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Do physical activity and trip characteristics differ when commuting to and from school?: The PACO study

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A R T I C L E I N F O

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A B S T R A C T

Purpose: To determine whether trip characteristics (i.e., length, duration, and speed) and physical activity (PA) (i.e., light PA [LPA], moderate-to-vigorous PA [MVPA], and PA energy expenditure [PAEE]) differ by trip direction (i.e., home-school and school-home trips), and to examine differences in trips characteristics and PA levels between modes of commuting (walking, multimodal, and motorized-vehicle).
Methods: 181 adolescents wore a belt on their hip with an accelerometer and a GPS. The HABITUS and PALMSplusR softwares were used to combine accelerometer and GPS data and identify trip characteristics and PA levels during home-school and school-home trips. Mixed model analysis was used to examine the differences in trip characteristics and PA levels between the trip directions and across modes of commuting.
Results: The percentage of school-home walking trips was higher (54.4% vs 46.9%) and had longer duration than the home-school walking trips ($p < 0.01$). In contrast, multimodal and vehicle trips had a longer duration during the home-school direction than the school-home direction ($p < 0.01$). Regarding PA levels, the school-home direction presented higher LPA during walking trips ($p < 0.01$), but lower MVPA ($p < 0.01$), compared to the home-school direction. Walking trips presented higher MVPA and PAEE than multimodal and motorized-vehicle in both directions, but smaller LPA minutes in home-school direction than multimodal and motorized-vehicle ($p < 0.01$).
Conclusion: The percentage of walking trips, the characteristics of the trips, and PA levels during school-home direction differed from home-school direction. In addition, walking trips were associated with higher MVPA levels and PAEE in both directions compare to multimodal or motorized-vehicle.

1. Introduction

Being physically active during adolescence provides physical, social, and psychological benefits (Poitras et al., 2016). In addition, the development of healthy habits during this period, such as the regular practice of physical activity (PA), may persist into adulthood (Batista et al., 2019). However, despite these well-recognised benefits, four out of five adolescents in the world are not considered sufficiently physically active (Guthold et al., 2020), as they do not meet the World Health Organisation's (WHO) recommendation of 60 daily minutes of moderate-to-vigorous physical activity (MVPA) (Bull et al., 2020). Therefore, the promotion of PA in this age group has been recognised as

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a main public health concern (Bull et al., 2020).

In this sense, active transportation, defined as the act of going from one place to another that requires energy expenditure, the most common of which are walking and cycling, has been deemed important (Cook et al., 2022). In particular, active commuting to/from school (ACS) has been proposed as a strategy to increase regular PA especially in the adolescent population (Martin et al., 2016). In fact, walking trips to and from school can account for up to 23% of PA recommendations in children and 36% in adolescents (Martin et al., 2016). Moreover, ACS is associated with other health, environmental, and economic benefits (Gössling et al., 2019; Larouche et al., 2014; Waygood et al., 2017). For these multiple reasons, interventions focusing on promoting ACS are becoming popular and prioritized in many countries (Chillón et al., 2021).

Indeed, PA-related ACS (hereinafter referred to as ACS-PA) is one of the main outcomes evaluated in ACS studies (Cooper et al., 2012; Kek et al., 2019; Pizarro et al., 2016; Stewart et al., 2017). However, studies focused on analysing ACS-PA have mainly assessed the home-school direction, and little is known about the benefits of the school-home direction (Ginja et al., 2017; Martinez-Martinez et al., 2019; Villa-Gonzalez et al., 2019). The strength of promoting ACS is based on being a habit that is performed at least 10 times per week (i.e., twice on school days). Despite the great value that ACS can bring to daily PA levels, if only home-school direction is assessed, only 50% of their potential PA benefits is measured. An easy solution could be to extrapolate the same result obtained on the home-school direction to the school-home direction, but those studies that have analyzed both directions showed different PA levels (Kek et al., 2019; Gale et al., 2021; Remmers et al., 2020). Even if the routes are similar or the same, the commuting intensity might be different (i.e., slower commuting speed leading to longer commuting time). For example, on the home-school direction there is a fixed time of arrival whereas on the school-home direction there is no necessarily fixed time of arrival, which could mean higher intensities in one direction than the other (Herrador-Colmenero et al., 2019). In addition, it maybe that the routes chosen for each direction are different and therefore different PA benefits are obtained (i.e., the greater distance, the greater possibility to have more MVPA). Nevertheless, studies have not focused on comparing these directions, so it is not known which of these reasons might influence the PA differences according to the trip direction.

The identification of accurate ACS-PA levels requires a clear capture of the times when occurring commuting in the home-school and school-home trip directions. Campos-Garzón et al. (2023) point out that the methodology to accurately measure ACS-PA is complex. Most studies assessing ACS-PA have identified the temporal space of this behaviour using time intervals of 30 (Chillón et al., 2017) or 60 (Kek et al., 2019) minutes before/after school to quantify PA mainly by accelerometry. However, other studies are focusing on the combination of device-based measures such as accelerometry and GPS (Pizarro et al., 2016; Stewart et al., 2017; Villa-Gonzalez et al., 2019). In the first case, it is likely that activities outside the ACS were influencing the results (i.e., extracurricular activities) especially on the school-home direction, whereas the accelerometer-GPS combination allows a more accurate analysis of this behavior. Nevertheless, processing accelerometry and GPS data together can be challenging (Jankowska et al., 2015). In the past decade, the Personal Activity Location Measurement System (PALMS) (Patrick et al., 2008) software helped researchers with this task. More recently, the Human Activity Behavior Identification Tool and Data Unification System (HABITUS) software has improved the performance of the older software. HABITUS is a web-based application (https://www.habitus.eu) that helps researchers merge and process accelerometer and GPS data through a user-friendly interface.

All the previous rationale, makes it inevitable that both trips direction need to be analyzed separately to find out the real daily impact of ACS on the PA levels of adolescents. In addition, interventions to promote ACS have mainly focused on the home-school direction (Buckley et al., 2013; Mendoza et al., 2011; Villa-González et al., 2016). However, the literature indicates that a higher percentage of students commute actively on the school-home direction compared to the home-school direction (Herrador-Colmenero et al., 2019; McDonald et al., 2014; Samimi and Ermagun, 2013), which may suggest that interventions to promote ACS in school-home direction may be better received as for example parental convenience is reduced (Panter et al., 2013). Thus, in order to know the real impact of ACS on PA levels, it is essential to analyze both trips direction, because in this way it will be possible to know 100% of the PA benefits that the ACS can bring to adolescent population. Moreover, by understanding how the trip's characteristics and the PA levels vary between the two directions, it will be possible to carry out more individualized interventions that promote healthier and more active behaviours. Researchers, educators, and practitioners will benefit from the results of this article because they will be able to promote interventions according to the needs present in the home-school or school-home direction, thus maximising the ACS-PA benefits.

