The Study on Typically Ignored Groups of Menstruating Adults: Computational Analysis of Biometric and Survey Data

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Background

Menstrual health research has historically relied on small, homogeneous samples and exclusionary criteria. As a result, populations such as Black and Brown menstruating people, individuals using hormonal contraception, lactating participants, and those with irregular cycles remain underrepresented. These gaps limit our understanding of cycle variability, equity, and the role of social determinants of health.

The Study on Typically Ignored Groups of Menstruating Adults (STIGMA) aims to address these gaps by recruiting a diverse cohort of 304 participants and combining detailed surveys with continuous Oura ring measurements to capture high-resolution biometric data (heart rate, sleep, temperature). By integrating social and biological data, we aim to generate new insights into population-specific menstrual health patterns and highlight equity considerations often overlooked.

Cohort Demographics

A significant contribution of this work is the diversity of the recruited cohort, particularly across ancestry. There is also quite a bit of heterogeneity across skin pigment, education level, and income level, seen in the demographics plots below.

Figure 1. Ancestry distribution. Participants were asked to select multiple ancestries that they belong to. Bars show the number and percent of participants selecting each category; most common ancestries were African (57%) and Latinx (31%).

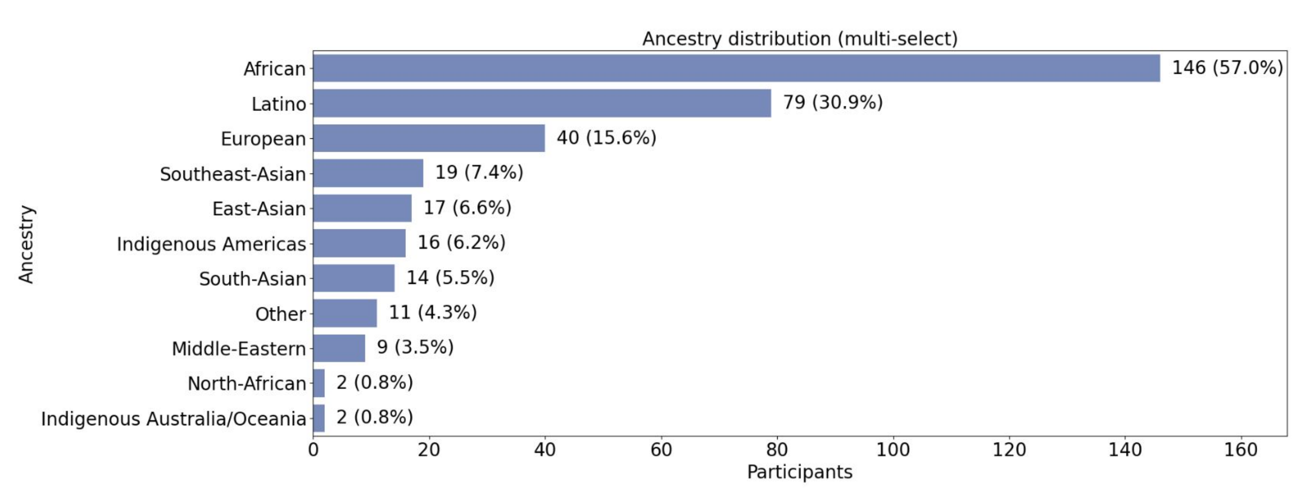


Figure 2. Income distribution. Most participants report household income in the $125k+ or $76–120k brackets; ~17% are in $10–35k.

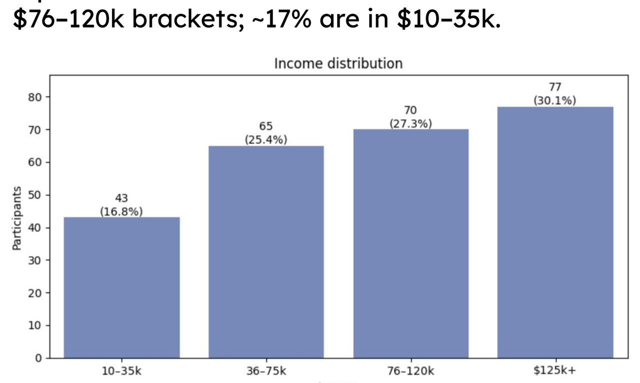


Figure 3. Pigment distribution. Self-reported pigment codes span the full scale with a long-tailed, multi-modal spread.

