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ARTICLE

Prediction of human active mobility in rural areas: development and validity tests of three different approaches

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Abstract

Background/aim Active mobility may play a relevant role in the assessment of environmental exposures (e.g. traffic-related air pollution, livestock emissions), but data about actual mobility patterns are work intensive to collect, especially in large study populations, therefore estimation methods for active mobility may be relevant for exposure assessment in different types of studies. We previously collected mobility patterns in a group of 941 participants in a rural setting in the Netherlands, using week-long GPS tracking. We had information regarding personal characteristics, self-reported data regarding weekly mobility patterns and spatial characteristics. The goal of this study was to develop versatile estimates of active mobility, test their accuracy using GPS measurements and explore the implications for exposure assessment studies.

Methods We estimated hours/week spent on active mobility based on personal characteristics (e.g. age, sex, pre-existing conditions), self-reported data (e.g. hours spent commuting per bike) or spatial predictors such as home and work address. Estimated hours/week spent on active mobility were compared with GPS measured hours/week, using linear regression and kappa statistics.

Results Estimated and measured hours/week spent on active mobility had low correspondence, even the best predicting estimation method based on self-reported data, resulted in a R^2 of 0.09 and Cohen's kappa of 0.07. A visual check indicated that, although predicted routes to work appeared to match GPS measured tracks, only a small proportion of active mobility was captured in this way, thus resulting in a low validity of overall predicted active mobility.

Conclusions We were unable to develop a method that could accurately estimate active mobility, the best performing method was based on detailed self-reported information but still resulted in low correspondence. For future studies aiming to evaluate the contribution of home-work traffic to exposure, applying spatial predictors may be appropriate. Measurements still represent the best possible tool to evaluate mobility patterns.

Keywords Active mobility · Mobility estimation method · GPS validation · Walking · Biking · Exposure · Assessment

Introduction

Environmental epidemiological studies aim at evaluating risks to human health from environmental exposures [1], examples of environmental exposures are for instance; ultrafine particles of air pollution [2], electromagnetic fields [3] or livestock-associated emissions [4]. Personal exposure in environmental health studies is often approximated by assigning or measuring exposure levels at a single location, usually the home address. The fact that people are mobile is often ignored. Active mobility, using only physical activity for locomotion (in this study walking and biking), may affect exposure of persons to different environmental substances, especially if exposure levels display strong spatial, or spatio-temporal variation [5–9]. Examples include: exposure to traffic-related air pollution near roads [10], but

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also exposure expected to be beneficial to health, such as time near urban green space during daily mobility [11]. Ignoring (active-) mobility may therefore increase misclassification of exposure and thus change measures of association [12]. In general, misclassification usually biases risk estimates towards the null, in particular when misclassification is non-differential, meaning that true effects may remain unobserved [13].

Detailed self-reported data on (active-) mobility has been infrequently collected in previous studies, partly because collecting this type of information is laborious for participants, especially when using activity diaries [14]. Furthermore, data quality, in particular responder bias, is an issue of concern. In a previous study we found that study participants strongly overestimated their time spent on active mobility when compared with GPS measured data [15]. Collecting outdoor activity data using GPS loggers or mobile phones is only sometimes performed, or performed in smaller subpopulations, due to associated costs and work time [7, 8, 10, 11, 14, 16–24]. Several studies have reported that underlying general characteristics of study participants may explain part of observed variability in mobility patterns [15, 25–27].

Because measuring mobility patterns is challenging, other methods have been based on location information using Geographic Information Systems (GIS). Such GIS based methods have been used for example to assess exposure experienced during commutes on commonly used routes (e.g. home to work, home to school) [10, 11, 16, 20, 21]. When GIS based methods were applied, the predicted routes can be validated using GPS logging. Such validation efforts were generally performed in smaller study populations (max $N = 175$) [10, 11, 16, 20, 21] and results of these analyses vary in the sense that estimated and measured exposure may [16], or may not show correspondence [10, 11, 20, 21].

The goal of this study was to design different methods to estimate active mobility based on available data in a study cohort, namely general characteristics, self-reported data and location information. All data were available from the VGO GPS study and in a second step we validate our approaches using GPS measurements originating from this study. Finally, we discuss the implications of these approaches for exposure assessment studies.

