Travel Behaviour and Society 43 (2026) 101196

Contents lists available at ScienceDirect

Travel Behaviour and Society

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

Correlates of pregnant women's active and passive mobility: A smartphone-based tracking study in Barcelona, Spain

Karl Samuelsson [a,b,c,d,*], Ioar Rivas [a,c,d,e], Marta Cirach [a,c,d], Bruno Raimbault [a,d], Alan Domínguez [a,c,d], Yu Zhao [a,c,d], Toni Galmés [a,c,d], Antònia Valentin [a,c,d], Maria Foraster [f], Mireia Gascon [a,c,d,g], Cecilia Persavento [a,c,d], Maria Dolores Gomez Roig [h,i], Elisa Llurba [j,k], Efstathios Boukouras [l], Oriol Marquet [m], Monika Maciejewska [m], Mark J. Nieuwenhuijsen [a,c,d], Xavier Basagaña [a,c,d], Jordi Sunyer [a,c,d], Achilleas Psyllidis [n,1], Marco Helbich [o,1], Payam Dadvand [a,c,d,1]

[a] ISGlobal, Barcelona Biomedical Research Park (PRBB), C/ Doctor Aiguader 88, 08003 Barcelona, Spain
[b] Department of Building Engineering, Energy Systems, and Sustainability Science, University of Gävle 801 76 Gävle, Sweden
[c] Universitat Pompeu Fabra (UPF), Barcelona, Spain, C/ Doctor Aiguader 80, 08003 Barcelona, Spain
[d] CIBER Epidemiología y Salud Pública (CIBERESP), Instituto de Salud Carlos III, c/ Monforte de Lemos 3-5, 28029 Madrid, Spain
[e] Instituto de Diagnostico Ambiental y Estudios del Agua (IDAEA), CSIC, Carrer Jordi Girona 18-26, 08034 Barcelona, Spain
[f] Blanquerna School of Health Science, Universitat Ramon Llull (URL), c/ Padilla 326-332, 08025 Barcelona, Spain
[g] Unitat de Suport a la Recerca de la Catalunya Central, Fundació Institut Universitari per a la Recerca a l'Atenció Primària de Salut Jordi Gol i Gurina (IDIAPJGol), C/ de Soler i March 6, 08242 Manresa, Spain
[h] BCNatal – Barcelona Center for Maternal Fetal and Neonatal Medicine (Hospital Sant Joan de Déu and Hospital Clínic), University of Barcelona, C/ Sabino Arana, 38 08028 Barcelona, Spain
[i] Institut de Recerca Sant Joan de Déu, C/ Santa Rosa 39-57, 08950 Esplugues de Llobregat, Spain
[j] Department of Obstetrics and Gynaecology, Hospital Santa Creu i Sant Pau. Women and Perinatal Health Research Group, IR SANT PAU, C/ de Sant Quintí 77-79, 08041 Barcelona, Spain
[k] Spanish network in maternal, neonatal, child and developmental health research (RICORS-SAMID, RD24/0013/0001), Instituto de Salud Carlos III, Spain, 28040 Madrid, Spain
[l] School of Architecture, National Technical University of Athens, Patission 42, 10682 Athens, Greece
[m] Department of Geography, Autonomous University of Barcelona, Bellaterra Campus, Building B, Carrer de la Fortuna, s/n, Bellaterra, Barcelona 08193, Spain
[n] Department of Sustainable Design Engineering, Faculty of Industrial Design Engineering, Delft University of Technology, Landbergstraat 15, 2628 CE Delft, the Netherlands
[o] Department of Human Geography and Spatial Planning, Faculty of Geosciences, Utrecht University, Princetonlaan 8a, 3584 CB Utrecht, the Netherlands

ARTICLE INFO

Keywords:
Maternal physical activity
GPS tracking
Social determinants of health
Ethnic disparities
COVID-19 impact
Daily mobility

ABSTRACT

Understanding the factors that shape daily mobility during pregnancy is essential for inclusive transportation planning that promotes active travel for all. Using smartphone-based Global Positioning System data from 860 pregnant women in Barcelona, Spain, we evaluated the correlates of active and passive travel in early and late pregnancy. We identified 33 correlates from 48 candidate variables including personal characteristics, the residential physical environment, the social environment, and temporal factors. The most important correlate across pregnancy was non-European ethnic origin, being associated with 10–15 min less daily active travel. In early pregnancy, commuting distance was the most important correlate, being positively associated with passive travel, while the COVID-19 pandemic was associated with less passive travel. In late pregnancy, residential walkability and having a university degree were positively associated with active travel. The neighbourhood education level was associated with more active travel, particularly during weekends. We discuss key priorities for supporting active travel during pregnancy.

* Corresponding author at: ISGlobal, Barcelona Biomedical Research Park (PRBB), C/ Doctor Aiguader 88, 08003 Barcelona, Spain.
E-mail address: karl.samuelsson@hig.se (K. Samuelsson).
[1] Joint last authors.

https://doi.org/10.1016/j.tbs.2025.101196
Received 1 July 2025; Received in revised form 29 September 2025; Accepted 19 November 2025
Available online 1 December 2025

1. Introduction

Active modes of daily mobility, such as walking and cycling, provide greater public health benefits than passive modes, like motorized or public transport (Nieuwenhuijsen, 2020). Efforts to promote active mobility for all must recognise that how people travel changes across different life stages. Pregnancy is one such stage of shifting mobility patterns (Samuelsson et al., 2025; Skreden et al., 2015; Yi et al., 2022). Understanding mobility during this period is crucial, as maternal behaviours in pregnancy can have short- and long-term health implications for mother and child (Gluckman et al., 2010). For example, active travel is an important source of physical activity in pregnancy (Skreden et al., 2016). Physical activity during pregnancy has been associated with decreased risks of pregnancy complications including gestational diabetes (Dempsey et al., 2005; Dipietro et al., 2019) and pregnancy-induced hypertensive disorders such as preeclampsia (Chasan-Taber et al., 2015; Da Silva et al., 2017). In terms of adverse pregnancy outcomes, physical activity has been related to decreased risks of preterm birth (Aune et al., 2017) and fetal macrosomia (Currie et al., 2014). Meanwhile, long work commutes and spending time in cars can be significant sources of stress among pregnant women (O'Toole and Christie, 2022; Wang and Yang, 2019). This could in turn increase the likelihood of preterm birth and low birth weight (Preis et al., 2021), with one study suggesting a link between long commutes and increased risks of low birth weight (Wang and Yang, 2019). Moreover, total daily travel time has been associated with higher exposure to traffic-related air pollution (Tang et al., 2018). Although this evidence is not specific to pregnant women, exposure to air pollution during pregnancy is a known risk factor for adverse outcomes, making total travel time a relevant indicator for this population.

Understanding pregnant women's mobility is also relevant with respect to broader transport equity concerns, as mobility constraints during pregnancy can disproportionately affect women from disadvantaged socioeconomic backgrounds who may face limited access to opportunities and/or resources to compensate (Pereira et al., 2017). Due to intersecting systemic inequalities, travel choices and burdens are shaped and often constrained by a combination of social and spatial structures (Pereira and Karner, 2021). Thus, planning for health-promoting mobility requires understanding its many interrelated correlates, meaning the factors, characteristics and conditions that are associated with it. Comparing different sociodemographic groups in the Global North, low active travel levels were among high incomers, those with lower education, and ethnic minorities (Agrawal and Schimek, 2007; Brondeel et al., 2016; Buehler et al., 2020). The urban physical environment constitutes another domain of correlates, as evidenced in mobility frameworks such as the 3Ds, i.e., built-up density, land-use diversity and pedestrian design (Cervero and Kockelman, 1997), and the 5Ds that additionally include destination accessibility and distance to transit (Ewing and Cervero, 2010). For example, built environment characteristics around the home have been shown to correlate with walking behaviour in European cities (Gascon et al., 2019). Furthermore, the social environment has been linked to individuals' travel choices, with a Scottish study reporting an association between area-level social deprivation and more trips undertaken by active travel (Olsen et al., 2017). Mobility can also be influenced by temporal factors. For example, seasonality accounts for a substantial proportion of the variation in individuals' month-by-month travel (Järv et al., 2014). Moreover, the COVID-19 pandemic altered mobility behaviour of urban populations (Paul et al., 2022; Santana et al., 2023).

While most studies on correlates of mobility have focused on the general population, only a few dealt with pregnant women's mobility. A Norwegian study, for example, found that lower education was associated with a higher reliance on public transport among pregnant women (Skreden et al., 2015). Another study of Hispanic pregnant women in Los Angeles, United States (US), found that higher education was associated with longer trips and that women who perceived their neighbourhood as safe undertook fewer vehicle trips (Yi et al., 2022). In terms of physical environment factors, self-reported physical activity during pregnancy was positively associated with walkability in a US study (Porter et al., 2019) and living near a safe greenspace in a study from Colombia (López-Gil et al., 2022). However, these physical environment factors have not been studied in relation to pregnant women's mobility and travel modes used.

Despite these findings, a comprehensive and systematic evaluation of the correlates of pregnant women's mobility is lacking. Such an evaluation helps prioritize key areas for mobility planning towards healthy pregnancies and pregnancy outcomes. Here, we used Global Positioning System (GPS) data from a large birth cohort in Barcelona, Spain, to objectively quantify pregnant women' s active and passive mobility, and comprehensively collected data on 48 possible correlates, including personal factors, the physical environment, the social environment and temporal factors. Our aims were to 1) systematically identify the most relevant correlates with a data-driven feature selection approach, and 2) evaluate the relative importance of correlates of mobility in early as well as late pregnancy. The term *correlate* here is used broadly to encompass factors that may be causal drivers, contextual characteristics, or simply variables statistically associated with mobility. Because individuals' mobility patterns differ markedly between weekdays and weekends (Raux et al., 2016; Shao et al., 2019), we analyzed them separately, treating them as distinct behaviours, since pooling them could mask key correlates. We examined both travel time and travel distance as mobility outcomes, and here report time-based results while providing distance-based results in the Supplementary Materials.

2. Materials and methods

2.1. Study area and participants

Barcelona is the capital of the Catalonia autonomous community, located at the north-eastern part of the Iberian Peninsula. It has a Mediterranean climate with mild winters and warm to hot summers. Barcelona has one of the highest population densities in Europe, with 16,793 inhabitants/km^2 (Idescat, 2025). The modal split of trips in the city in 2023 was 20 % by private motor vehicles, 34 % by public transport, and 46 % using active travel modes (Ajuntament de Barcelona, 2024).

The study was part of the Barcelona Life Study Cohort (BiSC), an ongoing mother–child cohort (Dadvand et al., 2024). BiSC enrolled 1,080 pregnant women in their first trimester of pregnancy between October 2018 and April 2021, at three major 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 aged 18–45 years, having singleton pregnancy without known congenital anomalies, residing in the hospitals' catchment areas, and being able to communicate in Spanish/Catalan. Data were managed using privacy-secure Research Electronic Data Capture (REDCap) tools hosted at ISGlobal (Harris et al., 2019, 2009). The study was approved by the corresponding ethical committees in all the participating institutions and hospitals. Participants signed an informed consent before being enrolled in the study.

