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

Rebecca Hurwitz[1], Naiomi Hunter[2], Sarah Nyquist[3], Morgan Smith[2], Alina Gavrilov[4], Tania Mergudich[3], Jiachen Cai[3], Jillian Melbourne[5], Leah McGillicuddy[1], Ally Nicolella[6], Mike Snyder[2], Barbara Engelhardt[1,3]

[1] Department of Biomedical Data Science, Stanford University; [2] Department of Genetics, Stanford University; [3] Gladstone Institutes; [4] Institute for Computational and Mathematical Engineering, Stanford University; [5] Department of Vascular Surgery, Stanford University; [6] Department of Biological and Medical Informatics, University of California, San Francisco

Background

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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.

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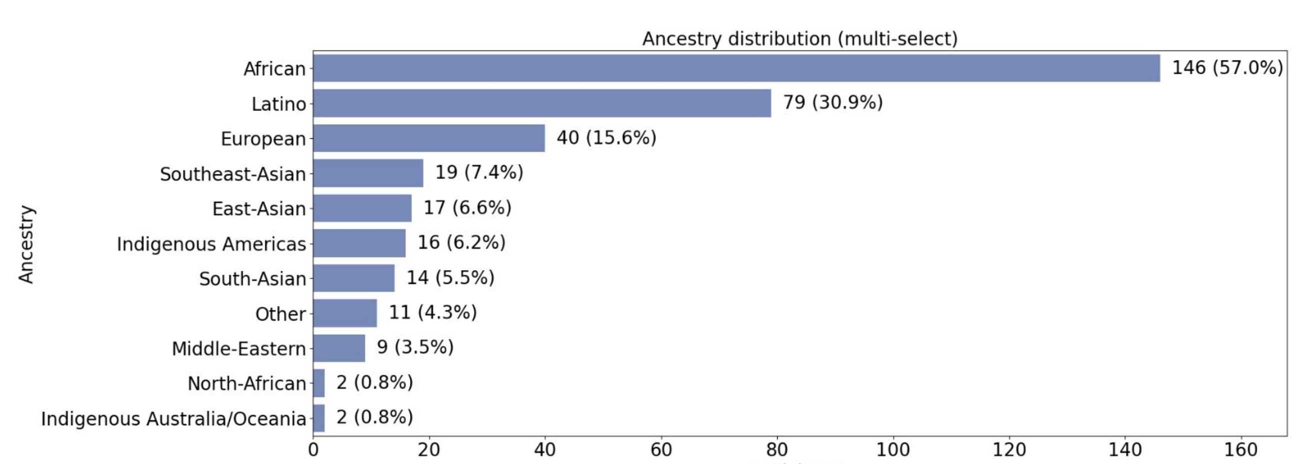

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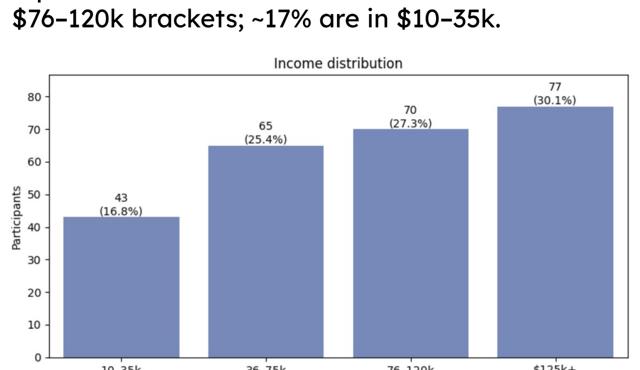

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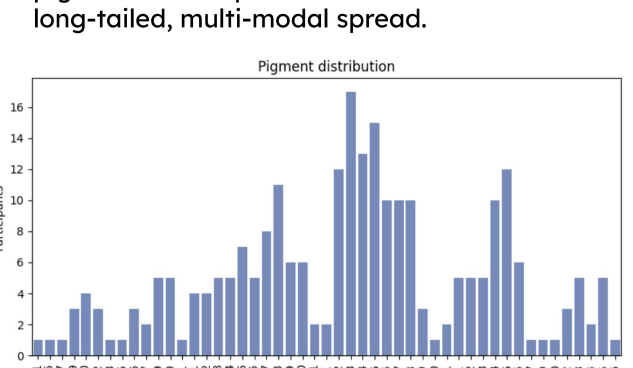