Methods

Study population

In 2012 the "Farming and Neighbouring Residents' Health" study (Dutch acronym: VGO study) was initiated. The focus of the VGO study was on the health of non-farming resident's living in an area with a high density of livestock farms (Supplementary Fig. 1). For this study 2494 people volunteered to undergo a medical examination (lung function measurements, blood, nasal- and buccal-epithelia collection, stool sample) in a field study that took place in between March 2014 and February 2015. Participants were also asked to fill in a baseline questionnaire (VGO questionnaire), including questions about participant characteristics, health and lifestyle [28, 29]. Farmers and people living on farms were excluded a priori from the VGO study, since the focus was on health of non-farming residents.

From the VGO population a representative subgroup [30] was recruited to take part in the VGO GPS study. Initially 1517 VGO cohort members were invited, 67% participated in the GPS study, resulting in 1014 logged GPS tracks. After GPS data cleaning, 941 usable GPS tracks remained for further analysis, with a median of 186 h of GPS data logged [30]. Participants in the VGO GPS study filled in a mobility baseline questionnaire (Q1). For each VGO GPS study participant information was available on employment status, the nature of work activities and the home and work address (if applicable) from the VGO questionnaire. Medical ethical approval was obtained for the VGO study from the Medical Ethical Committee of the University Medical Centre Utrecht (protocol number 13/533), and all participants provided informed consent.

Estimation method development

We developed three estimation methods to predict time spent in active mobility, all based on different types of determinants. We predicted the number of hours/week spent on active mobility and compared intra-individually with GPS measured hours/week spent on active mobility. The aim of our first estimation method (Estimation method 1) was to develop a regression model that could be broadly applied in environmental epidemiology. In order to predict active mobility, we used individual general characteristics of study participants. The method makes use of previously identified determinants of GPS measured movement patterns in the VGO GPS study population [15]. The following determinants were identified: age group (<45, 45–55, 55–65 and >65 year), BMI (normal weight [<25 kg/m^2], overweight [25–30 kg/m^2], obese [>30 kg/m^2]), smoking status (never, former, current), working status (job yes/no), hay fever (yes/no) and number of workdays (N/week from Q1). Using these determinants, we calculated per participant (see Supplementary Table 1) the expected hours/week spent on active mobility. For an overview of the applied calculations and formulas see supplementary data (Estimation method 1).

For our second estimation method (Estimation method 2) we used adjusted self-reported data regarding mobility patterns from questionnaire data of the VGO GPS study. In this questionnaire, participants were asked to report weekly mobility. Items in this questionnaire included time spent for commuting, during work hours, during leisure time and as outdoor activity (see supplement Estimation method 2 for an overview of used questions as input for this method). Walking and biking were assessed separately and subsequently added, resulting in a total of hours/week spent biking and walking. From our previous study we knew that VGO GPS study participants strongly overestimated their time spent on mobility (walking, biking and motorised) [15]. We therefore adjusted the calculated weekly hours walking by 1/13.7 and weekly hours biking by 1/2.8, since these numbers represented the amount of overestimation of walking and biking, respectively [15].

The third estimation method (Estimation method 3) made use of location information to predict weekly active mobility. For these type of estimations data regarding commonly visited locations (e.g. home, work, school) were necessary, which enabled calculation of commonly used routes. For every participant the home address and, if applicable, the work address was available. Addresses were geo-coded using cadastral data from the Netherlands (BAG data 2015). Information about supermarkets was obtained from the national information system on work locations (Dutch acronym: LISA [31], 2017). Addresses and coordinates of all locations selling groceries within the research area were obtained and the closest shop was assigned to every individual home address [32]. Distance calculations were based on the road network from topographical maps (TOP10NL [33], 2017) [34]. For every participant the home address, assigned closest supermarket, and, if available, work address were selected and the shortest, road based, route was calculated in km (see Supplementary Fig. 1 for a visual example of the analysis) [35]. Based on these distances, most likely transport modes were assigned using a recent representative survey from the Netherlands Ministry of Infrastructure and the Environment [36]. This survey reports distances travelled using specific transport modes. We used reported median distances, to indicate whether a used route was most likely travelled walking, (E-) biking or using motorised transport. In a next step, we calculated approximate durations spent in active transport using reported average speeds for these travel modes (see Supplementary Table 2 for an overview of distance cut-offs and used average speeds). Since calculated routes were one-way, all estimated distances were multiplied by 2. We assumed that people went to the supermarket once a week and for the route to work we multiplied with the number of workdays participants reported to work, see Supplementary Table 3 for an overview of this process.