2.2. Geotracking data collection

Participants were tracked via smartphones for one week (i.e., seven consecutive days) during both the first trimester (T_1, around week 12 of gestation) and third trimester (T_3, around week 32 of gestation). We used ExpoApp (Donaire-Gonzalez et al., 2019), a validated smartphone application combining the smartphone's assisted Global Positioning System (GPS) reception, cellular triangulation, and WiFi triangulation, to record timestamped locations (hereafter "GPS data"). ExpoApp collected data at a 1-second resolution when using the GPS sensor and a 20-second resolution when using cellular or WiFi triangulation, with each measurement having an associated accuracy measurement in metres. ExpoApp was installed on a Samsung Galaxy J3 Smartphone provided to participants at home by trained field workers. The participants were instructed to carry the phone in the most external part of their bags or backpacks and to charge it overnight.

The GPS data was preprocessed by downsampling based on 10-second buckets and removing points based on low accuracy (>100 m), GPS/triangulation switching, as well as abnormal velocities and signal interruptions (based on a sliding window calculation, see Samuelsson et al. (2025) for details). We also removed the first and last (incomplete) days of the tracking period. After preprocessing, we limited the sample to tracking periods with at least one weekday and one weekend day with >5 h of GPS data during waking hours (910 participants, 1,435 tracking weeks), to ensure sufficient coverage of both weekday and weekend mobility, in line with criteria applied elsewhere (Samuelsson et al., 2025; Yi et al., 2022; Zenk et al., 2018). Furthermore, as many of the environmental variables used were available for the Barcelona Metropolitan Area, only participants living in this area were included (902 participants, 1,413 tracking periods). Finally, we excluded tracking periods containing a trip outside the Catalonia region. As a result of these exclusions, some participants contributed data from only one trimester. Our final sample included 860 participants, and 1,276 tracking periods.

2.3. Mobility variables as outcomes

GPS points occurring between 00:30 and 08:00 were removed from analysis, to focus on the cohort's typical waking time (Samuelsson et al., 2025). We identified trips using sliding three-minute windows, where regions with mean velocity > 0.5 m/s were classified as trips. These were further classified as active or passive using a fuzzy logic approach (Rasmussen et al., 2015), using commutes mapped during fieldwork visits for labelling. Further details on these operations are provided in the Supplementary Materials (Section 1), while Samuelsson et al. (2025) provides an exhaustive description. This approach captures walking trips of at least three minutes, which could include short walks to access or leave other modes of transport, such as public transport or parked cars. Based on the trips, we computed average daily duration in minutes of (1) all travel (*total travel time*), (2) passive travel, including private motorised transport and public transport (*passive travel time*), and (3) active travel, including walking and cycling (*total travel time*) (Buehler et al., 2020; Wu et al., 2013; Yi et al., 2022). To reflect the relative prominence of active travel for an individual's overall mobility, we further computed (4) the proportion of active travel time to total travel time (*active travel ratio*) (Renninger et al., 2022). This ratio was log-transformed to an unbounded variable. Each outcome variable was quantified separately for weekdays and weekends, as well as separately for each trimester, resulting in a total of 16 outcome variables.

2.4. Correlates

Below, we provide an overview of the 48 variables that were evaluated as potential correlates. For further details on how they were calculated, we refer to Section 2 of the Supplementary Materials.

2.4.1. Personal characteristics

From fieldwork visits and questionnaires administered in T_1 and T_3, we collected womens' personal characteristics including (1) age (numeric, in years), (2) education (binary, university degree, yes/no), (3) stay-at-home work status (including unemployed participants, housewives, and participants on leave; binary:, yes/no), (4) self-reported financial difficulties (binary, yes/no), (5) non-European ethnic origin (categorical, yes/no), (6) parity > 0 (i.e., having previously given birth) (binary, yes/no), (7) street network-based commuting distance to work, calculated from routes drawn during fieldwork (numeric, kilometres that were log-transformed due to a skewed distribution), (8) self-rated poor pre-pregnancy health status (binary: yes/no), and (9) self-rated poor recent health status (binary: yes/no). The last two variables were rated by respondents on a 5-step Likert scale from "excellent" (1) to "Poor" (5); we dichotomized the answers to indicate poor health status (4–5: yes, 1–3: no).

2.4.2. Social environment

We characterised the social environment at the area-level, including (1) average household income (numeric, in Euros), (2) poverty rate (numeric, in %), (3) education level (numeric, share of adults with a higher education degree), and (4) unemployment rate (numeric, %). These variables were sourced from the 2020 Standard of Living and Living Conditions survey by the Spanish National Institute of Statistics with data aggregated within census tracts (Instituto Nacional de Estadística, 2023). In addition, we also obtained (5) feeling unsafe in the neighbourhood (binary: yes/no) from the questionnaire.

2.4.3. Urban physical environment

Our characterisation of the urban physical environment around participants' homes used 100-, 300-, and 500-meters buffers around the address coordinate. These distances were chosen to capture the residential environment at different scales while avoiding larger buffers that could mask exposure contrasts (Tian et al., 2024). These variables were: (1, 2, 3) building footprint area (numeric, m^2), (4–6) average building height (numeric, metres), (7–9) residential population (numeric), (10–12) greenness (numeric, represented through the Normalised Difference Vegetation Index (NDVI) from 1-m resolution orthoimages), (13–21) natural, urban and total (i.e., natural plus urban) greenspace area (numeric, m^2), and (22–24) walkability (numeric, composite index ranging from 0 to 5 including residential density, commercial density, diversity of plot uses, and intersection density; see Section 2 in the Supplementary Materials). In addition to buffer-based variables, we included Euclidean distances to the nearest (25–28) greenspace, major greenspace (>5,000 m^2), blue space, and major blue space (which included the Mediterranean sea; numeric, metres), and (29, 30, 31) street network-based closeness and betweenness centrality, constrained to local network distances of 1.5 km and 5 km from each location (numeric). Closeness centrality captures how easily a location can reach all others in the network, while betweenness centrality reflects how often it lies on the shortest routes between other locations. Using a small radius shows how well connected a location is in its immediate surroundings, while a larger radius captures how important it is for reaching or linking places across a wider area.

2.4.4. Temporal correlates

We included a binary variable to capture the warm season (May-October, yes/no) and distinguish it from the cold season (November-April), based on the month of the first tracking day. Finally, a binary variable indicated whether the measurement period overlapped with the COVID-19 pandemic (yes/no), defined as occurring after March 14, 2020. GPS data collection was temporarily suspended from this date to early June 2020 due to COVID-19 lockdown restrictions in Spain.

2.5. Statistical analysis

We calculated medians and interquartile ranges (IQRs) of outcome variables and potential correlates, across all measurement periods as well as separately for each trimester.

To identify the relevant correlates, we used the deletion/substitution/addition (DSA) algorithm with the R package `DSA` (Neugebauer, 2016). DSA is a regression-based approach that iteratively deletes an independent variable, substitutes one for another or adds one, while seeking to minimise the cross-validated root mean squared error. Several simulation studies have found DSA to perform well for feature selection in an environmental health context (Agier et al., 2016; Barrera-Gómez et al., 2017; Warembourg et al., 2023). Following Santos et al.

(2020), for each outcome variable, we ran the algorithm 50 times with 5-fold cross-validation and retained independent variables that were selected at least twice. All continuous variables were median-centred and scaled so the IQR was 1, ensuring that coefficients represent the different between typical low and high values within the sample distribution, aiding comparison between continuous and dichotomous correlates. To facilitate interpretability, we focused only on first-order independent associations and limited the maximum number of selected variables in each run to 10 (Barrera-Gómez et al., 2017).

The final models were specified using multiple linear regression. We assessed multicollinearity by screening for variance inflation factors (VIF). While there is no universal level of unacceptable multicollinearity, we used a conservative threshold of VIF > 3 to detect potential multicollinearity where associations with the outcome could be distorted (Zuur et al., 2010). This could arise if DSA alternates between collinear correlates across different runs. However, collinear correlates may alternatively have distinct associations with the outcome conditioned on each other. In such cases we were interested in retaining both. We defined moderate collinearity as VIF values between 3 and 5 (Neter et al., 2004). In these cases, we assessed whether removing each collinear variable individually led to a lower mean Akaike Information Criterion (AIC). If removal increased AIC, we retained the variable, whereas if it lowered the AIC, we excluded it. We did not apply a strict threshold for ΔAIC. Instead, given the large set of models evaluated, we prioritised parsimony and interpretability (Burnham and Anderson, 2004) and favoured simpler models even when AIC improvements were modest. In cases of severe collinearity (VIF > 5), we removed the variable whose removal resulted in the lowest AIC. We further evaluated whether removing the variable with the weakest association with the outcome reduced AIC. If no further improvement could be achieved, the remaining independent variables were retained as correlates of the outcome.

To rank correlates in terms of their importance, we performed dominance analysis (Azen and Budescu, 2003; Budescu, 1993) using the R package `domir` (Luchman, 2024). Dominance analysis assesses the importance of correlates by computing decreases in model R^2 values due to their exclusion, a value known as dominance. We calculated model-wise dominance of correlates and averaged these across all outcomes, to obtain a measure of overall importance, as well as separately for the four combinations of time of week and trimester.

2.6. Further analysis

With our main analysis focused on mobility based on time, as an additional analysis we selected and evaluated correlates of mobility based on distance (see Section 1 in the Supplementary Materials for variable descriptions). While travel distance and travel time are obviously related, some correlates may primarily relate to how far people travel while others to how long the trips take.

3. Results

3.1. Descriptive statistics

In total, 860 participants and 1,276 measurement periods (651 in T_1, 625 in T_3) were included in the analysis. The median age among participants was 34. They were mostly highly educated (72 % obtained a university degree) and of European origin (77 %). Compared with women aged 30–39 in Barcelona (Table S1), this represents a substantially higher proportion with university education (58 % in the city). Participants also reported European ethnic origin slightly more often than the proportion of women with European nationality (72 %) or born in Europe (62 %) in the city, although these administrative indicators are not directly equivalent to self-reported ethnic origin. The COVID-19 pandemic overlapped with 48 % of the measurements. Medians and IQRs of the outcome variables are shown in Table 1. During weekdays, median daily minutes travelled across both trimesters were 68.0, with a median of 19.0 min travelled with passive modes and 42.8 min with active modes. During weekends, median daily minutes travelled were 63.5, with a median of 18.3 min travelled with passive modes and 34.5 min with active modes. Descriptive statistics of all correlates are shown in Table 2 (see also Supplementary Fig. S1 and S2 for correlation matrices).