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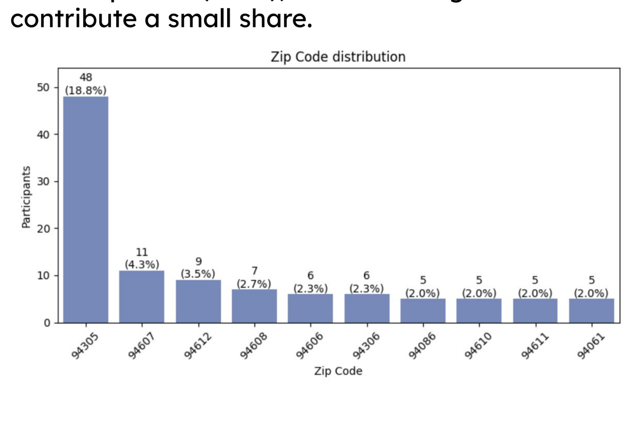

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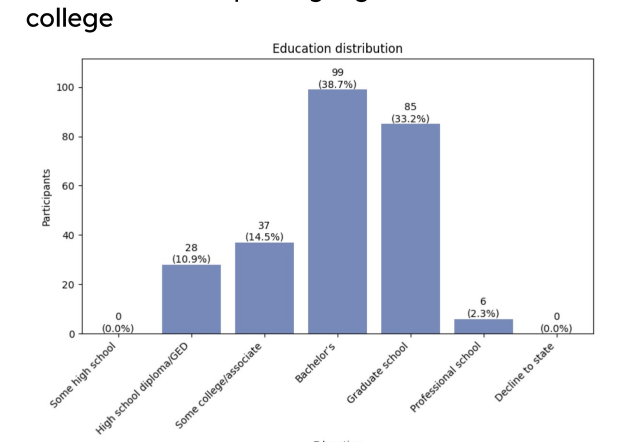

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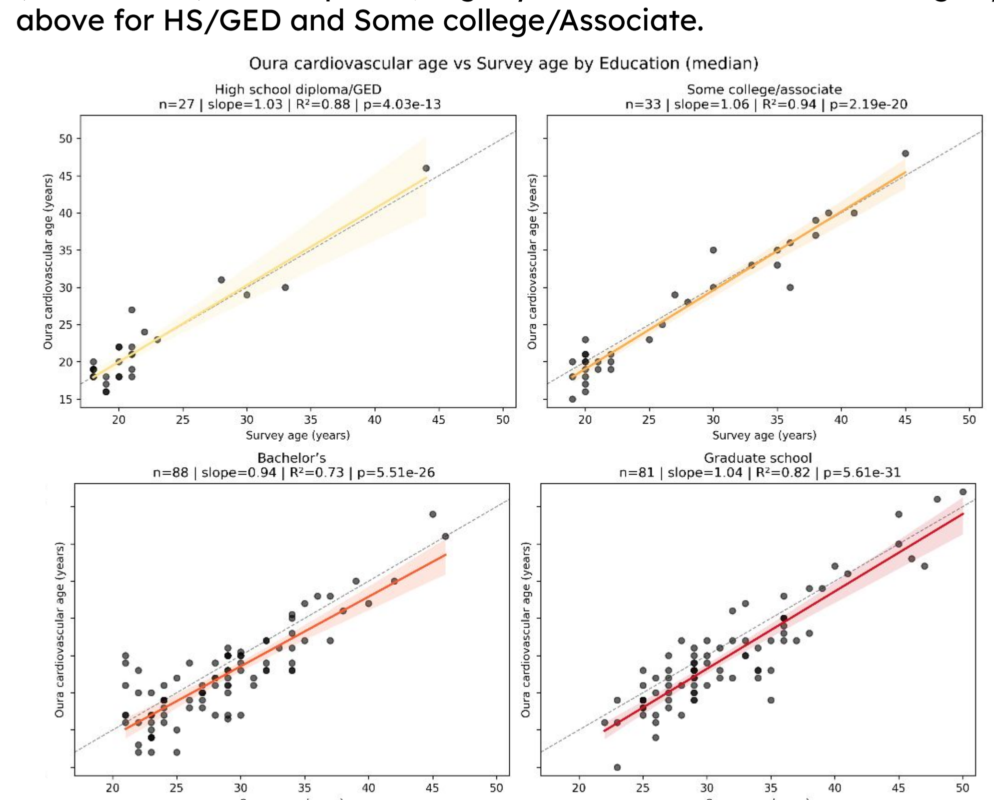
- Integration & equity: Linking social determinants with biometric signals to highlight population-specific variation.

