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Time-activity and daily mobility patterns during pregnancy and early postpartum – evidence from the MADRES cohort

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Abstract

Introduction: Pregnant women's daily time-activity and mobility patterns determine their environmental exposures and subsequently related health effects. Most studies ignore these and assess pregnancy exposures using static residential measures.

Methods: We conducted 4-day continuous geo-location monitoring in 62 pregnant Hispanic women, during pregnancy and early post-partum then derived trips by mode and stays, classified by context (indoor/outdoor, type). Generalized mixed-effect models were used to examine whether these patterns changed over time.

Results: Women spent on average 17.3 h/day at home. Commercial and service locations were the most popular non-home destinations, while parks and open spaces were seldom visited. Women made 3.5 daily (63.7 min/day and approximately 25% were pedestrian-based). Women were less likely to visit commercial and services locations and make vehicle-based trips postpartum compared to the 3rd trimester.

Conclusion: Our findings suggest time-activity patterns vary across pregnancy and postpartum, thus assessing exposures at stationary locations might introduce measurement error.

Keywords

Pregnancy; Daily mobility; Exposure assessment; Global Positioning Systems; Time-activity

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1. Introduction

Chemical and physical environment exposures including air pollution, lack of access to parks and green space, and low walkability, have been associated with poorer health behaviors and increased risk of health problems in pregnant women and their offspring.[1–3] However, prior studies examining the influence of environmental exposures on health behaviors (e.g., physical activity, diet) and disease outcomes (e.g., asthma, obesity, diabetes) in pregnant women have mainly applied the residence-based assessment approach (i.e., measuring physical environment features and characteristics at or near residences) to estimate individual, personal exposures.[2,4,5] This approach assumes outdoor environmental exposures around home residences are surrogates of daily "true causally relevant contexts" (true contextual units or TCUs) that influence behaviors or outcomes of interest.[6] Nonetheless, this assumption has two limitations – it assumes participants stay within their residential neighborhoods at all times when they might be highly mobile on a daily basis or they may change their residential addresses during and after pregnancy, and that all exposures occur in outdoor environments whereas quite often they occur mainly indoors or in transit, resulting in exposure misclassification or measurement error.[7,8]

Indeed, past studies on time-activity and mobility patterns (hereafter referred to as time-activity patterns) of women during pregnancy have validated these concerns.[9–12] For example, a study in Shanghai, China, reported that pregnant women on average spent over a third of their time in work locations within three-day observation periods during the 2nd trimester.[9] Another study conducted in France reported a median of almost 12 non-home h/day for pregnant women during a 3-week observation period in the 1st trimester.[10] As a result, the failure to capture or model the non-home contribution to environmental exposures in past studies might lead to under- or over-estimation of exposures and therefore mask their true relationships with health behaviors or outcomes.[13] Nevertheless, very few studies of pregnant women have incorporated time-activity patterns into environmental exposure assessments largely due to either feasibility or burden-related challenges with tracking or capturing these patterns at high spatiotemporal resolutions in large population-based studies.

Moreover, unlike other populations, pregnant women have increased demands to prepare for childbirth, increased fatigue, difficulty physically moving around, and poor sleep, which might influence or lead to dramatic variations in their time-activity patterns across the pregnancy and postpartum periods.[14] For example, a Canadian study on time-activity patterns of pregnant women has reported that more time was spent at home during the 3rd trimester of pregnancy compared to the 1st trimester.[15] Another US study has found that in-vehicle travel times were longer during the early stages compared to later stages of the pregnancy.[16] While very few studies have examined changes in time-activity patterns of women across pregnancy, to the best of our knowledge, none have extended the investigation to the early postpartum period. Given that the timing of the environmental exposures during these critical windows of time could have different effects on fetal development, early childhood and postpartum maternal health,[2,4,5] it is important to better understand time-activity patterns and how they might change over pregnancy and early postpartum periods.

Although limited, a small number of studies have implemented various approaches to collect mobility data for pregnant women and integrate time-activity patterns into exposure assessments. Among them, most have relied on self-reported mobility surveys or diaries.[9,11,12,15,17,18] This approach is relatively cost-efficient with low technical barriers and thus may suit population-based studies with large sample sizes; however, the subjective nature of self-reported survey data also makes the approach prone to recall bias and measurement error. Additionally, it is difficult to collect highly space- and time-resolved data using diaries or surveys. Recently, a growing body of research has started to apply Global Positioning Systems (GPS) technology to objectively capture the mobility of participants.[10,19,20] The geolocation coordinates collected from the GPS device can be imported into the Geographic Information System (GIS) software, in which spatial clusters and trip detection algorithms can be applied to derive time-activity (i.e., time spent in specific contexts, and indoor/outdoor microenvironments) and mobility (i.e., modes and durations of trips) patterns of study participants.[21,22] Also, GPS data and these derived time-activity patterns can be integrated with fine-scale (e.g., 10-s) personal air pollution monitoring or other wearables data to construct highly individualized, contextualized, and space-time resolved exposure models.[10] Finally, activity spaces derived from GPS data can be integrated with other geospatial data layers (e.g., crime, parks and open spaces, walkability scores) to understand actual exposure to the physical, chemical, or built environment.[13]

To address the above gaps, this study combines GPS technology and geospatial analysis to describe time-activity patterns in a subset of 62 low-income, Hispanic women participating in the MADRES cohort study, during 4-day observation periods in the 1st and 3rd trimesters of pregnancy and at 4 to 6 months postpartum. By analyzing highly time-resolved (i.e., 10-sec epoch) GPS data from our customized smartphone app (madresGPS), we aimed to answer the following questions:

1. What are typical time-activity (i.e., time spent in multiple contexts, and indoor/outdoor microenvironments) and mobility patterns (i.e., trips performed, their duration, and mode) of women during pregnancy and during the early postpartum period?
2. Do daily time-activity and mobility patterns change over time, across pregnancy and early postpartum periods?
3. Do temporal (e.g., weekdays vs. weekend days), individual sociodemographic, and residential neighborhood factors explain some of the variation in these patterns?

We hypothesized that women's time spent at their home residences would increase, and time spent in non-home contexts and in transit would decrease as pregnancy progresses from the 1st to the 3rd trimesters, and such trends may continue into the postpartum period. Moreover, we hypothesized time-activity and mobility patterns may differ by other temporal, individual sociodemographic, and residential neighborhood factors.

2. Methods

2.1. Study design

Data for this study comes from the Real-Time and Personal Sampling sub-study of the Maternal and Developmental Risks from Environmental and Social Stressors (MADRES) cohort.[23] This study uses an intensive longitudinal, observational panel study design and examines the daily effects of environmental exposures and social stressors on maternal pre- and post-partum obesity-related biobehavioral responses.[24] A total of 65 Hispanic, women with lower incomes, were drawn from the larger MADRES prospective cohort study which recruited participants from prenatal care providers in Los Angeles serving predominantly medically-underserved populations.[23] To be eligible for the larger MADRES study, a participant needed to be 18 years old with a singleton pregnancy, and be at less than 30 weeks' gestation at time of recruitment. In addition, participants who were HIV positive, had physical, mental, or cognitive disabilities that prevented participation, or were currently incarcerated were excluded from the study. Recruitment of Hispanic 65 women occurred on a rolling basis between 2016 and 2018 from one county hospital prenatal clinic (N=16) and one non-profit community health clinic (N=49). Additional eligibility criteria for this sub-study are described in further detail in O'Connor et al.[24] The USC Institutional Review Board approved all study procedures and participants signed an informed consent before enrolling into the study.

2.2. Data collection

2.2.1. Global Positioning Systems (GPS) Based Location Information—GPS data were continuously collected from participants at 10-s intervals for four days (two weekdays and two weekend days) during the 1st and 3rd trimester of pregnancy and at 4-6 months postpartum.[24] MADRES researchers designed a custom smartphone application (madresGPS app) for Android operating systems to collect highly resolved and encrypted GPS data.[24] Study coordinators configured the application on dedicated study smartphones (Samsung MotoG phone) to gather geographic coordinates and geolocation/motion metadata.[24] The application logged instantaneous GPS location and sensor data every 10 s from the smartphone's multiple built-in location finding features (cell tower triangulation, WiFi networks, and GPS) and motion sensors. Along with the timestamp, metadata such as the number of satellites in use/view, geolocation accuracy, source of GPS, velocity (if GPS source), and network connection status (if network source) were recorded.[24]

2.2.2. Ecological Momentary Assessment (EMA)—EMA data were self-reported through a commercially available application (MovisensXS app) built for Android operation systems, which was pre-installed on the same study phone used to collect GPS data. The EMA survey was prompted at random times during each five pre-specified sampling windows (i.e., wake-up to 10 a.m.; 11 a.m. to 1 p.m.; 2 p.m. to 4 p.m.; 5 p.m. to 7 p.m., and 8 p.m. to bedtime) within the same four-day time GPS data collection windows during the three study periods.[24] Survey questions included physical and social contexts at the prompt time, current affective and physical feeling states, current perceived stress, and past two-hour exposure to a list of daily stressors. The complete list of EMA survey questions are described in further detail in O'Connor et al.[24]

2.2.3. Retrospective surveys and medical record abstraction—

Sociodemographic data including maternal height and weight race/ethnicity, enrollment age, education, parity, and country of origin were assessed in prenatal interviewer-administered questionaries with the women. Weight and height were also measured at study visits. Retrospective surveys were completed at various study timepoints to gather residential and occupational histories and assessed psychosocial stressors. Working status was also collected via questionnaire in the 1st trimester, 3rd trimester, and 6 months postpartum and perceived neighborhood cohesion and safety score was gathered in the 2nd trimester (chosen to represent pregnancy) and 6 months postpartum questionnaires. Additionally, residential locations at screening were geocoded and used to generate residential neighborhood characteristics in this work.

2.3. Data processing

2.3.1. GPS processing—The major processing steps of raw GPS data are described in Fig. 1. In total, we collected 6,948,118 GPS observations for 62 of the 65 participants. Raw observations collected outside of the 4-day designated monitoring period (during device set up and return) were dropped ($N_{dropped}$=1,893,013). Then, we dropped a small number of observations with erroneously logged zero values of latitude and longitude ($N_{dropped}$=28,848). After that, we devised a logic to drop the least accurate source of geolocation data for every 10-s epoch when two sources of data (GPS/Network) were available as follows. This logic was informed by comparing the time-series of GPS vs. network source coordinates in relation to the participants' potential movement in space and time. Based on preliminary analyses, the GPS source usually exhibited the fastest update frequency compared to the network especially when individuals were mobile. Whereas, when individuals appeared to be stationary (i.e., at home), both sources seemed to be frequently updating, but the network source generally exhibited higher accuracy. Of particular note, participants were asked to connect study smartphones to their home WiFi networks when possible to complete study-related EMA surveys on the same smartphones, resulting in a high likelihood of phones connecting to home WiFi networks (and thus network source geolocation data being available often when stationary/at home) during this study (averaging 12.8% per observation day). When both GPS and network sources were available were examined and the less accurate source was dropped ($N_{dropped}$=542,213).