3.2. Correlates of weekday mobility

Five of the eight weekday mobility models had a correlate excluded due to multicollinearity (Table S3). We discovered one case of severe multicollinearity, between the street network's closeness centrality at 1.5 and 5 km radii as correlates of active travel time in T_3. Walkability within a 500 m radius was excluded in two models (passive travel time in T_1 and the active travel ratio in T_1), being collinear with the building area within a 300 m radius.

3.2.1. Total travel time

Fig. 1 shows forest plots of the correlates of weekday mobility behaviour (see also the Supplementary Table S4). In T_1, daily total travel time was positively associated with commuting distance to work (β = 11.6 min [4.33, 18.8]; square brackets indicate 95 % confidence intervals throughout) and negatively with non-European ethnic origin (β = −14.8 [−22.7, −6.9]) and COVID-19 (β = −7.5 [−14.6, −0.5]). In T_3, associations remained for non-European ethnic origin (β = −14.1 [−23.5, −4.6]) and COVID-19 (β = −10.1 [−17.4, −2.7]) but not for commuting distance.

3.2.2. Passive travel time

Some correlates of total travel time in T_1 were also correlates of passive travel time, including commuting distance (β = 14.9 [10.9, 18.8]) and COVID-19 (β = −6.4 [−10.2, −2.5]). Additionally, passive travel time in T_1 was negatively associated with building area within 300 m (β = −6.4 [−9.9, −2.9]) and 5 km closeness centrality (β = −6.1 [−9.9, −2.3]). In T_3, negative associations with passive travel time were found for several physical environment correlates, including 1.5 km closeness centrality (β = −7.8 [−12.6, −3.1]), urban greenspace within 500 m (β = −6.7 [−10.7, −2.7]), walkability within 500 m (β = −4.9 [−10.2, −0.4]), and building area within 100 m (β = −5.2 [−8.1, −2.3]).

3.2.3. Active travel time

Just as for total travel time, non-European ethnic origin was a

Table 1
Summary statistics (median values with Q1 and Q3 in brackets) of the mobility-based outcome variables.

Variable	Weekdays Total N = 1,279	T_1 n = 651	T_3 n = 628	Weekends Total N = 1,279	T_1 n = 651	T_3 n = 628
Daily travel time (min)	68.0 (42.5, 95.3)	70.8 (45.1, 97.9)	65.1 (39.7, 91.9)	63.5 (33.3, 101)	67.0 (37.0, 110)	59.0 (29.0, 94.6)
Daily passive travel time (min)	19.0 (5.8, 37.9)	21.7 (6.9, 41.4)	16.9 (4.9, 33.4)	18.3 (2.1, 42.5)	18.6 (2.4, 42.7)	17.8 (2.0, 42.1)
Daily active travel time (min)	42.8 (23.6, 64.0)	42.9 (24.5, 64.1)	42.8 (23.0, 63.6)	34.5 (15.0, 63.5)	36.2 (17.6, 67.0)	32.2 (13.3, 56.9)
Active travel time ratio (%)	69 (48, 87)	68 (46, 86)	71 (52, 88)	63 (35, 88)	65 (37, 89)	60 (33, 88)

correlate of less active travel time, in T_1 (β = −13.5 [−19.6, −7.4]) and T_3 (β = −15.2 [−21.9, −8.4]). A positive association was found for area-level education in T_1 (β = 5.3 [2.0, 8.7]). In T_3, active travel was positively associated with stay-at-home occupational status (β = 7.8 [2.5, 13.1]), having a university degree (β = 7.6 [0.9, 14.3]) and 5 km closeness centrality (β = 10.0 [5.1, 14.9]), and negatively with COVID-19 (β = −6.3 [−11.7, −1.0]).

3.2.4. Active travel ratio

The active travel ratio in T_1 was negatively associated with commuting distance ($e^β$ = 0.49 [0.36, 0.68]) and positively with having a university degree ($e^β$ = 1.60 [1.13, 2.26]), building area within 300 m ($e^β$ = 1.85 [1.32, 2.59]), total greenspace within 300 m ($e^β$ = 1.45 [1.14, 1.85]), and COVID-19 ($e^β$ = 1.72 [1.26, 2.35]). In T_3, the active travel ratio was positively associated with age ($e^β$ = 1.26 [1.06, 1.50]) and walkability within 500 m ($e^β$ = 2.09 [1.64, 2.65]).

3.3. Correlates of weekend mobility

Three of the eight weekend mobility models had a correlate excluded due to multicollinearity (Supplementary Table S5). We discovered severe multicollinearity between the population density at 300 and 500 m radii as correlates of total travel time and active travel time in T_3, between greenness within 300 and 500 m radii as correlates of active travel time in T_3, and between building area within 300 and 500 m radii as correlates of active travel time in T_3.

3.3.1. Total travel time

Fig. 2 shows forest plots of the correlates of weekend mobility behaviour (see also Supplementary Table S6). In T_1, total travel time was positively associated with area-level education (β = 25.4 [16.0, 34.9]) and feeling unsafe in the neighbourhood (β = 22.4 [6.5, 38.2]), and negatively with non-European ethnic origin (β = −17.9 [−28.9, −6.9]), having financial difficulties (β = −13.9 [−24.8, −3.0]), parity > 0 (β = −10.7 [−19.7, −1.8]), and building area within 100 m (β = −15.1 [−22.5, −7.6]). In T_3, the associations remained for non-European ethnic origin (β = −13.7 [−24.0, −3.4]) and parity > 0 (β = −10.8 [−19.5, −2.1]). A positive association was found for building height within 500 m (β = 15.8 [4.8, 26.8]) and a negative association for population density within 500 m (β = 14.2 [−23.6, −4.8]).

3.3.2. Passive travel time

Passive weekend travel in T_1 was negatively associated with stay-at-home work status (β = −14.0 [−22.0, −6.0]), having financial difficulties (β = −9.8 [−16.5, −3.1]), and COVID-19 (β = −11.8 [−17.8, −5.7]). In T_3, passive weekend travel was negatively associated with building area within 100 m (β = −6.6—10.5, −2.6) and greenness within 300 m (β = −5.3 [−8.4, −2.2]), and positively with the warm season (β = 7.2 [2.1, 12.3]).

3.3.3. Active travel time

Just as for total travel time, non-European ethnic origin was a correlate of less active travel time in T_1 (β = −15.8 [−23.3, −8.2]) and T_3 (β = −7.2 [−14.4, 0.0]). Also reflecting total travel time, active travel

Table 2
Summary statistics of independent variables used for correlate selection (48 in total). For categorical variables, values indicate the number and percentage belonging to each category, while for continuous variables they indicate median, Q1 and Q3.

Variable	N = 1,279	Variable	N = 1,279
Personal characteristics		**Urban physical environment**	
Age	34.0 (32.0, 37.0)	Building area, ha (100 m)	1.69 (1.32, 2.00)
University degree		Building area, ha (300 m)	13.8 (10.9, 16.1)
No	361 (28.3 %)	Building area, ha (500 m)	36.1 (28.6, 43.4)
Yes	915 (71.7 %)	Avg. building height, m (100 m)	24.9 (21.3, 29.2)
European ethnic origin		Avg. building height, m (300 m)	24.8 (21.2, 28.1)
Yes	983 (77.0 %)	Avg. building height, m (500 m)	24.9 (20.9, 27.7)
No	293 (23.0 %)	Population (100 m)	1,367 (1,091, 1,685)
Parity > 0		Population (300 m)	11,303 (8,344, 13,636)
No	775 (60.7 %)	Population (500 m)	28,964 (20,812, 35,182)
Yes	501 (39.3 %)	Greenness, avg. NDVI (100 m)	0.204 (0.174, 0.236)
Stay-at-home work status		Greenness, avg. NDVI (300 m)	0.216 (0.190, 0.237)
No	831 (65.1 %)	Greenness, avg. NDVI (500 m)	0.218 (0.198, 0.240)
Yes	445 (34.9 %)	Total greenspace, share (100 m)	0.025 (0.000, 0.101)
Financial difficulties (self-rated)		Total greenspace, share (300 m)	0.066 (0.032, 0.149)
No	870 (68.2 %)	Total greenspace, share (500 m)	0.090 (0.046, 0.179)
Yes	406 (31.8 %)	Urban greenspace, share (100 m)	0.017 (0.000, 0.084)
Poor general health (self-rated)		Urban greenspace, share (300 m)	0.060 (0.029, 0.134)
No	1,041 (81.6 %)	Urban greenspace, share (500 m)	0.080 (0.042, 0.19)
Yes	235 (18.4 %)	Natural greenspace, share (100 m)	0.000 (0.000, 0.000)
Poor recent health (self-rated)		Natural greenspace, share (300 m)	0.000 (0.000, 0.007)
No	1,025 (80.3 %)	Natural greenspace, share (500 m)	0.002 (0.000, 0.019)
Yes	251 (19.7 %)	Distance to greenspace, m	76 (40, 132)
Commuting distance, km	0.0 (0.0, 8.4)	Dist. to major greenspace, m	141 (66, 251)
Social environment		Distance to blue space, m	650 (429, 848)
Feeling unsafe in the neighbourhood		Dist. to major blue space, m	2,541 (1,943, 3,162)
No	1,166 (91.4 %)	Walkability (overlapping cell)	1.79 (1.63, 1.99)
Yes	110 (8.6 %)	Walkability (300 m)	1.73 (1.50, 1.86)
Area hh income, EUR/year	46,691 (42,425, 53,280)	Walkability (500 m)	1.67 (1.43, 1.86)
Area poverty rate	0.136 (0.107, 0.165)	Betweenness, 10^3 (1.5 km radius)	35.6 (21.0, 54.9)
Area education rate	0.461 (0.372, 0.545)	Closeness (1.5 km radius)	616 (417, 737)
Area unemployment rate	0.104 (0.090, 0.122)	Betweenness, 10^6 (5.0 km radius)	1.08 (0.42, 2.14)
Temporal factors		Closeness (1.5 km radius)	4,008 (2,283, 4,882)
Season			
Cold	652 (51.1 %)		
Warm	624 (48.9 %)		
During COVID-19			
No	664 (52.0 %)		
Yes	612 (48.0 %)		