Results

Chronological Cardiovascular Age vs. Oura Cardiovascular Age Analysis

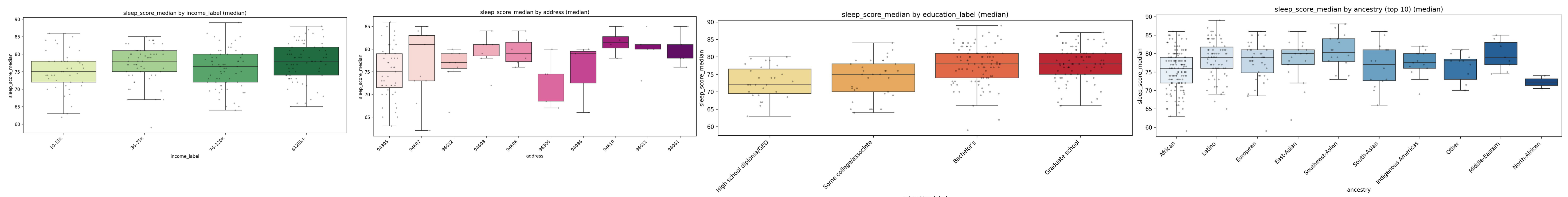
Figure 6. Participant-level Oura cardiovascular age (median across days) vs. chronological survey age and modeled separately within each education stratum (HS/GED, Some college/Associate, Bachelor's, Graduate) using simple linear regression. Panels show black points, a category-colored fitted line with 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.



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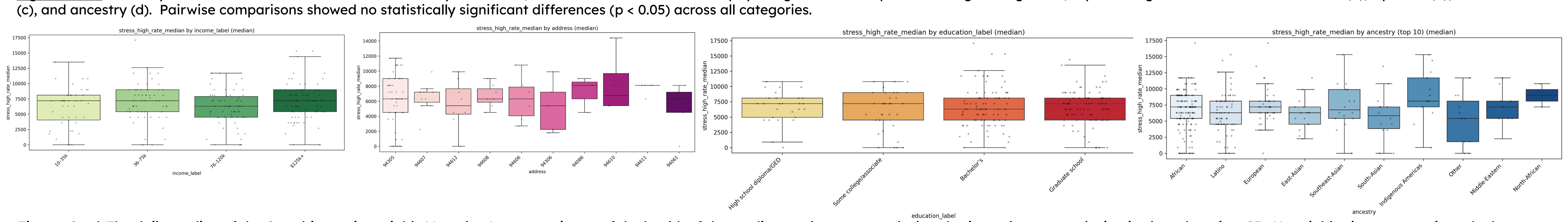

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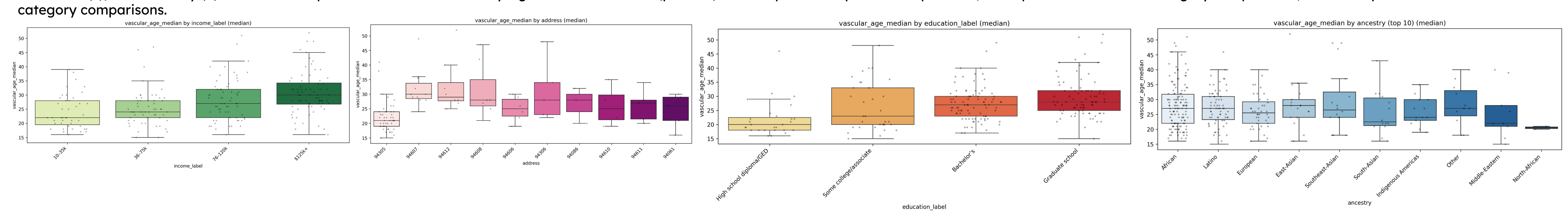

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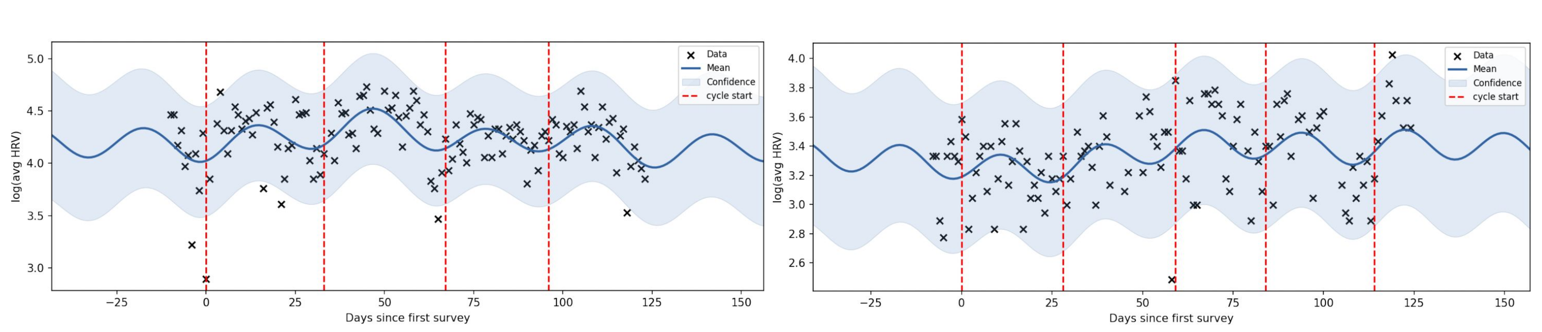
Figures 10a-b. GP fits for nightly log-transformed heart rate variability (left, a) and log-transformed breathing rate (right, b) across an individual participant. Black points show raw nightly data, dark blue lines the GP mean, and shaded areas 95% confidence intervals. Red vertical lines denote logged 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.



