Is Older Adults' Physical Activity during Transport Compensated during Other Activities? Comparing 4 Study Cohorts Using GPS and Accelerometer Data

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Highlights:

- Older adults with low regular physical activity seemed energized after active trips
- About 14% of additional transport physical activity was compensated the next day
- About 25% of additional transport physical activity was compensated the same day
- Transport intervention evaluations need to evaluate non-transport physical activity

Abstract

Introduction: Promoting active transport offers the potential to increase population physical activity levels. Compensation theories state that above-average physical activity in one activity is compensated in later activities; a mechanism that results in stable levels of total physical activity. Little is known about possible compensation of transport physical activity among older adults.

Methods: GPS (Global Positioning System) and accelerometer data collected among older adults (65+) were pooled from four cohorts in Canada, Luxembourg, and France (n=636, collected between 2012 and 2016). Physical activity was measured as total volume of physical activity for trips and non-trip activities. Robust linear regressions on person-centered data were used to test within-person associations between transport and total physical activity.

Results: 636 older adults – median age of 76 years, 49% women - provided accelerometer and GPS data for at least 4 days. 18% of the total volume of physical activity was related to transport. A positive association was found between physical activity during a trip and the physical activity during the next hour, among those with lower levels of regular physical activity. Negative associations - indicating partial compensation - were found between transport physical activity during a day, and both total physical activity during the next day and non-transport physical activity during the same day. No differences were found between the four study cohorts.

Conclusions: Transport physical activity is compensated partially by older adults during non-transport physical activity. Given the presence of compensation, we strongly recommend evaluations of transport interventions to measure and analyze both non-transport and transport physical activity.

Keywords:
Transport physical activity; Active transport interventions; Accelerometer; Global positioning system; Total volume physical activity; ActivityStat

1. Introduction

Physical activity levels are low and declining worldwide (1; 2), including among older adults (3; 4). This is concerning, given that physical activity appears to favor healthy aging (5), is associated with improved physical functioning and is preventive against non-communicable diseases such as diabetes, depression and certain cancers (6; 5; 7). Promoting active transport offers the potential to increase physical activity levels (8-10), especially among older adults, since few participate in sport and exercise (11). However, increasing active transportation may not translate into greater daily total physical activity (12). Physical activity performed during an active transport episode may later be compensated by reductions in other domains, such as leisure-time activity, nullifying gains in total physical activity. A recent Canadian study showed increasing participation in leisure-time activities and active transportation across five 10-year age cohorts between 1994 and 2010, while daily physical activity (e.g. household activities) decreased (13). Younger adults were more involved in leisure-time activities and active transport, but also reported less daily physical activity compared to older adults (13).

The ‘ActivityStat’ hypothesis – a commonly cited compensation theory – argues that compensation is driven by a biological mechanism which ensures a constant level of physical activity or energy expenditure over a certain period of time (14). Under this hypothesis, a period of increased physical activity will be followed by a period of lower than average physical activity. Similarly, a period of low physical activity will be followed by a period of greater than average physical activity. Under this hypothesis, a given level of transport-related physical activity (higher/lower) would subsequently be compensated by reductions in other activities (lower/higher) (e.g., leisure-time, occupational) or in so-called spontaneous physical activity (e.g., fidgeting) to maintain a ‘constant’ level of physical activity or energy expenditure. Note that the timeframe for compensation to occur is not well-defined in the ActivityStat theory (15).

In opposition to compensation hypotheses, ‘Generalization’ (16) hypotheses, also known as ‘Performance’ (17) or ‘Synergy’ (18) hypotheses, predict that the performance of additional physical activity in one domain will subsequently lead to increases in physical activity in other domains. Intermediate mechanisms may relate to a feeling of being energized (short-term generalization) or the translation of increased physical fitness into greater total physical activity (long-term generalization).

Finally, the ‘Independence’ or ‘Additive’ hypothesis, which is predominant in the literature but usually not explicitly stated (17), purports that an increase in physical activity (e.g. during transport) is not related to the physical activity during other activities. This means there is neither compensation nor generalization. This hypothesis is implicit in studies evaluating intervention effects on active transport behavior alone, without assessing the effect on total physical activity. In this article, the ‘Compensation’ and ‘Generalization’ mechanisms are considered antipodes, with a lack of either mechanism suggesting ‘Independence’.