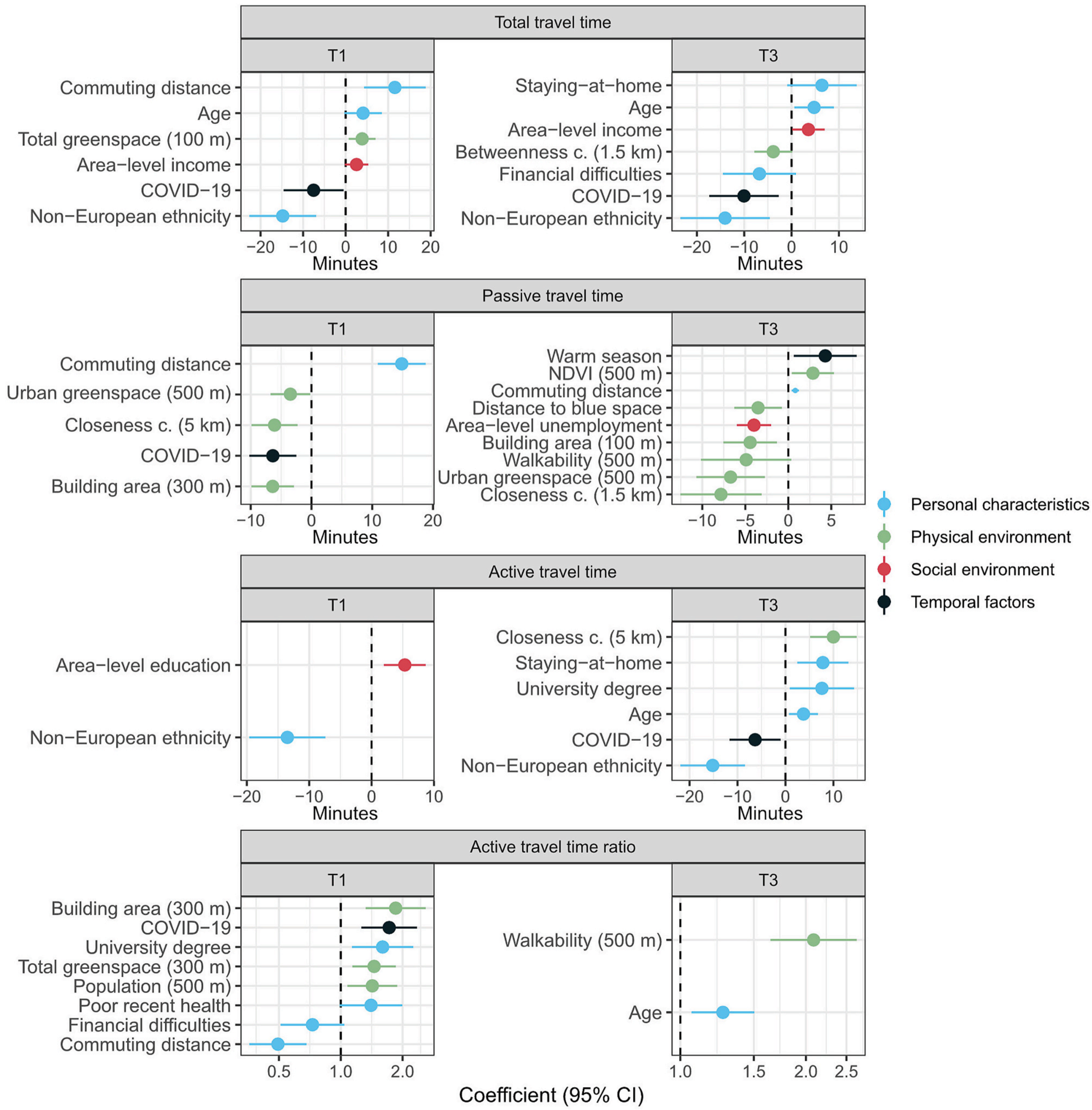

Fig. 1. Forest plots of correlates of weekday mobility behaviour in the first and third trimesters. All continuous correlates were median-centred and scaled so the IQR was 1, meaning that coefficients represent the difference between typical low and high values within the sample distribution.

time in T_1 was positively associated with feeling unsafe in the neighbourhood ($\beta = 14.6$ [3.1, 26.0]) and negatively with area-level education ($\beta = 7.8$ [2.9, 12.7]) and building area within 100 m ($\beta = -9.2$ [−14.4, −4.1]). We furthermore found a positive association with 1.5 km closeness centrality ($\beta = 12.3$ [5.1, 19.6]). Correlates of active travel time in T_3 were similar to those for total travel time, including a positive association with building height within 500 m ($\beta = 10.0$ [4.4, 15.6]) and a negative association with population within 500 m ($\beta = -9.1$ [−15.2, −3.1]). A positive association was found for having a university degree ($\beta = 10.1$ [3.1, 17.1]).

3.3.4. Active travel ratio

Similar to weekdays, the weekend active travel ratio in T_1 was positively associated with total greenspace within 300 m ($e^{\beta} = 1.70$ [1.20, 2.42]), building area within 300 m ($e^{\beta} = 2.17$ [1.34, 3.51]) and COVID-19 ($e^{\beta} = 1.82$ [1.20, 2.76]). We found a positive association with 1.5 km closeness centrality ($e^{\beta} = 2.45$ [1.45, 4.14]) and a negative with building height within 500 m ($e^{\beta} = 0.50$ [0.31, 0.81]). In T_3, the active travel ratio was positively associated with area-level education ($e^{\beta} = 2.81$ [1.86, 4.25]) and negatively with area-level income ($e^{\beta} = 0.72$ [0.55, 0.95]).

3.4. Ranking of correlates

The correlate with the overall highest importance across all dimensions of mobility behaviour was non-European ethnic origin (mean dominance (MD) = 0.0135) (Fig. 3), followed by commuting distance (MD = 0.0103), area-level education (MD = 0.0073), COVID-19 (MD = 0.0072) and having a university degree (MD = 0.0051). In terms of the physical environment, the importance was distributed across many

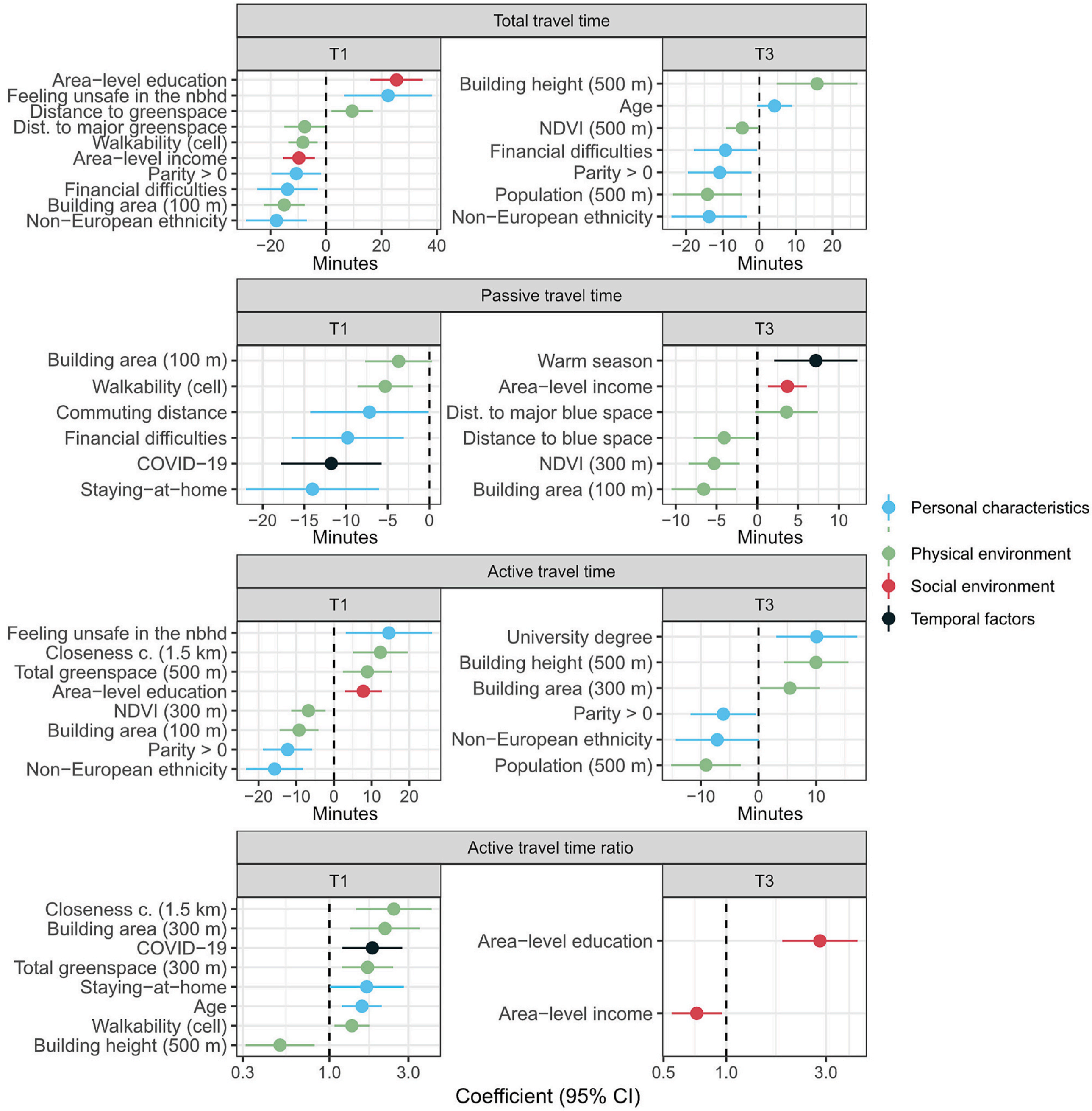

Fig. 2. Forest plots of correlates of weekend mobility behaviour in the first and third trimesters. All continuous correlates were median-centred and scaled so the IQR was 1, meaning that coefficients represent the difference between typical low and high values within the sample distribution.

correlates, with the most important one being walkability within 500 m (MD = 0.0046). Some groups of related correlates achieved importance on par with the most influential individual correlates (Fig. 3, inset): the street network and walkability (five correlates; MD = 0.0135), the social environment (four correlates; MD = 0.0121), and area and height of buildings (three correlates; MD = 0.0108).

Disaggregation by time of week and trimester revealed that non-European ethnic origin was consistently important across weekdays and weekends in both trimesters (Fig. 4a). Commuting distance, however, was most important during weekdays in T_1 (MD = 0.0358). The COVID-19 pandemic was likewise more important in T_1, primarily during weekdays (MD = 0.0159) but also weekends (MD = 0.0077). On the other hand, having a university degree was more important in T_3, both during weekdays (MD = 0.0100) and weekends (MD = 0.0073). Area-level education was important across both trimesters but mostly during weekends (T_1: MD = 0.0123; T_3: MD = 0.0120). Overall, personal characteristics were less important in T_3 (MD = 0.0364) compared with T_1 (MD = 0.0511) (Fig. 4b), which comes down almost exclusively to the waning importance of commuting distance. The residential physical environment on the contrary increased in importance later in pregnancy (T_1:MD = 0.0311; T_3: MD = 0.0348).