Estimation methods compared with GPS measured hours/week spent on active mobility

Processing of our GPS data has been described in detail previously [15]. In brief, we used an algorithm that assigned every logged point as either an indoors or outdoors point. Points assigned outdoors were grouped into episodes and for every episode a transport mode was assigned based on acceleration, deceleration and the 95th percentile of the maximum speed [15, 37]. Each GPS coordinate was thus categorised into walking, biking or motorised transport and time spent per specific transport mode was extracted as hours/week [15]. The GPS measured times were here considered as 'gold-standard' and reference data.

Statistical analysis

For all estimation methods, we compared intra-individually whether GPS measured hours/week of active transport (e.g. hours/week walking and biking) correlated with the hours/week of active transport predicted for that specific participant. Linear regression was used to compare estimated hours/week with GPS measured hours/week.

Next to linear regression we compared GPS measured and predicted hours/week spent on active mobility on a categorical level using Cohen's kappa analyses. Participants were indicated as 'high-', 'medium-' or 'low-' actively mobile based on tertiles for both estimated and GPS measured hours/week spent on active mobility.

Sensitivity analyses

We applied two sensitivity analyses to check for differences in specific groups. First, we reran the analyses, but stratified the dataset by age categories (<45, 45–55, 55–65 and >65 year [15]), since age is related to occupational status [38] and life situation [39] what might be related to differences in daily mobility. In the second sensitivity analysis we stratified based on reporting of a work address (Yes/No), since having a work address may explain the majority of weekly mobility, because of daily commuting and this is one of two driving factors in Estimation method 3.

All statistical analyses were performed using R (3.4.3.) and all GIS analyses were performed in ArcGIS ArcMap 10.5.1 (ESRI, Redlands, CA, USA) and automated using Python 2.7.

Results

Due to incomplete data (missing information for Estimation method 1, e.g. age, BMI, smoking status), data from seven individuals was removed from the original 941 usable

Table 1 Population characteristics

Age	Years (mean (range))	57.3 (20.4–72.0)
Gender	Female (*N*, (%))	513 (55.0%)
BMI	Normal weight [<25 kg/m^2] (*N*, (%))	305 (32.7%)
	Overweight [25–30 kg/m^2] (*N*, (%))	455 (48.8%)
	Obese [>30 kg/m^2] (*N*, (%))	173 (18.5%)
Smoking	Never (*N*, (%))	373 (40.0%)
	Former (*N*, (%))	484 (51.8%)
	Current (*N*, (%))	74 (7.9%)
	No data (*N*, (%))	3 (0.3%)
Hay fever	Yes (*N*, (%))	163 (17.5%)
Work	Yes (*N*, (%))	631 (67.5%)
Workdays[a]	Number (median (range))	2 (0–5)

[a]Information is provided for the whole study population and therefore does include zero values for those not working

datasets. Therefore, analyses were performed with data of 934 people in the VGO GPS population. The average age of participants was 57 years (range 20–72 years) and 55% of participants were women, hay fever was reported by 18% of participants ($N = 163$). Of participants, 33% were of normal weight (BMI <25), 49% overweight (BMI 25–30) and 19% were obese (BMI >30). Most participants were former smokers (52%), a minority was a current smoker (8%) and 40% had never smoked. Work participation was high, 68% indicated having a job, and the median number of workdays was 2 days/week (range 0–5 days/week) see Table 1 for an overview of population characteristics.

