., 2014) that found univariate, but not multivariate, associations between daily weather and ATS. Lacking associations are supported by Mitra and Faulkner (2012), who found no seasonal or weather effects for Toronto, Canada. It could be argued that significant seasonal or weather effects in previous studies might be statistical artifacts due to not considering exact hourly micro-climate characteristics before conducting a trip (Børrestad et al., 2011). An alternative explanation could be that urban morphology forms barriers to wind and precipitation, offering sufficient shelter from these inconveniences to make the actual weather less relevant to habitual, obligatory trips. In contrast to De Vries et al. (2010a) and van Kann et al. (2015), the elastic net indicates that the proportion of green space is unrelated to ATS. This finding is intuitive for educational commuting, because children face time constraints when travelling to or from school.

Built environmental variables (i.e., the closeness and betweeness index) describing neighborhoods on a micro-scale are associated with ATS. The vertical dimension of buildings en route does not influence ATS in our study. This can be explained by the limited variation in building heights. This is unexpected because Aarts et al. (2013) report that the degree of high-rise versus low-rise buildings matters. However, as their indicator is based on a questionnaire, it is not objectively and consistently measured. Similarly, land-use mix and building diversity are insignificant in our study. This lack of significance seems rational, as children's prime motive is commuting to/from school, and not chaining trips. While land-use mix brings more destinations close by and increases the likelihood of ATS for utilitarian trips among adults, this association is less clear for children (Larsen et al., 2009). Previous results concerning land-use and building diversity on children's ATS are mixed (Wong et al., 2011a). Our findings replicate those of, for example, Ewing et al. (2004), who found no significant relationship for the USA. Compared to studies that largely measured the built environment by means of descriptive measures of street patterns (Panter et al., 2010; Wong et al., 2011a), both newly introduced space syntax-based variables emerged as relevant determinants. Intuitively, it is expected that well-connected street layouts that have less severance encourage ATS by creating increased interaction possibilities and more meeting points with schoolmates (Cooper et al., 2010; Giles-Corti et al., 2011). That is exactly what Model 3 confirms. While the closeness index indicates that a less accessible network lowers ATS, the betweenness index indicates that well-connected streets increase ATS.

4.2. Strength and limitations

This study contributes to the very scarce evidence of exposure assessment along actually taken routes to/from school among children. As shown by Harrison et al. (2014), our GPS approach represents environmental features more realistically than utilizing shortest paths. A further key strength of this study is the consideration of a rich set of built environmental features on a spatial micro-scale, describing not only the horizontal dimension of neighborhoods, but also the vertical urban morphology (i.e., building roughness). Even though building roughness turned out to be insignificant, such an indicator has never been analyzed before among children's ATS. Although a few previous studies (Van Goeverden and de Boer, 2013; Oliver et al., 2014) included daily weather in their study designs, to the best of our knowledge, this is the first study to consider exact and objectively measured weather conditions before trip departure. Another major strength is the statistically sound analysis, which devoted precise attention to correlations between exposures as called upon by Wong et al. (2011a), while permitting the determination of individual effects instead of employing a difficult to interpret latent variable (e.g., walkability index).

However, the study also has some limitations. In contrast to longitudinal studies, the present models are cross-sectional and cannot deal with self-selection issues. That is, it remains unclear whether environmental features affect ATS or whether the subjects' parents choose neighborhoods that support active mobility behavior (Lee et al., 2009). Nevertheless, Saelens and Handy

(2008) stress the importance of cross-sectional studies in order to guide researchers toward relevant variables. Although the models are grounded on a sufficiently large number of trips to achieve reliable results ($n = 623$), the number of children tracked is only average. However, our sample was nearly twice as large as that of Wiehe et al. (2013). The research design only considers children who lived and attend a school within the same neighborhood. Like other studies (Aarts et al., 2013), the data collection comprised only a restricted period (i.e., winter and spring) and did not cover all seasons. Given that school travel is a decision made by both children and parents in this age group (Van Goeverden and de Boer, 2013), household variables (e.g., household income, car access, employment, number of siblings) might also be essential for mode choice. It would be informative to test such factors, even though studies have so far been inconclusive concerning their importance (Oliver et al., 2014). Of similar importance are variables representing parental perceptions (e.g., stranger danger and safety) (Mitra, 2013), which might interact with other variables. Finally, the general limitations of GPS (e.g., signal interference) remain, although they were attenuated during this study through careful data pre-processing.

Besides tackling these shortcomings, an extension of this study is a sensitivity analysis regarding buffer types and widths and how these parameters influence the statistical results. It would be interesting to study whether the association between distance and ATS is different when children living further away from school are included in the study population. Future work should also investigate walking and cycling to school separately in order to explore differences in the correlates and their magnitudes (De Vries et al., 2010a; Broberg and Sarjala, 2015). Another promising extension is the consideration of non-school trips (Smith et al., 2012). De Vries et al. (2010a) showed that built environmental correlates of children's walking and cycling behavior differ by purpose (e.g., to school, for recreation) and by commuting mode implying a behavior-specific approach for interventions and for future, preferably prospective, studies.

5. Conclusions

This study examined the impact of dynamic natural and built environmental exposures on Dutch children's mode choice when travelling to/from school. To the best of our knowledge, it is the first study to explore a) not only horizontal urban form characteristics (i.e., street layout) but also vertical ones (i.e., urban morphology) on a micro-level along children's travel routes assessed with GPS, and b) hourly weather conditions before leaving home or school. As such environmental exposures during transit are largely disregarded, this research adds significantly to the literature.

Whereas distance is inversely associated with active transport to school (ATS) when only personal, trip, and weather characteristics are considered, the opposite is true when the models are adjusted for traversed urban environments. Given the actual school locations, it can be hypothesized that distance is no longer perceived as a constraining travel determinant when moving through urban landscapes. In particular, local street connectedness, investigated through space–syntax based indices, stimulates ATS as such connectedness enlarges children's interaction possibilities and increases their number of meeting points. Neither green space nor actual weather conditions turned out to be significant, suggesting that the former might be more relevant to playing after school. Weather effects seem to be alleviated by the shelter provided by urban morphology or that children simply do not have an alternative mode choice and need to travel actively independent of the actual weather.

Our findings are promising for decision-makers, offering them a dimension to influence children's health outcomes through ATS and well-thought-out planning concepts. We recommend place-based planning strategies wherein good accessibility is key. The results are also a call to politicians not to remove schools from local communities, because doing so will increase the pressure not to rely on active transport modes. On the contrary, decision-makers are advised to provide well-designed cities that will encourage physical activity in schoolchildren.

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