In circumstances when the signal from either GPS or network source was lost for ≥1 min (i.e., signal loss scenario), the app was designed to log the latest known position for that source along with the latest update (or confirmation) time, both of which will be repeated and will not change for the duration of time the signal was lost. Once signal loss scenarios were identified (per source of data), the update frequency and positional accuracy of the geolocation data from both sources were compared and the less accurate source was dropped ($N_{dropped}$=81,987). For time windows when either the GPS or network source was updating (real sensor data logging timestamp changed) but the other was not because of signal loss, the connected source was kept. Then, under circumstances when both sources lost signal, the one that indicated no movement (no change in latitude and longitude) from the previous to the next interval of time when signal was available was dropped.

Next, we rounded timestamps to the nearest 10 s and retained the first-observation within a 10-s window ($N_{dropped}$=53,530). This step was performed to allow us to align and integrate GPS data with other simultaneously collected accelerometry and personal air pollution exposure monitoring data (in subsequent, ongoing analyses). In addition, it also ensures roughly similar temporal spacing and density of GPS data per participant to enable between-person comparisons of environmental exposures derived using this GPS data and the kernel density algorithm.[25]

Finally, a moving median filter was applied to remove outliers in windows of approximately 1-min duration (7 observations at a 10-s epoch) to correct extreme outliers that might occasionally be present in the data.[26] Outliers were defined as observations with a distance >450 m from the median latitude/longitude coordinates (corresponding to the maximum realistically possible distance moved in 10 s based on a speed of 45 m/s or 100 mph) and were replaced with the median coordinates within the moving window. The final processed dataset consisted of 4,375,774 observations across 552 person-days.

Throughout the GPS data processing, we created flags to indicate data quality or identify records affected by any assumptions or decisions made, which were used to inform sensitivity analyses. For example, we created day-level GPS data completeness flags (i.e., ≤6 h, ≤10 h, ≤16 h), which were then used to evaluate whether time-activity and daily mobility patterns were sensitive to day-level GPS data completeness. We also created flags indicating confidence in whether an individual likely stayed at the logged location or moved during signal loss windows (see Table S1). These flags were based on the plausibility of the distance moved within the window and total duration of the window. More specifically, higher confidence levels were assigned to signal loss windows with shorter duration (e.g., ≤120 min) and more reasonable distances traveled (e.g., ≤45 m/s times the time elapsed between the last known location before signal loss and the new location after signal loss). For our analyses, we removed signal loss windows ($N_{dropped}$=523,112) that we either could not make a judgement on (i.e., with no distance/duration data) or had extremely low confidence (e.g., distance traveled >45 m/s times the time elapsed, >120 mins in duration) on whether a participant likely remained in the same position when the signal was lost.

2.3.2. Stay-trip detection—

We imported the processed 10-s GPS data into geographic information system software ArcGIS 10.8 (Esri, 2020) to first identify trips and stays and then classify stays based on their spatial contexts and indoor/outdoor microenvironment. Fig. 2 describes the steps to process GPS tracks for each person and study period combination (i.e., 4-day GPS tracks were treated as one sequential time-series). In order to identify trips and stays, we used the “Activity Place Detection Algorithm” ArcGIS toolbox developed by Thierry et al.,[21] which builds a kernel density surface (50 m bandwidth or search radius) from GPS points and extracts local maxima from the surface as candidates for classification as stays. In comparison to methods that analyze data points sequentially, the kernel-based method has been shown to have better global performance (i.e., better agreement between number of stops detected vs. true stops), higher spatial accuracy (i.e., shorter Euclidean distance between a detected stop and the true stop), and lower sensitivity to bandwidth choices (e.g., 50 m, 100 m). [21] Minimum duration for a stay candidate to become a stay was ≥5 min, and two consecutive stay candidates within proximity to each other needed to be separated by at least ≥5 min timespan to be kept as separate stays. After stays and their respective start and stop times were detected, GPS points recorded between two consecutive stays were connected into trips (path trajectories) by sequences of timestamp and smoothed (snapped to road networks), and their start and stop times were recorded. This essentially means that stays also act as trip origin and destination points when trips occur. A minimum duration of ≥5 min was needed for a loop path trajectory (started and ended at the same location) to be kept as a trip.

2.3.3. Context classification of stays—We then classified the stays (i.e., trip origins and destinations) into one of seven spatial contexts (i.e., home residential, non-home residential, commercial and services, parks and open spaces, schools and public facilities, industrial and office spaces, and other). The stay with the longest duration in a study period (4-day monitoring period in 1st and 3rd trimesters, and at 4-6 months postpartum) was designated as at the residential home context given participants might have changed residence or lived with family or relatives across study periods. Non-home contexts were classified based on their spatial relationships with Southern California Association of Governments existing land use (2016) data (see Table S2). A 15 m buffer was applied to existing land use boundaries to account for potential combinations of indoor/outdoor activities within a stay and considering the average width of sidewalks in urban Los Angeles. Additionally, we also assigned an indoor/outdoor microenvironment to each stay point by examining its spatial relationship with Los Angeles County building footprints (2014). Aim buffer was applied to existing building footprints to account for scenarios when indoor activities occurred mainly in the corners of the building (i.e., corner apartments, stairwells, laundry rooms), resulting in a detected stay point that fell outside the building footprint polygon, which could then be misclassified as outdoor. Spatial parameters and data sources used in context classification are fully documented in Table S2.

2.3.4. Missing GPS data imputation using home context—Home residential locations detected via the stay-trip detection algorithm were then used to impute some of the missing records in the processed GPS data. More specifically, participants self-reported their sleep and waking times prior to each study period to help configure suitable timing and frequencies for the EMA survey. We used this sleep and wake time data to divide each four-day study period into day (from waking to sleep time in a data collection day) and night (from sleep time in a data collection day to the waking time on the next day) windows. For night windows, we used the identified visit-level home location to impute missing data if we had ≥ 60 mins of GPS logged data that was within ≤100 m of the home location. If this rule was not met, we used the median coordinates logged during the night to fill in any remaining missingness that night. If no GPS data was available during the night, then imputation was not attempted. As for day windows, we filled in missing records with home coordinates when available if the day was identified as a home day (i.e., all EMA survey prompts within the day reported current physical context as either “Home-Indoor” or “Home-Outdoor”). The entire workflow of the missingness imputation process is documented in Fig. S1. The imputed GPS records (*N*=306,915) were classified as “home-residential” and merged with processed epoch-level GPS data to produce a final time-activity pattern dataset that records location coordinates and contexts of each stay, its start and stop time, as well as method of classification (i.e., via algorithm or imputation). In addition, flags were created which labelled days with < 6 h of GPS data (post-imputation) as invalid days.

2.3.5. Trip mode detection—

We also applied a trip mode classification algorithm (Fig. 3) to classify all trips into either a walking- or vehicle-based mode. Both distance-based trip speed (i.e., sum of Euclidean distances of consecutive GPS records in a trip divided by duration of time elapsed) and total distance traveled (i.e., sum of Euclidean distances of consecutive GPS records in a trip) were considered in the decision-making process. Previous studies have reported a walking speed range of 1.0–1.8 m/s for women during pre- and post-pregnancy periods.[27–29] In this study, a relatively high threshold of 2 m/s (4.5 mph) was treated as the theoretically possible maximum walking speed for women to account for GPS data noise in areas that might obstruct or interfere with GPS signals (e.g., neighborhoods with multi-level residences or abundant and dense tree canopies). Given similarities in average speed between a true walking scenario and a slow driving one that could occur during Los Angeles rush hours or when passing through areas with frequent traffic lights, a condition was added such that a trip required a standard deviation of speed that was smaller than 1 m/s to be classified as walking-based. This criterion was based on observed patterns in the data showing that walking trips typically have a much smaller standard deviation in speed than slow driving trips comprising sudden acceleration, deceleration, and frequent stops. Furthermore, for a trip to be vehicle-based, it also needed to exceed the maximum possible distance a human can travel via walking (i.e., 3 m/s*trip duration). Lastly, for a limited number of trips (N=99) that exhibited patterns with multiple modes (e.g., walking to the parking lot, driving, riding the metro and walking), we relaxed the criteria and only used the mean speed to determine the primary trip mode (i.e., vehicle-based: ≥2 m/s; walking-based: <2 m/s). For these trips, we assigned lower confidence to their detected trip modes so that they could be excluded for sensitivity analyses purposes.

2.4. Statistical Analysis

2.4.1. Descriptive analysis—

Mean, medians, proportions, or standard deviations for covariates and time-activity and daily mobility outcomes were calculated by 1st and 3rd trimesters of pregnancy and 4-6 months postpartum. The number of stays were summarized by context and microenvironment and aggregated into day-level time-activity patterns (min/d at each spatial context and within indoor/outdoor microenvironments). Meanwhile, the number of trips were summarized by trip modes and aggregated into day-level mobility patterns (min/d and N/d in trip of vehicular or pedestrian mode). Non-valid days (<6 h of GPS data) were eliminated to reduce potential biases of estimating day-level outcomes.

2.4.2. Generalized mixed effects models—

To account for the interdependency of the nested data structure in the current study (Level 1-days nested within Level 2-persons), generalized linear mixed-effects models (GLMMs) with participant-level random intercepts were used. Additionally, negative binomial family functions were fitted because outcomes had over-dispersed distributions, which log-transformed the outcome during analyses. Lastly, a zero-inflated portion was added to all models due to the presence of excessive zero values except for the model that examined min/d at home residential context. These zero-inflated models estimated a participant's probability of having zero min/d at a given context (not visiting the context) or at a given trip mode (not performing the trip).

2.4.3. Model building strategy—For each outcome, we first fit GLMM models to test whether the derived time-activity and mobility patterns changed over time during pregnancy and postpartum (hereinafter referred to as the Base GLMM model). Then, we further included individual sociodemographic, neighborhood, and additional temporal factors to explore whether these factors can further explain these time-activity and mobility patterns. This was done by first entering all other covariates to construct the fully-adjusted model if the univariate analysis (one covariate at a time) reported a $p<.1$ (hereinafter referred to as the Fully-adjusted GLMM model). Lastly, covariates with reduced explanatory power (i.e., p-value became $>.05$ in the fully adjusted model) were dropped in the final model to ensure model parsimony (hereinafter referred to as the Final GLMM model). Following the recommended practice, covariates were kept the same for the count and zero parts of each zero-inflated GLMM.[30] Additionally, the day-level total GPS data collection hours were always included as a covariate to adjust for the varying amount of GPS data collected possibly due to individual device wearing behaviors or other factors.