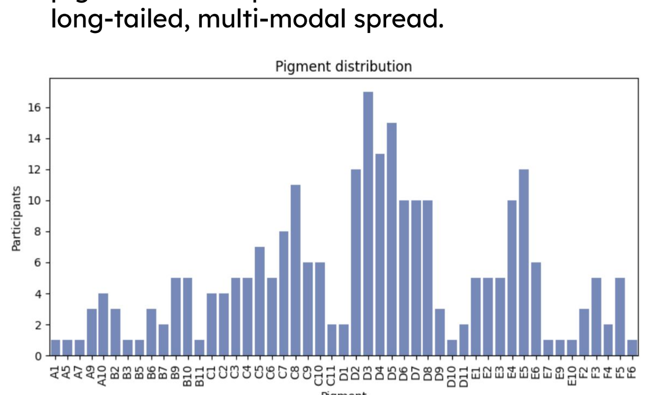


Figure 4. ZIP Code distribution (top 10). Participation is concentrated in the Stanford 94035 zip code (~19%); the remaining ZIPs each contribute a small share.

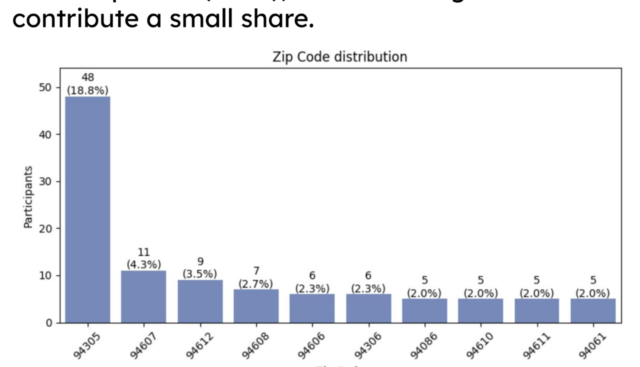
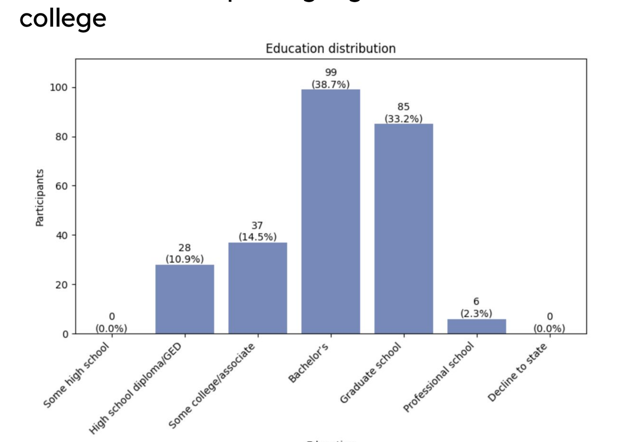


Figure 5. Education distribution. The largest groups hold Bachelor's or Graduate degrees, with smaller shares reporting high school or some college



Methods

Cohort:

- Inclusion: uterus, ages 18–51, ≥ 9 expected periods in 12 months, access to smartphone, ability to wear/charge Oura ring.
- Recruitment: flyers across the Bay Area, email blasts, BIPOC-centered teach-ins.
- Incentive: Oura ring + subscription.
- Consent: 30-minute 1:1 meetings covering study goals, responsibilities, and participant voices.

Data Collection:

- Weekly and background surveys: sociodemographics, lifestyle, diet/exercise, weekly symptoms, menstruation
- Continuous Oura ring biometrics: heart rate, heart rate variability, sleep, stress, activity, recovery skin temperature, etc.

