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Physical activity and sedentary behavior related to transport activity assessed from multiple body-worn accelerometers: the RECORD MultiSensor Study

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Abstract

Objective: The study explored the physical activity and sedentary behaviour related to transport activity, to support public health and transport policies aiming to encourage people to reach daily recommendation of physical activity. **Study Design:** Cross-sectional study design. **Methods:** In 2013-2015, the RECORD MultiSensor study collected data from 155 participants using two accelerometers worn on the thigh and trunk of participants and Global Positioning System (GPS) receivers complemented with a GPS-based mobility survey. Relationships between transport modes and the durations and partition patterns of physical behaviors were established at the trip stage (n=7692) and trip levels (n=4683) using multilevel linear models with a random effect at the individual level and taking into account temporal autocorrelation. **Results:** Participants travelled for a median of 1 hour 45 minutes per day. Trip stages and trips involving walking, other active modes, or public transport were associated with a lower sitting duration and a higher MVPA duration than those with a personal motorized vehicle. Using public transport was associated with a lower number of transitions between sedentary behaviors and non-sedentary behaviors but with a larger number of transitions between non-sedentary behaviors and moderate to vigorous physical activity than relying on a private motorized vehicle. **Conclusions:** Our study is the first to assess the association of transport mode used with physical activity and sedentary behaviors captured with thigh- and trunk-worn accelerometers at both the trip stage and trip levels. Our results demonstrate that in addition to active transport modes, encouraging people to use public transport increases physical activity and reduces sedentary time.

Key words: Active transport; Accelerometers; Sedentary Behaviours; Moderate to Vigorous physical Activity (MVPA); GPS; Physical Activity

Introduction

Surveillance article concluded that the level of physical activity is low throughout the world, where only about 69% of adults meet the recommended physical activity level (1). European commission in 2014 reported that 48% of the European adults were engaged in sports, 41% do other shorts of physical activity whereas 30% were totally inactive (2). WHO in 2010 recommended that adults (18-64 years old) need to do 75 minutes of vigorous-intensity aerobic physical activity once a week (3), howevere, only 56% of the adult French population were found following the recommendation (3). A report from the united kingdom reported that lack of physical activity is ranked as 4th leading cause of mortality (4). Apart from physical activity itself, studies have highlighted that prolonged sedentary behaviour is associated with the risk of diabetes, obesity, and some cancers among adults (5–7).

A pitfall of previous surveillance studies is that they have often aggregated the information on physical behaviors into daily or weekly averages of physical activity (8). However, such analyses ignore the continuous sequence of physical behaviors performed by individuals over the day in their different activities. Instead, studies should investigate physical activity and sedentary behavior, by aggregating the physical activity information over relevant subperiods during the day, such as places visited or trips, in order to better identify the most important physical activity contexts (9,10). Investigating the relationship at both the trip stage and trip level is useful to distinguish what a mode (e.g., public transport) yields in itself in terms of physical activity and sedentary time from what it yields when distances of access to the mode and potential transfer episodes between trip stages are accounted for.

Active transport (referring to all trip stages based on human-powered transport), as a component of physical activity, has positive health effects (11). Adults have been shown to be active when they are travelling back and forth to work, and particularly in trips made with public transport (12). However, measuring physical activity in trips is particularly challenging. For example, a study used Global Positioning System (GPS) receivers, movement sensors, and heart rate monitoring for measuring the physical activity in a limited number of trips, only home–work trips, and therefore had a limited generalizability (13). Many studies that used GPS receiver, accelerometers, and advanced algorithm to predict transport mode (14,15) have not verified the predicted transport mode with participants, which likely results in prediction error in their data. On the opposite, studies should develop reliable methods for validating the transport modes that were used by the participants with the participants themselves, to make the findings more trustworthy (12,16).

Most studies of physical activity in particular places or during trips have provided crude differences in cumulated times of moderate to vigorous physical activity or sedentary time (17,18). To provide a more accurate picture, studies establishing profiles of physical behaviors in terms of duration, partition (8,19), and transitions between categories of behaviors are needed. Partitions, as opposed to the cumulative time of a behavior, relate to the number and lengths of continuous periods over which the behavior is detected. The rationale for focusing on transitions is that it is currently emphasized that prolonged sedentary bouts are particularly detrimental for health and that for a given amount of time spent in sedentary postures, it is better to incorporate activity breaks into these sedentary episodes (20).

Overall, the objective of our study was to analyze the relationships between transport modes used and the duration and partition profile of physical behaviors, at both the trip stage and trip levels, using linear mixed models. Relatedly, a secondary aim of our paper was to compare an hip-worn accelerometer with two combined thigh- and trunk-worn accelerometers in their ability to assess physical behaviors and body postures such as sitting or standing in trips.