The ‘Compensation / Generalization’ hypotheses have mainly been tested in relation to exercise physical activity (15). A 2013 review (15) identified 28 experimental studies investigating the ‘ActivityStat’ hypothesis following the introduction of exercise interventions. Results were mixed, with fifteen studies detecting some compensation, and thirteen identifying none. From the few studies among older populations, there was somewhat greater support for the compensation hypothesis (4 out 5 studies). A similar review concluded that there was no compelling evidence to support either the Compensation or the Generalization hypothesis (19). Interestingly, they noted that the studies with some evidence of compensation were conducted among significantly older adults (median age of 61 years) than those that found no evidence of compensation (median age of 44 years).

Very few studies have investigated compensation / generalization in relation to transport physical activity, and those that have rely upon self-reported physical activity. Two longitudinal UK-based studies of 469 and 1628 adults found no evidence of compensation or generalization in relation to changes in transport-related physical activity over time (12; 20). A cross-sectional study found a positive association between transport-related physical activity and total physical activity, appearing to suggest an absence of compensation of transport physical activity (21). However, the study does not permit the identification of possible partial compensation, independence or generalization mechanisms. In order to further our understanding of these processes in relation to transport physical activity, there is a need to obtain objective measures of physical activity and to decompose total daily physical activity into specific episodes (e.g. transport vs. non-transport episodes). To our knowledge, only one study has used GPS-based recognition of activity locations in combination with accelerometer data to test the ‘Compensation / Generalization’ hypotheses (16). Analyzing data from 528 school-going adolescents, there was no evidence of compensation in moderate-to-vigorous physical activity between different activity locations (home, home neighborhood, school, school neighborhood, and other locations). However, this study did not analyze transport behavior specifically.

In summary, no study has explored possible compensation / generalization processes in relation to transport physical activity using objective measures. Moreover, there is no evidence (using objective or self-reported data) to support or refute such processes among older adults. This is despite the fact that exercise research suggests compensation may be age dependent, with older adults seemingly more likely to compensate physical activity than children or younger adults (17).

To address these current gaps in the literature, this study assesses the association between transport, non-transport, and total physical activity levels, using GPS and accelerometer data obtained from older adults in Canada, Luxembourg and France. Compensation and generalization hypotheses were assessed by testing associations between objectively measured physical activity: i) during a given transport episode and during the hour following that episode, ii) during transport episodes on one day and during the entire next day, and iii) during transport episodes and non-transport periods within the same day. The first two associations test whether compensation occurs subsequent to periods of above or below average physical activity. The third hypothesis considers compensation within the same day, allowing compensation to occur before (pre-compensation) and not only after (post-compensation) a given activity. Pre-compensation could be linked to activity planning; for instance, people might engage in lower levels of non-transport physical activity in anticipation of active transport activities during the same day. Considering the large differences in physical functioning between early retirees and older retirees (3), each model tested the dependency of compensation on age, study cohort, and mean daily physical activity.

2. Methods

2.1. Participants

The study uses 7-day GPS and accelerometer data collected among older adults in Canada, Luxembourg and France. Participants were pooled from the CURHA (Contrasted URban settings for Healthy Aging) (22), RECORD (Residential Environment and COronary heart Disease) (23), and PACTE-ROSEMONT (Participation sociale, ACTivité physique et Environnement bâti) study cohorts

The 636 CURHA study participants used for this analysis included i) 148 participants from Montreal and Sherbrooke area, Canada, recruited among the pre-existing Quebec Longitudinal Study on Nutrition and Successful Aging (NuAge) cohort (24) and followed during the Autumn 2014 or Spring 2015; and ii) 319 participants from Luxembourg, recruited in 2015-2016 among a representative random sample of the Luxembourgish Social Security files, and stratified by age, gender and five spatial strata. 94 participants residing in the Paris Region, France, were drawn from the RECORD GPS (25; 26) and RECORD MultiSensor studies (27) recruited in 2012-2013 and 2014-2015, respectively. Finally, data were used from the first wave of the PACTE-Rosemont study conducted in autumn 2016 (n = 75). The PACTE-Rosemont study is a longitudinal study of older adults with 6 planned waves of data collection (2016-2019) taking place in Rosemont, a central borough of Montreal.