Comparisons predicted versus GPS measured hours/week spent on active mobility

Figure 1 shows boxplots of GPS measured and estimated hours/week spent on active mobility. Figure 2a–d displays more detailed distributions of hours/week spent on active mobility, Fig. 2b–d shows the predictions from Estimation methods 1–3, respectively, Fig. 2a pertains to GPS measured hours/week spent on active mobility. From these distributions we observe that only Estimation method 2 (Figs. 1, 2c) shows variation and a range in observed values that is similar to the GPS measured hours/week (Figs. 1, 2a). The distributions of Estimation methods 1 and 3 (Fig. 2b, d) are not in line with the GPS measured spread and range of hours/week spent on active mobility (Figs. 1, 2a).

When we compared estimated and measured hours/week spent on active mobility using linear regression, the predicted and measured hours/week for Estimation method 2 showed low agreement ($R^2 = 0.09$) (Fig. 3). In line with the distribution plots, estimated hours/week spent on active mobility from Estimation methods 1 and 3 had a low agreement with GPS measured hours/week in the linear regression analyses, with R^2 values of: 0.05 for Estimation

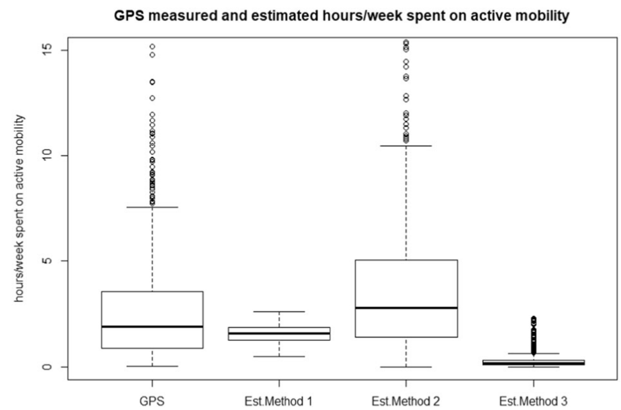

Fig. 1 Boxplots of GPS measured and estimated hours/week spent on active mobility. Est. method 1 is Estimation method 1, Est. method 2 is Estimation method 2 and Est. method 3 is Estimation method 3. We set the maximum *Y*-value to 15 h/week to allow for a better visual comparison, therefore, outliers >15 h/week are not visible in this plot. A boxplot with all outliers visible is available in Supplementary Fig. 2

method 1 (Fig. 3) and <0.01 for Estimation method 3 (Fig. 3). An overview of R^2 values of the linear regression analyses and descriptions of the used input for the estimation methods and the reference are provided in Table 2.

Kappa analyses

Cohen's kappa analyses showed a very low agreement between estimated and GPS measured hours/week spent on active mobility when participants were categorised into low, medium or high groups of active mobility, again the highest agreement was observed for Estimation method 2 (0.07). An overview of the used cut-offs and kappa statistics are given in Table 3.

Sensitivity analyses

We repeated all estimation methods stratified for reported work address (yes and no) and for different previously determined age categories (<45, 45–55, 55–65, >65 year). The stratified analyses did not result in material differences between the strata and were similar to calculations in the whole population. The stratified estimated hours/week spent on active mobility were in the same range as the estimated hours/week of the whole population and we observed a low agreement between estimated and measured values for both linear comparisons and kappa analyses. An overview of hours/week spent on active mobility of sensitivity analyses is provided in Supplementary Table 4.

Discussion

Active mobility may play a relevant role in exposure to spatially variable environmental substances, therefore,