2.4.4. Model covariates selection—A list of temporal factors, individual-level sociodemographic, and neighborhood-level characteristics were included as covariates in the models. Past studies have associated these covariates with time-activity patterns of pregnant women.[9,11,12,16,19,30–33] Temporal factors included weekend versus weekday (weekend=1), daily average temperature in degrees Celsius, and study period (1st trimester, 3rd trimester [reference group], and 4-6 months postpartum). We chose the 3rd trimester as the reference group since most prior pregnancy studies examining the relationship between environmental exposures and maternal or birth outcomes usually characterize environmental exposure based on location at a single point in time late in pregnancy or at delivery.[2,34,35] Since the 3rd trimester is closest to infant delivery, we wanted to contrast changes in time-activity and mobility patterns over time relative to this commonly used assumption. Individual sociodemographic characteristics from MADRES questionnaires were included, including age, education (less than or equal to high school diploma), marital status (married/living together, single/divorced/separated/widowed, or declined to answer/missing response), birth country (foreign- vs. US-born), parity (first born vs. second or greater birth) as well as employment status at each time period. We also calculated Body Mass Index (BMI) categories (recoded as normal vs. overweight/obese) determined based on height and weight measured during pre-natal visits. Additionally, we included individual-level neighborhood cohesion and safety scores from questionnaires administered during pregnancy and postpartum.[36] We assigned neighborhood characteristics to participants' residences based on the 2010 census block group boundary within which their home residences were situated. These included the National Walkability Index Score from the Environmental Protection Agency (EPA) EnviroAtlas and the Deprivation Index Score from the Neighborhood Atlas.[37,38] A full list of covariates measures and corresponding data sources is documented in Table S3.

2.4.5. Sensitivity analysis—Finally, sensitivity analyses were run by excluding days with <10 h or <16 h of GPS data to examine the influence of GPS completeness on observed associations, and by replacing study periods with binary (pregnancy vs. postpartum) and continuous time (continuous week from conception to post-birth) variables, and by testing non-linear (quadratic) terms. The R 4.0.2 (R Core Team, 2020) and *glmmTMB* package (version 1.0.2.1) were used for generalized mixed-effects modeling.[30] Exponentiated effect estimates which are interpreted on a multiplicative scale were reported for all models. Reversed odds ratios (i.e., odds to accumulate any minutes at a given time activity or mobility pattern outcome) of zero-inflated models were calculated for easier interpretation.

3. Results

3.1. Data completeness

A total of 65 participants were initially enrolled in the study, of which, 62 provided at least one valid GPS observation day (≥6 h of data) across three study periods. Within these 62 participants, 35 had at least one valid day in all three study periods; 17 in two of three periods; and 10 in one of three periods. The final analytical sample comprised a total of 552 valid days of GPS data from 62 participants across the 1st (*N*=205 person-days) and 3rd trimesters (*N*=180 person-days) of pregnancy and 4–6 months postpartum (*N*=167 person-days). Each participant provided an average of 8.9 (*SD*=3.0; *Range*: 3.0-12.0) valid GPS days across the three periods. The average number of hours of GPS observations collected on valid days was 21.7 h (*SD*= 5.0; *Range*: 6.2-24.0). The average number of hours was highest in the 3rd trimester (*Mean*=22.3h; *SD*=4.4; *Range:* 6.5-24.0) followed by the 4-6 months postpartum period (*Mean*=21.8h; *SD*=4.7; *Range:* 7.0-24.0) and the 1st trimester (*Mean*=21.1; *SD*=5.6; *Range:* 6.2-24.0). Almost half of the valid person-days (49.3%) were weekend days across the three periods.

3.2. Descriptive statistics of covariates

Descriptive statistics for the participant- and day-level covariates are shown in Tables 1a and 1b. Participants' mean age at study entry was 29 years (*SD*=6.1; *Range:* 18-45). All of the participants were Hispanic and more than half were born outside of the U.S. (53.2%). About one-third (32.3%) had some college or above education, and 80.6% were either married or living together with their partners at study entry. 36.4% were employed during the 1st trimester compared to 39.6% during the 3rd trimester, and 19.6% at 4-6 months postpartum. At recruitment, 25.8% were pregnant with their first child, 74.2% were overweight or obese according to their pre-pregnancy BMI. The recruited participants lived in neighborhoods with an average walkability index score (on 1-20 scale; where 1=least walkable) of 14.4 (*SD*=2.0, *Range:* 9.3-19) and average deprivation index score (on 1-10 scale; where 1=least deprived) of 6.5 (*SD*=1.7, *Range:* 2.0-9.0). The average neighborhood safety and cohesion score (on 1-5 scale; where 1=least safe and cohesive) self-reported by women was 3.1 (*SD*=0.7, *Range:* 1.0-4.4) at the 1st and 3rd (*SD*=0.7; *Range:* 1.0-5.0) trimesters, and 3.3 (*SD*=0.9, *Range:* 1.4-4.8) at 4-6 months postpartum.

3.3. Descriptive statistics for time-activity and daily mobility patterns

3.3.1. Time-activity patterns—The descriptive statistics for derived time-activity patterns (N stays and min/day by context and indoor/outdoor microenvironment) are shown in Tables 2 and 3. Overall, 2,621 stays were detected from 552 valid GPS person-days across three study periods (Table 2). The 1st trimester (*N*=947 stays) had larger numbers of different stays detected compared to the 3rd trimester (*N*=914 stays) and 4-6 months postpartum (*N*=760 stays). Among all stays, 42.4% (*N*=1,112) were at home, with an average duration of 17.3 h/day (*SD*=6.6 h/day). Commercial and services locations were the most popular destinations (28.9% of all stays; *N*=757 stays; *Mean*=1.1 h/day; *SD*=1.8 h/day) among all non-home contexts, followed by non-home residential locations, industrial and office spaces, and schools and public facilities, each of which constituted 5~10% of all stays (Table 2). Lastly, women in this panel study rarely visited parks and open spaces (1.9% of all stays; *N*=51 stays; *Mean*=8.73 min/day; *SD*=48.3 min/day).

In terms of descriptive trends across the three study periods, the number of visits to industrial and office spaces, and to commercial and services locations increased from the 1st trimester to the 3rd trimester but decreased at 4-6 months postpartum. However, women's visits to non-home residential places increased at 4-6 months postpartum compared to the 3rd trimester (10.4 vs. 6.6% of all stays). Additionally, women's visits to parks and open spaces showed a decreasing trend from the 1st to the 3rd trimester of pregnancy and onto the 4-6 months postpartum (2.3, 1.9, and 1.6%, respectively of all stays in these time periods).

Approximately one in three (35.1%) of stays detected across the three study periods occurred in outdoor microenvironments including locations outside of the home (e.g., porch, lawns, sidewalks) (4.2% of all stays; *Mean*=2.1 h/day; *SD*=3.4 h/d) and at non-home outdoor locations (e.g., parks, sports venues, sidewalks) (30.9% of all stays; *Mean*=1.9 h/day; *SD*=4.3 h/day). Overall, the 3rd trimester had the lowest fraction of stays (39.8%) at home (both indoor and outdoor) and the highest fraction of stays (27.7%) at non-home indoor microenvironments (Table 3).

3.3.2. Daily Mobility Patterns—The summary statistics for derived mobility patterns (N and min/d for trips, and N/d by trip mode) are also shown in Tables 2 and 3. Overall, participants took 1,925 trips over the duration of the study spread across 552 person-days, one in four of these trips (24.9%) was pedestrian-based (*N*=489; *Mean*=16.4 min; *SD*=30.8 min). The number of trips made varied slightly between the 1st and 3rd trimesters (*N*=682 vs. *N*=692) and decreased at 4-6 months postpartum (*N*=551). This pattern was replicated across all trip modes.

Fig. 4 shows the most popular trip origins and destinations by mode and purpose. For pedestrian-based trips (*N*=489), around 1 in 5 (21.7%, *N*=103) were between different commercial and services locations, followed by walking within the same commercial and services locations (14.5%; *N*=71). For vehicle-based trips (*N*=1445), about 2 in 5 (37.8%; *N*=546) were between home and commercial and services locations, followed by commuting between different commercial and services locations (18.5%; *N*=268) and between home and non-home residential locations (9.0%, *N*=130).

3.4. Base GLMM results

The base GLMM results examining whether day-level time-activity and mobility patterns varied across the three study periods are illustrated in Fig. 5. The odds of visiting commercial and services locations were 58% lower at 4-6 months postpartum compared to the 3rd trimester (*OR*=0.42, *95%CI*: 0.23–0.76) (Fig. 5). No other stay contexts (in terms of frequency or duration of time spent within them) were significantly different across the three time periods. These results did not change in sensitivity analyses restricting to days with ≥10 h or ≥16 h of GPS data, using binary (pregnancy vs. postpartum) and continuous (week number from conception to post-birth) time variables, and using non-linear (quadratic) time terms. Moreover, the odds of staying outdoors and time spent outdoors did not vary significantly across the three study periods (Fig. 5). Lastly, in terms of mobility patterns, the odds of performing a vehicular trip were 56% lower at 4-6 months postpartum compared to the 3rd trimester at the day level (*OR*=0.44, *95%CI*: 0.21–0.92) (Fig. 5). These results did not change in sensitivity analyses restricting trips to those with ≥ 5% of epoch-level GPS data within trip segments detected. The odds of performing any trips overall or in pedestrian-mode did not vary by study period in these base models using min/d spent in trips or N/d trips taken. The full model results of base GLMM can be found in Table S4.

3.5. Final GLMM results

3.5.1. Three study periods—The results of the final GLMM exploring whether individual sociodemographic, neighborhood, and other temporal factors such as weekdays vs weekend days additionally explained the women's time-activity and daily mobility patterns are summarized in Table 4. All significant results found in the base models examining variation over time remained in the fully adjusted models (see Tables 4a for odds of visiting commercial and services locations, and 4c for odds of performing any vehicle-based trip). Additionally, the final GLMM results showed that when women visited non-home residential locations in the 4-6 months postpartum period, their mean min/day spent there increased by 83% (*Incidence Rate Ratio or IRR*=1.83, *95%CI*: 1.03-3.25) compared to when they visited this same context in the 3rd trimester (Table 4b).

3.5.2. Weekdays vs. weekends—Other temporally varying factors including weekdays vs. weekend days and daily temperature were not significantly associated with duration of time (min/day) spent at the home residence (when participants were there). Results remained unchanged in sensitivity analyses excluding days with <10 h or <16 h of GPS observations, or self-reported sleeping hours. As for non-home contexts, when women visited non-home residential locations or parks and open spaces during weekend days, they spent 64% (*IRR*=1.64, *95%CI:* 1.05-2.56) and 202% (*IRR*=3.02, *95%CI:* 1.32-6.92) more min/day at each context, respectively, as compared to weekdays. Additionally, during weekend days, the odds (*OR*=0.48; *95%CI:* 0.35–0.82) of accumulating any minutes in trips decreased by 52%.