The RECORD sample was approved by the French Data Protection Authority; the Luxembourg CURHA sample by the 'Commission Nationale de la Protection des Données' (CNPD, #408/2017); and the PACTE-Rosemont and Canadian CURHA samples by the 'Comité d'Éthique de la Recherche of the Centre de Recherche du Centre Hospitalier de l'Université de Montréal' (CRCHUM, #13.073 and #15.355). All participants signed an informed consent form prior to participation.

Participants were instructed to wear devices with GPS and accelerometer capabilities at the right hip for 7 consecutive days, from wake-up to bed time. CURHA and PACTE-Rosemont participants wore the SenseDoc 2.0 (Mobysens Technologies) device – which includes a GPS receiver and a tri-accelerometer. RECORD participants wore a BT-Q1000XT (QStarz) for GPS tracking and a wGT3X+ accelerometer (ActiGraph).

2.2. Data

Start and end times of visits (stay at a location, e.g. residence) and trips were extracted from the GPS tracks using a kernel-based algorithm (28). Transport versus non-transport time was linked to the accelerometer data through timestamps.

Raw accelerometer data in gravitational units were extracted from the SenseDoc and ActiGraph devices using SenseAnalytics (version 1.9) and ActiLife (version 6). The raw data were then converted into activity counts in MATLAB (version R2017a) using a documented algorithm to calculate commonly used ActiGraph activity counts with data from Actigraph devices and other devices with the same accelerometer-chip (29). Non-wear time of the devices was defined as 90 min of consecutive zero activity counts, allowing for 2 minutes of non-zero counts (30). Observation days with less than 10 hours wear time (i.e. non-valid days) were excluded, and participants with less than 4 valid days were completely excluded. Additional material S1 provides full details about the devices and the processing of raw GPS and accelerometer data.

Physical activity was measured as the total volume of physical activity, i.e. the sum of the vector magnitude of activity counts. The vector magnitude counts were calculated per second as the square root of the sum of the counts on the three axes. Physical activity measures were computed per trip and per day.

2.3. *Analyses*

The compensation hypothesis was tested in 3 separate models assessing potential compensation processes in different time frames. We analyzed the associations between *'Physical activity during a trip'* and '*Physical activity during the hour following the trip*' (Model 1, observation: trip)*; 'Transport-related physical activity during a day' and 'Total physical activity during the next day*' (Model 2, observation: day); and *'Transport-related physical activity during a day' and* '*Non-transport physical activity during the same day*' (Model 3: observation: day). Because these associations may by themselves be dependent on participants' overall physical functioning, the interactions with participants' 'Mean daily physical activity' were further tested. In all models, the interaction term between trip-related physical activity and *'Age'* (in years) and '*Study Cohort*' (4 categories) were tested. Model 1 was controlled for '*Time of day at arrival'* (6 categories: 3am-9am, 9am-12pm, 12pm-3pm, 3pm-6pm, 6pm-9pm, 9pm-3am); Model 2 and Model 3 were controlled for '*Weekday'* (7 categories).

To facilitate comparison with previous papers, physical activity intensity measures were included in the descriptive analyses. We used cut-points based on the vector magnitude counts per 15 seconds, developed for older adults (31): moderate-to-vigorous physical activity (MVPA: $vm = [519; +\infty[$), high-light physical activity (HLPA: $vm = [226; 519[$), low-light physical activity (LLPA: $vm = [19; 226[$), and physical inactivity (PI: $vm = [0; 19[$, also known as sedentary behavior).

All regression analyses were performed on person-centered physical activity measures, i.e. the person-mean was subtracted from the measures. Subtracting the personal mean from a measure removes between-person variance, enabling estimating strictly within-person associations. The results indicated if trips with above average physical activity were followed by non-travel episodes with above (or below) average physical activity. The results did NOT indicate if persons engaging in more active travel (e.g. a regular biker), also engaged in more non-transport related activity, compared to people engaging in less in active travel. Even though these between-person associations could be interesting by themselves for other research questions, they would potentially confound the findings on the compensation of transport physical activity. Carlson et al. (16) applied this method to investigate the compensation of physical activity between different locations adolescents frequent. Other studies used a difference score as the dependent variable to study compensation over time (20) which is identical to the person-centered approach in the context of only 2 time points for each person. In our study, we used each trip (or each day, depending the model) as a different time point, so the difference score method was not applicable. Another approach would be limited the between-person variability by using a randomized study design in a controlled setting.