3.5. *Further analysis*

Distance-based mobility variables were strongly correlated with the time-based ones, with Spearman's rank correlations ranging roughly 0.75–0.95 (Table S8). Using distance-based mobility variables produced results that were largely consistent with the main analysis based on time (Supplementary Materials Section 5). Personal characteristics, the social environment, and temporal factors showed similar patterns across both

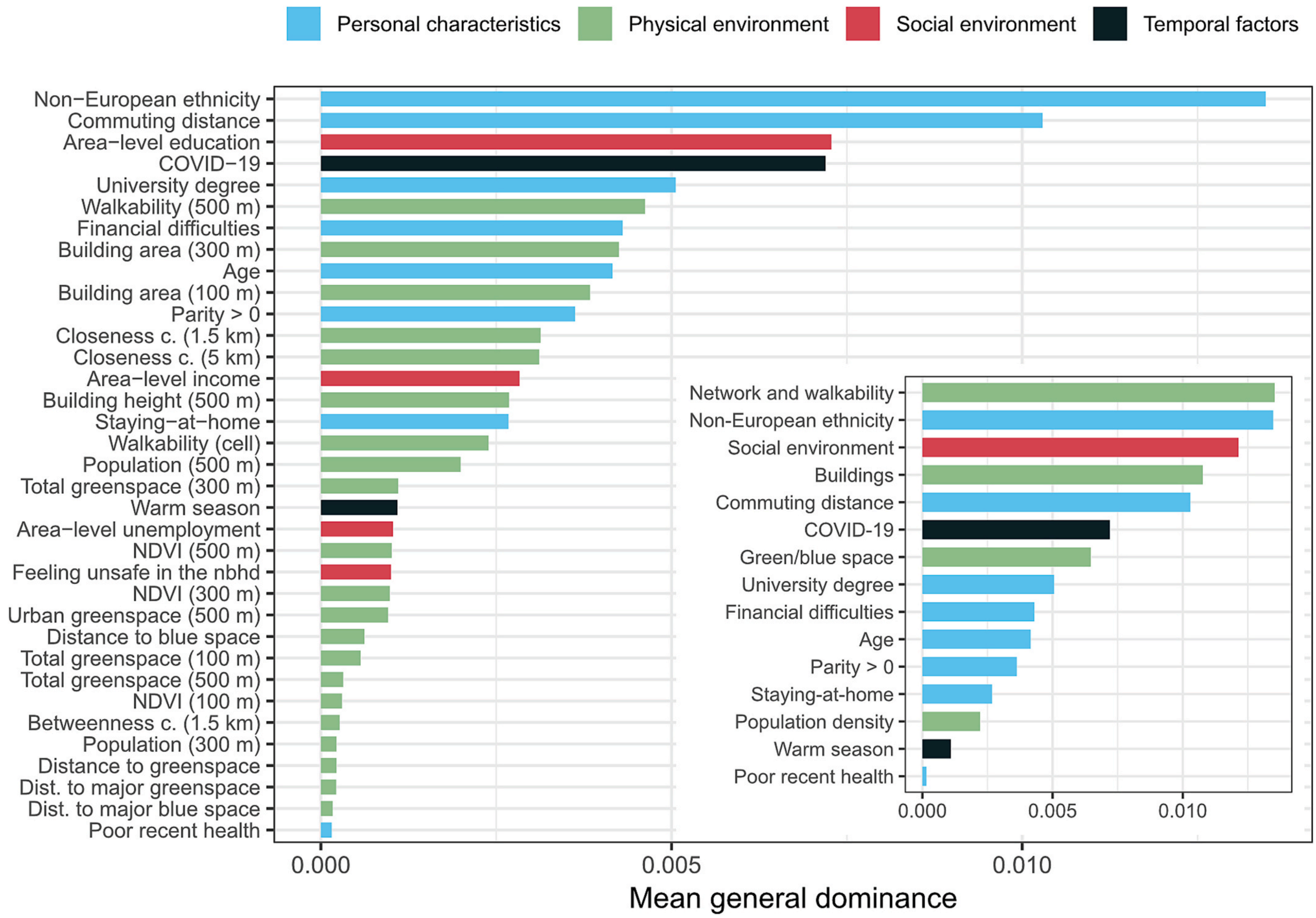

Fig. 3. Correlates ranked for mean dominance across both trimesters. The inset displays values for groupings of correlates: street network and walkability (five correlates), social environment (four correlates), buildings (three correlates), green/blue space (eleven correlates), and population density (two correlates).

analyses. Non-European ethnicity remained as the most important correlate, and commuting distance, area-level education, COVID-19, and having a university degree were all additionally important ones. However, associations for physical environment correlates were generally somewhat attenuated, though still statistically significant. For example, the combined importance of street network and walkability correlates were roughly halved, while that of building area and height was reduced to about one third of the main analysis. On the other hand, population density correlates roughly doubled in importance.

4. Discussion

In this study, we used smartphone tracking data from a large population-based birth cohort to identify the correlates of pregnant women's mobility behaviour. Our results offer detailed insights into the travel behaviour of a population that has not been extensively studied in transport research. The correlates were selected among 48 candidate variables by a robust data-driven feature selection approach. This comprehensive evaluation showed that pregnant women's mobility is a multifaceted phenomenon that is not reflected in any single correlate or even any group of correlates. On the contrary, the wide range of correlates spanned from personal characteristics to the physical environment, the social environment and temporal factors.

In our sample, median weekday travel times were 43 min for active travel and 19 min for passive travel. For comparison, data from the Barcelona Metropolitan Transport Authority (Àrea Metropolitana de Barcelona, 2021) indicate that in 2020 women in the city tended to spend roughly equal amounts of time, around 30–35 min per day, in active and passive travel. This suggests that participants in our study may have been somewhat more active and spent less time in passive transport than women in Barcelona overall.

4.1. Personal correlates

The single most important correlate across all of pregnancy was ethnic origin. Non-European ethnic origin was associated with on average 10–15 min less daily active travel, a pattern consistent across weekdays and weekends, and during both early and late pregnancy. Following this finding, we examined personal characteristics disaggregated by ethnic origin (Table S9) and found that individuals of non-European origin were more likely to lack a university degree, experience financial difficulties, and have stay-at-home work status. However, independent associations for ethnic origin remained despite adjustment for socioeconomic variables, a wide range of neighbourhood characteristics, work situation, health status, and perceived safety, suggesting that ethnic origin contributes additional information beyond these factors. Ethic origin could covary with some potentially relevant environmental features that we did not account for, including proximity to recreational or service destinations and the quality or pleasantness of active travel infrastructure. Alternatively, the association may reflect cultural or social norms that shape travel behaviour. Importantly, such norms could also shape how individuals interpret and respond to survey

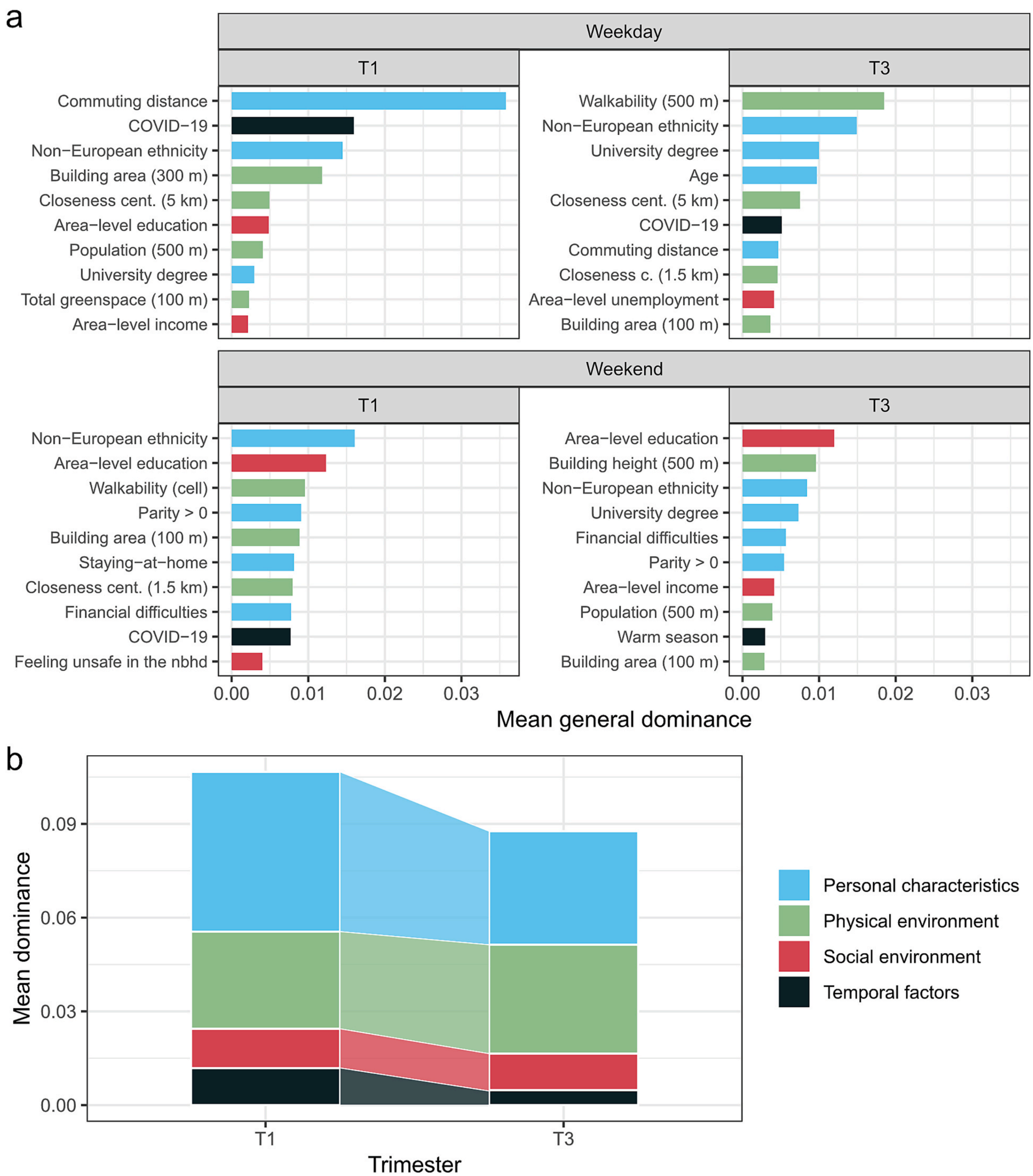

Fig. 4. a) correlates ranked for dominance disaggregated by time of week and trimester. the 10 most important correlates for each time of week-trimester combination are shown. for the full set of correlates, see SI Section 4. b) Dominance of correlate groups in T_1 and T_3.

items, including questions on perceived health status and neighbourhood safety.

Possession of a university degree was on its own an important correlate, especially in T_3 when it was associated with around 5–10 min more per day spent on active travel. Our results are in agreement with prior US studies indicating that ethnic minorities and those without higher education engage in less active travel (Agrawal and Schimek, 2007; Buehler et al., 2020). An Australian study similarly found a positive association between education and leisure time walking among women, after accounting for environmental correlates (Ball et al., 2007). However, in direct contrast to ours, a UK study found a negative relationship between educational attainment and active travel among women, and furthermore no indication of ethnicity playing a decisive role (Fluharty et al., 2020). In addition, Yi et al. (2022) found that among low-income Hispanic women in the US, university education was not associated with pedestrian travel but positively with vehicular travel. It should be noted that no prior study accounted for as many potential correlates as we did here, which is important due to confounding between personal correlates such as education, work status, and wealth.