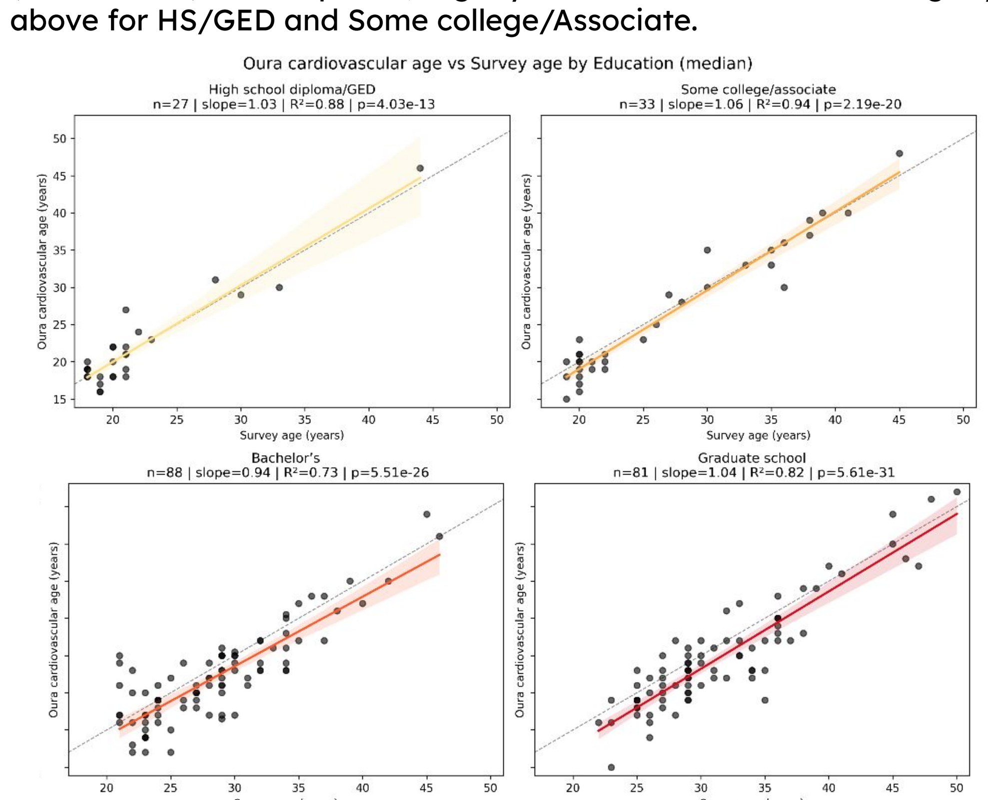
Analytic Framework:

- Preprocessing: Weekly survey aggregation, missingness handling, quality checks, merging/reconciling of background survey, weekly surveys, and Oura biometric data.
- Exploratory: Descriptives for demographics, stress, readiness, BDI (breathing disturbance index), and Oura biometrics; subgroup comparisons; cardiovascular vs. chronological age.
- Dimension reduction: NMF to identify latent factors.
- Trajectory modeling: Gaussian processes for bleeding, stress, HR, and sleep with subgroup contrasts.
- Integration & equity: Linking social determinants with biometric signals to highlight population-specific variation.

Results

Chronological Cardiovascular Age vs. Oura Cardiovascular Age Analysis

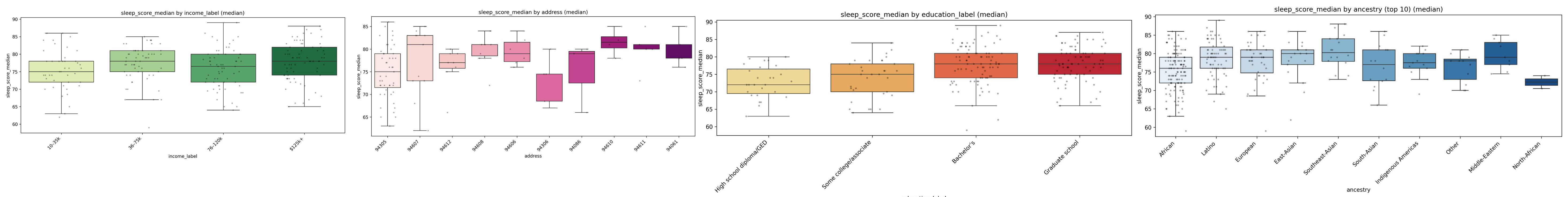
Figure 6. Participant-level Oura cardiovascular age (median across days) vs. chronological survey age and modeled separately within each education stratum (HS/GED, Some college/Associate, Bachelor's, Graduate) using simple linear regression. Panels show black points, a category-colored fitted line with 95% CI, and a dashed y = x reference; titles report n, slope, R^2, and p. Associations are strong across groups (R^2 0.73–0.94) with slopes ~1; slightly below for Bachelor's and slightly above for HS/GED and Some college/Associate.



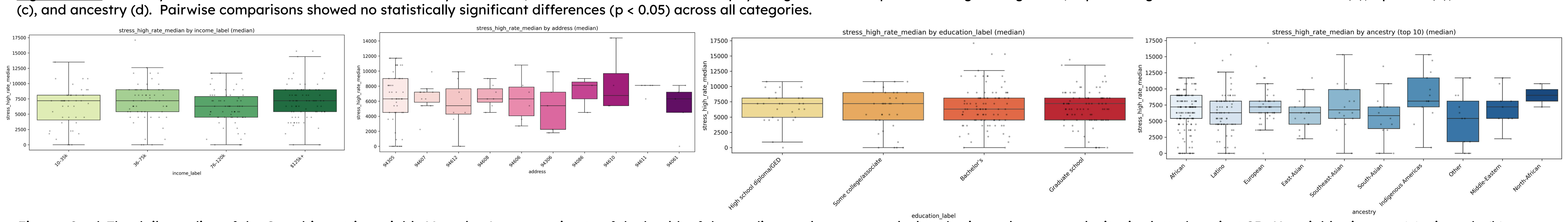
Results (continued)

