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DOI
10.1016/j.healthplace.2025.103413

Publication date
2025

Document Version
Final published version

Published in
Health and Place

Health & Place 91 (2025) 103413

Contents lists available at ScienceDirect

Health and Place

journal homepage: www.elsevier.com/locate/healthplace

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ARTICLE INFO

Keywords:
Active travel
Location tracking
Urban environment
Spatiotemporal method
Cohort

ABSTRACT

Health implications of mobility during pregnancy entail a need to understand pregnant women's activity spaces. We present ActMAP, a framework for quantifying multiple aspects of activity spaces from distinct trips and stays derived from GPS data. We applied ActMAP to data from 238 pregnant women in Barcelona, Spain (2018–2020) and explored weekday, weekend and intraday associations between pregnancy trimester and activity spaces. Activities were more centred around the home later in pregnancy. However, the number of visited places and daily trips remained largely constant throughout pregnancy. By constructing activity spaces from individual trips and stays, ActMAP could provide a framework for GPS-based holistic assessments of mobility.

1. Introduction

Exposure to environmental factors, such as air pollution, noise, or greenspace, during pregnancy can influence birth outcomes and childhood development and such influences can spill over to later stages of life (Dzhambov and Lercher, 2019; Nyadanu et al., 2022; Zare Sakhvidi et al., 2023). Studies of environmental exposure during pregnancy commonly measure the environment surrounding the home (Hu et al., 2021; Yi et al., 2024a). However, since most adults spend considerable time away from home, residence-based proxies entail an exposure misclassification risk (Christensen et al., 2022; Kwan, 2018; Wilt et al., 2023), especially for some environmental factors such as noise and greenspace that can be highly spatially variable (Wei et al., 2023a). A comparison among pregnant women between environmental exposures using residence-based buffers and Global Positioning Systems (GPS) measurements found correlations that were weak (greenspace) to moderate (walkability) (Yi et al., 2024a). Furthermore, late in pregnancy, women tend to spend more time at home (Nethery et al., 2009)

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https://doi.org/10.1016/j.healthplace.2025.103413
Received 24 May 2024; Received in revised form 21 November 2024; Accepted 8 January 2025
Available online 16 January 2025

and less time at work (Zhu et al., 2019) and travel less (Wu et al., 2013). Thus, to study environmental exposure in pregnancy, mobility-based methods that accurately capture movements across space-time are needed.

The notion of the environmental settings of individuals changing over time has been central to health geography since the emergence of time geography (Hägerstrand, 1970). More recently, Kwan's (2012) formulation of the uncertain geographic context problem highlighted that uncertainties regarding the spatial areas that exert an influence on health outcomes and the timing and duration at which they do so require delineations of people's movement in space-time. To accurately reflect mobility and/or environmental exposure, studies are increasingly measuring *activity spaces*, defined as *"all locations within which an individual has direct contact as a result of [their] day-to-day activities"* (Golledge and Stimson, 1997, p. 279). As used in research, activity spaces constitute spatial summary measures of movement, behaviour, activities, and/or visited locations (Smith et al., 2019). Studies implementing activity spaces have proliferated with the increasing availability of tracking devices utilising GPS technology. A simple way to delineate activity spaces is the minimum convex polygon (MCP), which is the smallest polygon with convex angles encompassing all measured locations (Kraft et al., 2019; Zenk et al., 2018). However, as these include (sometimes vast) unvisited areas between the visited locations (Smith et al., 2019; Vich et al., 2017), more accurate exposure assessments require sophisticated methods such as kernel density estimation. Such methods can furthermore be used for distinguishing between activity places, i.e. distinct locations of relevance for a particular participant (e.g. the workplace), and trips between these places (Thierry et al., 2013; Yi et al., 2022), a division that is valuable for several reasons. First, it is a prerequisite for addressing potential selective daily mobility bias (SDMB) that might results from environmental exposure being influenced by conscious decisions about where to go to undertake specific activities (Chaix et al., 2013) (although there is empirical evidence to indicate that its relevance is limited (Wei et al., 2023b)). Second, it enables exploration of health impacts of exposure to specific places of subjective significance for individuals (Perchoux et al., 2013). Third, active travel might be distinguished from passive travel, as the implications for environmental exposure during travel are different (Cepeda et al., 2017), and active travel in itself can confer health benefits (Lee and Buchner, 2008).

The separation of activity spaces into activity places and trips can be based on the spatial dimensions or the time dimension. Studies using spatial coordinates for this separation (e.g., Thierry et al., 2013; Yi et al., 2022) run the risk of not being able to discriminate between separate stays at the same activity place. Hägerstrand (1970, p. 10) remarked that *"location in space cannot effectively be separated from the flow of time. [...] As long as [they are] alive at all, [people have] to pass every point on the time-scale. Every point in space does not demand the same of [them]."* This means that trips and stays are mutually exclusive in time but not necessarily in space. Another important consideration in this context is that of temporal data aggregation. Over the course of the week, weekend mobility differs from weekday mobility, for example by people being more likely to visit a park (Sevtsuk and Ratti, 2010) or in greater variability in how far they travel from home (Wei et al., 2023). While the general population might be more likely to engage in physical activity on the weekend (O'Donovan et al., 2017), a study on pregnant women found that they were less likely to do so (Yi et al., 2024b). Meanwhile, mobility patterns over the course of the day can illuminate links between mobility and activities (e.g., work commutes) (Lee and Ki Eom, 2020) and might matter for time-varying environmental factors such as air pollution (Li et al., 2022). Thus, constructing activity spaces bottom-up based on the time dimension enables identification of different stays in the same locations and provides flexibility to later perform different temporal aggregations (e.g., separating morning from evening activity).

A recent study (Yi et al., 2022) explored the daily time-activity and mobility patterns of 62 pregnant women in Los Angeles, United States, using kernel density-based detection of activity places and trips. However, to the best of our knowledge, no research has to date studied pregnant women's activity spaces using time-based trip and stay segmentation for activity place delineation, travel mode detection and flexible temporal aggregation to distinguish different times of week as well as times of day. Accordingly, the main aim of our study was to (i) develop such a framework to comprehensively characterise pregnant women's activity spaces, i.e., their time-activity patterns, mobility, and activity places. Our secondary aims were to (ii) assess correlations between the activity space variables, and (iii) explore and statistically model associations between trimester of pregnancy (first vs. third) and these multiple aspects of activity spaces across weekdays and weekends, respectively, as well as over the course of the day. The findings are discussed both in relation to mobility behaviour in pregnancy and the study of activity spaces more generally.

2. Methods

2.1. Participants and study area

The Barcelona Life Study Cohort (BiSC) (Dadvand et al., 2024) is an ongoing mother-child cohort in Barcelona, Spain. Barcelona is a port city and the capital of the Catalonia autonomous community, located at the north-eastern part of the Iberian Peninsula, with a Mediterranean climate with mild winters and warm to hot summers. Barcelona has one of the highest population densities in Europe, and the modal split of trips in the city is 20% by private motor vehicles, 34% by public transport and 46% using active modes (Ajuntament de Barcelona, 2024).