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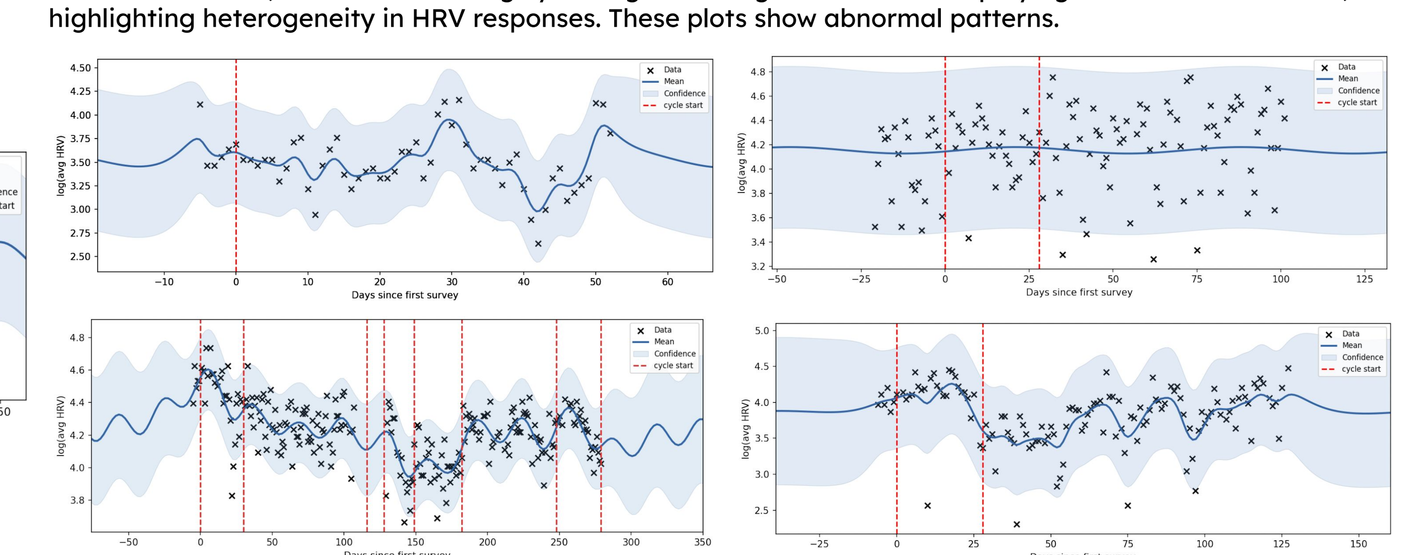

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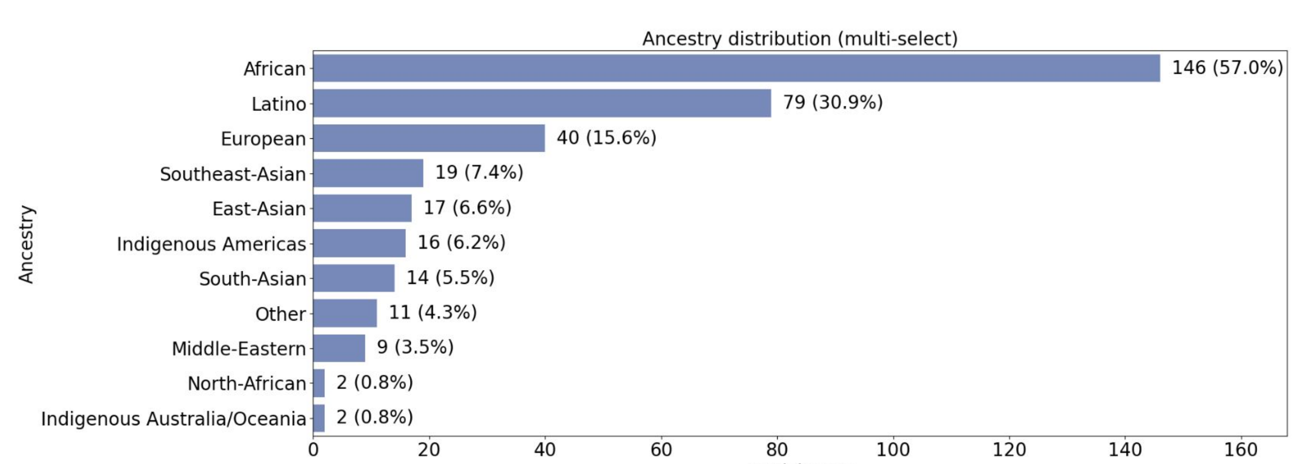