Social Determinants of Health (SDoH) Analysis

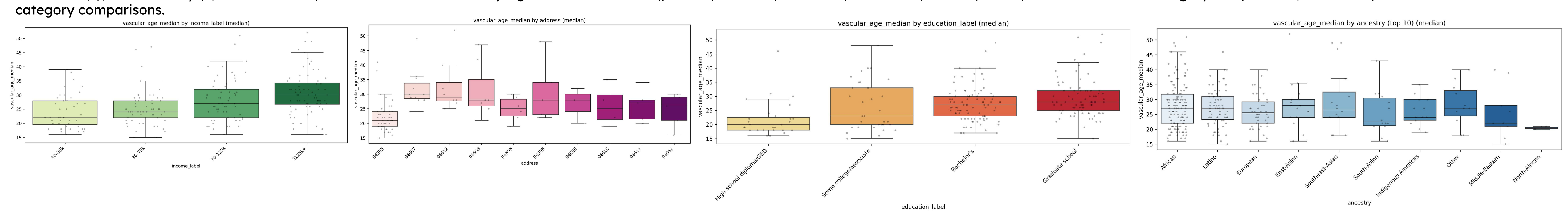
Figures 7a-d. The daily median of the Oura biometric variable Sleep Score, which reflects the quality and quantity of sleep, is plotted against SDoH variables income (a), zip code (b), education (c), and ancestry (d). Pairwise comparisons showed statistically significant differences ($p < 0.05$) in four pairwise education category comparisons and two pairwise ancestry comparisons.



Figures 8a-d. The daily median of the Oura biometric variable Daytime Stress, defined as a measurement of physiological stress responses during waking hours, is plotted against SDoH variables income (a), zip code (b), education (c), and ancestry (d). Pairwise comparisons showed no statistically significant differences ($p < 0.05$) across all categories.



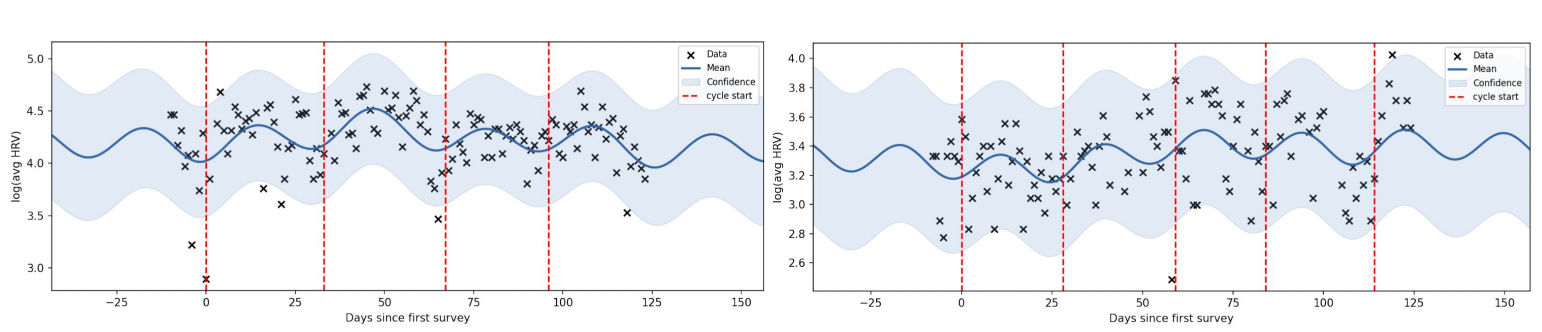
Figures 9a-d. The daily median of the Oura biometric variable Vascular Age, an estimate of the health of the cardiovascular system calculated using pulse wave velocity, is plotted against SDoH variables income (a), zip code (b), education (c), and ancestry (d). Pairwise comparisons showed statistically significant differences ($p < 0.05$) in three pairwise zip code comparisons, three pairwise education category comparisons, and three pairwise income category comparisons.