Preliminary analyses revealed that both the outcome variables and the residuals had a normal-like distribution, but with presence of extreme values. To obtain reliable confidence intervals, we used robust linear regressions within the ‘robust’ package in R (32).

3. Results

From the 752 older adults providing any accelerometer and GPS data, 636 participants provided 10 hours of valid data during at least 4 days. The median age was 76 years old (interquartile range (IQR): 70 - 82), and 49% were women. During valid days, participants wore the sensors on average 13h31 min, of which 1h10 min was during transport. Descriptive statistics per study cohort are provided in Table 1.

Table1. Age and Gender distributions for total sample and by study cohort.

	Number of participants in analyses	% of total participants	Age in years Median (IQR)	Gender (% Women)
Total	636	85 %	76 (70; 82)	49 %
CURHA – Canada	148	88 %	83 (81; 87)	52 %
CURHA – Luxembourg	319	81 %	76 (71; 81)	49 %
QADA – Canada	75	82 %	71 (68; 75)	68 %
RECORD – France	94	96 %	70 (67; 73)	31 %

Statistics on Age and Gender are calculated for the participants in the analysis only. Participants were excluded if they did not provide at least 4 valid days of accelerometer and GPS data. Valid days were determined on at least 10 h of wear time. Data collected in four cohorts in Canada, Luxembourg, and France between 2012 and 2016.

On average, 480,000 activity counts per day were recorded during transport, corresponding to 21% of the total daily physical activity (Table 2). 23% of MVPA, 12% of HLPA, 17% of LLPA (25 min), and 14% of physical inactive time per day was spent during transport.

Table 2. Daily total, transport and non-transport physical activity levels across 5 indicators

	TVPA (/1000)		MVPA (min)		HLPA (min)		LLPA (min)		PI (min)	
	Mean (sd)	Median (IQR)	Mean (sd)	Median (IQR)	Mean (sd)	Median (IQR)	Mean (sd)	Median (IQR)	Mean (sd)	Median (IQR)
Total (per day)	408 (224)	357 (253; 512)	65 (48)	54 (29; 90)	94 (40)	88 (65; 116)	156 (54)	150 (118; 188)	497 (120)	498 (414; 578)
Transport (per day)	84 (130)	33 (4; 113)	15 (25)	5 (0; 20)	11 (20)	3 (0; 14)	26 (34)	15 (2; 37)	72 (108)	29 (2; 91)
Non-Transport (per day)	312 (191)	279 (186; 401)	48 (40)	38 (19; 65)	79 (42)	76 (50; 103)	124 (58)	122 (85; 160)	407 (160)	421 (315; 518)

TVPA = Total volume physical activity; MVPA = moderate-to-vigorous physical activity; HLPA = high-light physical activity; LLPA = low-light physical activity; PI = physically inactive time (also referred to as sedentary behavior); sd = standard deviation; IQR = interquartile range. Sample size = 3899 days from 636 persons. Data collected in four cohorts in Canada, Luxembourg, and France between 2012 and 2016.

Model 1 (Table 3) analyzed within-person associations of *'physical activity during a trip'* and *'physical activity during the next hour'*. The results indicated that for people with low *'Mean daily physical activity'*, there was a positive association between *'Physical activity during a trip'* and *'Physical activity during the following hour'*, whereas for people with high *Mean daily physical activity'*, the relation was negative to non-existent. Figure 1 illustrates the interaction by presenting the association for the lower 1st decile and top 9th decile in mean physical activity.

Table 3. Within-person associations between transport and total physical activity using robust linear regression

	Model 1 - TVPA during following hour Estimate [95% CI]	Model 2 - TVPA during next day Estimate [95% CI]	Model 3 - Non-transport TVPA same day Estimate [95% CI]
TVPA during trip	**16.76 [3.16; 30.36]**	-	-
Transport TVPA per day [a]	-	**-136.82 [-188.12; -85.52]**	**-245.52 [-286.23; -204.8]**
Mean daily TVPA	**-19.57 [-22; -17.13]**	-9.61 [-29.9; 10.67]	-14.16 [-30.22; 1.89]