Thus, using a combination of accelerometry and GPS, this study aims (1) to determine whether trip characteristics (i.e., length, duration, and speed) and PA (i.e., light PA [LPA], MVPA, and PA energy expenditure [PAEE]) differ by trip direction (i.e., home-school and school-home trips), and (2) to examine differences in trips characteristics and PA levels between modes of commuting (walking, multimodal, and motorized-vehicle). The findings of this study will be useful to researchers and practitioners in the design of future interventions focusing on maximising the PA benefits of both the home-school and school-home directions.

2. Methods

This cross-sectional study was conducted under the umbrella of the "Cycling and Walk to School" (PACO study). The PACO study is focused on the analysis of travel patterns to/from school among adolescent population, as well as promoting the use of cycling as the main mode of commuting to/from school. In the PACO study, all the secondary public schools within 4 Spanish cities (Almería, Granada, Jaén, and Valencia) were randomly selected. For the current study, only the participating schools that compiled accelerometry and GPS data were included, being 10 secondary schools (i.e., two from Almería, three from Granada, three from Jaén, and two from Valencia). Briefly, Almería and Valencia are coastal cities and have a population density (i.e., number of people per city area in km^2 -people/km^2) of 83 people/km^2 and 239 people/km^2, and a city income of 20,604€ and 26,114€, respectively. On the other hand, Granada and Jaén are inland cities with a population density of 73 people/km^2 and 47 people/km^2, and a city income of 22,804€ and 19,795€, respectively. Data on population density and city income were obtained from the Spanish Public Tax Agency. As for the schools, they were all within the cities, they were public schools and only two 3rd grade classes per school (i.e., students around 14–15 years old) were invited. In addition, in order to participate in the PACO study, these schools had to meet the following inclusion criteria: the school had to have two 3rd grade classes with at least 15 students per class; the students could not have participated in any other activity promoting active commuting during the last year; the school could not offer school transport to students. In Fig. 1, it shows the four participating Spanish cities location, as well as the schools that participated in each city. Regarding the recruitment of the participants after the school's acceptance into the PACO study, the research team provided an overview of the study to interested adolescents in selected classes. Those who were unable to attend physical educations lessons due to physical or mental illness during the data collection period were not included in the study. The participation of adolescents was limited to those who had obtained parental consent through a signed form and the representativeness of adolescents living at different distances from the school was not considered. More information about the PACO study (e.g., school recruitment and randomization process) can be found elsewhere

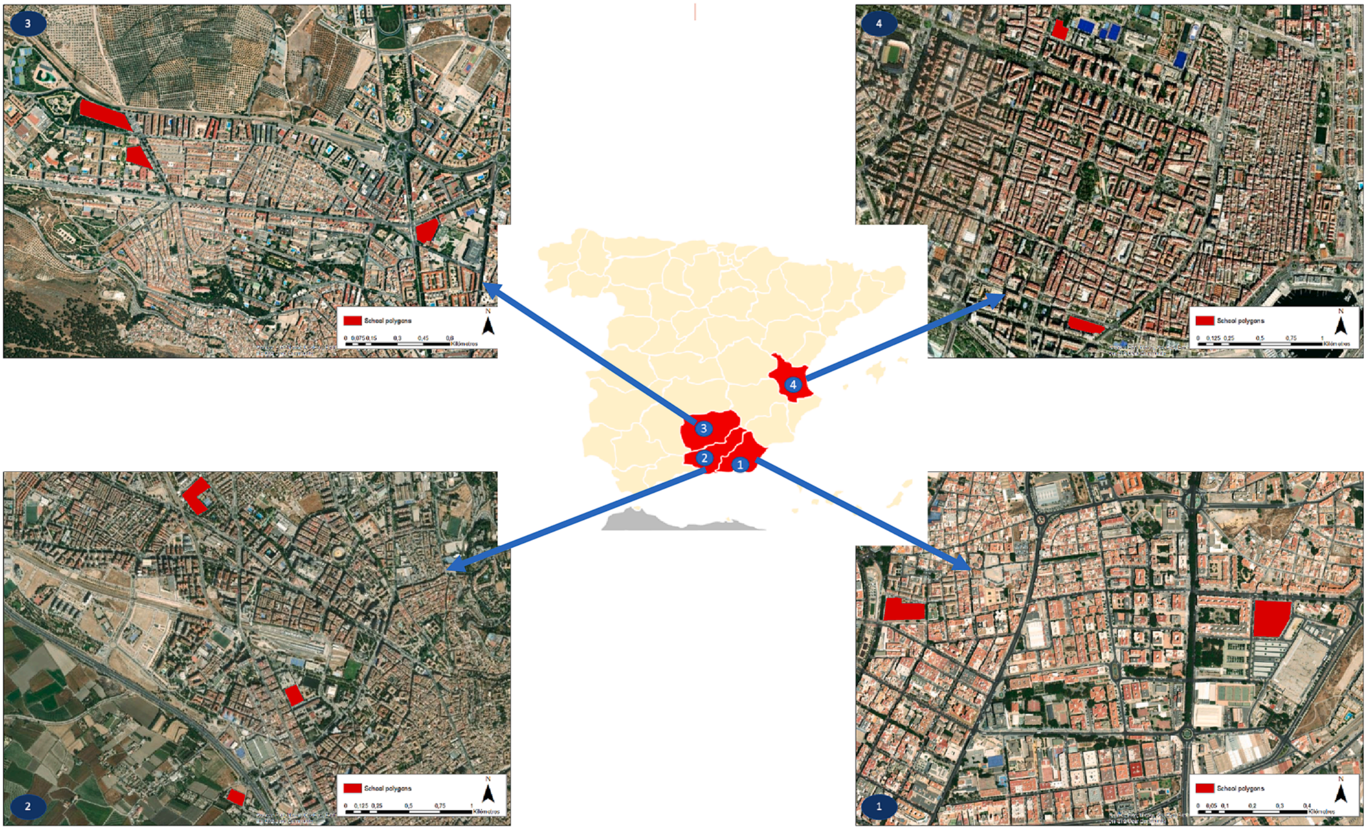

Fig. 1. Location of participating cities and schools: (1) Almería; (2) Granada; (3) Jaén; (4) Valencia.

(Chillón et al., 2021). The PACO study was approved by the Review Committee for Research Involving Human Subjects (Reference: 162/CEIH/2016).

2.1. Participants

The total number of trips to/from school were analysed, and only participants with sufficient data were included. The inclusion criteria were to: (1) provide informed consent and (2) provide valid accelerometer and GPS data from at least one, home-school or school-home trip. After excluding those participants with no valid accelerometer and GPS data, the final sample for this study was 181 adolescents (50.8% females) aged 14.4 ± 0.6 years.