BiSC enrolled 1080 pregnant women in their first trimester of pregnancy between October 2018 and March 2021, at three university hospitals in Barcelona (Hospital Sant Joan de Déu, Hospital de la Santa Creu i Sant Pau, and Hospital Clínic de Barcelona). Inclusion criteria were being 18–45 years old, having singleton pregnancy without known congenital anomalies, residing in the hospitals' catchment areas, and being able to communicate in Spanish/Catalan. Study data were collected and managed using Research Electronic Data Capture (REDCap) tools hosted at ISGlobal (Harris et al., 2009, 2019).

Participants were tracked for one week in the first trimester (T1, around week 12 of gestation) and one week in the third trimester (T3, around week 32 of gestation). Here, we focus on the period before the COVID-19 pandemic to avoid the impact of severe mobility restrictions that were enforced by the authorities during the early phases of the pandemic. We thus included participants with both tracking periods ending before March 14th, 2020, when the strict lockdown started in Spain (N = 297, excluding 147 participants that did not complete the second tracking period and 466 participants with at least one tracking period overlapping with the pandemic). We further limited the sample to participants with GPS data for at least one weekday and one weekend day with >5 h of waking time during both weeks (N = 250) similar to criteria applied in previous studies (Yi et al., 2022; Zenk et al., 2018). Finally, we excluded participants that undertook a longer trip, here defined as leaving the Catalonia region, yielding a final sample size of N = 238.

2.2. ActMAP

We developed an activity space framework revolving around three components: time-**Act**ivity patterns, **M**obility, and **A**ctivity **P**laces (ActMAP; Fig. 1). With ActMAP, activity spaces were constructed bottom-up from temporally distinct trips and stays, which allowed assigning travel modes, accurately delineating activity places (i.e., locations of stationary activity) and calculating the time spent in them, and considering different levels of temporal aggregation over the course of the day and the week. ActMAP included five steps. First, input GPS data were pre-processed with temporal downsampling and data cleaning measures. Second, distinct trips and stays were identified by temporally

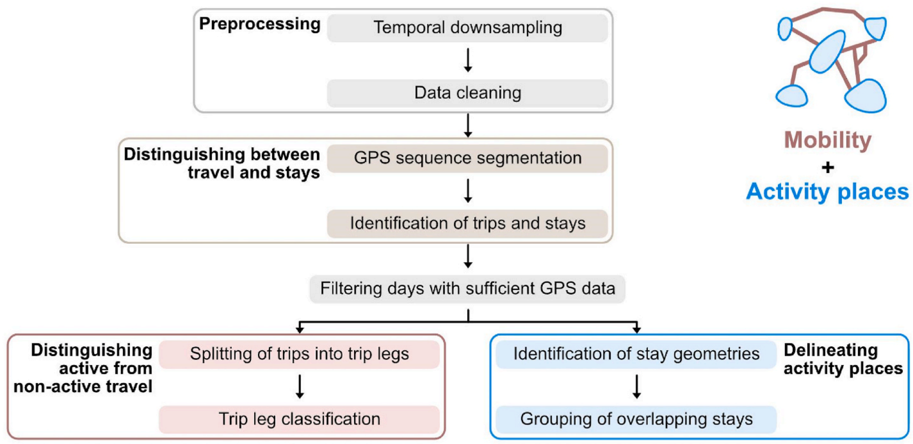

Fig. 1. The sequence of steps in ActMAP.

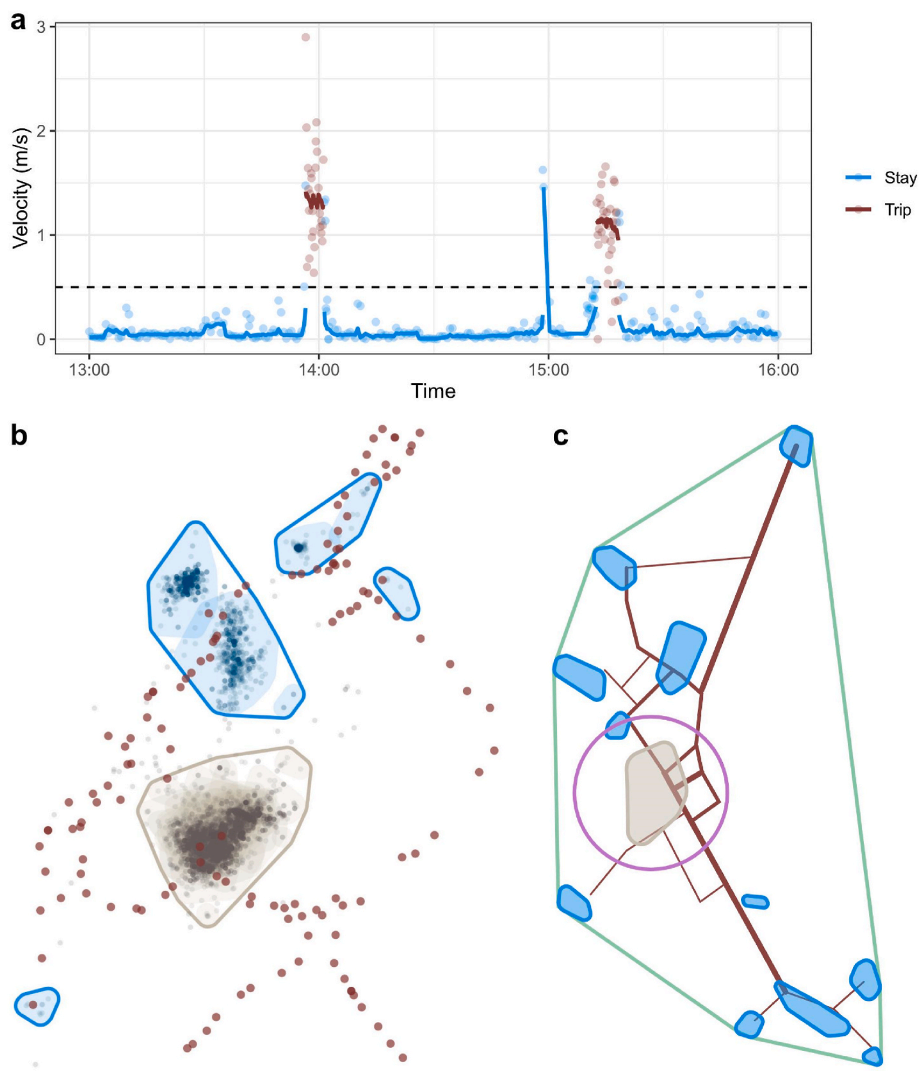

Fig. 2. **a)** Example of how GPS points were divided into stays and trips based on 3-min sliding windows. Lines show 3-min means. At least three consecutive points with 3-min mean velocity >0.5 m/s (dashed line) were classified as trips. Note two points around 15:00 that were not classified as a trip. **b)** GPS points belonging to stays (small points) were clustered into stay geometries (translucent polygons) that were further grouped into activity places (solid polygon boundaries).The activity place coded as home is coloured grey, with remaining activity places in blue. GPS points belonging to trips are shown in red. **c)** Schematic illustration of an activity space. Eleven activity space variables were calculated: 1) time staying at or near home (grey polygon), 2) time staying away from home (blue polygons), 3) time travelling (red lines), 4) number of trips per day, 5) kilometres travelled per day, 6) active travel distance ratio, 7) active travel time ratio, 8) number and 9) area of activity places (grey and blue polygons), 10) activity space MCP (green boundary), 11) time-weighted standard distance from home (the radius of the purple circle).

segmenting the GPS sequence. Third, daily GPS data coverage was quantified and days with insufficient coverage were removed. Fourth, the trips were split into trip legs and trip modes were estimated using classification. Fifth, stays were geographically delineated and grouped into activity places. The framework was implemented in R and Python (see Supplementary Information (SI) section 1 for packages and code).