3.5.3. Individual sociodemographic and residential neighborhood characteristics—Other than weekdays vs weekend days, individual sociodemographic and residential neighborhood characteristics, including employment status, maternal education, and self-reported neighborhood cohesion and safety scores, were also significantly associated with time-activity (Table 4b) and mobility (Table 4c) patterns. Specifically, those employed spent on average 48% more min/d (*IRR*=1.48, *95%CI*: 1.10-1.99) when they visited non-home contexts and had 133% higher odds (*OR*=2.33, *95%CI*: 1.10-5.00) of visiting industrial and office spaces compared to non-employed counterparts. In addition, women who already had at least one child (*IRR*=0.65; *95%CI:* 0.45-0.93) spent 35% fewer min/day visiting commercial and services locations compared to women experiencing their first pregnancy.

In terms of mobility patterns, maternal education was significantly associated with longer duration of time spent in trips when they were taken. Specifically, women with post high school education had 223% greater odds (*OR*=3.33, *95%CI:* 1.41-7.69) of accumulating minutes on vehicle-based trips and 113% greater odds (*OR*=2.13, *95%CI:* 1.05-4.35) of accumulating minutes on all trips regardless of mode (Table 4c) compared to women with high school diploma and below. Moreover, women living in safer neighborhoods (based on reported safety and cohesion score) took 14% fewer vehicle-based trips per day (*IRR*=0.86; *95%CI:* 0.76-0.97) overall.

4. Discussion

The overarching goal of this analysis was to examine how dynamic time-activity and mobility patterns vary for both the pregnant woman and the fetus, and how these might differ across levels of personal, socioeconomic, or neighborhood level disadvantage. In this work, we developed a data processing and analysis pipeline for highly resolved GPS data in a panel study of Hispanic pregnant women who were continuously monitored for 4 days during each of the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum. We identified stays and trips and classified their spatial and indoor/outdoor microenvironmental contexts (for stays) and modes (for trips). We then tested whether time-activity and mobility patterns varied over time during pregnancy and the early postpartum period, and by individual sociodemographic, residential neighborhood, and other temporal factors. This work also highlights the inadequacy of assuming individuals are stationary when assessing environmental exposures during pregnancy and their effects on maternal and child health.

4.1. Time-activity and mobility patterns of pregnant women

To start, we found that participants on average spent nearly 70% (17.3 h/day) of their time at their home residences during pregnancy and the early postpartum period, a finding that is consistent with several studies examining the time-activity and mobility patterns of pregnant women.[10,16,19] For instance, Nethery et al. reported a cohort of Canadian pregnant women spent 16.2 h/day at/near home during pregnancy while Zhu et al. reported a cohort of Chinese pregnant women spent 15 h/day at/near home.[9,19] Moreover, although we could not directly compare our findings with other pregnancy studies among Hispanic women in the U.S., our finding that this group of Hispanic women rarely visited parks and open spaces indicates a potential public health concern since multiple studies have shown that exposure to greenness is associated with lower exposure to environmental hazards and decreased risk of adverse pregnancy outcomes.[1,12,39] Past studies have indicated that minority and low socioeconomic status (SES) populations have lower parks and open spaces availability (e.g., no park within walking distance) and quality (e.g., crime, lack of maintenance), which might help explain the low utilization of parks and open spaces in our cohort. Consistently, because urban Los Angeles has limited parks and green infrastructure in general and higher quality parks and open spaces occur in the more expensive areas of the city, the low-income participants in our study may have had less access to parks and open spaces.[40,41] We plan to examine greenness exposure and parks and open spaces access in participants' residential neighborhoods, as well as interactions with individual health characteristics to further understand the reasons behind this finding in the future.

The daily mobility patterns of participants in our study differed from results reported by Wu et al. in the other GPS-based Southern California study that also examined mobility patterns of pregnant women.[16] Specifically, our participants spent 1.7 times more min/day on average in vehicle-based trips compared to the prior study. However, Wu et al.'s study participants were from different counties with a more diverse racial and ethnic composition and wider SES range compared to our study that focused on predominantly low income, Hispanic participants from Central, East, and South Los Angeles. A study by MacLeod et al. found low-income, pregnant women in another urban cohort in Los Angeles reported significantly more time in vehicle-based trips in a cross-sectional survey, which might explain this discrepancy since low SES groups may have longer commuting times and make more frequent use of public transit than higher SES groups.[42]

4.2. Changes in time-activity and mobility patterns during pregnancy and postpartum

Longitudinally, we did not find women's time spent at home differed significantly across pregnancy and early postpartum. This finding differs from the results of other studies examining time-activity patterns of women across pregnancy.[9,19] Nethery et al. reported that increasing weeks of pregnancy until the 3rd trimester were associated with increased time spent at home in a sample of 62 pregnant women living in Vancouver, BC, Canada. The authors hypothesized this might be due to the decrease in physical activity in later trimesters of pregnancy.[19] However, our study focused on a group of Hispanic women that were primarily low SES. Consequently, they might not be able to afford or have time to engage in leisure activities due to increased home or work responsibilities.[43]

In terms of time spent in non-home contexts, we found women's odds of visiting commercial and services locations decreased at 4-6 months postpartum compared to the 3rd trimester of pregnancy. This change may be explained by increasing stays at home residence due to childcare responsibilities or the fact that women permanently or temporarily left their jobs at these times since the employment rate dropped from 39.6 to 19.6% between the 3rd trimester and the 4-6 months postpartum. We did not find any difference between women's time spent in commercial and services locations between the 1st and 3rd trimesters. However, a similar study in Shanghai, China reported women's time spent working decreased by two hours in the 3rd trimester compared to the 1st trimester.[39] We were able to disentangle whether the purpose of visiting commercial and service locations was for work or fulfilling daily life needs such as visiting hospitals, schools, and supermarkets, which might explain why our results differed from the Shanghai study above.

Regarding daily mobility patterns, our finding of no meaningful changes in time spent in vehicle- or pedestrian-based trips between the 1st and 3rd trimesters of pregnancy adds to the mixed results reported in the literature. Our results were consistent with the study by Nethery et al. that reported no longitudinal changes in time spent in transit across the 1st, 2nd, and 3rd trimesters of pregnancy,[19] but inconsistent with Zhu et al. who reported pregnant women's time spent in vehicles increased between the 1st and 3rd trimester.[9] However, the latter study was located in Shanghai, China, a city with an urban planning system that heavily incorporates pedestrian-oriented street networks and public transit systems in contrast to the Los Angeles metropolitan area, which may result in different travel behaviors. Until now, there are few studies that have examined daily mobility patterns of pregnant women and more are needed to understand how mobility patterns change across pregnancy and postpartum periods.

4.3. Additional predictors of time-activity and mobility patterns

Our findings that pregnant women's time-activity and daily mobility patterns vary with additional temporal, individual sociodemographic, and residential neighborhood factors suggest that there may be highly variable patterns even among a primarily low-income, Hispanic population. We found that those who were employed spent more time at industrial and office spaces during the week and more time at parks and open spaces during weekends. Participants with higher educational attainment were more likely to take vehicle-based trips, a fact that was consistent with study results of Wu et al. and might be explained different employment status.[44] We also found that women living in safer neighborhoods performed fewer vehicle-based trips daily, which might be explained by their preference to take more walking trips given safer streets, although we did not find a statistically significant relationship between neighborhood safety and numbers and durations of pedestrian-based trips.

4.4. Implications for future studies

Our results found pregnant and early postpartum women spent a substantial portion of their time at indoor locations, visited several locations and took several trips per day—approximately a quarter of which were pedestrian trips. These patterns also differed over the course of the pregnancy and the postpartum period. Our findings have important implications for future studies that aim to investigate the association between environmental exposures of pregnant women and maternal or child health outcomes. The residential-based approach used by most studies in the past may under- or over-estimate physical, built, and social environment exposures of interest (e.g., $PM_{2.5}$, greenspace, crime). Consequently, the true relationships between environmental exposures and targeted health behaviors (e.g., physical activity) and outcomes (e.g., respiratory diseases) may be masked, especially when investigating acute or short-term dose-response relationships (e.g., daily, weekly, monthly). In addition, our findings of variations in time-activity patterns across pregnancy and postpartum periods suggest the need for more longitudinal studies to complement cross-sectional studies.

Kwan argues that spatial and temporal mismatches and uncertainties make it difficult to clarify the influence of contextual variables on health behaviors or outcomes.[45] Given the need to prepare for child birth, infant care, and other responsibilities during pregnancy and early postpartum, women's day-to-day time-activity and daily mobility patterns may vary more than those of the general population.[14] As a result, future studies should move from "snapshot" to activity space based approaches to assess environmental exposures of pregnant women.[13] Mobile sensing technologies, such as GPS, can provide fine-grained mobility trajectories that can be used to assess environmental exposures that reflect time-activity patterns. As a result, these technologies can reduce the uncertainties in contextual exposures (i.e., the disparities between the true contextual and measured contextual units).[6,46,47] Lastly, our findings that pregnant and early postpartum women's time-activity and mobility patterns varied across weekend days vs. weekdays, employment status, education attainment, and neighborhood cohesion and safety suggests that these might be important exposure determinants to account for in future studies.

4.5. Study limitations and strengths

To the best of our knowledge, this is the first study that examines time-activity and daily mobility patterns of pregnant women across pregnancy and early postpartum periods. A major strength is the application of GPS to repeatedly collect highly resolved geospatial location data across the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum. As a result, we overcame recall biases inherent in self-reported time-activity or mobility surveys and provided insights into longitudinal changes in these patterns. Additionally, the study applies a kernel density-based algorithm to classify stay contexts and trip modes, achieving higher accuracy and better sensitivity than the point-by-point classification approach. Compared to computationally intensive methods, our GPS processing and stay/trip detection workflow may offer a lower technical difficulty threshold for future studies that aim at utilizing mobile-phone collected location-tracking data to generate time-activity patterns We collected highly time-resolved (10-s epoch) GPS data, based upon which we detected stays and trips and classified spatial context, indoor/outdoor microenvironments, and trip modes in GIS. These fine-grained data and advanced GIS analytical tools helped us to examine the time-activity and mobility patterns during pregnancy and early postpartum at various temporal spacings. The longitudinal design used for this study allowed us to examine both the variations in time-activity patterns between women and the day-to-day variations for each woman.

Our study also has a few limitations. First, the GPS data we collected had some missingness. To mitigate its impacts on analyses, we made efforts to impute GPS data using existing information and re-run the analysis with stricter thresholds of daily observation hours or excluding data collected during sleep hours. Our study results remained largely unchanged. Additionally, missing data did not demonstrate diurnal patterns (i.e., it was roughly invariant throughout the day). However, there are other factors that may still potentially affect our study outcomes. For instance, missingness patterns of GPS data may be correlated with spatial contexts (e.g., tall buildings, trees) that could obstruct receiver signals. Second, although we tackled the signal loss issue by flagging signal loss scenarios with confidence levels and excluded those with extremely low confidence, we still could not be sure that the locations recorded by the device during signal loss matched the true location. Third, we could not distinguish a trip to and from work locations from other trips, which might inform the interpretation of results of time-activity patterns for certain respondents and the types of contexts in play. Fourth, we had a relatively small sample size and only collected 4-day GPS data in two weekdays and two weekend days during each study period. Thus, the time-activity and mobility patterns detected from our samples may not capture some infrequently activities that tend to occur on a weekly basis or on other days of the week such as grocery shopping. Lastly, we focused on a health disparity group of low-income, Hispanic women, a population that has been understudied and disproportionally exposed to various environmental hazards. Thus, our results may not generalize to pregnant women in other regions or SES or racial/ethnic groups; nevertheless, they shed light on an important population, and they may pave the way for future studies to examine pregnant women's environmental exposures within their everyday activity spaces.