2.2. Positional data

To assess the characteristics of the home-school and school-home trips, the GPS QStarz BT-Q1000XT (Travel Recorder, Intentational Co., Ltd. Taipei, Taiwan) was used to record positional data. Besides being the device most widely used by researchers to geolocate position (Pizarro et al., 2016; Remmers et al., 2020; Stewart et al., 2017; Tarp et al., 2015; Villa-Gonzalez et al., 2019), it has a dynamic median error of 3.9 m during walking, 2.0 m cycling, 1.5 m in public transport, and 0.5 m during car trips (Schipperijn et al., 2014). Qtravel software was used for initializing and downloading the GPS raw data. Each GPS device was set up to log data every 15 s.

2.3. Physical activity and physical activity energy expenditure

PA was assessed using ActiGraph GT3X+ accelerometers (ActiGraph, Pensacola, FL). It is the device most widely used to measure PA levels during the commute to/from school (Campos-Garzón et al., 2023), and using an accelerometer avoids most biases associated with self-reported measures (Sallis and Saelens, 2000). The ActiLife software (v.6) was used for initializing and downloading the accelerometer raw data. The accelerometers were initiated with a sampling frequency of 30 Hz and were placed on the right hip of the participants. During download, both the raw data-file and ActiLife data table with activity counts were stored. The PA levels classified in the current study were LPA, MVPA, and counts per minute (CPM) during the commute to/from school. PAEE was calculated using the Freedson children (2005) equation (2.757 + [0.0015 * CPM] – [0.08957 * Age] – [0.000038 * CPM * Age]) obtaining the average of Metabolic Equivalents (METs) for each identified trip.

2.4. Procedure

Data collection was conducted from January 2019 to June 2021 during the students' school calendar and without evaluation during holidays (i.e., from July to August inclusive). Due to the limited number of accelerometers and GPS devices, only two schools could be assessed simultaneously. Thus, between January and February 2019, four schools were evaluated, two in Granada and two in Jaén. Then, between April and June 2019, two more schools were evaluated, one in Granada and one in Jaén. The next data collection was carried out in the city of Valencia, evaluating two schools simultaneously during the months of January and February 2020. Following restrictive measures by COVID 19 in Spain, data from two school in the city of Almería were not collected until February and March 2021. It should be noted that during the 2020/2021 academic year, four schools that had already participated in the PACO study, two in Granada and two in Jaén, were re-evaluated in order to meet the target number of participants in the PACO study (Chillón et al., 2021).

During the data collection process, the participants were instructed to wear the accelerometer and GPS device on opposite sides of their hips on a belt. They were instructed not to wear the belt during water activities or while showering, as well as to remove it during sleep. The number of days that participants were required to wear both devices varied from the start of the PACO study. Initially, the GPS protocol specified 7 days and participants were instructed to charge the GPS device overnight (from January 2019 to January 2020). However, due to problems with charging the devices (e.g., participants forget to charge it), it was decided that participants would carry the GPS for around 40 h (battery life without charging the GPS) (Kerr et al., 2011), to record two home-school and two school-home trips (from January 2020 to June 2021). This protocol was also maintained during the COVID-19 pandemic (from September 2020 to June 2021), due to health restrictions. Given that seven days of GPS data collection would not have been possible because due to the restrictions of schools in Spain, in some cases the timetables of them were modified, as well as participants did not go to school every day. The accelerometer protocol remained at seven days throughout the study.

Furthermore, participants' weight was assessed using a digital scale (Seca 876, Seca, Ltd., Hamburg, Germany) and height using a measuring tape (Seca 2013, Seca, Ltd., Hamburg, Germany), which were used to calculate Body Mass Index (BMI) as weight (kg)/height (m)^2. Demographic characteristics such as birth date and gender were self-reported by participants through the PACO questionnaire (https://profith.ugr.es/paco). In addition, adolescents self-reported their socio-economic status (SES) using an adaptation of the family affluence scale (FAS) (Currie et al., 2008). Participants were asked about the number of computers: (0), no; (1) one; (2) two; (3) two or more) and 4-wheeled vehicles: (0), no; (1) Yes, one; (2) Yes, two or more in their household. The final FAS outcome was the average score from 0 (not having) to 4 (having two or more computers and vehicles). Moreover, following previous studies that have analysed the characteristics of the built environment using GIS (Adams et al., 2014; Molina-García et al., 2017), the walkability index around the schools were calculated. Since several studies have indicated that the variables that make up the walkability index have been associated with PA or walking to school (e.g., residential density and mixed land use) (Carlson et al., 2015; Ding et al., 2011), three representative characteristics of the school built environment were used: net residential density, land use mix, and intersection density. Net residential density was calculated by dividing the number of residential units in an area by the amount of land designated for residential use. Land use mix, which ranged from 0 to 1, captured the distribution of different land use types (e.g., such as residential, office, recreational, and retail) within schools' neighbourhoods. Intersection density was calculated by dividing the number of street intersections in a block group by the total land area, with freeways and inaccessible roads excluded. In addition, road intersections were defined as points where three or more segments intersected. Therefore, the walkability index for each school was calculated as: [(z-score of intersection density) + (z-score of net residential density) + (z-score of land use mix)] (Molina-García et al., 2017).

2.5. Data processing

Data processing was divided in two steps: the first step was carried out using the HABITUS software and it consisted of cleaning GPS points, combining the accelerometer and GPS data by timestamp, categorising PA intensity from accelerometer data, identifying all participants' trips, and categorising the mode of commuting for each trip (as motorized-vehicle, pedestrian, or cycling). For the second step, the PALMSplusR R package was used (https://thets.github.io/palmsplusr/index.html) through which home-school and school-home trips were identified, and trip characteristics (i.e., length, duration, and speed) as well as the PA and PAEE levels of each trip were determined.

2.5.1. HABITUS step

2.5.1.1. Processing accelerometer data and cleaning GPS data. Before combining accelerometer and GPS data, PA intensity had to be calculated from the accelerometer data, and GPS data had to be cleaned (i.e., invalid data had to be removed). For all accelerometer files, activity intensity was estimated using Evenson cut-off points (i.e., MVPA was defined as >2296 counts/minutes) (Evenson et al., 2008). Non-wear time definition was defined as consecutive periods of sixty minutes of zero values (Cain et al., 2018). Regarding GPS files, invalid data were considered when data points inferred extreme speed (>130 km/hour), changes of distance (>1000 m), and elevation (>100 m) between two points (Kerr et al., 2011). Invalid data points were replaced with the last known valid point for a maximum of 10 min.