Step 1: GPS data collection and preprocessing

GPS data was collected for one week in T1 and one week in T3 using ExpoApp, a validated smartphone application combining assisted GPS, cellular triangulation, and WiFi triangulation (Donaire-Gonzalez et al., 2019). Using this combination, smartphones generally work better than commercially available GPS devices in indoor environments (where satellite signals are weak) and are quicker to determine location. ExpoApp collected data at a 1-s resolution when using the GPS sensor and a 20-s resolution when using cellular or WiFi triangulation. ExpoApp was installed on a Samsung Galaxy J3 Smartphone provided to each participant at home by a trained fieldworker. The participants were asked to carry the phone in the most external part of their bags or backpacks, and to charge it during sleep to avoid data loss.

We down-sampled the data by splitting each participant's timeline into 10-s buckets while preserving the highest-accuracy point in each bucket. This down-sampling reduced the dataset from 147,848,319 to 20,267,606 points (an 86.3% reduction), yet retained a resolution that is on par with previous recommendations (Burkhard et al., 2020; Zeng et al., 2023). GPS data cleaning involves removing points based on anomalous velocity, low accuracy and GPS/triangulation switching (Tsuda et al., 2013; Wei et al., 2023a). We consequently removed points with velocities >100 m/s, accuracy values > 100 m, and with a different provider than the preceding point within less than 5 s.

Step 2: Distinguishing between travels and stays

Each participant's GPS sequence was divided into segments separated by breaks. We followed the procedure outlined by Zeng et al. (2023) to identify breaks. In brief, this method moved a sliding window across the sequence and successively added points to a segment until a break was detected based on a set of parameters, after which a new segment was started (see SI section 2 for a detailed description).

Within each segment we identified trip and stay regions based on velocity (Fig. 2a). To avoid erroneously detecting a trip during a stay (e.g. measurement errors due to low accuracy) or vice versa (e.g. stopping for a red light), we used sliding 3-min windows. This window size can detect short stays and trips while excluding stops during trips (Cich et al., 2016; Du and Aultman-Hall, 2007). For each point, we calculated the mean and standard deviation of velocity during 3 min 1) before the point, 2) centred at the point, and 3) after the point, and retained the mean velocity of the window with the smallest standard deviation, classifying it as moving if this velocity was >0.5 m/s. We classified each segment of at least three consecutive moving points as a trip (as an additional precaution to filter out artefacts) and the remaining sequences as stay segments.

Step 3: Calculating daily GPS data coverage

To only include participants with sufficient GPS data, we objectively identified typical waking hours using sleep and waking times derived from ActiGraph wGT3X-BT accelerometers (ActiGraph, Pensacola (FL), USA) also worn during the GPS tracking periods. The mean sleep onset time across all days (rounded to the nearest half-hour) was 00:30, and the mean wake-up time was 08:00 (see SI section 3, Fig. S1). For each day, we summed up the total duration of trips and stays between 08:00 and 00:30 (i.e. 00:00–00:30 was shifted to the preceding day). Days with >5 h coverage were included in the main analysis (cf. Yi et al., 2022).

Step 4: Distinguishing active from passive travel

We divided trips into trip legs and delineated them by identifying regions at and above walking speed, respectively (Rasmussen et al., 2015; Schuessler and Axhausen, 2009) within 3-min sliding time windows consistent with those used in step 2 (for further details, see SI section 4). Distinguishing active from passive trip legs using only GPS data is challenging in environments with high-rise buildings and narrow streets such as central Barcelona. Hence, we leveraged geographical features to initially create a more detailed classification (walking, bicycle, private motor vehicle, bus, or above-ground rail transport (metro added later, see below)) before collapsing it into active vs. passive. We downloaded data on railway tracks (rail, subway, light rail, tram, and narrow gauge tracks) and bus stop locations across Catalonia from OpenStreetMap (OpenStreetMap contributors, 2023). For each trip leg, we calculated six features related to velocity, acceleration and distance to railways and bus stops (SI section 4).

Classification of travel modes was done with fuzzy logic (Zadeh, 1965). Fuzzy logic is a method for assessing class multi-memberships that can be used for transport mode classification by assigning a so-called membership degree (ranging from 0 to 1) for each mode class (Das and Winter 2018). Adopting the method from Rasmussen et al. (2015), we extrapolated from a subset of trip legs (n = 1844) that aligned well with commutes mapped during prior fieldwork visits. Refer to SI section 4 for more information about fuzzy logic and our implementation of it. As trip legs by metro are carried out underground without GPS signal, we identified and added these post-hoc (SI section 4). Lastly, walking and bicycle legs were collapsed to active and all other modes to passive.

Step 5: Delineating stays and activity places

Activity places were derived from stays using clustering and geoprocessing techniques (Fig. 2b) (Mousavi et al., 2017). We first derived stay polygons by performing mean-shift clustering (Comaniciu and Meer, 2002) on each stay segment. Mean-shift clustering identifies local density maxima across a point pattern with a circular search window. We used a 25-m radius to identify clusters within each stay segment, as this is a small radius that can nevertheless reliably identify stop locations in GPS trajectories (Gong et al., 2015). Similar to step 2, we retained clusters with at least three points and 3 min duration. A convex hull was drawn around the points of each cluster and buffered by a margin-of-error parameter, here set to 5 m based on visual inspection of the resulting geometries. Activity places were then derived by grouping overlapping polygons. Based on visual inspection, we decided to group small stay polygons together with other polygons they were adjacent to but non-overlapping with, and defined small polygons as <2000 m^2 and two polygons as adjacent if their boundaries were within 10 m of each other. The entire procedure was performed separately for weekday and weekend stays. To allow time-weighted analyses, time spent in an activity place was obtained by summing the duration of its stays.

2.3. Analysis

To characterise activity spaces, we calculated three time-activity variables, four mobility variables and four activity-place variables separately for weekdays and weekends (totalling 22 variables) (Fig. 2c; see SI section 5 for further details on variable calculation). The time-activity variables were hours per day (i) staying at or near home, (ii) staying away from home, and (iii) travelling. The mobility variables were: (iv) trips per day, (v) kilometres travelled per day, and ratios of (vi) active travel distance and (vii) active travel duration (the total distance/duration of active travel trip legs divided by the total distance/duration of all trips). The activity place variables were: (viii) the number of activity places, (ix) the total area of activity places, (x) the area of the activity space MCP drawn around the activity places, and (xi) standard distance from home (SD_h), a variable established by Xu et al. (2015) that we here further developed using time-weighting. SD_h was calculated by measuring the Euclidean distances from stay polygon centroids to the home, weighing each by the proportion of time spent staying in that polygon to the total duration of stays.