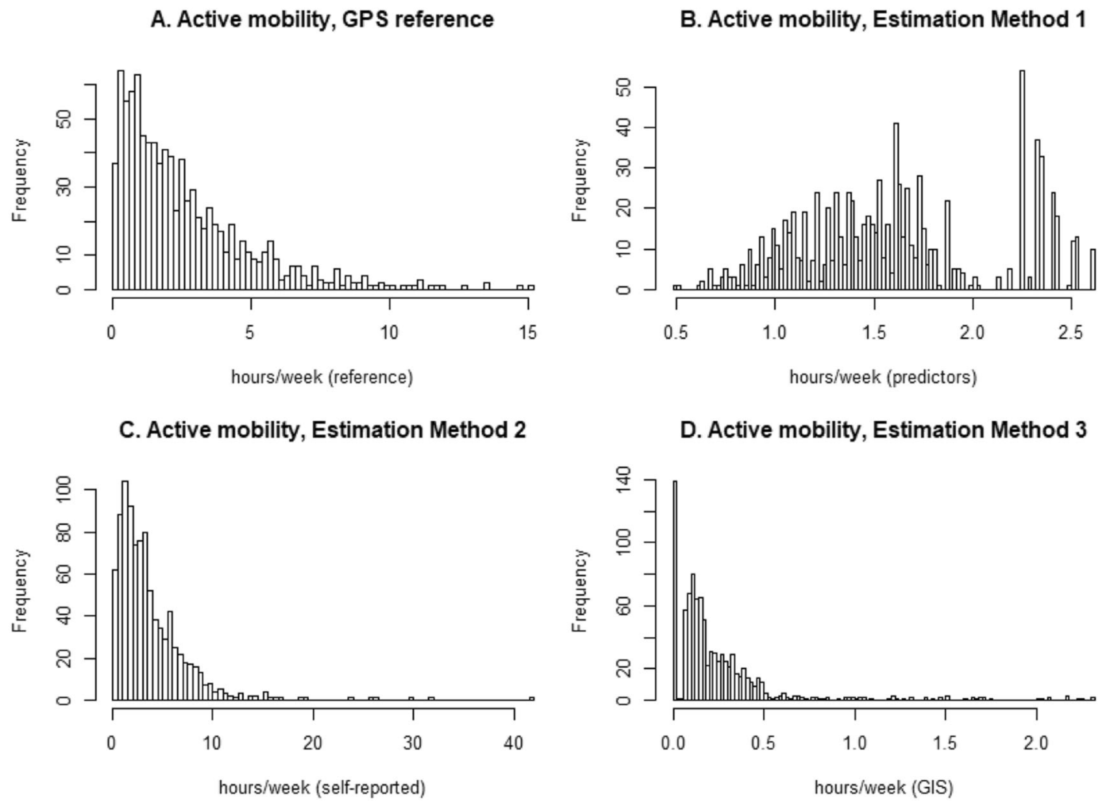

Fig. 2 Frequency distributions of hours/week spent on active mobility. **a** Provides on overview of GPS measured hours/week spent on active mobility, these acted as reference values. **b** Gives an overview of estimated hours/week spent on active mobility from Estimation method 1 (general characteristics method). **c** Shows an overview of estimated hours/week spent on active mobility from the method based on adjusted self-reported data: Estimation method 2. **d** Displays estimated hours/week spent on active mobility from Estimation method 3 (GIS based method). Note, that axis of the plots differ in range to allow for a better plot fit

active mobility should be included in environmental exposure assessment models. Collecting active mobility data however, is challenging especially in large study populations. Therefore, to include active mobility data in exposure assessment in large populations, we developed estimation methods for active mobility based on general characteristics, self-reported data and location information such as home and work address. Estimated hours/week spent on active mobility were compared with individually measured matching GPS data. We observed low agreement between estimated and GPS measured hours/week spent on active mobility for all three approaches.

Estimation method 1, based on individual general characteristics

Studies with a focus on mobility assessment often identify general characteristics that partially explain variability in mobility patterns [15, 23, 25–27]. Therefore, we explored a method based on previously identified general characteristics (e.g. age, BMI, smoking status, workdays/week) related to variability in active mobility patterns in the VGO GPS study [15]. The spread and range of estimated hours/week spent on active mobility was not in line with GPS measured hours/week. This method showed low agreement between estimated and GPS measured hours/week spent on active mobility ($R^2 = 0.05$, kappa = 0.05). Although the factors used in Estimation method 1 explained some of the variation in mobility patterns, other factors such as transport mode preferences [26] and distances to often visited locations [23, 27], were not considered in our previous analysis [15]. The limited spread and range of the estimated hours/week are most likely an effect of the limited explained variability of the used determinants. Note that our estimation method likely overestimated explained variability, as the development and validation dataset were identical.