Methods

Population

The data used come from the RECORD MultiSensor Study (21), of the Record Cohort (22). From February 2007 to March 2008, 7290 participants were recruited without a priori sampling (convenience sample) during preventive health cheakups conducted in four sites of the Centre d'Investigations Préventives et Cliniques (IPC) funded by the National Insurance System for Employees and Salaried Workers. People had to be 30 to 79 year old, had to live in 10 districts (out of 20) of Paris and 111 other municipalities of the Ile-de-France region, and had to be free of cognitive and linguistic disabilities to be eligible for the study. In 2011–2015, these participants as well as new participants from the IPC medical center were invited to take part in the second wave of the RECORD Study, in which 6460 participants were included. The RECORD MultiSensor Study sample was recruited among these participants. From September 2013 to June 2015, 919 participants from the second wave of RECORD were invited to participate in the RECORD MultiSensor Study (21) whenever sensor devices were available (i.e., brought back by previous participants). Of them, 319 accepted to participate and signed an informed consent form. Twenty-seven participants withdrew from the study and the data collection failed for 6 participants, resulting in a final acceptation and completion rate of 31.1% $(N = 286)$. The study has been approved by the French Data Protection Authority (Decision No. DR-2013-568 on 2/12/2013).

Among the 286 final participants to the RECORD Multisensor Study, 157 were included in the substudy where they had to carry a BT-Q1000XT GPS receiver, a wGT3X+ waist-worn accelerometer, and two combined accelerometers at the trunk and thigh (VitaMove, Temec Instruments, The Netherlands) over a period of 7 days. The other 131 participants were included in another cardiovascular substudy and are not considered here. Participants in the two substudies were not statistically different in terms of age, sex, education level, employment status, and area of residence, as reported in Web Appendix 1. Regarding our 157 participants, for 2 participants, the trunk and thigh accelerometers did not function properly; these participants were excluded from the analysis, leaving 155 participants for the analyses. Out of 8085 stages of trips made by these 155 participants, 393 (4.9%) were not included due to a failure of the VitaMove devices or because these devices were not worn. Therefore, 7692 trip stages from 4683 trips were included in our analysis.

Classification of trip stages and trips

Trip stages are portions of trips with a unique mode. Within a trip, two trip stages are necessarily separated by an episode of transfer between the two assigned to a punctual location, which also count as a trip stage.

The data extracted from the BT-Q1000XT GPS receiver were pre-processed after the 7-day data collection in order to identify the visited places as well as the start and end times of each trip stage, defined as a segment of a trip using a unique transport mode. Such processing algorithms are integrated in the TripBuilder web mapping application (23,24), and are briefly described in Web Appendix 2. Using this application, the trip data were then consolidated during a phone mobility survey with the participants, producing in the end a detailed timetable covering the 7-day observation period (see Web Appendix 2 for details). This timetable consisted of a time-stamped list of the visited places and trip stages between them.

Each trip comprises one or several trip stages. In trips with several stages, the whole trip also includes the transfer time between several trip stages. Our crude classification of trip stages was as follows: entirely walked, biking/rollers/skateboard (other active modes); public transport; privately owned vehicles; and other non-local trips involving long-distance trains and planes. Our detailed classification of modes further distinguished driving own personal vehicle from travelling through a private vehicle as a passenger (including taxi); and subdivided public transport into (i) bus/coach, (ii) metro, (iii) suburban train including RER (trains travelling within Paris and suburban cities), standard suburban trains, and TER (trains for joining Paris to suburbs or nearby regions), and (iv) trams.

At the trip level, trips were classified into the same categories. Trips that comprised two or more non-walking modes were assigned to a separate multi-mode trip category.

Additionnally, each trip or trip stage was coded as on a weekday vs. weekend day and performed in Spring or Summer vs. Automn or Winter.

Processing of accelerometer data

The VitaScore software was used to process the VitaMove trunk and thigh accelerometer data, and classify each second into 5 groups: sitting, lying, standing, light physical activity (LPA, including slow walking), and moderate-to-vigorous physical activity (MVPA). The VitaMove monitors and the VitaScore software have already been validated and used in several studies (25–27). The device on the trunk is a 3-axis accelerometer, with axes perpendicular to, longitudinal to, and transversal to the trunk, while the device on the thigh has only 1 axis, sagittal to the right upper leg. Information on the orientation of these axes compared to the gravitational axis are used to infer posture. For example, when both the trunk longitudinal axis and the leg sagittal axis are +1g and the other axes are zero, then the posture is assumed to be sitting.