2.5.1.2. Trips identification and mode of commuting categorisation. A trip was identified as a continuous movement longer than 120 s in duration with a minimum length of 100 m. Possible pauses during the trip (e.g., traffic lights) up to 120 s were also considered. The end of the trip was defined when the pause was longer than 180 s (Klinker et al., 2014; Pizarro et al., 2016; Stewart et al., 2017; Villa-Gonzalez et al., 2019). The mode of commuting was determined as walking (speed ≥1 km/hour, <10 km/hour), cycling (≥10 km/hour, ≤35 km/h), and by motorized-vehicle (speed >35 km/hour) (Carlson et al., 2015).

Once all the parameters were set and each accelerometer point was combined with each GPS point, the result was the HABITUS output file, which is a file with data every 15 s providing information about date, location, PA intensity, and mode of commuting. In the absence of GPS signal, the accelerometer data for this period were not retained for the analyses.

2.5.2. PALMSplusR step

2.5.2.1. Identification of the characteristics of the trips to/from school. It is necessary to locate the start point (home) and end point of the trip (school), and vice versa, to obtain the variables that describe the trip characteristics (i.e., length, duration, and speed), PA levels, and PAEE during the commute to/from school. Participants' addresses were geocoded using ArcGIS 10.3 (ESRI, Redlands, CA, USA) and a circular buffer of 50 m was considered as their home. School location was geocoded as the perimeter of each schoolyard using ArcGIS. These spatial definitions were imported into PALMSplusR.

Moreover, PALMSplusR is able to define multimodal trips, which are characterized as the sum of at least two trips with the following spatial and temporal criteria: (1) the start of the next trip must not be >200 m from the end point of the previous trip; and (2) the start of the next trip must not exceed 10 min from the end point of the previous trip (Stewart et al., 2017). Trips that contained multiple segments but only contained one mode were retained as single-mode trips (i.e., walking, cycling, or by motorized-vehicle), and multimodal if the trip contained at least two different travel modes (Stewart et al., 2017). Therefore, a trip mode could be walking, cycling, motorized-vehicle, or multimodal. However, none of the participants cycled to/from school. In this way, by combining the trips identified in the HABITUS step with the geospatial data (i.e., home and school) in PALMSplusR, automatically all trips detected that started within the home buffer and ended within the school buffer were classified as home-school trips, and all trips that started from the school buffer and ended within the home buffer were classified as school-home trips (See Fig. 2.).

Once PALMSplusR had been run, the result was the PALMSplus output file, which is a database with data of each trip identified providing information about date, start and end time, mode of commuting, duration, length, speed, CPM, time spent in each PA intensity level, and trip direction (i.e., home-school or school-home).

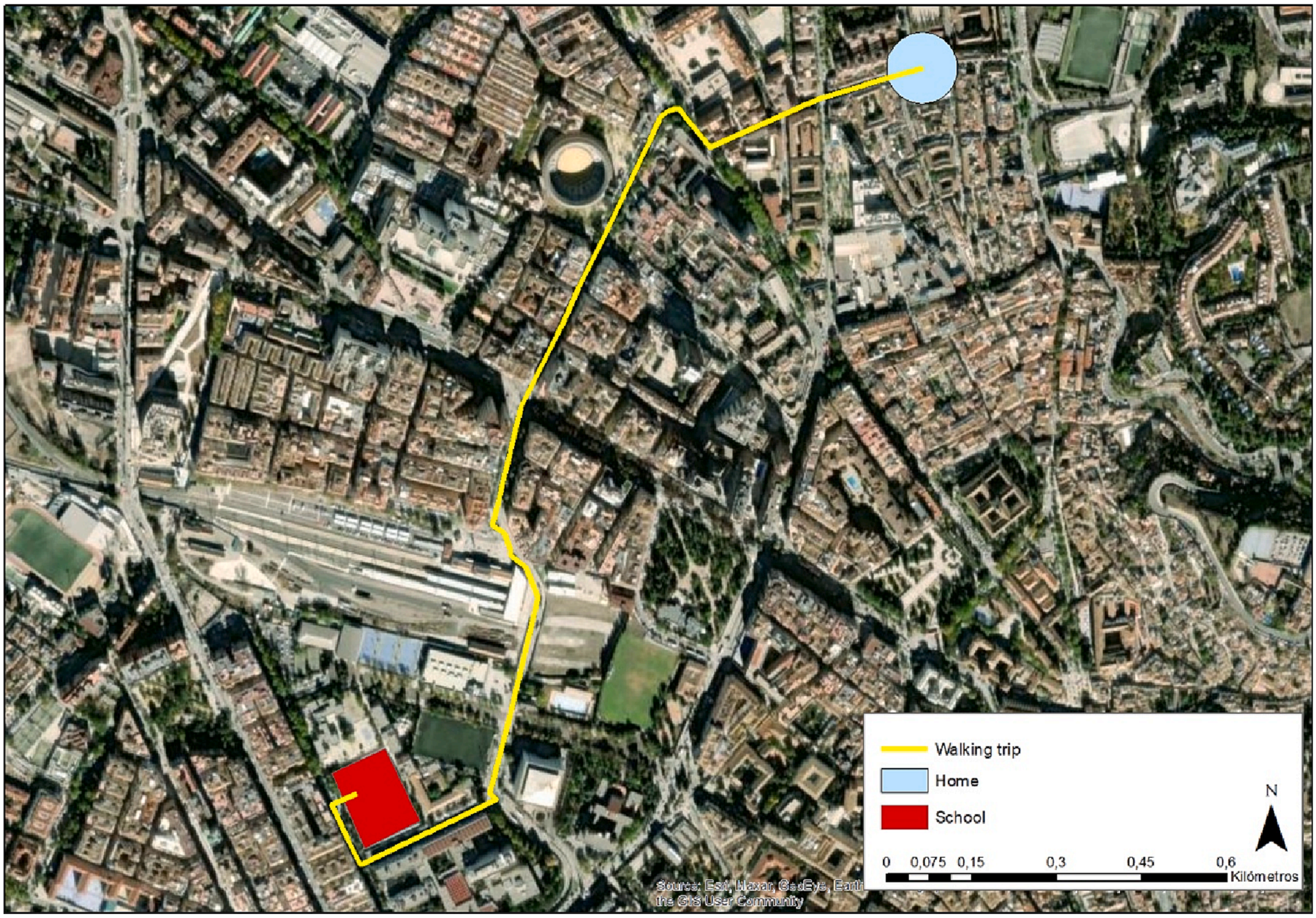

Fig. 2. Example of a home-school walking trip identified using PALMSplusR.

2.6. Statistical analysis

R software was used to perform the statistical analyses. Descriptive results were expressed as means and standard deviation (SD) of the mean for continuous variables, and frequency and percentage for categorical variables.