Estimation method 2, based on adjusted self-reported data

The method based on adjusted self-reported data about active mobility represented the best estimate of hours/week spent on active mobility, when compared with GPS measured hours/week. Still, when compared intra-individually using linear regression and kappa analyses, we saw a low

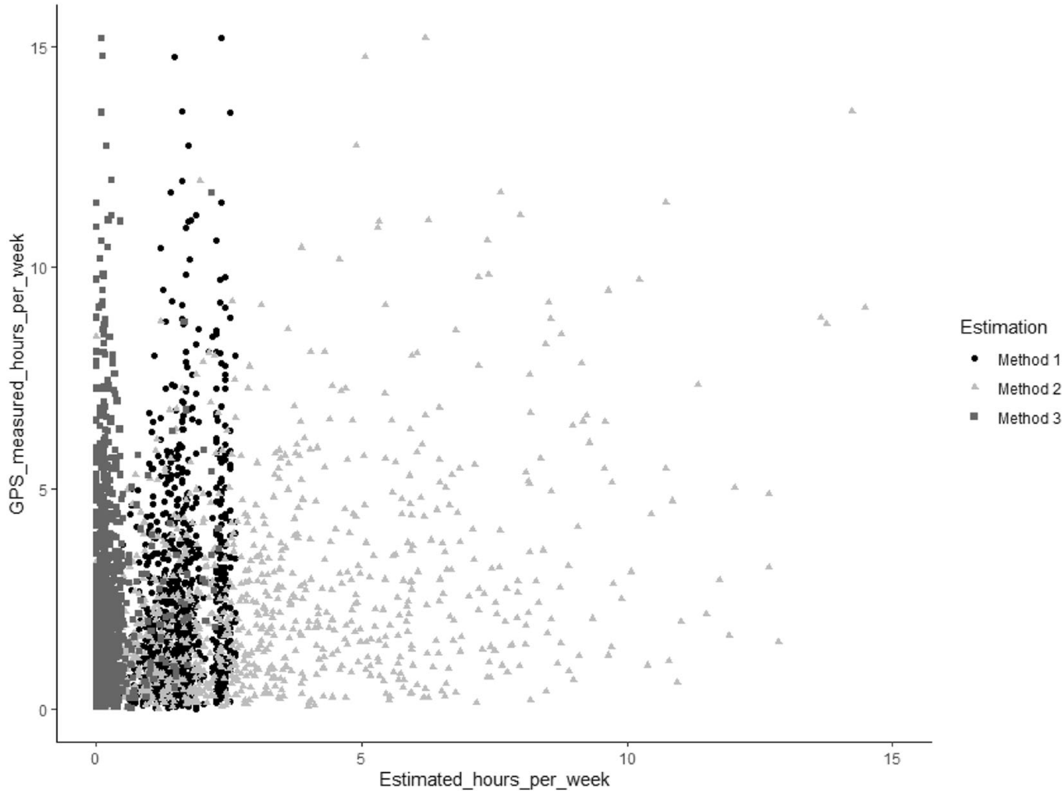

Fig. 3 Scatterplots of matched comparisons between estimated (*x*-axis) and GPS measured (*y*-axis) hours/week spent on active mobility. Black dot, predicted hours/week spent on active mobility from Estimation method 1 (general characteristics method) versus GPS measured. Light grey triangle predicted hours/week spent on active mobility from Estimation method 2 (adjusted self-reported data method) versus GPS measured. Dark grey squares predicted hours/week spent on active mobility from Estimation method 3 (GIS based method) versus GPS measured. We set the axis-maximum to 15 h/week to allow for a better visual comparison between plots, therefore outliers >15 h/week are not visible in these plots. Plots with all outliers visible are available in Supplementary Fig. 3

Table 2 Description of input data for estimation methods, GPS reference and R^2 values

Estimation method	Input data	Reference	R^2
1	GMRs of explanatory variables from [15], for non-motorised transport (age [categorical], BMI [categorical], smoking status, working status, hay fever, workdays [*N*/week]), estimates in hours/week	Combined GPS data of active mobility: data assigned as 'walking' and 'biking' by way of an algorithm [15, 37], outcomes in hours/week	0.05
2	Adjusted reported data from Q1, correction based on calculated overestimation from [15], estimates in hours/week		0.09
3	GIS network analyses of weekly time spent in active transport, calculated using commuting route and/or route to closest supermarket, estimates in hours/week		<0.01

agreement between estimated and GPS measured hours/week spent on active mobility.