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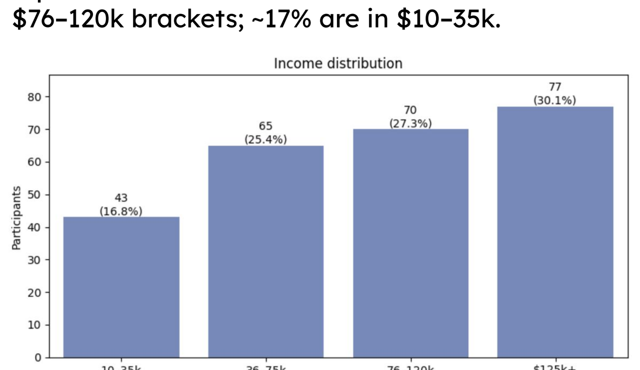

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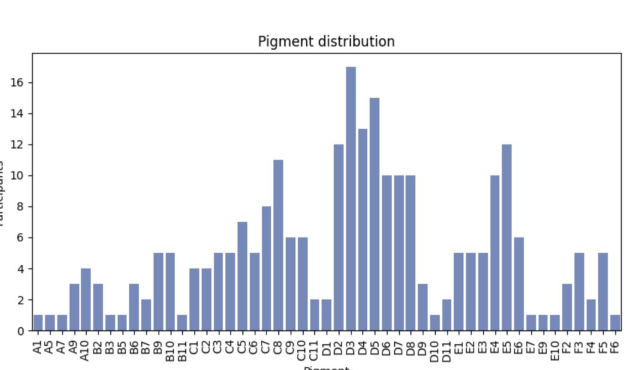

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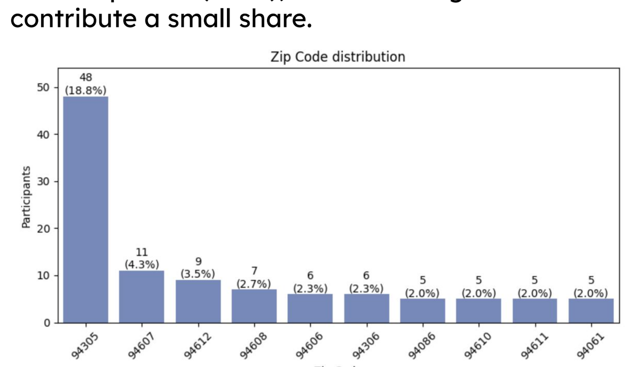

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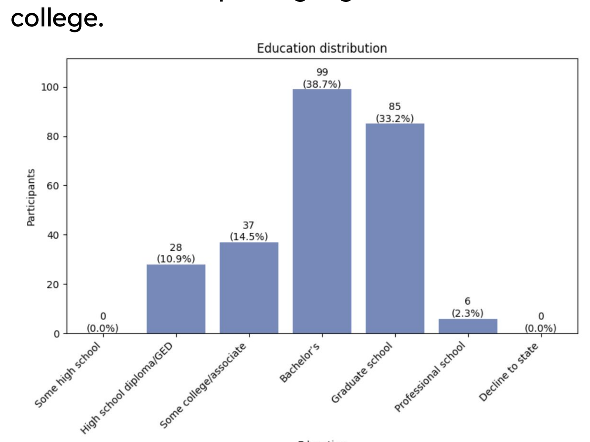