To determine the differences in trip characteristics (length, duration, and speed) and PA levels (LPA, MVPA, PAEE) by trip direction (Aim 1), and to examine differences in trip characteristics and PA levels by mode of commuting (Aim 2), a series of linear mixed models were used (a separate model for each outcome variable). The trip characteristics and PA metrics were treated as the outcome variable, while mode of commuting (walking, motorized-vehicle, multimodal) and trip direction (home-school, school-home) were added as fixed effects, including their interaction. This allowed any differences between travel models to vary by trip direction. For all models, a nested random effect was specified (participant [ICC: 0.893] nested within school [ICC: 0.355]), as the likelihood ratio test indicated this nested structure performed better than a random intercept with just the participant level (ICC:0.899). All mixed models were fit using the *lme4* package. To examine Aim 1, estimated means and contrasts between both trip directions were calculated for each model using the *emmeans* package. Similarly, for Aim 2, estimated means and contrasts between each pair of commuting modes were calculated, with multiple comparisons adjusted using the Holm correction. All models were adjusted for the gender, FAS, as the participant's socio-economic outcome, and for each school's walkability index. In addition, for the LPA, MVPA, and METs outcomes, commuting duration was also included as a covariate in the model. For inferential statistics, the level of statistical significance was set at $p < 0.05$. The R code used for the models and *emmeans,* as well as the model coefficients can be found in the Supplementary material (R code for the models and *emmeans*; Model coefficients).

3. Results

The characteristics of the participants are shown in Table 1. A total of 181 participants provided valid accelerometer and GPS data according to the inclusion criteria. From these participants, a total of 587 trips to/from school were identified, with an average of 3.3 trips per participant. These 587 trips were the sum of 232 (39.5%) home-school trips and 355 (60.5%) school-home trips. Walking was the main mode of commuting to and from school among the identified trips, with the shortest length,

Table 1
Descriptive data of the participants.

Participant characteristics (n = 181)	n (%) / mean ± SD
Gender	
Male	89 (49.1)
Female	92 (50.9)
Age (years)	14.4 ± 0.6
BMI (kg/m^2)	21.7 ± 4.1
FAS	3.2 ± 0.9
Walkability index	0.5 ± 2.1
Trips per participant (number)	3.3 ± 2.4
Trips per participant 7-day GPS protocol (number)	2.4 ± 1.8
Trips per participant 40-hour GPS protocol (number)	1.9 ± 1.7

%= percentage; **SD** = standard deviation; **BMI** = body mass index; **kg** = kilogram; **m** = metres; **FAS** = family affluence scale; **GPS** = global positioning system.

and slowest speed, but the highest MVPA levels and PAEE compared with multimodal or motorized-vehicle modes in both directions. Multimodal trips showed the highest number of minutes in LPA in both directions (see Table 2).

Estimated means and 95% confidence intervals for each trip characteristic, stratified by mode of commuting and trip direction, are shown in Fig. 3. Regarding trip length and speed, there were only significant differences in motorized-vehicles trips between the home-school and school-home directions (estimated means for length: 4856 m vs 4116 m, respectively, $p < 0.01$; estimated means for speed: 16.3 km/h vs 19.0 km/h, respectively, $p < 0.01$). Although there was no significant difference between walking speed between directions, home-school trips showed higher mean speed than school-home trips (estimated means: 5.3 km/h vs 4.8 km/h, $p = 0.31$).On the other hand, trip duration was shorter during home-school than school-home for walking (estimated means: 19.0 min vs 22.0 min, $p < 0.01$), and longer in multimodal trips (estimated means: 25.0 min vs 21.0 min, $p < 0.01$), and motorized-vehicle trips (estimated means: 19.0 min vs 16.0 min, $p < 0.01$).

The PA levels and PAEE by mode of commuting and trip direction are shown in Fig. 4. Significant differences were found between the home-school and school-home directions in LPA for walking trips (estimated means: 3.7 min vs 6.0 min, $p < 0.01$) and PAEE (estimated means: 2.0 METs vs 1.9 METs, $p < 0.01$). In addition, there were significant differences in MVPA between home-school and school-home direction in walking trips (estimated means: 10.6 min vs 9.6 min, $p < 0.01$) and multimodal trips (estimated means: 1.9 min vs 3.2 min, $p < 0.01$).

The differences in the trip characteristics between modes of commuting for both home-school and school-home directions are presented in Table 3. In both directions, multimodal and motorized-vehicle trips showed higher length and speed than walking trips (all, $p < 0.01$), motorized-vehicle trips also showed higher speed and shorter duration than multimodal trips in both directions (both $p < 0.01$), and shorter length in the school-home direction compared with multimodal trips ($p = 0.03$). For walking trips, they showed shorter duration than multimodal trips in the home-school direction ($p < 0.01$), but higher duration than motorized-vehicle trips in the school-home direction ($p < 0.01$). Regarding PA levels, walking trips showed higher MVPA levels and PAEE in both directions compared with multimodal and motorized-vehicle trips (all, $p < 0.01$). Multimodal and motorized-vehicle trips presented higher LPA in the home-school direction than walking trips ($p = 0.01$ and, $p = 0.03$, respectively).

Table 2
Descriptive data of trips characteristics, PA levels, and PAEE.

Trips data	Home-school trips (n = 232) [n (%) / mean ± SD]	School-home trips (n = 355) [n (%) / mean ± SD)]
Mode of commuting		
Walking	109 (46.9)	193 (54.4)
Multimodal	68 (29.3)	90 (25.4)
Motorized-vehicle	55 (23.8)	72 (20.2)
Trip duration (min)		
Walking	18.0 ± 9.2	20.0 ± 10.2
Multimodal	30.0 ± 10.9	24.0 ± 11.8
Motorized-vehicle	20.0 ± 9.5	16.0 ± 8.6
Length (m)		
Walking	1292 ± 732	1262 ± 725
Multimodal	7988 ± 5179	6051 ± 4613
Motorized-vehicle	7668 ± 5169	6397 ± 5157
Speed (km/h)		
Walking	4.1 ± 1.0	3.7 ± 0.9
Multimodal	15.3 ± 7.6	14.6 ± 7.3
Motorized-vehicle	21.0 ± 11.3	22.2 ± 14.7
Trip LPA (min)		
Walking	3.1 ± 2.3	5.8 ± 4.1
Multimodal	6.5 ± 4.0	5.9 ± 4.1
Motorized-vehicle	4.6 ± 2.5	4.1 ± 3.3
Trip MVPA (min)		
Walking	10.9 ± 7.9	9.8 ± 7.1
Multimodal	5.0 ± 4.9	4.6 ± 7.0
Motorized-vehicle	1.8 ± 2.2	1.6 ± 2.0
Trip PAEE (METs)		
Walking	2.0 ± 0.3	1.9 ± 0.3
Multimodal	1.6 ± 0.1	1.7 ± 0.2
Motorized-vehicle	1.6 ± 0.2	1.6 ± 0.2

% = percentage; **SD** = Standard deviation; **min** = minutes; **m** = metres; **km** = kilometres; **h** = hour; **LPA** = light physical activity; **MVPA** = moderate-to-vigorous physical activity; **PAEE**: physical activity energy expenditure; **METs** = Metabolic equivalent of task.