With ethnic origin and education emerging as some of the most important correlates of mobility in pregnancy, mobility support may benefit from a community-based healthcare approach. As Riza et al. note, effective community interventions require attention to communication, language, and cultural differences (Riza et al., 2020), which are likely central to addressing these mobility disparities.

Commuting distance to work was the most important of all correlates in T_1, when it was associated with more passive travel. With prior findings linking passive commuting to stress among pregnant women (O'Toole and Christie, 2022; Wang and Yang, 2019), reducing passive commuting in early pregnancy, e.g., by working from home, might be beneficial for avoiding stressors. Since commuting distance was not associated with active travel, we found no evidence to suggest that skipping the commute would reduce opportunities for women to stay active during pregnancy. In fact, the positive association between staying-at-home work status and active travel in late pregnancy could be taken to suggest the opposite.

4.2. Physical environment correlates

While the importance of commuting distance decreased in late pregnancy, the opposite is the case for the physical residential environment. This is likely because the participants increasingly spent more time at or close to home (Samuelsson et al., 2025). The most important physical environment correlates were street network and walkability variables. In T_3, a higher closeness centrality at the home location was linked to less passive and more active travel, in line with research showing that closeness centrality in locations is closely correlated with their pedestrian volumes (Hillier et al., 1993; Kang, 2015). We furthermore found that walkability was positively related to the active travel ratio in T_3, in agreement with a previous US study of pregnant women's physical activity (Porter et al., 2019).

The area and height of buildings constituted another important correlate group. Our results suggested that a higher built density around the home promotes less passive weekday travel primarily in early pregnancy. This could be because living in high-density areas entails a higher likelihood of working within a distance from home suitable for active travel (Yan et al., 2022). Furthermore, more active travel and/or less passive travel was in several models predicted by greenspace area and/or greenness, in line with a *meta*-analysis of the general population (Deng et al., 2023) as well as a Colombian study on physical activity in pregnancy (López-Gil et al., 2022).

Taken together, our results indicate that urban forms characterised by dense, decentralized street layouts with many intersections, that are known to promote walking generally (Gascon et al., 2019), can be beneficial for pregnant women staying active. Furthermore, the results support the notion that dense and green environments should be mixed on the neighbourhood scale traversable by active travel (Samuelsson, 2021). This underscores the importance of providing walkable, green, and well-connected neighbourhoods equitably, so that health-promoting mobility helps to reduce rather than exacerbate inequities in maternal health.

4.3. Social environment correlates

Area-level education was one of the most important correlates, predicting more active travel, in line with a French study of women's active commuting (Perchoux et al., 2017). At first glance, it could appear surprising that area-level variables are selected as correlates over individual-level ones if they measure the same characteristic, and especially if physical environment correlates of the area-level variable are accounted for. These findings could point towards the role of "soft" contextual effects such as local cultural norms and social influence (Galster, 2011). While social and cultural norms are emergent bottom-up phenomena, they matter for planning because the effects of physical or social interventions could potentially be amplified through social contagion, as has been suggested in simulations of travel behaviour (Kaaronen and Strelkovskii, 2020). Perceived neighbourhood safety, while an important factor in planning for social sustainability in neighbourhoods, appeared only of limited importance in our study. This might be because relatively few of our participants (8.6 %) reported feeling unsafe in their neighbourhoods.

As a note regarding the need to account for potential confounding between related correlates, we found generally opposing relationships for area-level education and area-level income. This indicates that using overall area deprivation indices could risk masking opposite associations among the different variables composing such indices.

4.4. The COVID-19 pandemic

Although the pandemic was one of the more important correlates of mobility, our results indicate that it did not radically alter travel behaviour. Although, our data did not cover the period from mid-March to early June 2020 when strict lockdown measures were implemented in Spain and, as a result, the data collection in the BiSC cohort was suspended. By excluding the strict lockdown period, when mobility was shaped almost entirely by external restrictions rather than personal behaviour, our results instead capture the longer-term adaptations to the evolving pandemic context over the fifteen months following June 2020. A study on post-lockdown changes of spatiotemporal mobility in the UK documented a gradual six-month recovery to pre-lockdown levels (Santana et al., 2023). It is possible that a similar dynamic was at play among our participants, which could account for the relatively small overall effect of COVID-19. The pandemic entailed a similar reduction in total weekday travel time, about 6 min per day, when comparing T_1 and T_3. In T_1, the reduction was reflected in reduced passive travel, in line with a general shift away from public transport and towards active travel in the wake of the pandemic (Paul et al., 2022), suggesting that our finding reflects a broader behavioural response and may extend to pregnant populations elsewhere. However, in T_3, the reduction was due to less active travel. With the women spending more time at or close to home in late pregnancy (Samuelsson et al., 2025), they might during COVID-19 have been more reluctant to undertake short local trips due to fear of infection. This association may be particularly pronounced in a city like Barcelona, which has comparatively high residential densities, while similar pandemic-related reductions in active travel may not be observed among pregnant women in lower-density settings. As for weekend travel, we found in T_1 a reduction in passive travel of about 12 min per day during the COVID-19 post-lockdown period, which could reflect a reduced propensity for taking trips outside the city. Overall, the effects of the pandemic were greater in T_1 than in T_3, likely because mobility shifted in late pregnancy already in pre-pandemic times (Samuelsson et al., 2025).

4.5. Strengths and limitations

In this study, we addressed some general shortcomings of the literature on mobility correlates. First, while data on objectively measured space–time activity patterns is becoming increasingly common, past mobility studies have most often relied on self-reported data from travel diaries or surveys. In contrast, we used GPS data from identical smartphone models to ensure consistent data quality. Second, with most past studies focusing on one or a few correlates, we contributed with a comprehensive and systematic evaluation of the relative importance of correlates spanning different categories. Our results highlight the breadth of factors associated with mobility, with correlates arising from multiple domains. Third, most studies did not explicitly differentiate between weekday and weekend mobility. The same individual's weekday and weekend mobility can be substantially different (Raux et al., 2016; Shao et al., 2019; Samuelsson et al., 2025; Wei et al., 2023), and, as we demonstrate herein, have different correlates.

Moreover, our study contributes knowledge about pregnant women's mobility by identifying several important correlates that were to our knowledge not previously reported, including area-level education, the COVID-19 pandemic and the area and height of buildings around the residence. Furthermore, we draw on a rich material of GPS tracking data from a large birth cohort (860 participants). In a previous study, we found that the GPS sequences generally captured the majority of participants' waking hours (Samuelsson et al., 2025), suggesting that the data provide a reliable representation of daily mobility patterns. Data collection campaigns in early and late pregnancy enabled identifying correlates at these respective pregnancy stages.

One week of GPS data is arguably sufficient for characterising daily mobility (Stanley et al., 2018), although some authors recommend two weeks (Zenk et al., 2018). Furthermore, it should be noted that two timepoints of data collection precludes a detailed understanding of how the correlates change over the course of pregnancy. For variables that were correlates in one trimester but not the other, we were unable to determine if their importance changed gradually or if there were windows of more abrupt change. This limits our ability to relate mobility changes to physiological or social changes across pregnancy and to distinguish groups of women with different trajectories. While our findings provide input for interventions to promote health-promoting mobility, studies with greater temporal resolution would allow further refinement related to the targeting and timing of such interventions.

We assessed only the environment around the home as a correlate of mobility, without considering the environments encountered along travel routes. The en-route environment may function as a correlate of mobility patterns or alternatively as an outcome of them and disentangling such relationships would require a different study design.

While our set of correlates was broad and covered multiple relevant domains, we were unable to include all potentially important factors. For example, elevation and proximity to public transport have been identified in previous studies as relevant to active mobility (Cole-Hunter et al., 2015; Gascon et al., 2019).

We aimed to identify not only which correlates matter for pregnant women's mobility but also how. For this reason, we limited the DSA algorithm's correlate search to at most 10 independent variable variables and excluded interactions and second order effects, allowing us to illustrate associations using standard forest plots. A study focused on prediction over interpretation of the associations themselves could have included variable interactions and non-linear relationships. We chose to exclude such relationships to avoid overly complex models and ensure interpretability.

Our study was designed to evaluate correlates of *mobility within pregnancy* without inclusion of a comparison group of non-pregnant women; therefore, we cannot determine whether the observed associations are unique to pregnancy or also present among women in general.

5. Conclusions

We comprehensively studied a wide range of correlates of maternal mobility patterns during early and late pregnancy using objective tracking data in a population-based cohort in Barcelona, Spain. We found that throughout pregnancy, non-European ethnic origin was associated with less active travel. Area-level education and street network closeness centrality were associated with more active travel, while both more building area and more greenspace around the residence were associated with less passive travel. Particularly in early pregnancy, a longer commuting distance was associated with more passive travel, while the COVID-19 pandemic was associated with less passive travel. Particularly in late pregnancy, the COVID-19 pandemic was instead negatively associated with active travel, while having a university degree and building height around the residence were positively associated with active travel, and residential walkability was negatively associated with passive travel.

Our results suggest important considerations both at the level of individuals and the urban environment when planning for healthy pregnancies and pregnancy outcomes from a mobility perspective. At the individual level, those of ethnic minority origin and/or without university education constitute groups that should be targeted in efforts to have women stay active throughout their pregnancies. Regarding the urban environment, the results suggest benefits with residential environments with decentralized street layouts, and where a dense built environment and presence of greenspace are combined within neighbourhoods. While achieving this balance poses design challenges, it could offer important co-benefits, including reduced risks of adverse birth outcomes from exposure to air pollution (Nyadanu et al., 2022). Reallocating space away from cars may facilitate a more effective balance between urban density, greenspace, and infrastructure that supports active mobility, thereby contributing to healthier pregnancies.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT (GPT-4o and GPT-5, OpenAI) to improve already drafted text both grammatically and communicatively. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Funding statement

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). 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.

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. **Marta Cirach:** Formal analysis, Data curation. **Bruno Raimbault:** Writing – review & editing, Formal analysis, Data curation. **Alan Domínguez:** Writing – review & editing. **Yu Zhao:** Writing – review & editing. **Toni Galmés:** Formal analysis. **Antònia Valentin:** Writing – review & editing, Methodology, Formal analysis. **Maria Foraster:** Investigation. **Mireia Gascon:** Writing – review & editing, Investigation. **Cecilia Persavento:** Investigation. **Maria Dolores Gomez Roig:** Resources. **Elisa Llurba Olivé:** Resources. **Efstathios Boukouras:** Writing – review & editing. **Oriol Marquet:** Formal analysis, Data curation. **Monika Maciejewska:** Formal analysis, Data curation. **Mark J. Nieuwenhuijsen:** Writing – review & editing. **Xavier Basagaña:** Writing – review & editing, Methodology. **Jordi Sunyer:** Supervision, Funding acquisition. **Achilleas Psyllidis:** Writing – review & editing. **Marco Helbich:** Writing – review & editing. **Payam Dadvand:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tbs.2025.101196.