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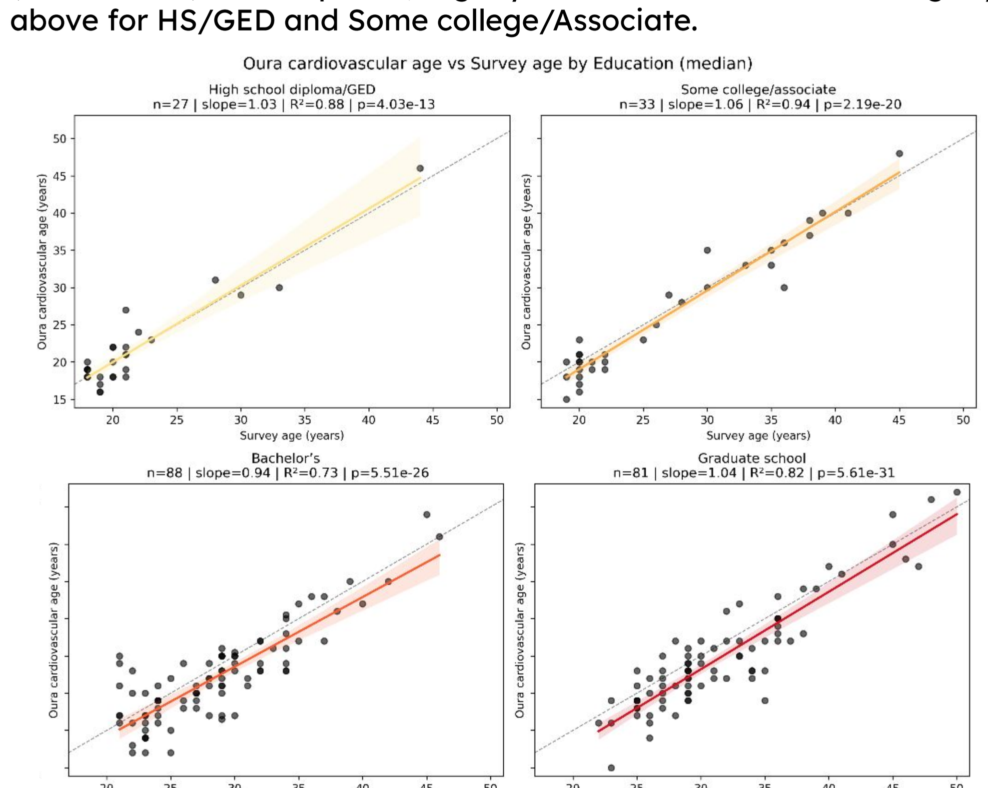

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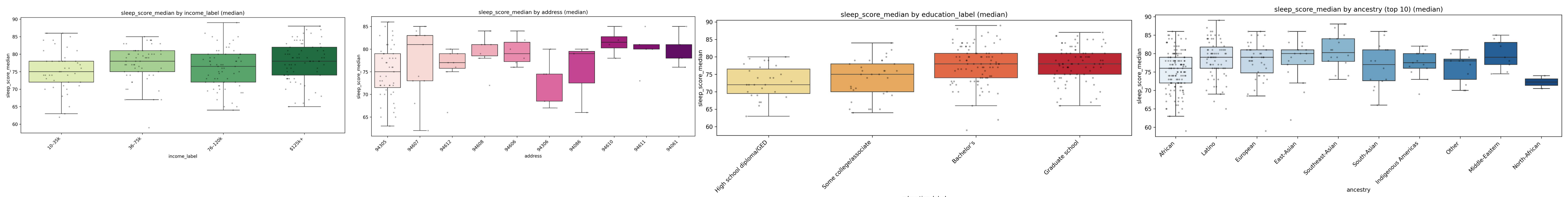

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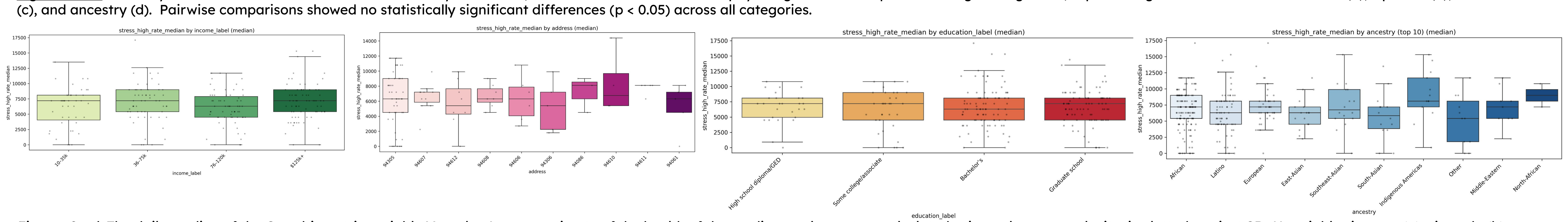

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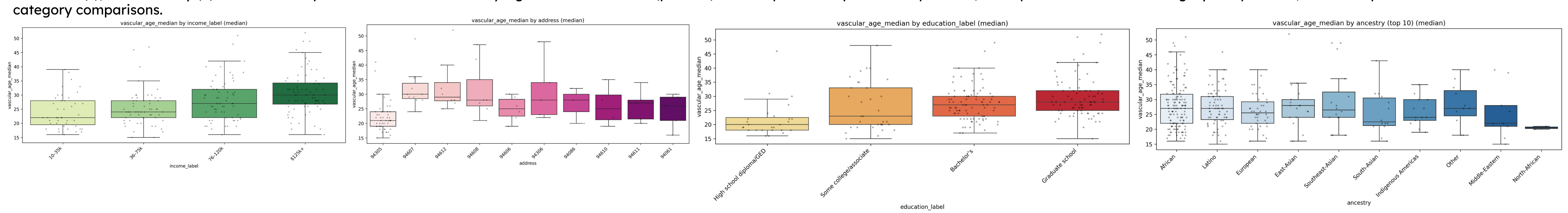