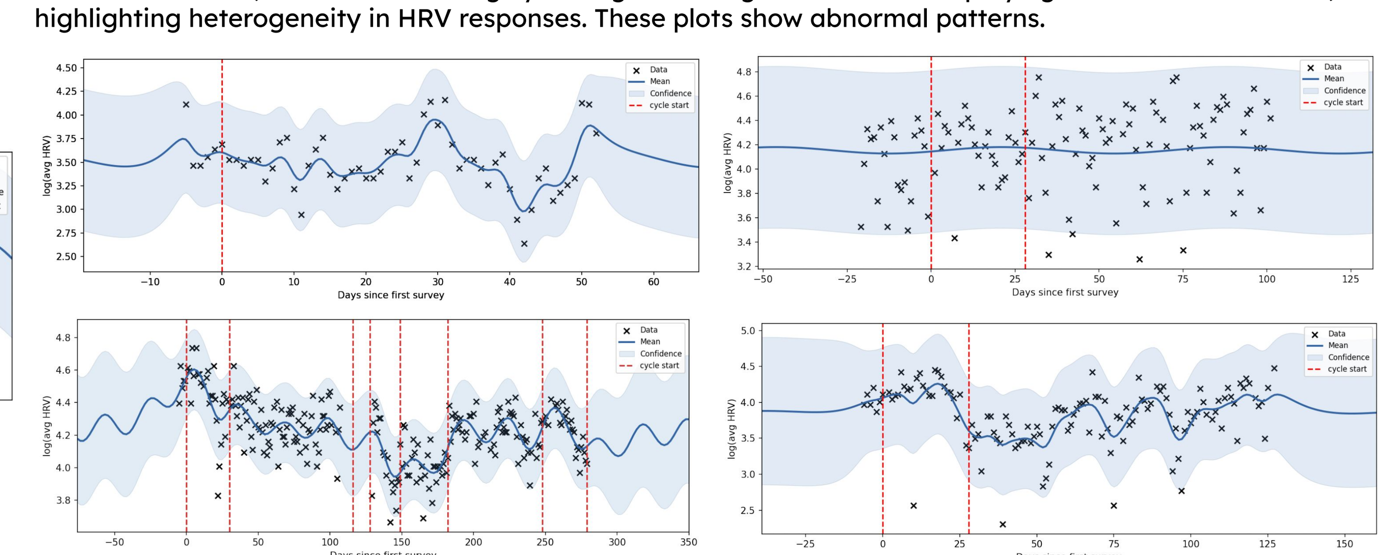
Gaussian Process Modeling

Gaussian Processes (GPs) provide a Bayesian framework for modeling smooth, non-linear variation over time in menstrual cycle signals (bleeding, stress, heart rate, sleep). A Gaussian random variable X~N(μ, Σ), where μ is the mean and Σ is the covariance matrix has the following probability density function: $P(x;\mu,\Sigma) = \frac{1}{2\pi^{\frac{d}{2}}|\Sigma|} e^{-\frac{1}{2}\left((x-\mu)^{\top}\Sigma^{-1}(x-\mu)\right)}$. A major model fitting consideration is kernel selection, and for this data, the team has determined that the periodic + the matern 32 fits best based on observed likelihood.

Figures 10a-b. GP fits for nightly log-transformed heart rate variability (left, a) and log-transformed breathing rate (right, b) across an individual participant. Black points show raw nightly data, dark blue lines the GP mean, and shaded areas 95% confidence intervals. Red vertical lines denote logged menstrual cycle starts. HRV displays clearer cycle-aligned variation, while breathing rate shows more subtle patterns; wider confidence bands toward the edges reflect lower data density.



Figures 11a-d. GP fits for nightly log-transformed heart rate variability. Patterns of HRV variation differ highly across individuals, with some showing cycle-aligned changes and others displaying little or no correlation, highlighting heterogeneity in HRV responses. These plots show abnormal patterns.



Next Steps

For next steps, we are hoping extend in four directions. A primary first goal is to annotate unannotated menstrual cycles and be able to predict various events including ovulation. Second, we want to develop multi-group Gaussian process models, and I specifically want to to assess how categorical factors such as income or education modify time-series trajectories of heart rate variability and other biometric signals. First, we want to develop multi-group Gaussian process models, and I specifically want to to assess how categorical factors such as income or education modify time-series trajectories of heart rate variability and other biometric signals. Third, I want to incorporate environmental exposures, testing associations between air pollution and discrepancies in cardiovascular age, and between wildfire smoke and sleep disruption over time. Fourth, we are exploring pursuing analyses that link survey-derived psychosocial measures with wearable data to identify latent factors underlying menstrual health variability using NMF or other dimension reduction techniques. Please reach out if you are interested in rotating on this project!