5. Conclusions

Pregnancy and early postpartum are critical periods for women's health, and we have shown that time-activity and mobility patterns of women will likely vary over this journey for many women. Time-activity and mobility patterns can also be used to directly determine environmental exposures that may affect both short- and long-term maternal and infant health outcomes. Therefore, future studies examining the impacts of environmental or contextual exposures on maternal or fetal health should consider the dynamics of these patterns as they will directly influence exposure measurement error and the ability to detect meaningful relationships.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- We analyzed time-activity and mobility patterns in pregnancy and postpartum
- Higher neighborhood safety was associated with less daily vehicular trips
- Parks were rarely visited during pregnancy and early postpartum
- Vehicular trips and visits to commercial/service locations decreased postpartum
- Dynamic changes in time-activity patterns have implications for exposure assessment

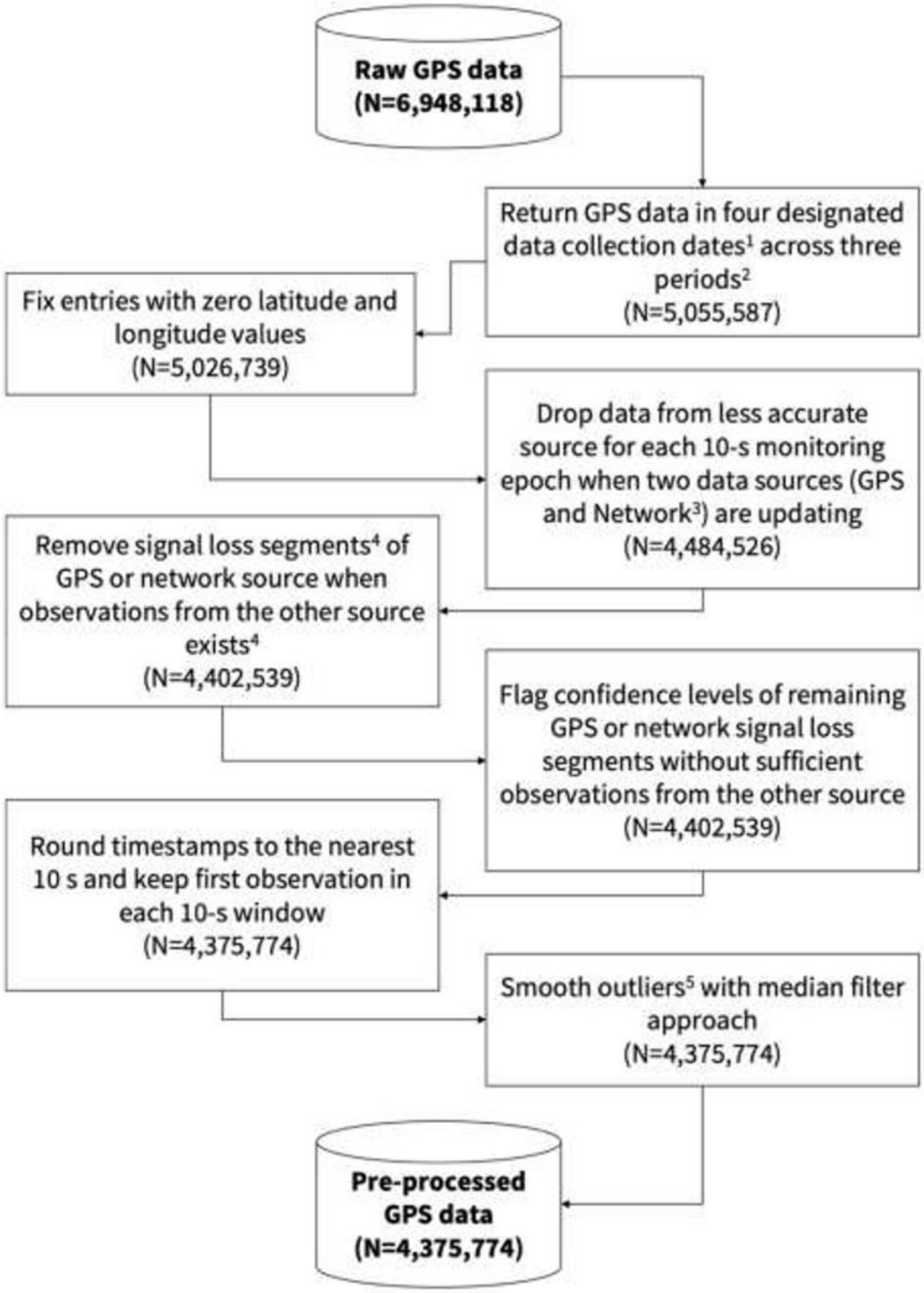

Fig. 1.

GPS pre-processing steps of MADRES real-time and personal sampling study GPS data.

Notes. MADRES = Maternal And Developmental Risks from Environmental and Social stressors. GPS = Global Positioning System.

[1] Data collection dates included two weekdays and two weekend days.

[2] Three periods were first trimester, third trimester, and four-to-six months postpartum.

[3] Network source included observations recorded by WiFi and cellular networks.

[4] Signal loss scenarios were defined as ≥ 1 min time windows with same timestamps.

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[5] Outliers were defined as observations with a distance > 450 m from the median latitude/longitude coordinates (corresponding to the maximum realistically possible distance moved in 10 s based on a speed of 45 m/s or 100 mph) and replaced with the median coordinates within the moving window.

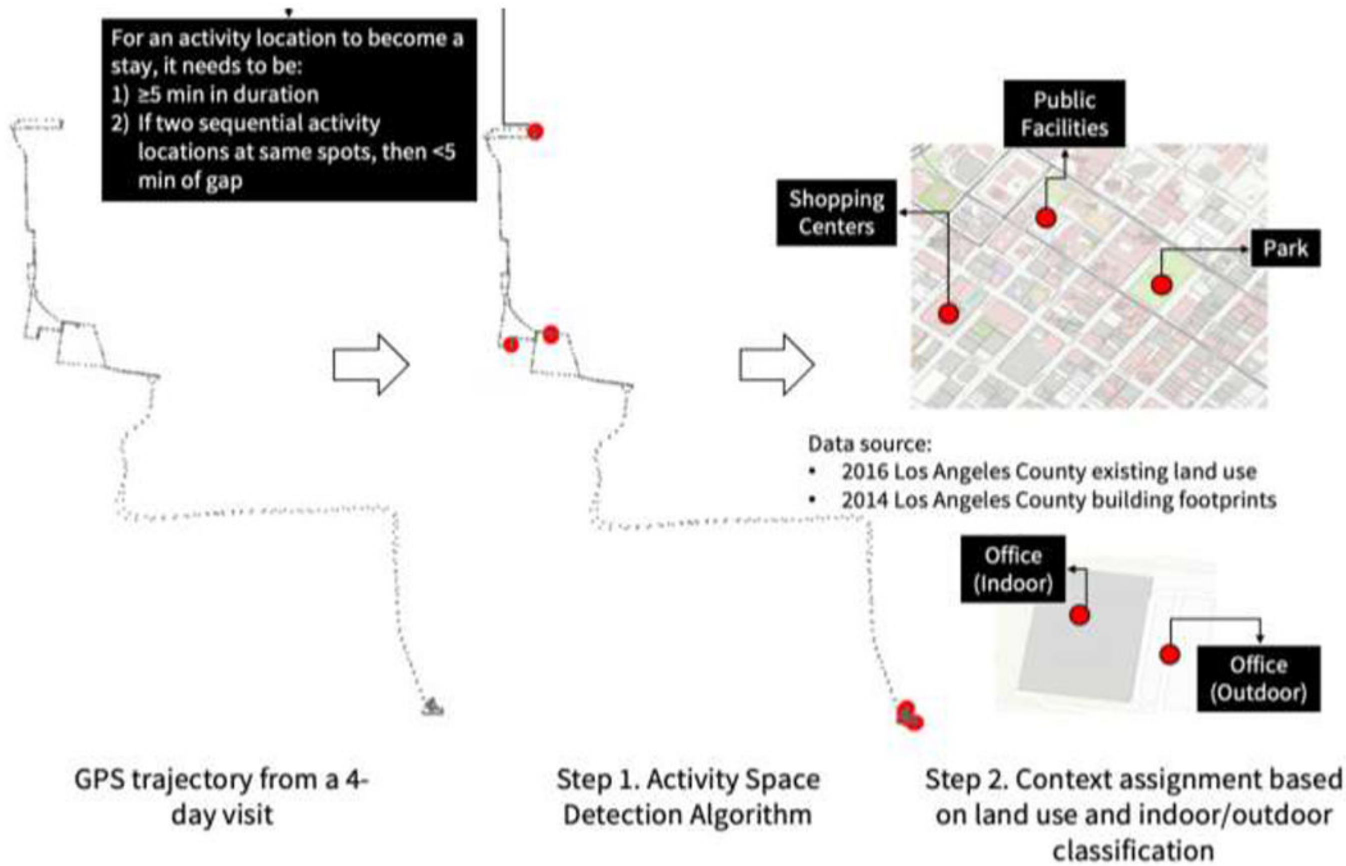

Fig. 2.

Geoprocessing steps to detect stays, classify their contexts based on land use, and their indoor/outdoor microenvironments based on building footprints.

Note. GPS = global positioning system.