Distributions were explored using histograms and probability density functions (PDFs) separately for each trimester. The PDFs were created non-parametrically using Gaussian kernels with Silverman's rule of thumb (Silverman, 1986) and rescaled to the same y-axis range as the histogram. For two variables (active travel variables during weekends), we iteratively adjusted the kernel width until the histograms and PDFs lined up.

Due to skewed variable distributions, we explored relationships between variables using non-parametric Spearman's rank correlations. To get an overview of how all 22 variables interrelated, we constructed an adjacency matrix with correlation coefficients denoting adjacency and plotted a graph with variables as nodes and their mutual correlations as edges.

Associations between trimester (predictor) and the 22 activity space variables (outcomes) were explored with mixed effects regression models with the participant as the random effect. Ten of the 22 variables (time-activity variables and active travel ratios) were modelled using mixed effects beta regression, an approach for modelling continuous ratios. We log-transformed the remaining ten continuous variables (trips and distance travelled per day, activity place area, MCP and SD_h) as their distributions were skewed, and used these variables as outcomes in linear mixed models. The number of activity places was modelled using Poisson regression, with overdispersion not being an issue (dispersion factor = 1.05 (weekdays), 1.04 (weekends)). Since all models included either log-transformed outcome variables or a log-link, we reported exponentiated trimester coefficients representing the multiplication factor of T3 compared to T1. We controlled our analyses for participant's age (continuous, years), ethnicity (categorical, European/Latin American/other), education (categorical, primary/secondary/university/postgraduate degree), and work situation (categorical, full-time work/part-time work/student/stay at home or out of work). As time-varying covariates, we included time of year (the number of months before or after August 6th (2018, 2019, or 2020), the historically warmest day of the year in Barcelona (Weather Spark, n.d.)), and weekly mean temperature (°C), relative humidity (%) and accumulated precipitation (mm) at the participants' home locations (gathered from the Raval monitoring station (Servei Metereològic de Catalunya, 2021)).

To further bolster our understanding of links between mobility behaviour and activity spaces, we explored intraday patterns of travel and stays during weekdays and weekends. Based on visual analysis of these patterns using histograms and hexagonal binning plots, we defined four time periods: morning (08:00–10:00), noon (10:00–14:00), afternoon (14:00–19:00), and evening (19:00–00:30). For each time period of each day, we defined two binary outcome variables: whether any travel occurred during the period, and whether a stay further than 1 km from home occurred. Using mixed effects logistic regression models, we modelled the association of these outcomes with the main effects of trimester and time of day and their interaction, controlling for the same covariates used in the activity space models. Estimated marginal means were calculated to visualise odds ratios (ORs) associated with trimester conditional on time of day.

2.4. Sensitivity analyses

To evaluate the robustness of our findings to different assumptions made during the implementation, we conducted sensitivity analyses. Firstly, as the procedure for determining activity places involved multiple ad-hoc parameters, we performed a sensitivity analysis by systematically varying (i) the clustering search radius, (ii) the margin of error buffer when drawing stay polygons, (ii) the threshold for small polygon areas, and (iv) the threshold distance for when a small polygon is adjacent to another polygon, after which we evaluated differences in the resulting numbers and areas of activity places.

Secondly, we evaluated the impact of GPS data completeness on activity spaces by analysing days with >10 h GPS data (Yi et al., 2022). For weekday and weekend activity spaces based on only these days (N = 209 participants), we calculated summary statistics and modelled associations with trimester using the same regression models as in the main analysis.

3. Results

The median age of the 238 participants was 35 (Q1-Q3: 32–38) years old. They were mostly highly educated (76.3% with university studies), and of European origin (78.3%) with a large minority of Latin American origin participants (19.6%). In total, 2699 days were analysed (median (Q1-Q3) days per participant and period = 6 (6-6)). The median daytime hours covered by GPS data per day were 13.8 (Q1-Q3: 12.8–14.7). Out of all days, 1825 were weekdays (median (Q1-Q3) days per participant and period = 4 (4-4)) and 898 were during weekends (median (Q1-Q3) days per participant and period = 2 (2-2)). The days were equally split between the trimesters, with 1362 in T1 and 1337 in T3 (median (Q1-Q3) days per participant and period was 6 (6-6) in T1 and 6 (5–6) in T3).

3.1. Weekday and weekend activity spaces

Table 1 shows summary statistics of the activity space variables. Across both trimesters, the participants spent most waking time at or near home, both during weekdays and weekends. In T1, the median daily hours spent at home was lower during weekdays (6.6 h) than weekends (7.9 h), while in T3, the corresponding numbers were nearly identical (weekdays: 9.6 h, weekends: 9.5 h) and greater than in T1 (Fig. 3). Across both trimesters, the median daily hours travelled was 1.3 h during weekdays and 1.2 h during weekends. In T1, these numbers were similar for weekdays and weekends (1.3 h), while in T3, they were higher during weekdays (1.3) than weekends (1.1).

Across both trimesters, more trips occurred during weekdays (median = 4.5) than weekends (median = 3.5). This was true also in both T1 (weekday median = 4.5, weekend median = 3.5) and T3 (weekday median = 5.3, weekend median = 3.5). Daily travel distance spanned several orders of magnitude in both trimesters and for both weekdays and weekends, from less than one km to tens of kilometres (Figs. S2a and S2b). Participants' reliance on active travel varied from 0% to 100%, both with regards to distance and time (Figs. S2a and S2b). In T1, the median active travel time ratio was nearly identical for weekdays (61.0%) and weekends (61.1%), while in T3, the corresponding ratio was higher during weekdays (70.5%) than weekends (61.9%).

Across both trimesters, the median number of activity places for weekdays and weekends were 8 and 5, respectively. The numbers were the same when disaggregated by trimester, except weekday activity places in T3 (9). The spatial scale of activity spaces, as reflected in MCP and SD_h, spanned several orders of magnitude in both trimesters and for both weekdays (Fig. S2c) and weekends (Fig. S2d). Across both trimesters, median SD_h was similar during weekdays (0.69 km) and weekends (0.67 km). However, in T1 median SD_h was greater during weekdays (1.34 km) than weekends (0.91 km), whereas the opposite was the case in T3 (weekday median = 0.34 km, weekend median = 0.49 km).

Exponentiated regression coefficients (reflecting multiplicative difference in means or odds ratios when comparing T3 to T1) varied on a spectrum from positive to negative (Fig. 4; Table S4). There was a decrease in hours per day away from home (weekdays: $e^{\beta} = 0.65$, $p < 0.0001$; weekends: $e^{\beta} = 0.75$, $p = 0.0001$) and SD_h (weekdays: $e^{\beta} = 0.47$, $p < 0.0001$; weekends: $e^{\beta} = 0.58$, $p = 0.015$), and increase in hours per day at or near home (weekdays: $e^{\beta} = 1.54$, $p < 0.0001$; weekends: $e^{\beta} = 1.43$, $p < 0.0001$) in T3 compared with T1. When comparing weekdays in T3 to those in T1, there was an increase in active travel time ratio (e^{β}

Table 1
Summary statistics of activity space variables for the whole sample and disaggregated by trimester. Medians are shown, with range between first and third quartiles in brackets.