4. Discussion

The aims of this study were (1) to determine whether trip characteristics (i.e., length, duration, and speed) and PA (i.e., LPA, MVPA, and PAEE) differ by trip direction (i.e., home-school and school-home trips), and (2) to examine differences in trips characteristics and PA levels between mode of commuting (walking, multimodal, and motorized-vehicle). Our main findings suggested that participants were more prone to ACS in the school-home direction than in the home-school direction, and thus in the school-home direction there was a lower percentage of multimodal and motorized-vehicle trips compared to the home-school direction. In addition, walking trips were slower and multimodal and vehicle trips were faster in the school-home direction compared to the home-school direction. Regarding PA levels, the home-school walking trips showed higher levels of MVPA and METS, and lower levels of LPA than the school-home direction. Regarding the differences by mode of commuting, as was expected, walking trips showed a shorter length and lower speed, but higher MVPA and METs than multimodal and motorized-vehicle trips in both directions. Nevertheless, LPA was higher in motorized-vehicle and multimodal trips than walking trips in the home-school direction, but no differences were found in the school-home direction.

The main mode of commuting in home-school and school-home trips in the current study was walking (46.9% and 54.5%, respectively). This finding is supported by other studies that have analysed commuting to and from school in Portugal (Pizarro et al., 2016), New Zealand (Stewart et al., 2017), and Spain (Villa-Gonzalez et al., 2019). Moreover, when splitting by the direction of the trip, the school-home direction showed a higher percentage of walking trips and a lower percentage of multimodal or motorized-vehicle trips, as opposed to the home-school direction. Likewise, studies carried out in North America (McDonald et al., 2014) and Iran (Samimi and Ermagun, 2013) also highlighted this difference. This change in the mode of commuting from school could be explained by the convenience of parents to drive their children to school in the morning (Panter et al., 2013), and/or lack of time when returning home (Herrador-Colmenero et al., 2019). This implies that it might be easier to change children's mode of commuting in the school-home direction than the home-school direction and interventions could therefore focus on promoting active commuting from school to home to maximise the benefits that this behaviour can provide to adolescents.

Trip characteristics also varied by trip direction, which has not been studied previously, as studies that analysed commuting to school tend to focus only on the home-school direction (Ginja et al., 2017; Martinez-Martinez et al., 2019; Villa-Gonzalez et al., 2019). In addition, given the difficulty of using GPS, the studies that do not use GPS defined the length from home to school as the length provided by the shortest route using the home and school postal address through Google maps (Chillón et al., 2017; Frazer et al., 2015). This implies that the length is the same

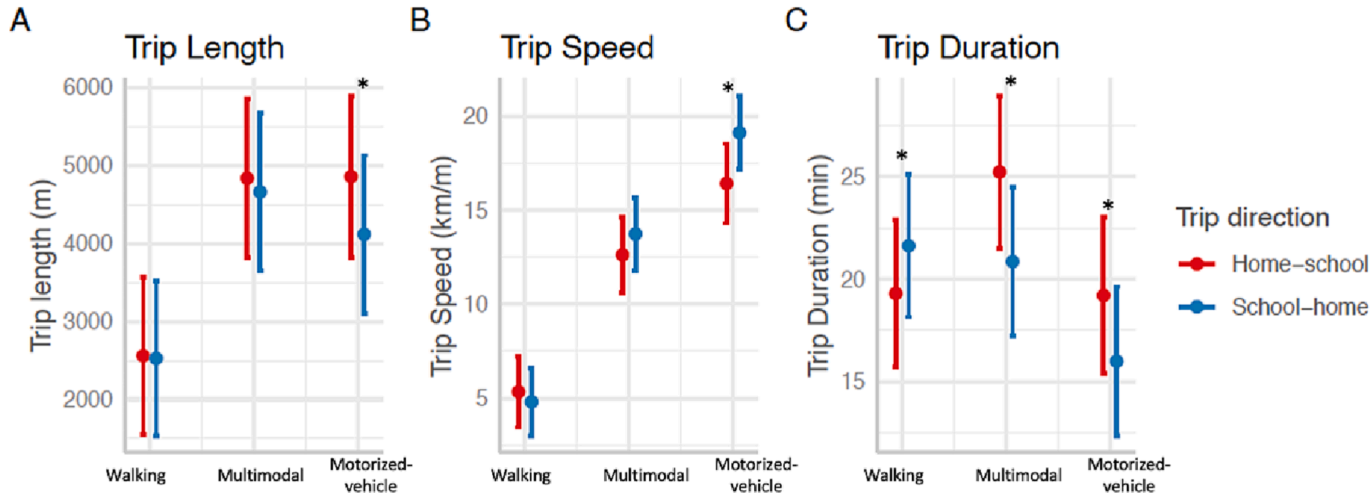

Fig. 3. Estimated means for each trip characteristic by mode of commuting and trip direction. **h** = hour; **k** = kilometre; **m** = metres; **min** = minutes. *Significant differences between home-school and school-home trips ($p < 0.01$).