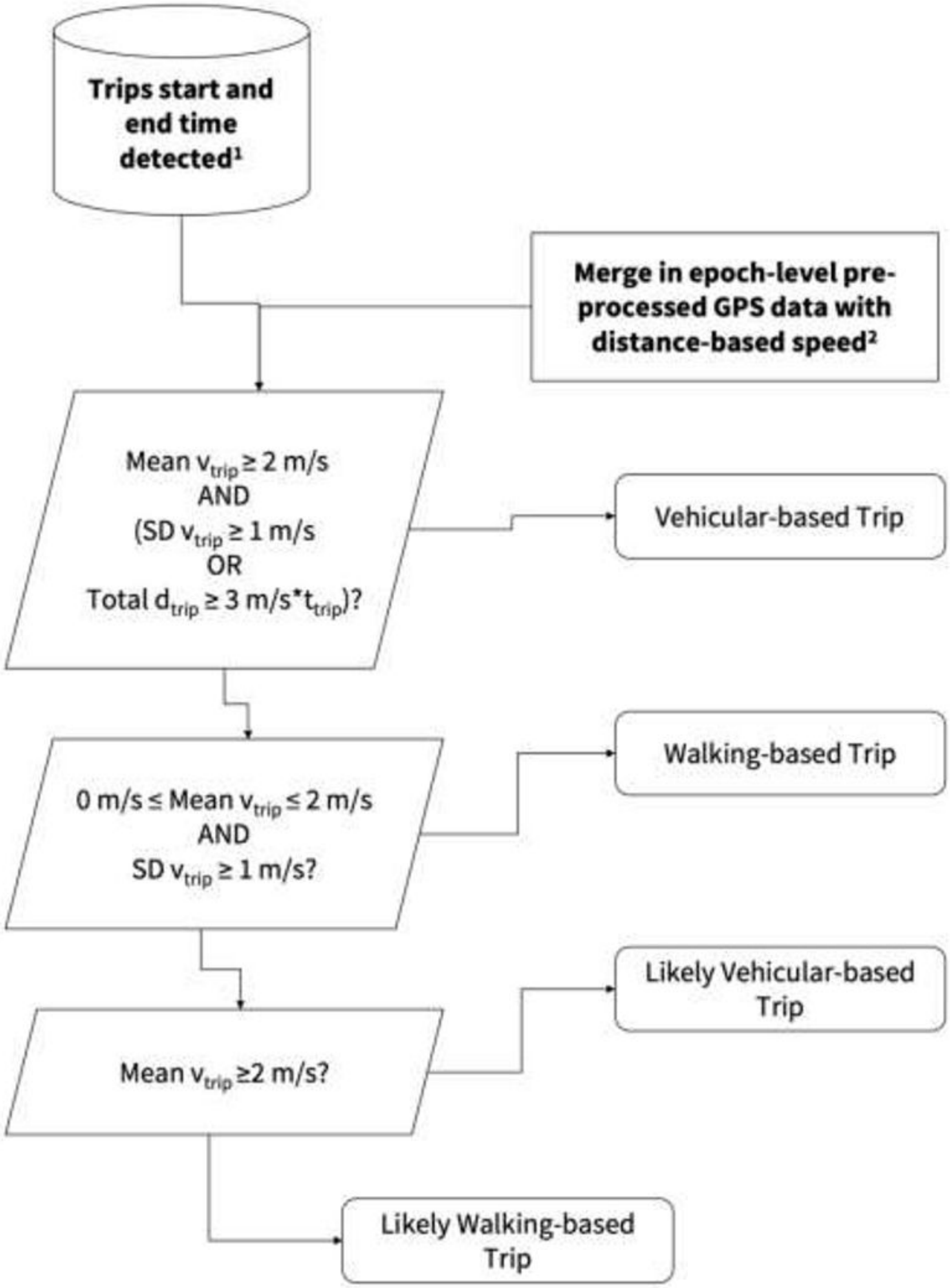

Fig. 3.

Geoprocessing steps to detect trips and classify their modes based on mean and SD of GPS observations in trips.

Notes. SD = Standard deviation. GPS = Global Positioning System.

1 Trips start time was identified as the end of previous stay and trip end time was identified as the start of the next consecutive stay.

2 Epoch-level distance-based speed (v_{trip}) was calculated by dividing the Euclidean distance traveled (d_{trip}) between two consecutive epochs with time elapsed (t_{trip}).

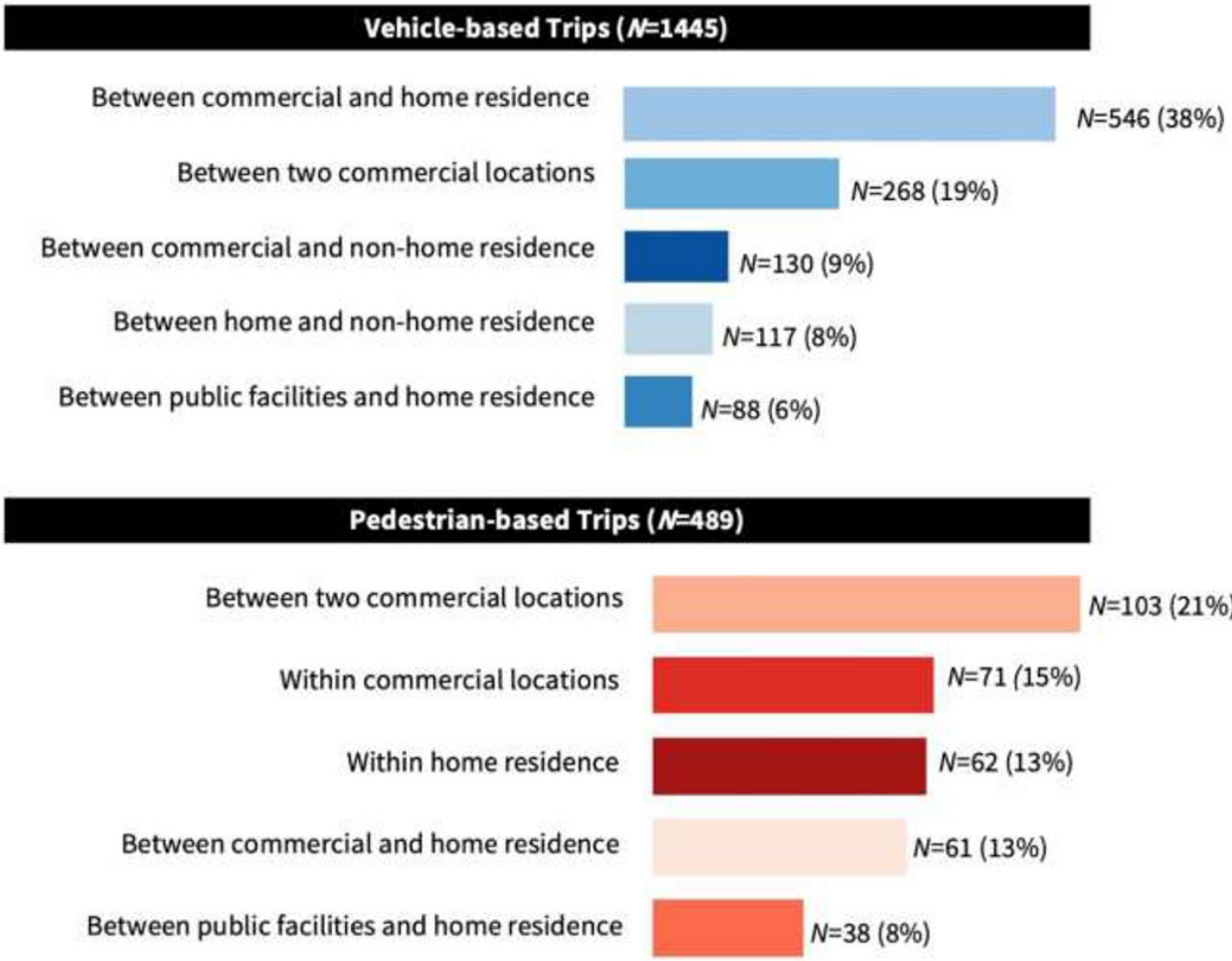

Fig. 4.

Distributions of top five origin-destination combinations by pedestrian- and vehicle-based trip modes.

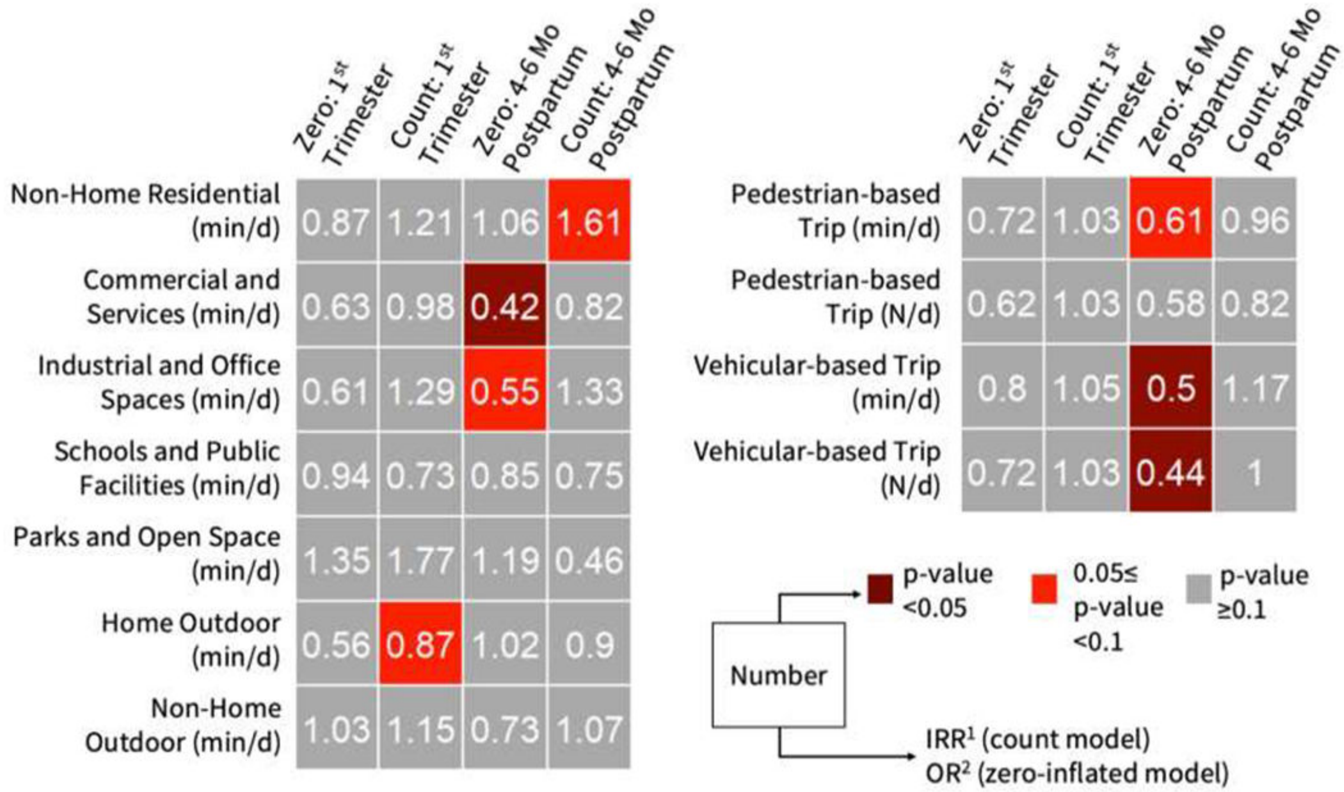

Fig. 5.

Base generalized mixed-effects model (GLMM) results of variations in time-activity and daily mobility patterns by 1st and 3rd trimesters of pregnancy and 4-6 months postpartum using 3rd trimester as the reference group.

Notes. IRR = Incidence Rate Ratio. OR = Odds Ratio. Variations of time-activity and daily mobility patterns by pregnancy and postpartum periods were tested using zero-inflated GLMM with the 3rd trimester as the reference group and controlling for day GPS observation hours.