Variable	Weekdays			Weekends		
	All periods	T1	T3	All periods	T1	T3
Time at or near home (h/d)	8.4 (5.8–10.7)	6.6 (5.0–9.1)	9.6 (7.9–11.4)	8.9 (5.8–11.3)	7.9 (4.8–10.7)	9.5 (7.0–12.1)
Time away from home (h/d)	3.6 (2.1–6.1)	5.5 (2.9–7.3)	2.8 (1.7–4.3)	3.0 (1.6–5.3)	3.2 (1.8–6.0)	2.8 (1.3–4.5)
Time travelling (h/d)	1.3 (0.93–1.7)	1.3 (0.97–1.8)	1.3 (0.89–1.7)	1.2 (0.68–1.8)	1.3 (0.77–2.0)	1.1 (0.63–1.7)
Trips per day	4.8 (3.5–6.3)	4.5 (3.2–5.8)	5.3 (3.5–6.5)	3.5 (2.0–5.0)	3.5 (2.5–5.0)	3.5 (2.0–5.0)
Travel distance (km/d)	8.8 (4.9–17.4)	9.4 (5.1–20.7)	8.3 (4.9–15.6)	9.0 (3.4–29.5)	9.5 (3.6–36.5)	8.5 (3.2–27.7)
Active travel distance (%)	42.9 (18.2–72.8)	38.5 (16.1–72.8)	45.3 (20.4–72.5)	31.4 (6.9–77.1)	36.0 (7.4–79.4)	27.8 (5.7–73.2)
Active travel time (%)	67.1 (47.2–83.3)	61.0 (43.5–80.2)	70.5 (53.9–85.5)	61.5 (34.3–86.7)	61.1 (35.8–86.1)	61.9 (33.1–87.1)
Activity places (n)	8 (6–11)	8 (5.75–11)	9 (6–12)	5 (3–7)	5 (3–7)	5 (3–7)
Activity place area (ha)	1.6 (1.1–2.1)	1.6 (1.1–2.1)	1.6 (1.2–2.2)	0.83 (0.53–1.13)	0.83 (0.55–1.12)	0.83 (0.48–1.17)
Activity space MCP[a] (km^2)	4.4 (1.4–18.2)	5.4 (1.6–23.7)	3.8 (1.3–12.5)	2.0 (0.21–16.5)	3.3 (0.22–22.2)	1.9 (0.18–11.6)
SD_h[b] (km)	0.69 (0.23–2.20)	1.34 (0.42–3.93)	0.34 (0.17–1.13)	0.67 (0.13–4.37)	0.91 (0.17–9.43)	0.49 (0.10–2.70)

[a] minimum convex polygon.
[b] standard distance to home.

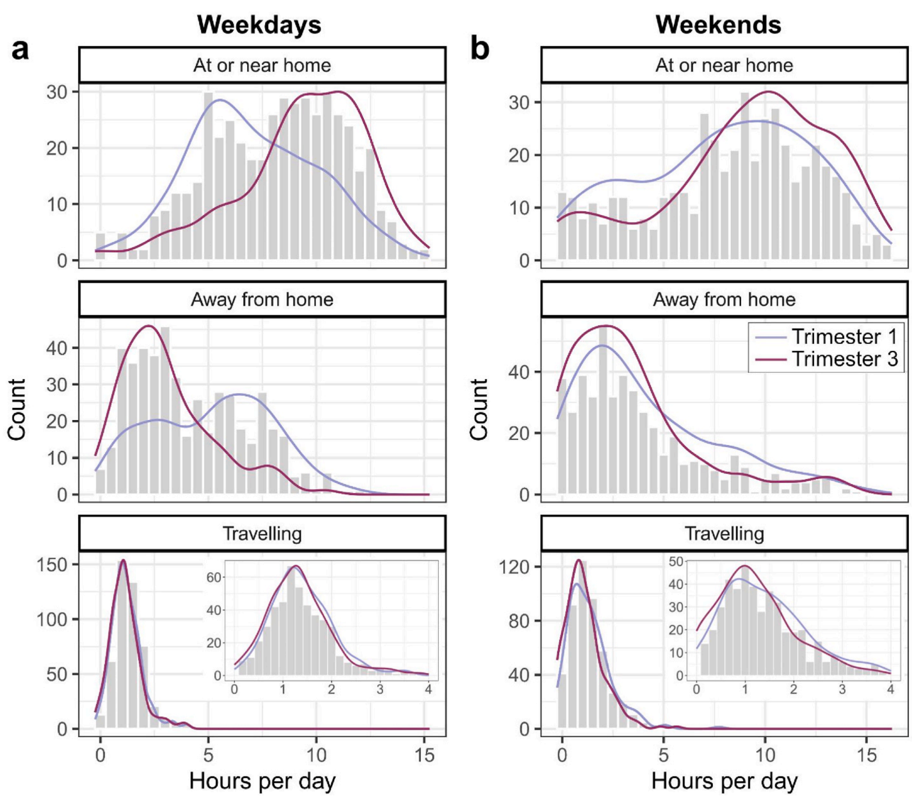

Fig. 3. Distribution of time-activity patterns. **a)** Histograms of distributions of hours per weekday spent at or near home (top), away from home (middle), and travelling (bottom). Density plots for each trimester are overlaid on top. **b)** Same as **a)** but with weekends instead of weekdays.

= 1.30, p = 0.004), number of trips (e^{β} = 1.10, p = 0.016) and number of activity places (e^{β} = 1.09, p = 0.013). However, the same variables during weekends did not significantly differ between trimesters.

3.2. *Intraday travel and stays*

Weekday travel peaked in the morning (09:00–10:00) and again in the early evening (18:00–19:00) (Fig. 5a). Participants travelled more in T1 during these peaks, whereas in T3 relatively more travel happened during noon (10:00–14:00) (Fig. 5a). Regression confirmed the lower likelihood of morning travel in T3 compared with T1 (OR = 0.62, p = 0.0002), and the higher likelihood of noon travel (OR = 2.05, p < 0.0001) (Fig. 5c; Table S8). Weekend travel displayed a nearly symmetrical pattern with a peak 12:00–13:00 and another 19:00–20:00 (Fig. 5a). No differences in intraday travel during weekends were identified between trimesters (Fig. 5c, see also SI section 6, Table S8).

The distance of stays from home during weekdays followed a bimodal distribution with many stays at home and a considerable number of stays a few kilometres from home but relatively few stays in between (Fig. 5b). On average, participants stayed farther from home in T1 than in T3 between 08:00 and 19:00 but not later in the evening (Fig. 5b). Lower likelihoods of staying farther than 1 km from home in T3 compared to T1 was observed for the morning (OR = 0.28, p < 0.0001), noon (OR = 0.53, p < 0.0001) and afternoon (OR = 0.48, p < 0.0001) but not for the evening (Fig. 5d–Table S10). Unlike weekdays, many stays during weekends were tens of kilometres from home (Fig. 5b). Differences between trimesters in the likelihoods of staying farther than 1 km from home were not statistically significant (Table S10).