ActiLife 6.11.9 was used to process the waist-worn accelerometer data. The standard inclinometer data indicated the number of seconds of sitting, lying, and standing for each of the 5-second epochs. For comparing the VitaMove posure data to the Actigraph inclinometer (28) data, the VitaMove standing, LPA, and MVPA were considered as standing. The Actigraph algorithm assumes that the person is standing when counts are above 100 per minute (29). When counts are less than 100, the accelerometer senses the acceleration due to gravity, which is a down vector from which the orientation of the device is determined. Based on the orientation of the 3 axes compared to gravity, two angles are calculated, which allow the device to distinguish between lying and sitting. Carr and Mahar concluded that in an average, standing, sitting, and lying were coded accurately for 88.0%, 82.9% and 96.3% of the time respectively by the Actigraph inclinometer function that we use (30).

For each trip or each trip stage, we calculated the cumulated duration in each physical behavior. We also calculated a version of these variables standardized per units of 10 minutes of trip or trip stage.

For a simplified partition analysis based on the VitaMove data, physical behaviours were categorized those into 3 broad groups: SB (combining lying and sitting), NSB (including standing and LPA), and MVPA. Identifying uninterrupted segments of SB, NSB, and MVPA within each trip / trip stage, we determined the median length of such segments separately for SB, NSB, and MVPA within each trip and trip stage. This indicator was standardized per 1 minute of trip or trip stage. We also calculated the number of transitions between SB and NSB, NSB and MVPA, and SB and MVPA within each trip and each trip stage. The latter partition indicator was standardized per units of 10 minutes of trip / trip stage.

Sociodemographic characteristics

Gender was coded in two categories. Age was coded as a continuous variable (age square was tested but not retained as useless). Education was subdivided in 4 categories: no formal education or primary or lower secondary education; higher secondary or lower tertiary education; intermediate tertiary education; upper tertiary education. Employment status was coded as having a stable job; having a fixed-term or precarious contract; or being unemployed. Finally, we took into account the area of residence: Paris; close suburb; far suburb.

Statistical Analysis

Unstandardized and standardized durations of physical behaviors and partition indicators were tabulated by transport modes at the trip and trip stage levels. Relationships between transport modes and unstandardized and standardized durations of physical behaviors were estimated separately at the trip level and trip stage level (one observation per trip and trip stage) using multilevel linear models (31) with a random effect at the individual level to account for trips nested within participants. Web Appendix Figure 1 in Web Appendix 3 (for sitting duration) shows that there was some residual autocorrelation between trip stages that were 1 hour apart or less. The AR(1) autoregressive correlation structure was applied to a continuous time variable (in hours) for modeling this time autocorrelation of errors within participants in the multilevel model (32,33). The Akaike Information Criterion indicated that a model with an individual-level random intercept, sociodemographic covariates, and the transport mode variable was markedly improved when AR(1) was added to the model (models' AIC were improved by >400 for sitting duration and by >1300 for MVPA duration).

All models were adjusted for sociodemographic characteristics. Sociodemographic groups differ in their usual trips with a given transport modes, as they live in and travel to different places. Even for a given trip with a particular mode from point A to point B, although they would all have to walk the same distance, climb the same stairs, etc., they could differ for example in their propensity to stand or sit during public transport trips. If our sample of participants and trips were representative of the Ile-de-France region, the relationship between transport modes and physical activity not adjusted for sociodemographic characteristics would meaningfully represent the average physical activity condition per transport mode in the region. However, because our sample is distorted towards well educated participants, it is needed to control for sociodemographic characteristics. However, it is important to emphasize that this statistical adjustment yields an abstract estimate artificially assuming a similar sociodemographic structure across transport modes (and thus for example ignoring the fact that a large share of itineraries with a particular mode are located in relatively disadvantaged neighborhoods or in relatively advantaged neighborhoods)

Weekday/weekend day and season of the trip were associated with durations of certain physical behaviors, but not with durations standardized by 10 minutes of travel time. Therefore, they were only introduced in models for unstandardized outcomes.

We also estimated multilevel models with interaction terms between transport mode and weekdays/weekend days and/or between transport mode and season. The destinations and transport modes of trips may vary between the week and the week-end and between seasons, and this may affect both the distribution of physical activity and sedentary behaviors within each mode and the hierarchy between modes in terms of physical activity and sedentary behaviors.

Since the ranking of transport modes was similar in the models with only one or with the two interaction terms, we used the models with a single interaction term for plotting the predicted durations of physical behaviors by weekday/weekend day and season. Models with two interaction terms are reported in Web Appendix 4.