1. IRR can be interpreted as: if mothers visit a particular context or perform trips with a particular mode, their min/d spent increase (if IRR>1) or decrease (if IRR<1), compared to the reference time point (i.e., 3rd trimester). For example, if mothers visit commercial and service locations at 4-6 months postpartum, their min/d spent at the locations decrease by 18% (1-0.82) compared to 3rd trimester, this is statistically insignificant (p ≥0.05).

2. OR can be interpreted as: mothers in a time point decrease (if OR<1) or increase (if OR>1) the odds of visiting a particular context or performing trips with a particular mode, compared to the reference time point (i.e., 3rd trimester). For example, mothers at 4-6 months postpartum decrease the odds of visiting commercial and services locations by 58% (1-0.42), this is statistically significant (p<0.05)

Table 1a.

Descriptive statistics of participant characteristics at baseline.

	Overall (*N*=62 Participants)
Age at consent (years)	
Mean (SD)	29 (6.1)
Median [Min, Max]	28 [18, 45]
Education	
High school or less	42 (67.7%)
Some college/Graduate	20 (32.3%)
Marital status	
Married/Living together	50 (80.6%)
Single/Divorced/Separated/Widowed	10 (16.1%)
Missing	2 (3.2%)
Acculturation	
US-Born Hispanic	29 (46.8%)
Foreign-Born Hispanic	33 (53.2%)
Maternal parity	
First-born	16 (25.8%)
Already had child	46 (74.2%)
Pre-pregnancy BMI category	
Normal	16 (25.8%)
Overweight/Obesity	46 (74.2%)
Neighborhood Walkability Score	
Mean (SD)	14.4 (2.0)
Median [Min, Max]	14 [9.3, 19]
Neighborhood Deprivation Score	
Mean (SD)	6.5(1.7)
Median [Min, Max]	7.0 [2.0, 9.0]
Missing	2 (3.2%)

Table 1b.

Descriptive statistics of person-day level temporally varying factors by period (1st trimester, 3rd trimester, and 4-6 months postpartum) and overall.

	1st Trimester (*N*=205 person-days)	3rd Trimester (*N*=180 person-days)	4-6 Months Postpartum (*N*=167 person-days)	Overall (*N*=552 person-days)
Valid GPS observation (h/ day)				
Mean (SD)	21 (5.6)	22 (4.4)	22 (4.7)	22 (5.0)
Median [Min, Max]	24 [6.2, 24]	24 [6.5, 24]	24 [7.0, 24]	24 [6.2, 24]
Average Daily Temperature (°C)				
Mean (SD)	21 (4.2)	21 (4.4)	19 (4.4)	20 (4.4)
Median [Min, Max]	21 [8.0, 31]	21 [9.0, 31]	20 [5.2, 28]	20 [5.2, 31]
Missing	19 (9.3%)	0 (0%)	0 (0%)	19 (3.4%)
Type of day				
Weekday	104 (50.7%)	91 (50.6%)	85 (50.9%)	280 (50.7%)
Weekend	101 (49.3%)	89 (49.4%)	82 (49.1%)	272 (49.3%)
	1st Trimester (*N*=55 Participants)	**3rd Trimester (*N*=48 Participants)**	**4-6 Months Postpartum (*N*=46 Participants)**	**Overall (*N*=149 Participants)**
Employment status				
Unemployed	35 (63.6%)	28 (58.3%)	29 (63.0%)	92 (61.7%)
Employed	20 (36.4%)	19 (39.6%)	9 (19.6%)	48 (32.2%)
Missing	0 (0%)	1 (2.1%)	8 (17.4%)	9 (6.0%)
Neighborhood Cohesion and Safety Score				
Mean (SD)	3.1 (0.7)	3.1 (0.7)	3.3 (0.9)	3.1 (0.8)
Median [Min, Max]	3.0 [1.0, 4.4]	3.1 [1.0, 5.0]	3.2 [1.4, 4.8]	3.0 [1.0, 5.0]
Missing	3 (5.5%)	0 (0%)	8 (17.4%)	11 (7.4%)

Notes. BMI = Body Mass Index, GPS = Global Positioning System. SD = Standard deviation.

Table 2.

Summary of total number of visits to multiple spatial contexts and indoor/outdoor microenviroments and total number of pedestrian and vehicular trips made.

	1st Trimester (N_{stay}=947; N_{trip}=682)	3rd Trimester (N_{stay}=914; N_{trip}=692)	4-6 Months Postpartum (N_{stay}=760; N_{Trip}=551)	Overall (N_{stay}=2,621; N_{Trip}=1,925)
	N(%)	**N(%)**	**N(%)**	**N(%)**
Spatial contexts				
Home residential	412 (43.5%)	363 (39.7%)	337 (44.3%)	1,112 (42.4%)
Non-home residential	64 (6.8%)	60 (6.6%)	79 (10.4%)	203 (7.7%)
Commercial and Services	281 (29.7%)	283 (31.0%)	193 (25.4%)	757 (28.9%)
Industrial and Office Spaces	84 (8.9%)	105 (11.5%)	64 (8.4%)	253 (9.7%)
Schools and Public Facilities	52 (5.5%)	61 (6.7%)	57 (7.5%)	170 (6.5%)
Parks and Open Spaces	22 (2.3%)	17 (1.9%)	12 (1.6%)	51 (1.9%)
Other	32 (3.4%)	25 (2.7%)	18 (2.4%)	75 (2.9%)
Indoor/outdoor microenvironment				
Home Indoor	363 (38.3%)	336 (36.8%)	302 (39.7%)	1,001 (38.2%)
Non-Home Indoor	220 (23.2%)	253 (27.7%)	168 (22.1%)	641 (24.5%)
Home Outdoor	49 (5.2%)	27 (3.0%)	35 (4.6%)	111 (4.2%)
Non-Home Outdoor	291 (30.7%)	288 (31.5%)	230 (30.3%)	809 (30.9%)
Out of LA County	24 (2.5%)	10 (1.1%)	25 (3.3%)	59 (2.3%)
Trip modes				
Pedestrian trips	175 (25.7%)	185 (26.7%)	120 (21.8%)	480 (24.9%)
Vehicular trips	507 (74.3%)	507 (73.3%)	431 (78.2%)	1,445 (75.1%)

Table 3.

Day-level summary of time spent in spatial contexts, indoor/outdoor microenvironments, and number of pedestrian/vehicular trips made.

	1st Trimester (N=205 person-days)	3rd Trimester (N=180 person-days)	4-6 Months Postpartum (N=167 person-days)	Overall (N=552 person-days)
Spatial Contexts				
Home Residential (h/day)				
Mean (SD)	16.8 (6.6)	17.5 (6.6)	17.6 (6.3)	17.3 (6.6)
Median [Min, Max]	18.8 [0, 24.0]	19.5 [0, 24.0]	19.4 [0, 24.0]	19.2 [0, 24.0]
Missing	2 (1.0%)	0 (0%)	1 (0.6%)	3 (0.5%)
All Non-Home Contexts (min/day)				
Mean (SD)	205 (324)	219 (328)	190 (295)	205 (316)
Median [Min, Max]	58.0 [0, 1440]	81.4 [0, 1440]	73.2 [0, 1440]	73.2 [0, 1440]
Non-Home Residential (min/day)				
Mean (SD)	51.9 (158)	40.8 (139)	68.7 (164)	53.1 (154)
Median [Min, Max]	0 [0, 1260]	0 [0, 1040]	0 [0, 831]	0 [0, 1260]
Missing	46 (22.4%)	26 (14.4%)	34 (20.4%)	106 (19.2%)
Commercial and Services (min/day)				
Mean (SD)	68.2 (109)	84.2 (134)	47.7 (68.9)	67.4 (109)
Median [Min, Max]	16.2 [0, 561]	22.2 [0, 619]	9.50 [0, 349]	16.2 [0, 619]
Missing	40 (19.5%)	25 (13.9%)	28 (16.8%)	93 (16.8%)
Schools and Public Facilities (min/day)				
Mean (SD)	21.1 (71.8)	26.2 (70.8)	23.4 (66.1)	23.6 (69.7)
Median [Min, Max]	0 [0, 480]	0 [0, 517]	0 [0, 521]	0 [0, 521]
Missing	49 (23.9%)	25 (13.9%)	32 (19.2%)	106 (19.2%)
Industrial and Office Spaces (min/day)				
Mean (SD)	103 (304)	93.2 (269)	72.5 (241)	90.4 (274)
Median [Min, Max]	0 [0, 1440]	0 [0, 1440]	0 [0, 1440]	0 [0, 1440]
Missing	44 (21.5%)	25 (13.9%)	29 (17.4%)	98 (17.8%)
Parks and Open Spaces (min/day)				
Mean (SD)	11.8 (55.9)	5.57 (30.1)	8.86 (55.4)	8.73 (48.3)
Median [Min, Max]	0 [0, 384]	0 [0, 275]	0 [0, 517]	0 [0, 517]
Missing	53 (25.9%)	29 (16.1%)	36 (21.6%)	118 (21.4%)
Indoor/outdoor microenvironment				
Home Outdoor (min/day)				
Mean (SD)	150 (389)	129 (389)	138 (391)	139 (389)
Median [Min, Max]	0 [0, 1440]	0 [0, 1440]	0 [0, 1440]	0 [0, 1440]
Missing	49 (23.9%)	26 (14.4%)	37 (22.2%)	112 (20.3%)
Non-Home Outdoor (min/day)				
Mean (SD)	109 (248)	117 (272)	112 (253)	113 (257)
Median [Min, Max]	15.5 [0, 1440]	12.0 [0, 1440]	12.0 [0, 1440]	12.3 [0, 1440]
Missing	40 (19.5%)	23 (12.8%)	24 (14.4%)	87 (15.8%)

	1st Trimester (N=205 person-days)	3rd Trimester (N=180 person-days)	4-6 Months Postpartum (N=167 person-days)	Overall (N=552 person-days)
Daily Mobility				
Trip (min/day)				
Mean (SD)	60.2 (73.3)	66.6 (69.4)	64.7 (76.6)	63.7 (73.0)
Median [Min, Max]	40.0 [0, 387]	49.6 [0, 363]	37.8 [0, 351]	44.2 [0, 387]
Pedestrian-based Trip (min/day)				
Mean (SD)	16.2 (30.8)	17.9 (31.7)	14.9 (29.8)	16.4 (30.8)
Median [Min, Max]	0 [0, 205]	0 [0, 186]	0 [0, 166]	0 [0, 205]
Missing	45 (22.0%)	23 (12.8%)	30 (18.0%)	98 (17.8%)
Vehicular-based Trip (min/day)				
Mean (SD)	57.3 (67.6)	58.1 (63.7)	60.9 (72.0)	58.7 (67.6)
Median [Min, Max]	36.3 [0, 372]	41.6 [0, 356]	35.3 [0, 351]	39.3 [0, 372]
Missing	35 (17.1%)	22 (12.2%)	23 (13.8%)	80 (14.5%)
Trip (N/day)				
Mean (SD)	3.33 (3.86)	3.84 (3.97)	3.30 (3.61)	3.49 (3.82)
Median [Min, Max]	2.00 [0, 18.0]	3.00 [0, 17.0]	2.00 [0, 16.0]	2.00 [0, 18.0]
Pedestrian-based Trip (N/day)				
Mean (SD)	1.09 (1.97)	1.18 (1.75)	0.876 (1.37)	1.06 (1.73)
Median [Min, Max]	0 [0, 13.0]	0 [0, 8.00]	0 [0, 6.00]	0 [0, 13.0]
Missing	45 (22.0%)	23 (12.8%)	30 (18.0%)	98 (17.8%)
Vehicular-based Trip (N/day)				
Mean (SD)	2.98 (2.97)	3.21 (3.32)	2.99 (3.31)	3.06 (3.19)
Median [Min, Max]	2.00 [0, 12.0]	2.00 [0, 15.0]	2.00 [0, 15.0]	2.00 [0, 15.0]
Missing	35 (17.1%)	22 (12.2%)	23 (13.8%)	80 (14.5%)

Notes. SD = Standard Deviation.