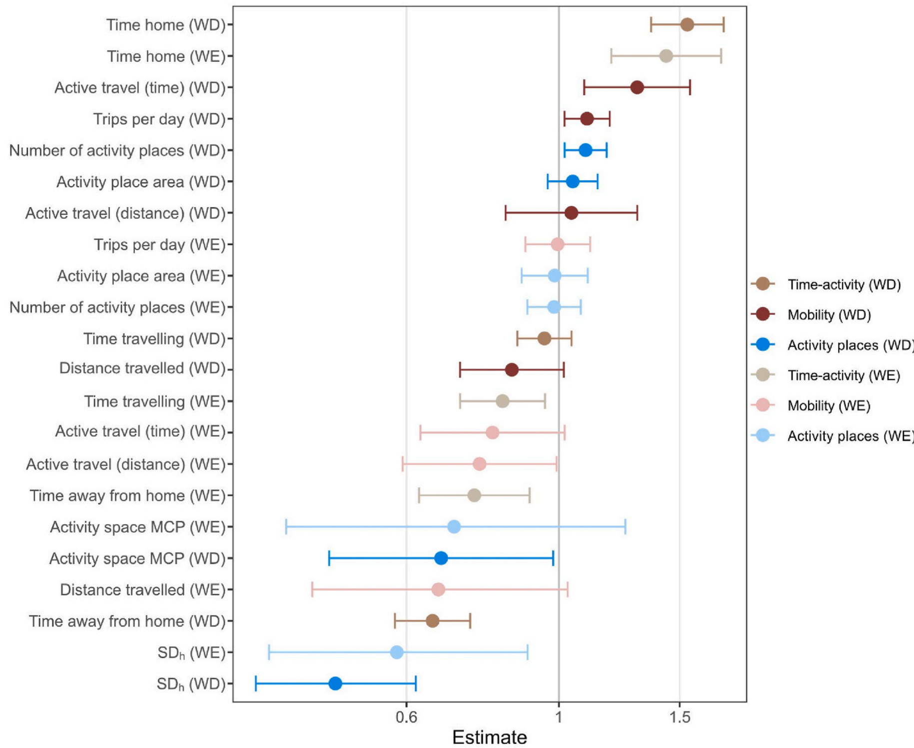

Fig. 4. Exponentiated regression coefficients of T3 with activity space variables as outcomes. Error bars represent 95% confidence intervals. MCP = minimum convex polygon. SD_h = standard distance from home.

3.3. Relationships between activity space variables

Correlations between activity space variables ranged from very high (r_s = 0.92 for active travel distance ratio and active travel time ratio during weekends) to non-existent (r_s = 0.00 for trips per day and active travel time ratio during weekdays). In the adjacency graph, weekday and weekend variables clearly separated into two mirroring halves (Fig. 6). Correlations tended to be greatest between two weekend variables (median (Q1-Q3) $|r_s|$ = 0.48 (0.36–0.65), slightly smaller between two weekday variables (median (Q1-Q3) $|r_s|$ = 0.37 (0.21–0.57), and smallest between a weekday and a weekend variable (median (Q1-Q3) $|r_s|$ = 0.16 (0.10–0.23).

Furthermore, the adjacency graph revealed a clear distinction between centre and periphery, with the centre constituted by the three time-activity variables, distance travelled, MCP, and SD_h, indicating a close connection between time-activity patterns and the spatial scale of activity spaces. The active travel variables inhabited one periphery of the graph, while the number of daily trips and the number and area of activity places inhabited the other, indicating that these two groups represent separate and less correlated aspects of activity spaces.

3.4. Sensitivity analyses

The numbers of activity places per participant were largely robust to modifications to the parameter values used for delineation (SI section 7). As for activity place area, two sensitivity analyses – changing the thresholds for small polygon areas and for the distance when a small polygon is adjacent to another polygon – yielded similar total areas, whereas the other two analyses – changing the clustering search radius and the margin of error buffer when drawing stay polygons – yielded activity space areas that were larger than those used in the main analysis (median values: 86 and 55 % larger, respectively; Table S3).

Summary statistics for weekday and weekend activity spaces based on days with >10 h GPS data were nearly identical to those in the main analysis (SI section 5, Table S5). Regression coefficients for trimester's associations with activity spaces variables and their significance levels were also nearly identical to those in the main analysis (Table S6).

4. Discussion

We developed and implemented ActMAP, a framework to characterise activity spaces by quantifying time-activity patterns, mobility, and activity places using GPS data. To our knowledge, this is so far the most comprehensive characterization of pregnant women's activity spaces and evaluation of how they are impacted by pregnancy stage (e.g. T1 vs. T3). A recent study (Yi et al., 2022) explored the daily time-activity and mobility patterns of 62 pregnant women in Los Angeles, United States. Here, we built on their study by constructing 238 womens' activity spaces bottom-up from spatiotemporally distinct trips and stays. This allowed calculating variables related to activity place visits with time-weighting as well as analyses of intraday patterns over the course of the day. The variable set includes variables that have previously not been reported for pregnant women (activity place area and active space MCP) or to our knowledge in any sample of any population (SD_h). This comprehensive set enabled an analysis of internal relationships among activity space variables. All of the aforementioned aspects add to the scarce available evidence related to pregnant women's activity spaces.

The findings revealed that the pregnant women in the BiSC cohort typically spent 5–10 h of their waking time at home, and 1–1.5 h per day travelling, with active travel constituting the majority of travel time. Although the sizes of activity spaces varied by several orders of magnitude, the women visited a limited number of places that commonly constituted <1% of the total activity space. Activity was generally more home-centred in the third trimester, reflected in time-activity patterns and the spatial scale of activity. Despite this, the number of activity places and trips per day were largely similar between the first and third trimesters, indicating that different aspects of mobility behaviour develop differently throughout pregnancy.