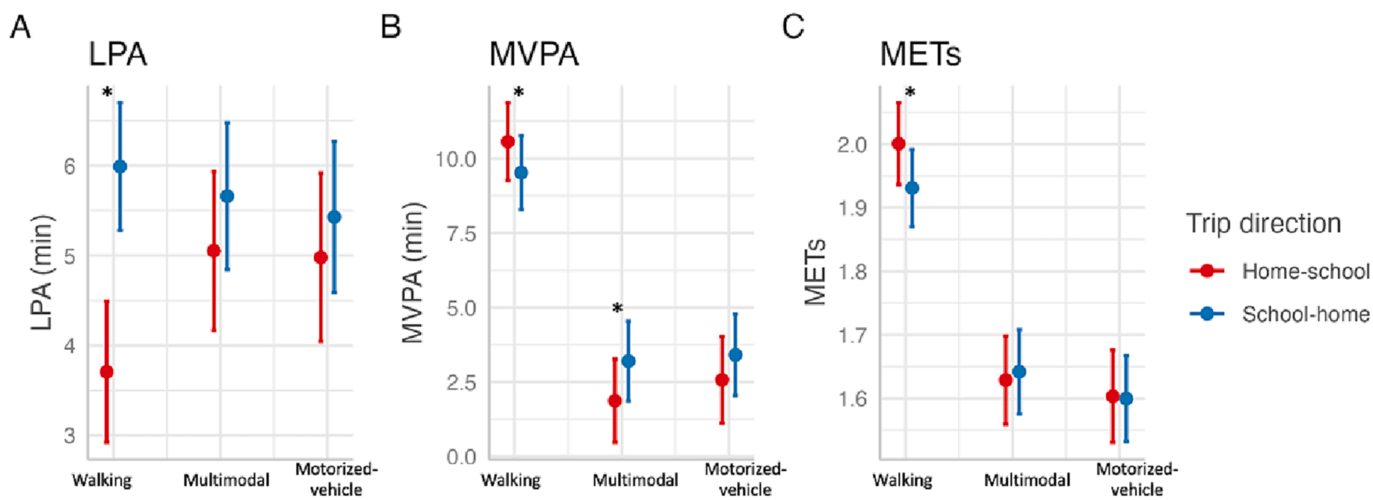

Fig. 4. Estimated means of PA intensity and PAEE by mode of commuting and trip direction. **LPA** = light physical activity; **METs** = metabolic equivalent tasks; **min** = minutes; **MVPA**: moderate-to-vigorous physical activity. *Significant differences between home-school and school-home trips ($p < 0.01$).

for both directions, which is not always correct. The current study provides novel insights since the GPS was implemented in both trip directions. The results of the present study suggested a longer duration of motorized-vehicle and multimodal trips in the home-school direction than in the school-home direction, and motorized-vehicle trips showed higher lengths and lower speeds in the home-school direction than in the school-home direction. These findings may explain a higher concentration of traffic in the morning, leading to longer passive trip duration and lower trip speed (Moyano et al., 2021). As for the difference between the length for motorized-vehicle trips by trip direction, the results differ from those obtained by Pizarro et al. (2016) in Portugal who found no difference between the length to and from school. This finding may be explained by error in the GPS signal (Jankowska et al., 2015) or that the motorized-vehicle route is different for the home-school direction and school-home direction because of the parents' convenience (Larsen et al., 2012). Regarding walking trips, they showed a longer duration in the school-home direction, but there were no differences in length or speed between trip directions. Nevertheless, home-school trips showed higher speed than school-home trips, although no significant differences were found. This fact may strengthen the hypothesis of not having a set arrival time at home (Herrador-Colmenero et al., 2019); then adolescents commute to home with a lower activity intensity because according to the results, they walk the same length but with a longer duration of time on this direction trip.

Consistent with this fact, there was the differences in the PA levels of walking between the home-school and the school-home direction. There were lower MVPA and METs and higher LPA during the school-home direction compared to the home-school direction. These findings differ from those obtained by different studies analyzing both trip directions in the scientific literature (Denstel et al., 2015; Gale et al., 2021; Kek et al., 2019; Remmers et al., 2020). In all these studies, MVPA and LPA levels tend to be higher in the school-home direction than in the home-school direction. This disagreement in results may be explained by the fact that the adolescents in the present study made the school-home direction travel more relaxed, as shown by the increased levels of LPA, while in the other studies, participants took longer to get home or were engaged in some kind of play on the school-home direction (Larsen et al., 2009; Pizarro et al., 2016). In addition, these differences could also be attributed to the PA cut-off points used in each study (Leppänen et al., 2022), the geographical characteristics of each area (Stewart et al., 2017), and the methodology used to identify the trips to and from school (e.g., depending on the range of the time interval used, PA in a 30-minute interval will be less than in a 60-minute interval). Therefore, the results of this study suggest the school-home direction is a good period of

Table 3
Estimated mean differences between modes of commuting in trip characteristics and PA levels, separately for home-school and school-home direction.

Home-school direction	Contrast	Estimate mean difference	L. CI – U. CI	*p*
Trip characteristics				
Length (m)	Walking – Multimodal	−2272	−3004–-1540	<0.01
	Walking – Motorized-vehicle	−2294	−3052–-1536	<0.01
	Multimodal – Motorized-vehicle	−22	−588–5441	0.99
Speed (km/h)	Walking – Multimodal	−7.3	−9.6–-5.0	<0.01
	Walking – Motorized-vehicle	−11.1	−13.5–-8.6	<0.01
	Multimodal – Motorized-vehicle	−3.8	−5.9–-1.7	<0.01
Duration (min)	Walking – Multimodal	−5.9	−9.2–-2.7	<0.01
	Walking – Motorized-vehicle	0.1	−3.3–3.6	0.99
	Multimodal – Motorized-vehicle	6.0	3.0–9.1	<0.01
Trip PA levels and PAEE				
LPA (min)	Walking – Multimodal	−1.3	−2.5–-0.2	0.02
	Walking – Motorized-vehicle	−1.3	−2.5–-0.1	0.03
	Multimodal – Motorized-vehicle	0.0	−1.1–1.2	0.99
MVPA (min)	Walking – Multimodal	8.7	7.1–10.4	<0.01
	Walking – Motorized-vehicle	8.0	6.4–9.7	<0.01
	Multimodal – Motorized-vehicle	−0.7	−2.1–0.8	0.52
PAEE (METs)	Walking – Multimodal	0.4	0.3–0.5	<0.01
	Walking – Motorized-vehicle	0.4	0.3–0.5	<0.01
	Multimodal – Motorized-vehicle	0.0	−0.1–0.1	0.69

School-home direction	Contrast	Estimate mean difference	L. CI – U. CI	p
Trip characteristics				
Length (m)	Walking – Multimodal	−2129	−2810–-1448	<0.01
	Walking – Motorized-vehicle	−1587	−2283–-890	<0.01
	Multimodal – Motorized-vehicle	542	41–1044	0.03

Table 3 (*continued*)

Home-school direction	Contrast	Estimate mean difference	L. CI – U. CI	*p*
Speed (km/h)	Walking – Multimodal	−8.9	−11.0–-6.8	<0.01
	Walking – Motorized-vehicle	−14.3	−16.4–-12.2	<0.01
	Multimodal – Motorized-vehicle	−5.4	−7.2–-3.6	<0.01
Duration (min)	Walking – Multimodal	0.8	−2.2–3.7	0.81
	Walking – Motorized-vehicle	5.7	2.7–8.7	<0.01
	Multimodal – Motorized-vehicle	4.9	2.3–7.6	<0.01
Trip PA levels and PAEE				
LPA (min)	Walking – Multimodal	0.3	−0.7–1.3	0.72
	Walking – Motorized-vehicle	0.5	−0.5–1.5	0.40
	Multimodal – Motorized-vehicle	0.2	−0.8–1.2	0.85
MVPA (min)	Walking – Multimodal	6.4	4.9–7.8	<0.01
	Walking – Motorized-vehicle	6.2	4.7–7.7	<0.01
	Multimodal – Motorized-vehicle	−0.2	−1.4–1.1	0.95
PAEE (METs)	Walking – Multimodal	0.3	0.2–0.4	<0.01
	Walking – Motorized-vehicle	0.3	0.3–0.4	<0.01
	Multimodal – Motorized-vehicle	0.0	−0.02–0.1	0.26

L. CI = lower confidence interval; **U. CI** = upper confidence interval; **m** = metres; **min** = minutes; **LPA** = light physical activity; **MVPA** = moderate-to-vigorous physical activity; **PAEE** = physical activity energy expenditure; **METs** = metabolic equivalent of task.

time to increase adolescents' daily MVPA levels through interventions that increase the intensity of this trip direction, in this way achieving the same or greater MVPA benefits than during the home-school direction.