In order to compare the associations between transport modes and the duration of physical behaviors as estimated from waist-worn accelerometrers (Actigraph) and trunk- and thighworn accelerometers (VitaMove), we re-estimated the regression models among 4008 trips and 6901 trip stages (154 participants) with information for both sensors.

All statistical analyses were conducted using R software (version 3.4.4) and R Studio (version 1.1.463) (34).

Results

Sample description

The 155 participants had an average age of 50 years (range: 34–82 years). Among them, 63% were males. Thirty-five percent of them were from Paris, 20% lived in the close suburb, and 45% in the far suburb. Twenty-five percent of participants had no formal education or had a primary education or lower secondary education; 21% had a higher secondary education or lower tertiary education; 19% had an intermediate tertiary education; and 35% of participants had an upper tertiary education. Among participants, 78% had a stable job, 19% had a fixed term or precarious contract, and 3% (4 participants) were unemployed.

Descriptive information on trips

The median follow up time of participants in our study was 7 days (mean 6.1 days, interdecile range: 5–7 days, standard deviation: 1.0 days). Participants had a median number of trips per day of 5 (mean: 5.1, interdecile range: 3–7, standard deviation: 2.1), corresponding to a median number of trip stages per day of 8 (mean: 8.5, interdecile range: 4–13, standard deviation: 3.7). Participants were travelling (as opposed to being at a place) for a median of 1 hour 45 minutes per day (mean: 1 hour 52 minutes, interdecile range: 56 minutes – 3 hours 2 minutes, standard deviation: 52 minutes). Following Web Appendix 5, the most frequently used mode of transport was walking, corresponding to 53.8% of trip stages 39.6% of trips, followed by private motorized vehicles, corresponding to 23.1% (19.9% as a driver and 3.2% as a passenger) of trip stages and 39.6% (31.8% as a driver and 4.5% as a passenger) of trips.

Association between transport mode and physical activity

Associations between sociodemographic characteristics and sitting time or MVPA (standardized outcomes) are shown in Web Appendix 6.

In models for both unstandardized and standardized outcomes (Tables 1 and 2), not only trips or trip stages by walking or with other active modes but also (although to a lesser extent) those with public transport were associated with a lower sitting time than when using a personal motorized vehicle (after adjustment for sociodemographic characteristics). In the models with standardized outcomes (Table 2), the coefficient showing that there was less sitting time in public transport was stronger in the model at the trip level than at the trip stage level (as opposed to public transport trip stages, public transport trips also include the walking episodes). This is not the case in the models with unstandardized outcomes (Table 1) that are difficult to interpret due to the fact that trips and trip stages with different modes have different durations.

Regarding MVPA, when durations of trips and trip stages were accounted for (standardized outcome, Table 2, third and fourth columns), trips and trip stages by walking, other active modes, and as expected to a lesser extent with public transport were all associated with more minutes of MVPA than those with a personal motorized vehicle (after adjustment for sociodemographic characteristics). The coefficient showing more minutes of MVPA associated with public transport was stronger in the model at the trip level (Table 2, column 4) than in the model at the trip stage level (column 3), as public transport trips also typically include walked trip stages.

Figure 1 reports average durations of sitting and MVPA in a trip by transport modes (predicted from separate models with an interaction of transport modes with either the weekend / weekday variable or the season variable and adjusted for sociodemographic characteristics, with the unstandardized outcome). MVPA duration in a trip was higher during weekends than on weekdays in trips with all modes, although the difference was particularly sharp only for multimodes trips (this finding is based, however, on 9 and 52 multi-mode trips on the weekend and on weekdays, respectively, and is attributable to the fact that these weekend trips had an average duration of 188 minutes vs. 81 minutes for the weekday trips). Regarding the interaction with seasons, spring or summer was associated with a longer duration of MVPA per trip for all transport modes (except perhaps multi-mode trips), with a non-overlapping confidence intervals only for trips with other active modes.

Partition profile: transition rates

As shown in Table 3, transport modes differ in the number of transitions among SB, NSB, and MVPA. For example, both at the trip stage and trip level, using public transport was related to a lower number of transitions between SB and NSB (or the other way round) than driving or being the passenger of a private motorized vehicle, but it was related to a larger number of transitions between NSB and MVPA. Walking or relying on other active modes had the largest number of transitions from NSB to MVPA. Compared to other two types of transitions, those between SB and MVPA were particularly rare.

Statistics on the length of uninterrupted episodes of physical behaviors (SB, NSB, and MVPA within trips and trip stages are reported in Web Appendix 7.