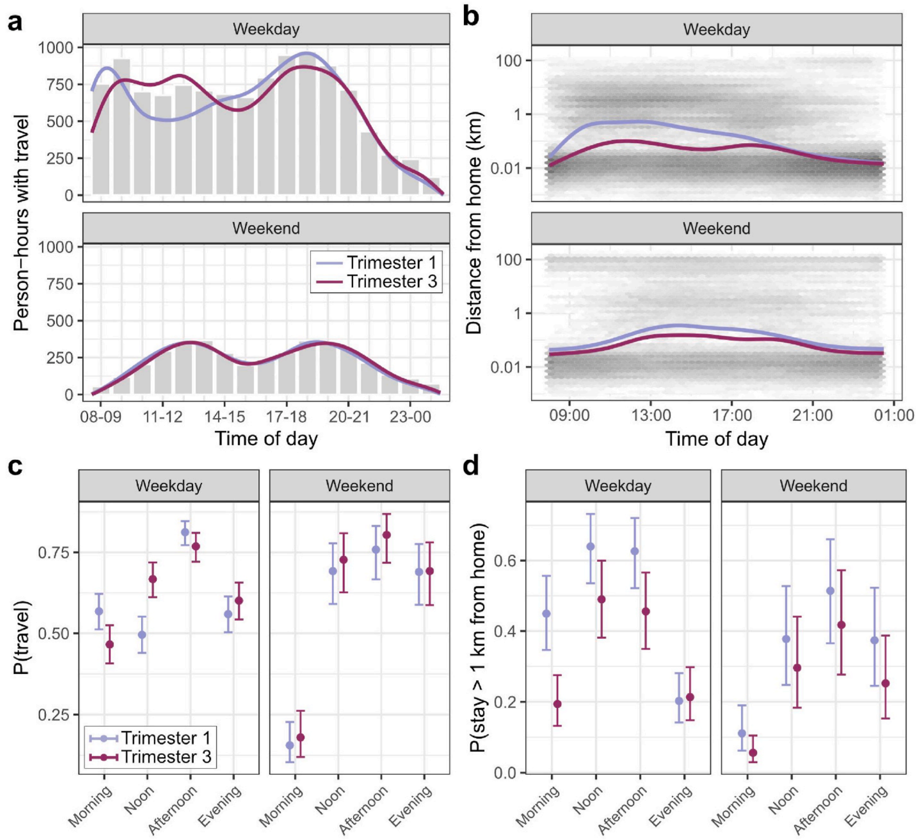

Fig. 5. a) Histograms of person-hours with travel over the course of the day, disaggregated by time of week. Density plots for each trimester are overlaid on top. **b)** Distance from home of stays (shown on a logarithmic scale) over the course of the day, disaggregated by time of week. Smoothed conditional means for each trimester are overlaid on top. **c)** Probabilities of travel depending on trimester and time of day, estimated from mixed-effect regression (n = 7236 for weekdays, n = 3560 for weekends). **d)** Probabilities of staying >1 km from home depending on trimester and time of day, estimated from mixed-effect regression (n = 7236 for weekdays, n = 3560 for weekends).

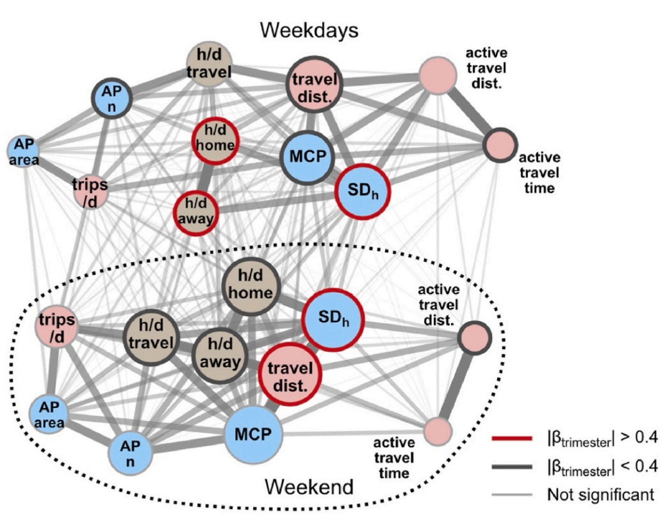

Fig. 6. Network illustration with activity space variables as nodes and their Spearman's rank correlations as edges (more correlated variables are closer together). The size and opacity of edges are proportional to the correlation between the nodes they connect and the size of nodes is proportional to their sum of absolute correlations. The node outline represents the association with trimester (black: significant association with an absolute coefficient >0.4, dark grey: significant association with an absolute coefficient <0.4, light grey: not significant association (p > 0.05)).

4.1. Activity spaces during pregnancy: changes and constants

Our results align with other studies from Canada (Nethery et al., 2009), China (Zhu et al., 2019) and the US (Yi et al., 2022) reporting that pregnant women often spend 15–18 h per 24 h at home. Yi et al. (2022) reported averages among Californian women of 3.3 trips and 1.0 h of daily travel in T1 and 3.8 trips and 1.1 h in T3. This resembles our results for weekends (3.5 trips, 1.2 h) but is lower than our findings for weekdays (5 trips, 1.3 h). In two studies of Californian women, mean daily vehicle travel was reported to be 59 min (Yi et al., 2022) and 69 min (Wu et al., 2013). However, the women in Barcelona mostly relied on active travel (especially during T3), in line with a previous study that found the inhabitants of Barcelona more inclined towards walking than those of other European cities (Gascon et al., 2019).

In terms of changes and constants between trimesters, we identified three main patterns. First, spatial activity generally occurred closer to home in the third trimester, reflected in time-activity patterns as well as SD_h and MCP. Previous studies reported that pregnant women tended to spend more time at home later in pregnancy (Nethery et al., 2009; Zhu et al., 2019). As our results additionally revealed that SD_h was smaller in late pregnancy, residential-based proxies for environmental exposure are likely to be more accurate then than in early pregnancy when participants more frequently travel far from home. However, even then participants' SD_h varied by several orders of magnitude, so location tracking is needed to obtain accurate environmental exposure assessment. Yi et al. (2022) speculated that women's time spent at home during pregnancy might reflect their socioeconomic means to forgo work. However, when analysing intraday mobility patterns controlling for work status, we still observed differences between trimesters in the likelihood of travelling during mornings through to afternoons on weekdays but not evenings or weekends. This could reflect a higher prevalence of work remotely from home in late pregnancy.

Second, participants generally spent less time travelling shorter distances in T3 compared with T1. However, the active travel time ratio increased during weekdays but decreased during weekends, indicating less passive travel during weekdays and less active travel during weekends. Reduced active weekend travel in T3 could reflect decreased recreational walking (Kang et al., 2017) and physical exercise (O'Donovan et al., 2017).

Third, we observed no major differences between trimesters in the number and area of activity places as well as the number of daily trips. This result resonates with a previous finding that the number of activity places in an activity space (so-called location capacity) could be largely constant over time (Alessandretti et al., 2018). The typical number of activity places in our sample was also in line with those reported by Alessandretti et al. (2018) for the general adult population across different countries. Our study thus suggests that location capacity could remain constant throughout pregnancy despite other aspects of activity spaces shifting considerably. However, it remains unclear whether the types of places visited also stays constant.

4.2. Weekly patterns of spatial scale of activity and active travel

The median workweek and weekend MCPs were 5.4 and 2.4 km^2, respectively, indicating that the spatial scale of activity is relatively small in a compact high-density city like Barcelona. For comparison, Kraft et al. (2019) reported medians among 35 adults in Chicago of 14 km^2 for daily MCPs and 155 km^2 over 14 days. Smaller activity space MCPs have been linked to more active travel (Hasanzadeh et al., 2019). Here, we found active travel to correlate with MCP size as well as SD_h during weekdays but less so during weekends. This observation might indicate that compact cities can promote active travel particularly through shorter distances between weekday activity places compared to sprawling cities. However, a considerable proportion of weekend stays were tens of kilometres from home, indicating that it was common among the participants to undertake longer weekend trips within Catalonia. Yet, the analysis of relationships among activity space variables showed that weekday and weekend variables were consistently weakly correlated, and there were no general signs of compensatory behaviour, such as weekend travel following a workweek close to home. In sum, our study echoes a previous one in Japanese adults (Susilo and Kitamura, 2005) to suggest that weekend behaviour is more variable than weekday behaviour, perhaps because then people are freer to decide where and how to spend their time, making personality or other unobserved factors stronger determinants.