References

Agier, L., Portengen, L., Chadeau-Hyam, M., Basagaña, X., Giorgis-Allemand, L., Siroux, V., Robinson, O., Vlaanderen, J., González, J.R., Nieuwenhuijsen, M.J., Vineis, P., Vrijheid, M., Slama, R., Vermeulen, R., 2016. A systematic comparison of linear regression–based statistical methods to assess exposome-health associations. Environ. Health Perspect. 124, 1848–1856. https://doi.org/10.1289/EHP172.

Agrawal, A.W., Schimek, P., 2007. Extent and correlates of walking in the USA. Transp. Res. Part Transp. Environ. 12, 548–563. https://doi.org/10.1016/j.trd.2007.07.005.

Ajuntament de Barcelona, 2024. Consulta les dades bàsiques de mobilitat de Barcelona [WWW Document]. URL https://dades.ajuntament.barcelona.cat/dades-basiques-de-mobilitat/ (accessed 5.15.24).

Àrea Metropolitana de Barcelona, 2021. Enquesta de mobilitat en dia feiner 2020: La mobilitat a l'àmbit de l'Àrea Metropolitana de Barcelona. https://www.iermb.uab.cat/ca/projecte/enquesta-de-mobilitat-en-dia-feiner-emeff/ (accessed 9.11.25).

Aune, D., Schlesinger, S., Henriksen, T., Saugstad, O., Tonstad, S., 2017. Physical activity and the risk of preterm birth: a systematic review and meta-analysis of epidemiological studies. BJOG Int. J. Obstet. Gynaecol. 124, 1816–1826. https://doi.org/10.1111/1471-0528.14672.

Azen, R., Budescu, D.V., 2003. The dominance analysis approach for comparing predictors in multiple regression. Psychol. Methods 8, 129–148. https://doi.org/10.1037/1082-989X.8.2.129.

Ball, K., Timperio, A., Salmon, J., Giles-Corti, B., Roberts, R., Crawford, D., 2007. Personal, social and environmental determinants of educational inequalities in walking: a multilevel study. J. Epidemiol. Community Health 61, 108–114. https://doi.org/10.1136/jech.2006.048520.

Barrera-Gómez, J., Agier, L., Portengen, L., Chadeau-Hyam, M., Giorgis-Allemand, L., Siroux, V., Robinson, O., Vlaanderen, J., González, J.R., Nieuwenhuijsen, M., Vineis, P., Vrijheid, M., Vermeulen, R., Slama, R., Basagaña, X., 2017. A systematic comparison of statistical methods to detect interactions in exposome-health associations. Environ. Health 16, 74. https://doi.org/10.1186/s12940-017-0277-6.

Brondeel, R., Pannier, B., Chaix, B., 2016. Associations of socioeconomic status with transport-related physical activity: combining a household travel survey and accelerometer data using random forests. J. Transp. Health 3, 287–296. https://doi.org/10.1016/j.jth.2016.06.002.

Budescu, D.V., 1993. Dominance analysis: a new approach to the problem of relative importance of predictors in multiple regression. Psychol. Bull. 114, 542–551.

Buehler, R., Pucher, J., Bauman, A., 2020. Physical activity from walking and cycling for daily travel in the United States, 2001–2017: Demographic, socioeconomic, and geographic variation. J. Transp. Health 16, 100811. https://doi.org/10.1016/j.jth.2019.100811.

Burnham, K.P., Anderson, D.R., 2004. Multimodel inference: understanding AIC and BIC in model selection. Sociol. Methods Res. 33, 261–304. https://doi.org/10.1177/0049124104268644.

Cervero, R., Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. Transp. Res. Part Transp. Environ. 2, 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6.

Chasan-Taber, L., Silveira, M., Pekow, P., Braun, B., Manson, J.E., Solomon, C.G., Markenson, G., 2015. Physical activity, sedentary behavior and risk of hypertensive disorders of pregnancy in Hispanic women. Hypertens. Pregnancy 34, 1–16. https://doi.org/10.3109/10641955.2014.946616.

Cole-Hunter, T., Donaire-Gonzalez, D., Curto, A., Ambros, A., Valentin, A., Garcia-Aymerich, J., Martínez, D., Braun, L.M., Mendez, M., Jerrett, M., Rodriguez, D., De Nazelle, A., Nieuwenhuijsen, M., 2015. Objective correlates and determinants of bicycle commuting propensity in an urban environment. Transp. Res. Part Transp. Environ. 40, 132–143. https://doi.org/10.1016/j.trd.2015.07.004.

Currie, L.M., Woolcott, C.G., Fell, D.B., Armson, B.A., Dodds, L., 2014. The association between physical activity and maternal and neonatal outcomes: a prospective cohort. Matern. Child Health J. 18, 1823–1830. https://doi.org/10.1007/s10995-013-1426-3.

Da Silva, S.G., Ricardo, L.I., Evenson, K.R., Hallal, P.C., 2017. Leisure-time physical activity in pregnancy and maternal-child health: a systematic review and meta-analysis of randomized controlled trials and cohort studies. Sports Med. 47, 295–317. https://doi.org/10.1007/s40279-016-0565-2.

Dadvand, P., Gascon, M., Bustamante, M., Rivas, I., Foraster, M., Basagaña, X., Cosín, M., Eixarch, E., Ferrer, M., Gratacós, E., Gómez Herrera, L., Jimenez-Arenas, P., Júlvez, J., Morillas, À., Nieuwenhuijsen, M.J., Persavento, C., Pujol, J., Querol, X., Sánchez García, O., Vrijheid, M., Llurba, E., Gómez-Roig, M.D., Sunyer, J., Group, B., 2024. Cohort profile: barcelona life study cohort (BiSC). Int. J. Epidemiol. 53, dyae063. https://doi.org/10.1093/ije/dyae063.

Dempsey, F.C., Butler, F.L., Williams, F.A., 2005. No need for a pregnant pause: physical activity may reduce the occurrence of gestational diabetes mellitus and preeclampsia: exerc. Sport Sci. Rev. 33, 141–149. https://doi.org/10.1097/00003677-200507000-00007.

Deng, Y., Liang, J., Chen, Q., 2023. Greenway interventions effectively enhance physical activity levels—A systematic review with meta-analysis. Front. Public Health 11, 1268502. https://doi.org/10.3389/fpubh.2023.1268502.

Dipietro, L., Evenson, K.R., Bloodgood, B., Sprow, K., Troiano, R.P., Piercy, K.L., Vaux-Bjerke, A., Powell, K.E., 2019. Benefits of physical activity during pregnancy and postpartum: an umbrella review. Med. Sci. Sports Exerc. 51, 1292–1302. https://doi.org/10.1249/MSS.0000000000001941.

Donaire-Gonzalez, D., Valentín, A., Van Nunen, E., Curto, A., Rodriguez, A., Fernandez-Nieto, M., Naccarati, A., Tarallo, S., Tsai, M.-Y., Probst-Hensch, N., Vermeulen, R., Hoek, G., Vineis, P., Gulliver, J., Nieuwenhuijsen, M.J., 2019. ExpoApp: An integrated system to assess multiple personal environmental exposures. Environ. Int. 126, 494–503. https://doi.org/10.1016/j.envint.2019.02.054.

Ewing, R., Cervero, R., 2010. Travel and the built environment: a meta-analysis. J. Am. Plann. Assoc. 76, 265–294. https://doi.org/10.1080/01944361003766766.

Fluharty, M.E., Pinto Pereira, S.M., Benzeval, M., Hamer, M., Jefferis, B., Griffiths, L.J., Cooper, R., Bann, D., 2020. Educational differentials in key domains of physical activity by ethnicity, age and sex: a cross-sectional study of over 40 000 participants in the UK household longitudinal study (2013–2015). BMJ Open 10, e033318. https://doi.org/10.1136/bmjopen-2019-033318.

Galster, G.C., 2011. The mechanism(s) of neighbourhood effects: Theory, evidence, and policy implications. In: Neighbourhood Effects Research: New Perspectives. Springer, pp. 23–56.

Gascon, M., Götschi, T., De Nazelle, A., Gracia, E., Ambròs, A., Márquez, S., Marquet, O., Avila-Palencia, I., Brand, C., Iacorossi, F., Raser, E., Gaupp-Berghausen, M., Dons, E., Laeremans, M., Kahlmeier, S., Sánchez, J., Gerike, R., Anaya-Boig, E., Panis, L.I., Nieuwenhuijsen, M., 2019. Correlates of walking for travel in seven European cities: the PASTA project. Environ. Health Perspect. 127, 097003. https://doi.org/10.1289/EHP4603.

Gluckman, P.D., Hanson, M.A., Buklijas, T., 2010. A conceptual framework for the developmental origins of health and disease. J. Dev. Orig. Health Dis. 1, 6–18. https://doi.org/10.1017/S2040174409990171.

Harris, P.A., Taylor, R., Minor, B.L., Elliott, V., Fernandez, M., O'Neal, L., McLeod, L., Delacqua, G., Delacqua, F., Kirby, J., Duda, S.N., 2019. The REDCap consortium: Building an international community of software platform partners. J. Biomed. Inform. 95, 103208. https://doi.org/10.1016/j.jbi.2019.103208.

Harris, P.A., Taylor, R., Thielke, R., Payne, J., Gonzalez, N., Conde, J.G., 2009. Research electronic data capture (REDCap)—A metadata-driven methodology and workflow process for providing translational research informatics support. J. Biomed. Inform. 42, 377–381. https://doi.org/10.1016/j.jbi.2008.08.010.

Hillier, B., Penn, A., Hanson, J., Grajewski, T., Xu, J., 1993. Natural movement: or, configuration and attraction in urban pedestrian movement. Environ. Plan. B Plan. Des. 20, 29–66. https://doi.org/10.1068/b200029.

Idescat, 2025. The municipality in figures. Barcelona (Barcelonès) [WWW Document]. URL https://www.idescat.cat/emex/?lang=en&id=080193 (accessed 4.15.25).

Instituto Nacional de Estadística, 2023. Atlas de Distribución de Renta de los Hogares (ADRH) - Metodología.

Järv, O., Ahas, R., Witlox, F., 2014. Understanding monthly variability in human activity spaces: a twelve-month study using mobile phone call detail records. Transp. Res. Part C Emerg. Technol. 38, 122–135. https://doi.org/10.1016/j.trc.2013.11.003.

Kaaronen, R.O., Strelkovskii, N., 2020. Cultural evolution of sustainable behaviors: pro-environmental tipping points in an agent-based model. One Earth 2, 85–97. https://doi.org/10.1016/j.oneear.2020.01.003.