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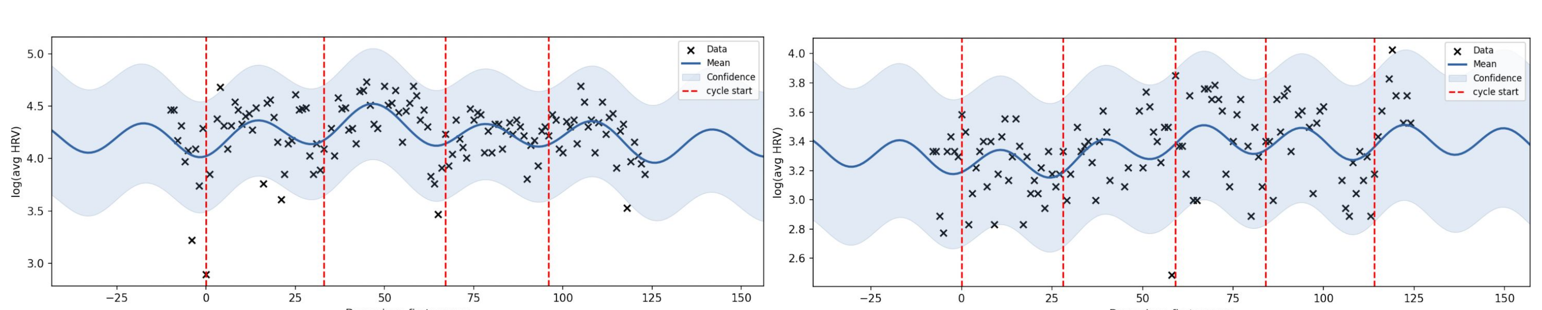

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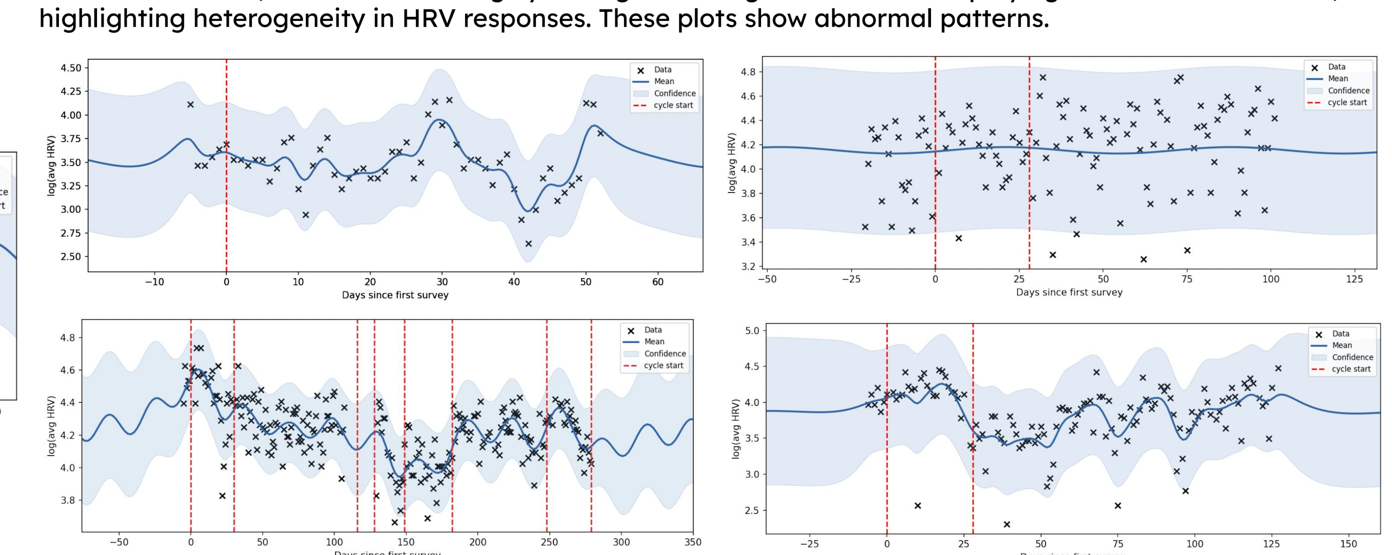