When comparing trip characteristics by mode of commuting in home-school and school-home directions, multimodal and motorized-vehicle trips showed higher length and speed than walking trips in both trip directions, but differences in duration only existed between walking trips and vehicle trips in home-school direction and between walking trips and multimodal trips in school-home direction. These results coincided with those obtained by studies that also combined GPS and accelerometry (Pizarro et al., 2016; Remmers et al., 2020; Stewart et al., 2017; Villa-Gonzalez et al., 2019). Moreover, they are expected since active commuting to and from the school generally decreases as the distance to the school increases (Rodriguez-Lopez et al., 2017), and thus the increase in passive modes leads to higher travel speeds. In this line, it has been studied that differences between multimodal or motorized-vehicle trips could be attributed to traffic congestion (Moyano et al., 2021), as well as to the characteristics of the environment (Adams et al., 2014). Therefore, it is important to consider different factors (such as the environment and geographical characteristics) of each area and country when making comparisons of these behaviours.

Regarding PA levels, as expected, walking trips showed higher levels of MVPA and METs in both directions compared to multimodal or vehicle trips. However, LPA levels were lower for walking trips in the home-school direction than for multimodal trips or motorized-vehicle trips. Although the results on MVPA and METs are consistent with other studies on this topic (Pizarro et al., 2016; Villa-Gonzalez et al., 2019), the LPA results were surprising. It has always been thought that active modes of commuting provide an increase in daily PA levels (Martin et al., 2016), but studies always tend to focus on MVPA levels, and little has been studied on LPA (Martinez-Martinez et al., 2019; Kek et al., 2019; Pizarro et al., 2016; Stewart et al., 2017). From these findings, it can be concluded that active commuting is mainly a behaviour performed at moderate-vigorous intensity, which could explain why no differences were found in LPA with the other modes of commuting. In fact, as a practical message, if ACS in both trip directions is performed by walking, it could account for up to 34% of the daily MVPA recommendations proposed by the WHO. It should also be noted that the METs in this study were lower than those reported in the study conducted by Villa-Gonzalez et al. (2019). This may be due to the equation used to predict them, as well as the fact that the accelerometer may not be a good instrument to measure PAEE (Jeran et al., 2016). Future studies could analyse the PAEE derived from commuting to and from school using indirect calorimetry or other more valid and reliable methods to measure this behaviour in free-living conditions. Finally, based on the results obtained in the current study, it would be useful to carry out different interventions depending on the trip direction: a) for the home-school direction, interventions should focus on reducing the number of passive trips and maintaining the intensity of the active trips; b) while for the school-home direction, interventions should focus on increasing the intensity of active trips to maximise MVPA minutes.

5. Strengths and limitations

The major strength of this study was the combination of accelerometer and GPS data to identify the trip modes, the trip directions to and from school and the trip characteristics, as well as to quantify the PA levels during both trip directions. Contrary to other methodologies used in the scientific literature, the methodology used in this study allows to, firstly, use a device-measure to identify the modes of commuting (in contrast to the self-report measures) and secondly, accurately know the time of departure from home and arrival at school, and vice versa. Another strength of this study was the possibility of obtaining multimodal trips, since using PALMSplusR can be determined whether a trip was the sum of different modes of commuting.

However, this cross-sectional study has a few limitations that should be mentioned. Depending on the environment in which the participants commuted, there may be a spatial error due to the quality of the satellite signal; modes of commuting in both directions were determined based on speed only, although these speed thresholds have been validated using SenseCam (Carlson et al., 2015), there is a possibility that some modes of commuting have been misclassified (e.g., some motorized-vehicle trips were classified as multimodal trips due to traffic congestion). There was also the possibility of missing some trips if the participant stayed for >10 min in the same position before arriving at the school or home. Finally, caution should be taken when extrapolating these results to other populations, since the spatio-temporal patterns of commuting to and from school may vary among populations living in other geographical settings. It is important to note that there may be a large range of variables that explain the differences observed between the home-school and school-home commuting trips. In the present study, we considered the participants' socio-economic status (using an adaptation of the FAS scale) and the walkability index (based on three built environment features) of school neighbourhoods. Future studies should explore other individual, social, and environmental variables in order to provide a broader explanation.

6. Conclusion

The main results of the current study suggest that the home-school and the school-home commuting trips differ in trip characteristics, PA, and PAEE, thus they should be analysed separately. There was a higher percentage of walking trips and a lower percentage of multimodal and motorized-vehicle trips in the school-home direction than in the home-school direction. In addition, there were significant differences in trip characteristics and PA levels between school-home and home-school directions. Especially, walking trips provided lower MVPA and PAEE and higher LPA during school-home direction compared to the home-school direction. Regarding the differences by mode of commuting to and from school, walking trips seem to have a positive impact on MVPA levels and METs compared to multimodal or motorized-vehicle. However, multimodal and motorized-vehicle presented higher LPA minutes than walking trips during the home-school direction.

Future strategies to increase daily MVPA levels and PAEE may focus on the promotion of the use of active modes of commuting to and from school, such as walking, and specifically, increasing the intensity of walking in the school-home direction.

CRediT authorship contribution statement

P. Campos-Garzón: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft. **T.T. Amholt:** Visualization, Writing – review & editing. **D. Molina-Soberanes:** Data curation, Investigation, Writing – review & editing. **X. Palma-Leal:** Data curation, Investigation, Writing – review & editing. **A. Queralt:** Investigation, Writing – review & editing. **A.J. Lara-Sánchez:** Investigation, Writing – review & editing. **T. Stewart:** Conceptualization, Formal analysis, Methodology, Visualization, Writing – review & editing. **J. Schipperijn:** Conceptualization, Methodology, Supervision, Visualization, Writing – review & editing. **Y. Barranco-Ruíz:** Conceptualization, Methodology, Supervision, Visualization, Writing – review & editing. **P. Chillón:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tbs.2023.100618.

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