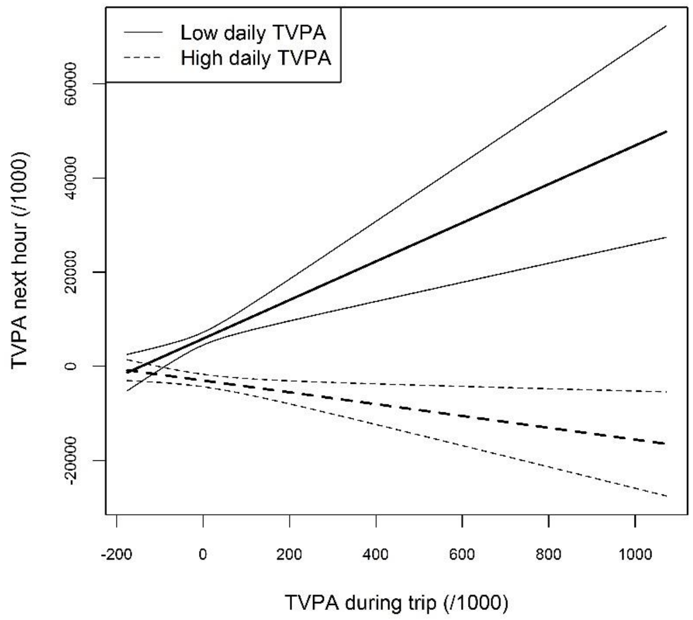
TVPA during trip [a] * Mean Daily TVPA [a]	**-0.12 [-0.16; -0.07]**	-	
Transport TVPA * Mean daily TVPA [a]	-	-0.08 [-0.26; 0.11]	0 [-0.14; 0.15]
(Intercept)	1861 [631; 3090]	-20318 [-29820; -10817]	6292 [-1054; 13637]

Model 1 includes 11389 trips during 2854 days from 623 persons, Model 2 includes 3410 days from 636 persons, and Model 3 includes 3899 days from 636 persons. The differences in numbers resulted from a lack of trips during a day (model 1), or because the next day was not observed (model 2). Model 1 was controlled for 'Time of the day', model 2 and 3 controlled for 'Weekday'. Interaction terms between 'Transport physical activity' and both 'Age' and 'Study' were tested; and the interaction term 'Study' was withheld. [a] The unit of the independent physical activity measures was 1000 counts to facilitate the reading of the tables. TVPA = Total volume physical activity; Ref. cat. = Reference category; 95% CI = 95% confidence interval. Data collected in four cohorts in Canada, Luxembourg, and France between 2012 and 2016.

Model 2 (Table 3) analyzed within-person associations of *'transport-related physical activity during a day'* and *'total physical activity during the next day'*. For people with an average level of '*Mean daily physical activity*', a day with 1000 counts above average during transport was associated with 137 counts (95% CI: -188; -86) below average the following day, suggesting a small compensation of transport-related physical activity. This association was not modified by the level of *'Mean daily physical activity'*.

Finally, Model 3 analyzed within-person and within-day associations of '*transport-related physical activity'* and *'non-transport physical activity'*. For people with an average level of '*Mean daily physical activity*', 1000 counts above average during transport was related to 246 counts below average during non-transport activities (95% CI: -286; -205). The association was not modified by the level of *'Mean daily physical activity'*.

Figure 1. The association between 'Physical activity during 1 hour after a trip' and 'Physical Activity during a trip' for two levels of 'Mean Daily Physical Activity' (Model 1) - slopes and 95% confidence bands



TVPA = Total volume physical activity; Low and High daily PA represent the 1st and 9th deciles of the variable *'Mean daily TVPA'*, respectively. Model 1 includes 11389 trips during 2954 days from 623 persons. Model 1 was controlled for '*Time of the day'.* The unit of all physical activity measures was 1000 counts, and all TVPA measures were person-centered. Data collected in four cohorts in Canada, Luxembourg, and France between 2012 and 2016.

4. Discussion

Promoting active transport is a promising means to improve older adults' physical activity levels, but, the evaluation of the expected benefits, requires knowledge of whether compensation occurs during other activities. Using GPS and accelerometer data from older adults in three countries, we analyzed within-person associations between transport physical activity and total physical activity to detect evidence of compensation across three time frames: within the next hour, within the same day, or during the following day. Results showed that net gains in transport physical activity translated into net gains in total physical activity. However, partial compensation was also observed, such that the total physical activity gain was somewhat smaller than the gain in transport physical activity. Evidence for compensation differed according to the time frame under consideration as well as participants fitness levels as indicated by their mean daily physical activity.