Comparison of waist-worn to and thigh- and trunk-worn accelerometers

Considering time periods with both waist-worn and thigh- and trunk-worn accelerometers, the standing duration per individual per eight hours of device wear time had a median of 290.4 minutes (interdecile range: 123.6, 434.1) when assessed with the thigh- and trunk-worn accelerometers, as compared to 271.6 minutes (interdecile range: 138.3, 388.5) when assessed with the single waist-worn accelerometer. The corresponding figures for sitting time were 183.8 minutes (interdecile range: 42.1, 352.2) and 208.6 minutes (interdecile range: 92.9, 330.0).

Table 4 shows that the contrast in sitting duration between using a personal motorized vehicle and the other modes (public transport, walking, and other active modes) was substantially underestimated by the waist-worn accelerometer compared to the the thigh- and trunk-worn accelerometers, in both duration-unstandardized and standardized models (trip stage model). The corresponding models at the trip level are reported in Web Appendix 8.

Discussion

Strengths and limitations compared to previous literature

Regarding strength of our approach, this paper is one of the few published studies to explore the association of transport mode with physical activity at the trip level using objective sensorbased measures measured outcomes (12,18). And it is the first to conduct such a detailed analysis with two complementary body-worn accelerometers that permit a more accurate assessment of body posture, including sitting. Two accelero-sensors placed on the trunk and thigh that provide information on the orientation of the body compared to the gravitation field are useful to infer body posture.

Another strength of this paper is that it performed this analysis comparatively at the trip stage level and trip level. Investigating the relationship between transport mode and physical behaviors is of interest both at the trip stage level, for a description of each transport mode, and at the trip level, to investigate how the different non-walking modes generate walking and physical activity. Previous studies did not reach this level of precision, for example those which modeled the relationship between transport mode and physical activity at the individual level rather than trip stage and trip levels (35). A study that analyzed trip-level information used selfreported rather than accelerometer-derived physical activity, which makes the findings less trustworthy (36). Another study investigated the association between transport mode and physical activity using a linear mixed model (12); however, trip level data but not trip stage level data were considered and temporal autocorrelation was not taken into account, which is important when analyzing repeated observations (31). To overcome these limitations, we collected trip data at the trip stage level, and timestamps were available for all transitions between modes within trips over 7 days, and had been pre-identified with algorithms and then verified on the phone with participants.

Regarding limitations, first, the recruitment of participants was not at random (convenience sample). Beyond non-randonmess, findings from a small sample of 155 participants cannot be generalized to the complex transport habits of a population of more than 24 million inhabitants (Paris and close and far suburbs). For instance, if the odds of participating in the study were lower for those public transport users living in municipalities far from recruitment area, then longer public transport trip stages would be underrepresented in the study. Since a larger segment of a public transport trip is related to walking when the trip is short than when the trip is long, such a hypothetical recruitment bias would influence the comparison of physical activity between private motorized vehicle trips and public transport trips. Second, there is certainly measurement error in the start and end times of trips due to the GPS data, processing algorithms, and mobility survey; and there is also measurement error in the inclinometry function of the accelerometers. These errors resulted in non-zero sitting time during entirely walked trip stages. the estimated time of physical behaviors assigned to transport modes was based on the accelerometer wear time. If specific trips in terms of physical behaviors were more frequently excluded due to nonwear of the accelerometer, then it would bias our comparisons.

Interpretation of findings

Trips and trip stages by walking or other active modes, but also (although to a lesser extent) with public transport, were associated with longer walking durations and shorter sitting durations than trips based on a personal motorized vehicle, and these findings hold whether sitting or MVPA time were standardized or not by trip or trip stage durations. This finding supports previous studies quantifying the physical activity gains of biking (37,38) and walking (12). Regarding public transport, our findings are in accordance with previous research; for example, it has been found that public transport users had 24.3 minutes of physical activity per day while travelling, which is a substantial portion of recommended physical activity levels in guidelines (39). The health benefits gained from the physical activity associated with the use of public transport have been investigated in previous literature (35).

In our study, in models with standardized outcomes, the coefficient showing that there was less sitting time in public transport and the coefficient showing more minutes of MVPA with public transport were stronger in the models at the trip level than at the trip stage level. This is because, in addition to the potential active movements within public transport vehicles, trips also typically include walked trip stages to and from public transport stations (12). Thus our study comparing analyses at the trip level and trip stage level was useful to distinguish between these two sources of physical activity. Walked distances to and from public transport stations and standing in public transport vehicles may thus help people achieve physical activity recommendations, especially people who do not have time for other kinds of physical activity (35,39). However, it is critical to keep in mind that it may not be possible for everyone to increase their level of physical activity by transport mode, due to various types of health, environmental, or time constraints. It should also be emphasized that the physical activity gains from choosing public transport instead of a private motorized vehicle as a

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transport mode is likely to differ from one city to the other, because of variations in the configuration of transport systems and travel habits of people.