Self-reported data has long been considered as a standard method to obtain information about mobility in a population [40, 41] and has for example also been applied to improve exposure estimates to air pollution [6]. The information available from the mobility baseline questionnaire (Q1) of the VGO GPS study, was relatively extensive. From 934 participants we had detailed self-reported mobility data and a GPS dataset [30]. Essential for this method is reliable questionnaire data regarding active mobility, however, correctly estimating time spent on mobility is difficult for participants leading to reporting errors [14, 15, 19, 42]. We tried to adjust reporting error by applying a correction factor based on previous research, to correct for the previously observed overestimation [15], but this adjustment did not materially improve agreement between self-reports and measurements.

Recently, a new approach was tested, namely map-based questionnaires (MBQ's) which seem to provide a new, possibly inexpensive method to assess mobility in large

Table 3 Kappa analysis of estimated and measured outcomes

Estimation method	Cut-offs				Kappa
	Estimation		GPS reference		
	1st quantile	3rd quantile	1st quantile	3rd quantile	
1	1.265 h	1.870 h	0.877 h	3.567 h	0.05
2	1.387 h	4.905 h			0.07
3	0.090 h	0.329 h			<0.01

study populations. MBQ's showed high agreement between GPS measured and MBQ indicated activity locations [24]. So far, it remains unclear if assessment of activity locations can be expanded to evaluate time spent in active transport in a valid way.

Estimation method 3, GIS based approach

More recent attempts target location-based GIS analyses to include mobility data in exposure assessment approaches [10, 11, 16]. Our GIS based method used the residential address, the location of the closest supermarket, and, if available, the work address to calculate the shortest routes between these locations. Based on route lengths, people were assigned to a likely mobility mode and duration of time spent in active transport was calculated [37, 43]. Several underlying reasons may contribute to the poor performance of this approach:

Firstly, we used specific route length cut-offs (<0.5 km: walking, 0.5–2.5 km: bike, 2.5–3.7 km: E-bike, adapted from [36]), to assign most likely mobility modes. Misclassification may occur by performing this step. Median travel distances for mobility modes were based on a recent survey, which were used as cut-offs in our analyses. When we repeated our analysis using the 75th-percentile instead of medians, this did not improve the fit of the estimation (data not shown).

Secondly, this last method was developed using only the residential address, closest supermarket, and, if available, the work address. GIS can be used to estimate shortest routes between locations, and GIS calculated routes tend to estimate travelling distance correctly when compared with actual (GPS-) measured routes [10, 20, 21]. This was indeed what we observed when we visually compared a sample of estimated commuting routes with matching GPS tracks. What also followed from this check was that peoples' activities display a larger spatial distribution than can be estimated using these three locations. Clearly, people also spend time with their family, are involved in sports activities, go to other shops than supermarkets, or visit (nature-) parks or beaches.

Study implications for exposure assessment studies

This study was performed in residents of a rural area in the Netherlands and results from this study may be not generalisable to other settings. Our estimation methods were unable to predict active mobility; this means that these methods are unlikely to improve exposure assessment. Still, active mobility is not the only situation where people are exposed to environmental emissions. One may also be exposed while travelling in motorised transport [44], but this was not the focus of our study. In a previous analysis we observed that self-reported time spent outdoors in the vicinity of the home was associated with pneumonia risk in people living in the vicinity of goat farms, but active mobility appeared not to be associated to this increased risk [30]. The contribution of active mobility to health relevant levels of environmental exposures will likely depend on spatial and spatio-temporal distributions of the respective exposure of interest.

Conclusions

Our main objective was to test different approaches to predict active mobility based on accessible data in a study cohort, since data regarding active mobility is challenging to obtain in large cohorts. Our estimation methods based on general characteristics, self-reported data and location-based information were equally unable to accurately predict active mobility. Estimated commuting routes did to some degree match GPS tracks, so if the goal is to analyse the contribution of homework traffic to an exposure, using a GIS based method may be applicable but requires further study. Overall, measurements still represent the best possible tool to evaluate mobility patterns [11, 18, 19, 21, 45, 46].

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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