Table 4a.

Zero-inflated generalized mixed-effects model (GLMM) results for time spent in home and non-home contexts and microenvironments adjusted for pregnancy and postpartum period, temporal factors, individual sociodemographics, and neighborhood characteristics.

Predictors	**Home Residence (h/day)**	**Home Residence Excluding Sleep Hours (min/day)**	**Home Residence Outdoor (min/day)**	**All Non-Home Contexts (min/day)**	**All Non-Home Contexts Outdoor (min/day)**
Count Model			***Incidence Rate Ratio (95%CI)***		
Period: 1st Trimester	0.98 (0.93 – 1.05)	0.95 (0.85 – 1.06)	0.87 (0.74 – 1.02)	1.18 (0.94 – 1.47)	1.15 (0.84 – 1.57)
Period: 4-6 Months Postpartum	1.00 (0.93 – 1.07)	1.01 (0.90 – 1.13)	0.90 (0.75 – 1.10)	1.08 (0.86 – 1.36)	1.07 (0.78 – 1.47)
Valid GPS observation (h/day)	1.06 *** (1.05 – 1.07)	1.15 *** (1.13 – 1.17)	1.06 *** (1.04 – 1.08)	1.05 ** (1.01 – 1.08)	1.03 (0.98 – 1.07)
Employment status: Employed	0.92 (0.84 – 1.01)			1.48 ** (1.10 – 1.99)	
Type of day: Weekend				1.06 (0.89 – 1.27)	
Maternal age at consent				1.00 (0.97 – 1.02)	0.99 (0.95 – 1.03)
Zero-Inflated Model			***Odds Ratio (95%CI)***		
Period: 1st Trimester		1.14 (0.4 – 3.23)	0.56 (0.15 – 2.13)	0.71 (0.42 – 1.22)	1.05 (0.62 – 1.82)
Period: 4-6 Months Postpartum		1.49 (0.53 – 4.35)	1.02 (0.21 – 5.00)	0.83 (0.45 – 1.54)	0.72 (0.42 – 1.27)
Valid GPS observation (h/day)		1.92 *** (1.67 – 2.38)	0.20 (0.02 – 1.85)	1.19 *** (1.15 – 1.25)	0.23 * (0.07 – 0.79)
Employment status: Employed				0.59 * (0.38 – 0.93)	
Type of day: Weekend				1.89 (1.00 – 3.70)	
Maternal age at consent				1.10 ** (1.11 – 1.18)	1.10 ** (1.11 – 1.16)

* p<0.05.

** p<0.01.

*** p<0.001.

Exponentiated parameter estimates are shown. Reversed odds ratio (i.e., odds for an outcome to be non-zero) of zero-inflated models were calculated for easier interpretation. Zero-inflated model was not applied to home residence related outcomes given that extremely rare cases of having zero min/day spent at home residence.

Notes. GPS = Global Positioning System.

Table 4b.

Zero-inflated generalized mixed-effects model (GLMM) results for time spent in five non-home spatial contexts adjusted for pregnancy and postpartum period, temporal factors, individual sociodemographics and neighborhood characteristics.

Predictors	Non-Home Residential (min/d)	Commercial and Services (min/d)	Industrial and Office Spaces (min/d)	Schools and Public Facilities (min/d)	Parks and Open Spaces (min/d)
Count Model		*Incidence Rate Ratio (95%CI)*			
Period: 1st Trimester	1.14 (0.65 – 1.98)	1.01 (0.79 – 1.30)	1.37 (0.89 – 2.10)	0.81 (0.49 – 1.34)	1.07 (0.37 – 3.11)
Period: 4-6 Months Postpartum	1.83 * (1.03 – 3.25)	0.88 (0.66 – 1.17)	1.51 (0.96 – 2.36)	0.91 (0.56 – 1.46)	0.45 (0.16 – 1.31)
Valid GPS observation (h/day)	1.01 (0.94 – 1.09)	1.07 ** (1.02 – 1.13)	1.03 (0.97 – 1.09)	1.05 (0.96 – 1.15)	0.95 (0.80 – 1.13)
Type of day: Weekend	1.64 * (1.05 – 2.56)				3.02 ** (1.32 – 6.92)
Average air temperature (°C)	1.04 (0.99 – 1.10)				
Maternal parity: Already had child		0.63 ** (0.46 – 0.86)			
Employment status: Employed		1.43 ** (1.11 – 1.85)	2.01 * (1.06 – 3.79)	2.25 *** (1.40 – 3.64)	
Maternal age at consent		0.99 (0.97 – 1.01)			
Neighborhood safety and cohesion score		0.83 * (0.71 – 0.97)			
Zero-Inflated Model		*Odds Ratio (95%CI)*			
Period: 1st Trimester	0.95 (0.53 – 1.79)	0.60 (0.33 – 1.09)	0.63 (0.34 – 1.18)	0.88 (0.45 – 1.72)	1.35 (0.50 – 3.85)
Period: 4-6 Months Postpartum	1.05 (0.59 – 2.00)	0.37 ** (0.19 – 0.72)	0.63 (0.32 – 1.27)	0.96 (0.48 – 1.96)	1.2 (0.40 – 3.70)
Valid GPS observation (hay/day)	0.34 * (0.12 – 0.97)	0.28 * (0.10 – 0.85)	0.20 (0.04 – 1.01)	0.14 ** (0.03 – 0.59)	0.22 (0.02 – 2.70)
Type of day: Weekend	0.74 (0.45 – 1.22)				1.37 (0.59 – 3.23)
Average air temperature (°C)	1.00 (1.00 – 1.06)				
Maternal parity: Already had child		0.53 (0.18 – 1.59)			
Employment status: Employed		0.62 (0.29 – 1.33)	2.33 * (1.11 – 5.00)	0.61 (0.28 – 1.35)	
Maternal age at consent		1.10 * (1.01 – 1.19)			
Neighborhood safety and cohesion score		1.16 (0.77 – 1.82)			

* p<0.05.

** p<0.01.

*** p<0.001.

Exponentiated parameter estimates are shown. Reversed odds ratio (i.e., odds for an outcome to be non-zero) of zero-inflated models were calculated for easier interpretation.

Notes. BMI = Body Mass Index. GPS = Global Positioning System.

Table 4c.

Zero-inflated generalized mixed-effects model (GLMM) results for time spent in pedestrian and vehicular trips and number of pedestrian and vehicular trips performed adjusted for pregnancy and postpartum period, temporal factors, individual sociodemographics, and neighborhood characteristics.

Predictors	**All Trip (min/d)**	**Pedestrian-based Trip (min/d)**	**Vehicular-based Trip (min/d)**	**All Trip (N/d)**	**Pedestrian-based Trip (N/d)**	**Vehicular-based Trip (N/d)**
Count Model			*Incidence Rate Ratio (95%CI)*			
Period: 1st Trimester	1.03 (0.86 – 1.24)	1.03 (0.75 – 1.41)	1.05 (0.86 – 1.28)	1.00 (0.85 – 1.18)	1.04 (0.73 – 1.47)	1.04 (0.88 – 1.23)
Period: 4-6 Months Postpartum	1.04 (0.87 – 1.25)	0.96 (0.69 – 1.32)	1.17 (0.95 – 1.43)	0.90 (0.76 – 1.06)	0.86 (0.59 – 1.25)	1.00 (0.84 – 1.20)
Valid GPS observation (h/day)	1.05 *** (1.02 – 1.08)	1.02 (0.97 – 1.08)	1.05 ** (1.02 – 1.09)	1.04 ** (1.01 – 1.07)	0.97 (0.92 – 1.03)	1.05 ** (1.02 – 1.08)
Type of day: Weekend	0.96 (0.83 – 1.11)			0.93 (0.82 – 1.06)		
Maternal age at consent	1.01 (0.99 – 1.03)	0.99 (0.96 – 1.02)	1.01 (0.99 – 1.03)	1.03 * (1.00 – 1.05)		1.02 (1.00 – 1.04)
Education: Some college/Graduate	1.08 (0.86 – 1.36)		1.05 (0.82 – 1.35)			1.13 (0.87 – 1.48)
Neighborhood deprivation score					1.12 * (1.01 – 1.25)	
Neighborhood safety and cohesion score						0.86 * (0.76 – 0.97)
Zero-Inflated Model			*Odds Ratio (95%CI)*			
Period: 1st Trimester	0.76 (0.45 – 1.27)	0.74 (0.43 – 1.25)	0.79 (0.45 – 1.41)	0.75 (0.42 – 1.37)	0.51 (0.21 – 1.27)	0.71 (0.37 – 1.43)
Period: 4-6 Months Postpartum	0.78 (0.45 – 1.35)	0.6 (0.34 – 1.03)	0.5 * (0.28 – 0.92)	0.79 (0.42 – 1.49)	0.48 (0.18 – 1.28)	0.53 (0.24 – 1.18)
Valid GPS observation (h/day)	1.05 *** (1.11 – 1.23)	0.2 * (0.05 – 0.86)	0.36 * (0.14 – 0.94)	1.18 *** (1.11 – 1.23)	0.21 (0.03 – 1.82)	0.31 (0.08 – 1.18)
Type of day: Weekend	0.54 ** (0.36 – 0.82)			0.53 * (0.33 – 0.87)		
Maternal age at consent	1.08 ** (1.01 – 1.14)	1.06 * (1.01 – 1.11)	1.10 ** (1.11 – 1.18)	1.06 * (1.01 – 1.14)		1.09 * (1.01 – 1.16)
Education: Some college/Graduate	2.13 * (1.11 – 4.35)		3.33 ** (1.43 – 7.69)			3.33 * (1.25 – 9.09)
Neighborhood deprivation score					0.74 (0.56 – 1.01)	
Neighborhood cohesion and safety score						1.3 (0.83 – 2.13)

* p<0.05.

** p<0.01.

*** p<0.001.

Exponentiated parameter estimates are shown. Reversed odds ratio (i.e., odds for an outcome to be non-zero) of zero-inflated models were calculated for easier interpretation.

Notes. GPS = Global Positioning System.