In the context of the transport behavior of older adults, we found little to no evidence of compensation in the hour following a trip (Model 1). For participants with lower levels of daily physical activity, there was even evidence of generalization – i.e. increased physical activity during the following hour. This suggests that transportation episodes might energize some of the older adults for a short period of time. By contrast, the observation of partial compensation within the full day (Model 3) and even the following day (Model 2) indicates that the energizing effect is only part of the picture.

Transport physical activity translated in a higher net gain of total physical activity for older adults with low levels of mean daily physical activity (Model 1). This finding resonates with the ‘Constrained Total Energy Expenditure’ theory, which states that there is a ceiling to improving energy expenditure levels (17; 33). While it is relatively easy for people with low energy expenditure to achieve marginal increases in energy expenditure, it is naturally more difficult for people whose level of energy expenditure is already high. Even though there is no perfectly linear relation between physical activity and energy expenditure, the results indicate there might be a similar ceiling effect in physical activity. People with low levels of physical activity might be able to increase their physical activity levels more easily compared to people with already high levels of physical activity. People with high levels of physical activity might therefore be more likely to compensate additional transport physical activity.

Higher levels of transport physical activity were partially compensated by lower levels of non-transport physical activity during the same day (Model 3). Specifically, an increase of 100 counts in transport-related physical activity was related to a decrease of 25 counts (95% CI: 20; 29) in non-transport physical activity during the same day. This indicates there was some compensation of transport physical activity during the same day, large enough to be meaningful for active transport interventions. This finding could reflect time limitations, whereby the time-consuming nature of active transport prevents older adults from engaging in other activities during that day. Alternatively, older adults might anticipate active transport by being less active earlier during the day (for example, delaying household work). Future research is needed to clarify the contradiction of compensation during the same day, and no or hardly any compensation during the time following active transport.

Interestingly, we did not observe any difference between study cohorts. For all models, an interaction term between transport physical activity and study cohort was tested. Despite overall differences in physical activity levels between the studies (supplementary material S2), there were no meaningful or statistical significant differences between the four study cohorts in terms of compensation or generalization of transport physical activity.

A major strength of this study was the unique data set, which included objective accelerometer and GPS data from a large number of older adults (n = 636) residing in Canada, Luxembourg and France. Datasets with objective measures of both transport behavior and physical activity are often small, due to technical difficulties in measuring detailed transport behavior. A limitation to this approach is the comparability of sensors and how they are worn between studies. In this study, the sensors were worn the same (right hip) and the raw data was processed by the same algorithms. Also the technical aspects of the SenseDoc (integrated GPS and accelerometer), and the Qstarz (GPS) combined with the ActiGraph (accelerometer) were very comparable (supplementary material S1). However, we cannot exclude that the accumulation of small differences in the devices might still have had some influence on the results. A second strength was the within-person analyses, which enabled comparing physical activity levels during trips and days within a person. This method corresponds well with a longitudinal design to measure within-person changes, compared to analyses on interpersonal differences. However, a data set with a longer observation period would have arguably been better to analyze compensation behavior, since there is no consensus on the time frame in which compensation potentially occurs (15). Ideally, the observation period should also include a transport intervention, so that changes in transport and non-transport physical activity could be causally linked to the intervention.

5. Conclusion

Transport and other urban interventions are important to promote physically activity, also among older adults. However, evaluating the impact of interventions by measuring transport physical activity only - and not total physical activity - can be problematic. Possible compensation of transport physical activity during non-transport time should be considered in public health studies analyzing the possible increase in physical activity levels through active transport or other activities. The results of this study indicated that for older adults in Canada, Luxembourg and France, there was little to no compensation of transport physical activity during subsequent physical activity, indicating there might be no biological ground for compensation related to transport physical activity. For people with low average levels of physical activity, there was even some evidence of a short-term energizing effect of active transport for older adults with less regular physical activity. However, the results also indicated meaningful lower levels of non-transport physical activity during a day with above average transport physical activity, about 25% of transport-related physical activity compensated during non-transport activities. These findings suggest that compensation may be a result of planning or anticipation, rather than a biological response to high levels of transport physical activity. Even though there is not a complete compensation of transport physical activity by older adults, we strongly recommend active transport intervention evaluations to measure and analyze total physical activity along with the active transport.

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