Conclusion

In conclusion, our study is the first to assess the relationship between various transport modes and physical behaviors based on GPS, mobility survey, and waist, thigh, and trunk accelerometer data, with a comparative analysis at the trip stage and trip levels. This pioneering approach allowed us to accurately measure differences in physical behaviors between transport modes.

Even if future research will have to rely on larger and more representative study samples to yield more generalizable findings, our study shows that promoting walking and biking but also public transport in daily routines may have a significant impact at the population level in terms of increasing the share of people reaching the physical activity recommandation. Our study thus add evidence to recent calls (40) to promote these transport modes at the expense of car driving through urban and transport policies (including ensuring the local access to services, greening cities, developing networs of walking paths and biking lanes as well as public transport).

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Conflict of interest

None were declared.

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	Sitting duration in minutes		MVPA duration in minutes	
Transport mode	Trip stage level β (95%CI)	Trip level β (95%CI)	Trip stage level β (95%CI)	Trip level β (95%CI)
Detailed classification				
Private motorized (driver)	Ref	Ref	Ref	Ref
Private motorized				
(passenger)	$-2.19(-3.70, -0.68)$	$-1.18(-4.13, 1.77)$	-1.26 $(-2.07, -0.45)$	1.49(0.09, 2.89)
Bus/coach	$-10.71(-11.82, -9.60)$	-6.08 $(-9.61, -2.55)$	1.25(0.72, 1.79)	7.97(6.24, 9.70)
Metro	$-10.58(-11.54, -9.62)$	$-3.95(-6.57,-1.33)$	0.90(0.42, 1.37)	10.89 (9.61, 12.16)
Tram	-10.63 $(-12.66, -8.60)$	$-9.89(-16.92, -2.86)$	$-0.13(-1.06, 0.81)$	8.57 (5.18, 11.96)
Suburban train	-6.01 $(-7.22, -4.80)$	$-2.39(-6.56, 1.78)$	-0.24 $(-0.84, 0.35)$	17.09 (15.11, 19.06)
Biking and other active	-13.69 $(-15.19, -12.19)$	$-13.36(-16.58, -10.14)$	5.53 (4.75, 6.30)	6.82(5.33, 8.31)
Entirely walking	-14.07 $(-14.78, -13.36)$	$-15.30(-16.87, -13.73)$	2.00(1.63, 2.37)	4.38(3.64, 5.12)
Multi-mode	NA	12.36 (9.85, 14.87)	NA.	15.29 (14.06, 16.51)
Other ^b	3.17(0.51, 5.83)	$1.37(-3.95, 6.69)$	2.60(0.99, 4.21)	3.21(0.80, 5.62)
Crude classification				
Private motorized	Ref	Ref	Ref	Ref
Public transport	$-9.28(-10.07, -8.49)$	-1.07 $(-2.95, 0.81)$	0.98(0.58, 1.38)	11.58 (10.68, 12.48)
Other active mode	$-13.38(-14.88, -11.88)$	-13.20 (-16.40 , -10.00)	5.77(5.01, 6.53)	6.65(5.16, 8.14)
Entirely walking	-13.64 (-14.30 , -12.98)	-15.24 (-16.72 , -13.76)	2.24(1.90, 2.58)	4.17(3.46, 4.88)
Multi-mode	NA	24.65 (20.04, 29.26)	NA	20.98 (18.66, 23.30)
Other ^b	3.52(0.88, 6.16)	$1.34(-3.99, 6.67)$	2.83(1.22, 4.44)	3.02(0.60, 5.44)

Table 1. Association between transport mode used and physical behaviors (trip stage level n =7692, trip level n = 4683, N = 155 participants)^a , unstandardized outcome

CI: Confidence interval, MVPA: Moderate to vigorous physical activity, NA: Not applicable at the trip stage level. ^aThe multilevel linear models included a random effect at the individual level. The crude and the detailed transport mode variables were introduced in separate models. The models took account of temporal autocorrelation and were adjusted for sociodemographic characteristics and day of week and season.

^bLong-distance train and plane.

Table 2. Association between transport mode used and physical behaviors (trip stage level n = 7692, trip level n = 4683, N = **155 participants)^a , standardized outcome**

CI: Confidence interval, MVPA: Moderate to vigorous physical activity, NA: Not applicable at the trip stage level. ^aThe multilevel linear models included a random effect at the individual level. The crude and the detailed transport mode variables were introduced in separate models. The models took account of temporal autocorrelation and were adjusted for sociodemographic characteristics.

^bLong-distance train and plane.