4.3. Implications for activity space and environmental health studies

Our comprehensive characterisation of activity spaces illustrated that their different aspects are meaningful for different purposes. For example, the median areas covered by activity places are <1% of the median areas of MCPs, meaning that commonly >99% of the MCP consists of unvisited spaces. Thus, and as argued elsewhere (Wang and Kwan, 2018; Wei et al., 2023a), using MCPs for exposure assessment could likely result in notable misclassifications. Of particular importance for environmental health studies is ActMAP's distinction between the mobility component and the activity place component of activity spaces. This distinction could address the uncertain geographic context problem (Kwan, 2012) by accurately defining distinct visited places and the time spent in them, while simultaneously accounting for travel behaviour that might be relevant for many health outcomes. When evaluating the effect of parameter values on identified activity places (SI section 7), the numbers of activity places were largely robust, indicating that the identified places are meaningful with respect to daily mobility behaviour. Thus, ActMAP enables researchers to accurately quantify (unweighted or time-weighted) exposure to an environmental factor (e.g., greenspace or air pollution) while being still and/or while travelling, or alternatively use a place-based approach (i.e., how the number and/or regularity of visits to a distinct activity place or the amount of time spent in it is associated with a health outcome). We showed that variability in activity spaces ought to be thought about in multiplicative rather than additive ways, in agreement with previous work on human mobility (Alessandretti et al., 2020). In concrete analytical terms, this calls for evaluating log-transformed outcome variables or models that otherwise estimate associations multiplicatively. Some aspects of activity spaces (e.g., travel distance, MCP and SD_h) have distributions spanning several orders of magnitude. Although less extreme, there are considerable individual differences also in daily travel time and activity place area. Thus, caution is warranted regarding the use of one activity space variable as a proxy for another, as doing so could yield estimates an order of magnitude off or more.

4.4. Limitations

The findings in this paper should be understood in light of a few important limitations. First, collecting GPS data is logistically challenging and often not feasible for a long period and/or large sample size. Here, we collected data for one week in T1 and one week in T3 for each participant. One representative week of GPS data is arguably sufficient for characterising activity spaces (Stanley et al., 2018), but this does not allow investigating within-person seasonal changes. Thus, researchers collecting GPS data for activity space characterisation and/or environmental exposure assessment should consider the trade-off between tracking period and sample size in relation to their research questions.

We did not categorise activity places according to the activities undertaken in them or their environmental resources. Such a categorisation could be useful for different purposes. For example, future studies employing ActMAP for estimating environment-health associations might do it to evaluate the presence of the SDMB (Chaix et al., 2013). Categorisation of activity places according to the likely activities undertaken in them could be done using their outputted geometries in combination with point-of-interest data (e.g. from OpenStreetMap). However, this was beyond the scope of the current study.

A limitation of ActMAP is that it relies on many modifiable parameters. We found that some parameters used for identifying activity places could notably influence activity place areas (SI section 7). This influence is expected, as these parameters directly govern the areas of stay polygons. It highlights how contextual methodological decisions (e.g., related to study setting, population, or environmental exposures of interest) might impede between-study comparability of some activity space variables (e.g., activity place area). Another limitation is that compared with many other activity space frameworks, ActMAP is computationally complex. For some applications, going through this complexity might not add much value over a simpler and quicker method. For example, research questions focused on activity places might not require travel mode classification. Thus, the steps in ActMAP could be viewed in a modular way where some might be more relevant than others depending on the study objectives.

5. Conclusion

We comprehensively characterized activity spaces and evaluated their changes during the course of pregnancy in a sample of 238 pregnant women residing in Barcelona, Spain. We found that pregnant women's activity spaces were highly variable and that some aspects of activity spaces changed during pregnancy while others stayed constant. Our participants typically spent 5–10 h of their waking time at home, and 1–1.5 h per day travelling with active travel constituting the majority of travel time. Although the sizes of activity spaces varied by several orders of magnitude, the women visited a limited number of places that commonly constituted <1% of the total activity space. The number of activity places and trips per day did not differ much between trimesters. However, activity was generally more home-centred in the third trimester, as reflected not only in more time spent at home but also in a shrinking size of the activity space.

The comprehensive mapping of activity spaces was enabled by the ActMAP framework. The main strength of ActMAP is that participants' mobility and activity places are constructed as separate components from distinct trips and stays. Future environmental health studies utilising GPS data should consider an activity space approach that addresses the uncertain geographic context problem as well as the separate roles of mobility and stationarity, and might use ActMAP as a resource for activity space variable selection and/or downstream exposure assessment.

CRediT authorship contribution statement

Karl Samuelsson: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Ioar Rivas:** Writing – review & editing, Investigation, Data curation. **Bruno Raimbault:** Formal analysis, Data curation. **Alan Domínguez:** Writing – review & editing, Data curation. **Toni Galmés:** Formal analysis. **Antònia Valentin:** Methodology, Formal analysis. **Maria Foraster:** Investigation. **Mireia Gascon:** Writing – review & editing, Investigation. **Cecilia Persavento:** Investigation. **Achilleas Psyllidis:** Writing – review & editing. **Maria Dolores Gomez Roig:** Resources. **Elisa Llurba Olivé:** Resources. **Mark J. Nieuwenhuijsen:** Writing – review & editing. **Marco Helbich:** Writing – review & editing. **Jordi Sunyer:** Supervision, Funding acquisition. **Payam Dadvand:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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.

Acknowledgement

Research described in this report was conducted under contract to the Health Effects Institute (HEI), an organization jointly funded by the United States Environmental Protection Agency (EPA) (Assistance Award No. R-82811201) and certain motor vehicle and engine manufacturers. The contents of this article do not necessarily reflect the views of HEI, or its sponsors, nor do they necessarily reflect the views and policies of the EPA or motor vehicle and engine manufacturers. BiSC cohort also received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (785994 – AirNB project) and from the European Commission under the European Union's Horizon 2020 research and innovation programme (874583 - ATHLETE project). A full list of the funding sources that supported specific parts of the project can be found at https://projectebisc.org/en/funding-sources/. Karl Samuelsson's work was funded by Forte Swedish Research Council for Health, Working Life and Welfare (grant number 2022-00841). The publication is part of the fellowship RYC2021-032781-I awarded to Ioar Rivas, funded by the MCIN/AEI/10.13039/501100011033 and by the European Union NextGenerationEU/PRTR. Mireia Gascon holds a Miguel Servet fellowship (Grant CP19/00183) funded by Acción Estratégia de Salud - Instituto de Salud Carlos III, co-funded by European Social Fund "Investing in your future". Achilleas Psyllidis and Payam Dadvand acknowledge support by the European Union's Horizon 2020 research and innovation programme under grant agreement No 874724. Maria Dolores Gomez Roig and Elisa Llurba Olivé acknowledge funding through the project Primary Care Interventions to Prevent Maternal and Child Chronic Diseases of Perinatal and Developmental Origin (RICORS; RD21/0012/0003, Instituto de Salud Carlos III, Madrid, Spain). ISGlobal acknowledges support from the grant CEX2023-0001290-S funded by MCIN/AEI/ 10.13039/501100011033, and support from the Generalitat de Catalunya through the CERCA Program.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2025.103413.

Data availability

The data that has been used is confidential.

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