Kang, C.-D., 2015. The effects of spatial accessibility and centrality to land use on walking in Seoul, Korea. Cities 46, 94–103. https://doi.org/10.1016/j.cities.2015.05.006.

López-Gil, J.F., Izquierdo, M., García-Hermoso, A., Alonso-Martínez, A.M., Rincón-Pabón, D., Morales-Osorio, M.A., Ramírez-Vélez, R., 2022. Factors associated with meeting the WHO physical activity recommendations in pregnant Colombian women. Sci. Rep. 12, 19500. https://doi.org/10.1038/s41598-022-23947-7.

Luchman, J., 2024. domir: Tools to Support Relative Importance Analysis.

Neter, J., Kutner, M.H., Nachtsheim, C.J., Wasserman, W., et al., 2004. Applied Linear Statistical Models, 5th ed. McGraw-Hill/Irwin, New York.

Neugebauer, R., 2016. DSA [WWW Document]. URL https://github.com/romainkp/DS.

Nieuwenhuijsen, M.J., 2020. Urban and transport planning pathways to carbon neutral, liveable and healthy cities; A review of the current evidence. Environ. Int. 140, 105661. https://doi.org/10.1016/j.envint.2020.105661.

Nyadanu, S.D., Dunne, J., Tessema, G.A., Mullins, B., Kumi-Boateng, B., Lee Bell, M., Duko, B., Pereira, G., 2022. Prenatal exposure to ambient air pollution and adverse birth outcomes: An umbrella review of 36 systematic reviews and meta-analyses. Environ. Pollut. 306, 119465. https://doi.org/10.1016/j.envpol.2022.119465.

Olsen, J.R., Mitchell, R., Mutrie, N., Foley, L., Ogilvie, D., 2017. Population levels of, and inequalities in, active travel: A national, cross-sectional study of adults in Scotland. Prev. Med. Rep. 8, 129–134. https://doi.org/10.1016/j.pmedr.2017.09.008.

O'Toole, S.E., Christie, N., 2022. Pregnancy and commuting on public transport. J. Transp. Health 24, 101308. https://doi.org/10.1016/j.jth.2021.101308.

Paul, T., Chakraborty, R., Anwari, N., 2022. Impact of COVID-19 on daily travel behaviour: a literature review. Transp. Saf. Environ. 4, tdac013. https://doi.org/10.1093/tse/tdac013.

Perchoux, C., Nazare, J.-A., Benmarhnia, T., Salze, P., Feuillet, T., Hercberg, S., Hess, F., Menai, M., Weber, C., Charreire, H., Enaux, C., Oppert, J.-M., Simon, C., 2017. Neighborhood educational disparities in active commuting among women: the effect of distance between the place of residence and the place of work/study (an ACTI-Cités study). BMC Public Health 17, 569. https://doi.org/10.1186/s12889-017-4464-8.

Pereira, R.H.M., Schwanen, T., Banister, D., 2017. Distributive justice and equity in transportation. Transp. Rev. 37 (2), 170–191. https://doi.org/10.1080/01441647.2016.1257660.

Pereira, R.H., Karner, A., 2021. Transportation equity. In: Vickerman, R. (Ed.), International Encyclopedia of Transportation, Vol. 1. Elsevier, pp. 271–277. https://doi.org/10.1016/B978-0-08-102671-7.10053-3.

Porter, A.K., Rodríguez, D.A., Frizzelle, B.G., Evenson, K.R., 2019. The association between neighborhood environments and physical activity from pregnancy to postpartum: a prospective cohort study. J. Urban Health 96, 703–719. https://doi.org/10.1007/s11524-019-00376-y.

Preis, H., Mahaffey, B., Pati, S., Heiselman, C., Lobel, M., 2021. Adverse perinatal outcomes predicted by prenatal maternal stress among U.S. women at the COVID-19 pandemic onset. Ann. Behav. Med. 55, 179–191. https://doi.org/10.1093/abm/kaab005.

Rasmussen, T.K., Ingvardson, J.B., Halldórsdóttir, K., Nielsen, O.A., 2015. Improved methods to deduct trip legs and mode from travel surveys using wearable GPS devices: a case study from the Greater Copenhagen area. Comput. Environ. Urban Syst. 54, 301–313. https://doi.org/10.1016/j.compenvurbsys.2015.04.001.

Raux, C., Ma, T.Y., Cornelis, E., 2016. Variability in daily activity-travel patterns: the case of a one-week travel diary. Europ. Transp. Res. Rev. 8 (4), 26. https://doi.org/10.1007/s12544-016-0213-9.

Renninger, D., Kelso, A., Reimers, A.K., Marzi, I., Beck, F., Engels, E.S., Standage, M., Demetriou, Y., 2022. Motivation and active travel in adolescent girls and boys in Germany – Findings from the ARRIVE study. Transp. Res. Part F Traffic Psychol. Behav. 90, 425–437. https://doi.org/10.1016/j.trf.2022.09.015.

Riza, E., Kalkman, S., Coritsidis, A., Koubardas, S., Vassiliu, S., Lazarou, D., Karnaki, P., Zota, D., Kantzanou, M., Psaltopoulou, T., Linos, A., 2020. Community-based healthcare for migrants and refugees: a scoping literature review of best practices. Healthcare 8 (2), 115. https://doi.org/10.3390/healthcare8020115.

Samuelsson, K., 2021. The topodiverse city: urban form for subjective well-being. Front. Built Environ. 7, 735221. https://doi.org/10.3389/fbuil.2021.735221.

Samuelsson, K., Rivas, I., Raimbault, B., Domínguez, A., Galmés, T., Valentin, A., Foraster, M., Gascon, M., Persavento, C., Psyllidis, A., Gomez Roig, M.D., Olivé, E.L., Nieuwenhuijsen, M.J., Helbich, M., Sunyer, J., Dadvand, P., 2025. A comprehensive GPS-based analysis of activity spaces in early and late pregnancy using the ActMAP framework. Health Place 91, 103413. https://doi.org/10.1016/j.healthplace.2025.103413.

Santana, C., Botta, F., Barbosa, H., Privitera, F., Menezes, R., Di Clemente, R., 2023. COVID-19 is linked to changes in the time–space dimension of human mobility. Nat. Hum. Behav. 7, 1729–1739. https://doi.org/10.1038/s41562-023-01660-3.

Santos, S., Maitre, L., Warembourg, C., Agier, L., Richiardi, L., Basagaña, X., Vrijheid, M., 2020. Applying the exposome concept in birth cohort research: a review of statistical approaches. Eur. J. Epidemiol. 35, 193–204. https://doi.org/10.1007/s10654-020-00625-4.

Shao, F., Sui, Y., Yu, X., Sun, R., 2019. Spatio-temporal travel patterns of elderly people–A comparative study based on buses usage in Qingdao. China. J. Transp. Geo. 76, 178–190. https://doi.org/10.1016/j.jtrangeo.2019.04.001.

Skreden, M., Øverby, N.C., Sagedal, L.R., Vistad, I., Torstveit, M.K., Lohne-Seiler, H., Bere, E., 2016. Change in active transportation and weight gain in pregnancy. Int. J. Behav. Nutr. Phys. Act. 13, 10. https://doi.org/10.1186/s12966-016-0332-7.

Skreden, M., Øverby, N.C., Sagedal, L.R., Vistad, I., Torstveit, M.K., Lohne-Seiler, H., Bere, E., 2015. Changes in mode of transportation to work or school from pre-pregnancy to early pregnancy in the Norwegian Fit for Delivery study. Prev. Med. Rep. 2, 429–435. https://doi.org/10.1016/j.pmedr.2015.05.002.

Stanley, K., Yoo, E.-H., Paul, T., Bell, S., 2018. How many days are enough?: capturing routine human mobility. Int. J. Geogr. Inf. Sci. 32, 1485–1504. https://doi.org/10.1080/13658816.2018.1434888.

Tang, R., Tian, L., Thach, T.Q., Tsui, T.H., Brauer, M., Lee, M., Allen, R., Yuchi, W., Lai, P.-C., Wong, P., Barratt, B., 2018. Integrating travel behavior with land use regression to estimate dynamic air pollution exposure in Hong Kong. Env. Int.l 113, 100–108. https://doi.org/10.1016/j.envint.2018.01.009.

Tian, T., Kwan, M.-P., Vermeulen, R., Helbich, M., 2024. Geographic uncertainties in external exposome studies: A multi-scale approach to reduce exposure misclassification. Sci. Total Environ. 906, 167637. https://doi.org/10.1016/j.scitotenv.2023.167637.

Wang, Y., Yang, M., 2019. Long commutes to work during pregnancy and infant health at birth. Econ. Hum. Biol. 35, 1–17. https://doi.org/10.1016/j.ehb.2019.03.006.

Warembourg, C., Anguita-Ruiz, A., Siroux, V., Slama, R., Vrijheid, M., Richiardi, L., Basagaña, X., 2023. Statistical approaches to study exposome-health associations in the context of repeated exposure data: a simulation study. Environ. Sci. Technol. 57, 16232–16243. https://doi.org/10.1021/acs.est.3c04805.

Wei, L., Kwan, M.-P., Vermeulen, R., Helbich, M., 2023. Measuring environmental exposures in people's activity space: The need to account for travel modes and exposure decay. J. Expo. Sci. Environ. Epidemiol. https://doi.org/10.1038/s41370-023-00527-z.

Wu, J., Jiang, C., Jaimes, G., Bartell, S., Dang, A., Baker, D., Delfino, R.J., 2013. Travel patterns during pregnancy: comparison between Global Positioning System (GPS) tracking and questionnaire data. Environ. Health 12, 86. https://doi.org/10.1186/1476-069X-12-86.

Yan, X., Zhou, J., Sheng, F., Niu, Q., 2022. Influences of built environment at residential and work locations on commuting distance: evidence from Wuhan. China. ISPRS Int. J. Geo-Inf. 11, 124. https://doi.org/10.3390/ijgi11020124.

Yi, L., Xu, Y., Eckel, S.P., O'Connor, S., Cabison, J., Rosales, M., Chu, D., Chavez, T.A., Johnson, M., Mason, T.B., Bastain, T.M., Breton, C.V., Dunton, G.F., Wilson, J.P., Habre, R., 2022. Time-activity and daily mobility patterns during pregnancy and early postpartum – evidence from the MADRES cohort. Spat. Spatio-Temporal Epidemiol. 41, 100502. https://doi.org/10.1016/j.sste.2022.100502.

Zenk, S.N., Matthews, S.A., Kraft, A.N., Jones, K.K., 2018. How many days of global positioning system (GPS) monitoring do you need to measure activity space environments in health research? Health Place 51, 52–60. https://doi.org/10.1016/j.healthplace.2018.02.004.

Zuur, A.F., Ieno, E.N., Elphick, C.S., 2010. A protocol for data exploration to avoid common statistical problems. Methods Ecol. Evol. 1, 3–14. https://doi.org/10.1111/j.2041-210X.2009.00001.x.