Table 3. Number of transitions between physical behaviors (SB, NSB, and MVPA) standardized by 10 minutes of trip, by transport mode, at the trip stage and trip levels: median (10th and 90th percentiles)

RECORD MultiSensor Study, 155 participants, 7692 trip stages and 4683 trips

SB: Sedentary behaviour, NSB: Non-sedentary behaviour, MVPA: Moderate to vigorous physical activity, NA: Not applicable at the trip stage level.

aLong distance train and plane.

Table 4. Association between transport mode and sitting duration, comparing a waist-worn accelerometer with two thigh- and trunk-worn accelerometers (analyzed at the trip stage level, $n = 6901$ **,** $N = 154$ **participants)^a**

CI: Confidence interval.

^aThe multilevel linear models included a random effect at the individual level. The crude and the detailed transport mode variables were introduced in separate models. The models took account of temporal autocorrelation and were adjusted for sociodemographic characteristics and day of week and season.

^bLong-distance train and plane.

Figure 1: Predicted duration of physical activity according to transport mode, by season or weekend/weekdays: unstandardized models at the trip level^a

MVPA: Moderate to vigorous physical activity.

^aThe multilevel linear models included a random effect at the individual level, took account of temporal autocorrelation, and were adjusted for sociodemographic characteristics.

Physical activity and sedentary behavior related to transport activity assessed from multiple body-worn accelerometers: the RECORD MultiSensor Study

Appendix 1: Comparison of sociodemographic characteristics of participants included in the two substudies of the RECORD MultiSensor Study

Appendix Table 1. Comparison of sociodemographic characteristics of participants included in the two substudies of the RECORD MultiSensor Study; values are number (%) if not stated otherwise (N = 286)

Appendix 2: the GPS-based mobility survey

Processing algorithms

Throughout the study period, participants were asked to maintain a travel diary recording the places they visited and the modes of transport taken. This diary was just used as a supporting piece of evidence during the mobility survey.

The GPS data (one point every 5 seconds) were uploaded in the TripBuilder Web mapping application where GPS data were processed with algorithms (1,2). These algorithms (i) identified the places visited by the participants over 7 days; (ii) decomposed the trips between visited places into segments of trips with unique modes; (iii) imputed information on the activities performed in each place based on the geolocated regular visited places of each participant pre-identified with the VERITAS application (3) and on geolocated points of interest; and (iv) imputed information on the travel modes used in each trip segment based on speeds, survey information on typical modes used by the participant, and on the presence of public transport stations of the same line or mode at the beginning and end of the trip segment.

The algorithms for the identification of trips and mode-specific trip stages are explained in details in the article by Simas Oliveira and colleagues (4). Briefly, the overall trips are identified using stops (no moving points) of at least 120 seconds. The application first removes any point with speed < 1 (km/h) and then look for gaps in the point sequence that are longer than or equal to 120 seconds, which are identified as stops.

The algorithm developed to split the trips based on transport mode transitions is based on the one proposed by Tsui (5). A moving window was used to detect if a mode transition existed in a short sequence of points within a trip (which equated to approximately 44 seconds). The window's average point speed and standard deviation of speed values as a

proxy for acceleration were used to determine if the window's mode was motorized and whether or not it was likely to contain a mode transition:

- If the average point speed was above 16 m/s the window was classified as motorized.

- The window was determined to contain a mode transition if its motorized flag was different than that of the previous window and if the standard deviation of speeds was greater than 2.25 m/s.

Once a given window was determined to contain a mode transition, the location of the transition was assigned by examining the GPS points within the window and locating the last point with characteristics either below or above the non-motorized mode speed threshold (16 m/s). Once the mode transition points were assigned, the trips were split and the resulting list was run through mode selection.

Like the method proposed by Stopher et al. (6), the mode selection process used GPS point speeds. More specifically, pre-computed values for average, maximum and standard deviation of mode speeds were used. The first step in the process was to compute average and standard deviation values of the trip segments' point speeds. Using these values, estimates of the mode segments' 95th percentile speeds were computed by adding / substracting 1.96 times the point speed standard deviation to the segment's average speed (assuming a normal distribution of point speeds). The logic selected the travel mode for a trip segment that most closely matched its average and standard deviation of point speeds, while having its 95th percentile speed lower than or equal to the mode's maximum speed. If a segment could not be assigned a travel mode, then it was given a null travel mode.

Mobility survey

Based on the TripBuilder Web application, a GPS-based mobility survey was conducted through a telephone interview as soon as possible after the data collection (median time of 10 days, interquartile range: 7, 15). Only the research assistants had access to the application, while participants had access to detailed screen copies of their trips sent by email or postal mail. Using these computer and paper supports, the research assistants walked the participant through the different days, reviewing and complementing information trip by trip. The research assistants confirmed the detected visits to places and trips between these places; they removed visits to places and trips that were incorrect; they could generate visits to places or trips to places undetected by the GPS receiver and/or algorithm (with itineraries then imputed as the shortest street network path and edited if needed). The research assistants manually edited each trip itinerary, if needed, to remove residual artefacts in the GPS track that would bias the assessment of the travel distance. Finally, research assistants confirmed or collected and modified the type of activity practiced at each visited place and the travel mode used in each trip segment.

A SAS program generated a detailed timetable over 7 days indicating the succession of places visited and trips subdivided in trip stages. Within a trip, two trip stages are necessarily separated by an episode of transfer between the two assigned to a punctual location. These transfer episodes coded with a spatial point in the mobility survey typically last from 0 minute to several minutes and correspond to no walking at all, walking few meters outdoor, or walking indoor, e.g., within a train or metro station (but these punctual transfer episodes cannot imply movement with any other mode). A transfer between two trip stages by bus would be coded as a walking trip stage if there was a detectable walking track between them, but would be coded as a punctual location if the two buses were few meters apart outdoor. Start/end times are available for each visited place, trip, trip stage, and episode of transfer between trip stages.

Due to costs, the mobility survey was only performed on days (i) where there was GPS data and (ii) where the additional sensors (VitaMove system) employed in this study were worn by the participants. On those days, the mobility survey was systematically performed for the whole day, even if GPS data were partly missing. In the latter case, missing portions of itineraries were complemented during the mobility survey, so that the day had full distance information. On the opposite, if the two conditions above were not satisfied, the whole day was excluded.

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Appendix 3: Evidence of time-related residual autocorrelation in level-1 residuals for the model on sitting time

Appendix Figure 1

Empirical autocorrelation plot from a multilevel model for sitting time with a random effect at the individual level

The Figure shows that for a lag of 1 hour between the trip stage observations for a given individual, there is some correlation between these observations. The AR(1) autocorrelation structure was intended to take it into account.

Appendix 4: Models including interactions between transport modes and

both weekdays/weekend days and season

CI: confidence interval, MVPA: moderate to vigorous physical activity.

^aThe multilevel linear models included a random effect at the individual level, taking account of temporal autocorrelation. It was also adjusted for sociodemographic characteristics.

^bLong-distance train and plane.

Appendix Table 3. Associations between the transport mode used (crude classification) and physical behaviors, and their interaction with season and day of week at the trip level ($n = 4683$ **trips,** $N = 155$ **participants)^a**

CI: confidence interval, MVPA: moderate to vigorous physical activity.

^aThe multilevel linear models included a random effect at the individual level, taking account of temporal autocorrelation. It was also adjusted for sociodemographic characteristics.

^bLong-distance train and plane.

Appendix 5: Descriptive statistics on trip stages and trips

Appendix Table 4. Descriptive statistics on trip stages according to the transport mode used [Median (10th and 90th percentiles)]

RECORD MultiSensor Study, 155 participants, 8085 trip stages

^aThe numbers and durations of trip stages are calculated across the 155 individuals, including those who do not use the corresponding modes.

bLong-distance train and plane.

Appendix Table 5. Descriptive statistics on trips according to the transport mode used [Median (10th and 90th

RECORD MultiSensor Study, 155 participants, 4930 trips

^aThe numbers and durations of trips are calculated across the 155 individuals, including those who do not use the corresponding modes.

^b Long-distance train and plane.

Appendix 6: Association between sociodemographic characteristics and sitting

time and MPVA time

CI: confidence interval, MVPA: moderate to vigorous physical activity.

^aThe multilevel linear models included a random effect at the individual level. The models took account of temporal autocorrelation.

bLong-distance train and plane.

Appendix 7: Statistics on length of uninterrupted episodes of physical behaviors in trip stages and trips

Appendix Table 7. Length of uninterrupted episodes of physical behaviors within trip stages and trips (standardized by travel time, for each minute of trip) by transport mode: median length (10th and 90th percentiles)

RECORD MultiSensor Study, 155 participants, 7692 trip stages and 4683 trips

*For a trip stage that would last 1 minute, the continuous/uninterrupted episodes of sedentary behaviour would have a median length of 0.17 minute.

aLong distance train and plane.

Appendix 8: Comparison of waist-worn to thigh- and trunk-worn

accelerometers

CI: confidence interval

^aThe multilevel linear models included a random effect at the individual level. The crude and the detailed transport mode variables were introduced in separate models. The models were adjusted for sociodemographic characteristcs and day of week and season, and took account of temporal autocorrelation.

^bLong-distance train and plane.