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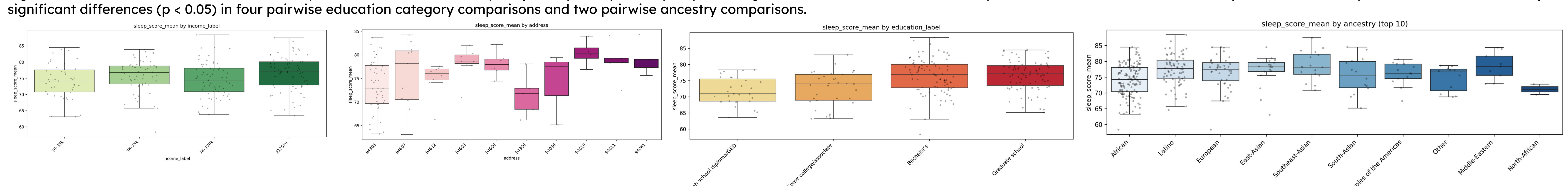

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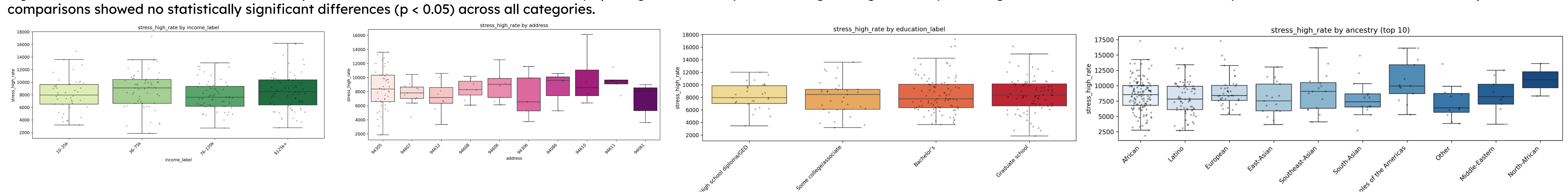

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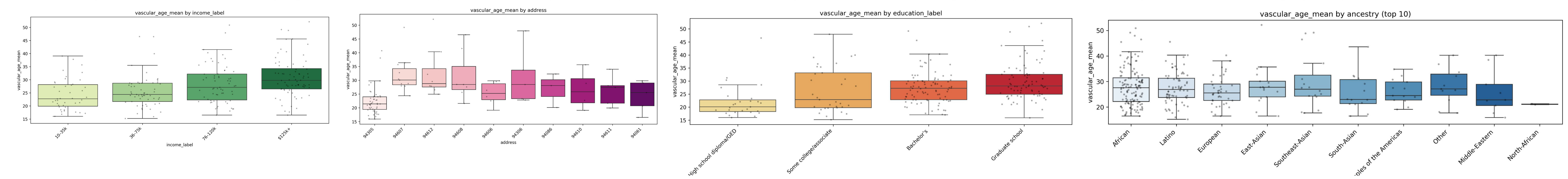
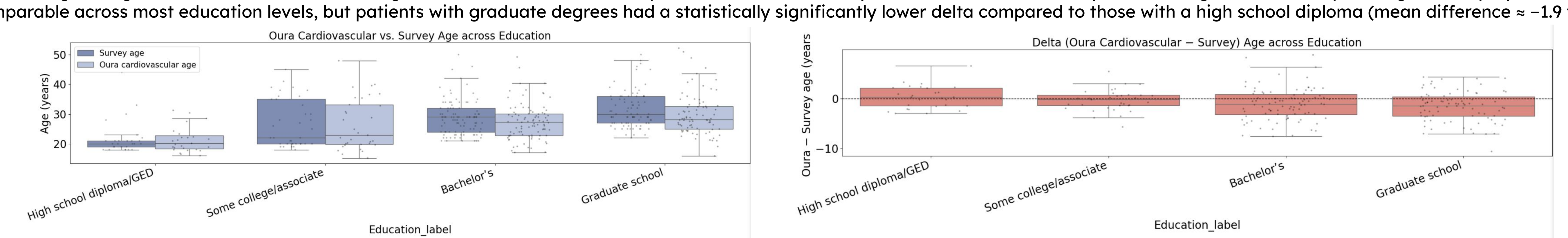


Chronological Cardiovascular Age versus Oura Cardiovascular Age Analysis

Figures 4a-b. Survey (chronological) age versus Oura cardiovascular age across education levels. Boxplots (left, a) show side-by-side distributions of survey and Oura ages, while delta plots (right, b) display the within-person difference. The two measures were comparable across most education levels, but patients with graduate degrees had a statistically significantly lower delta compared to those with a high school diploma (mean difference ≈ −1.9 years, p = 0.02, Tukey HSD).



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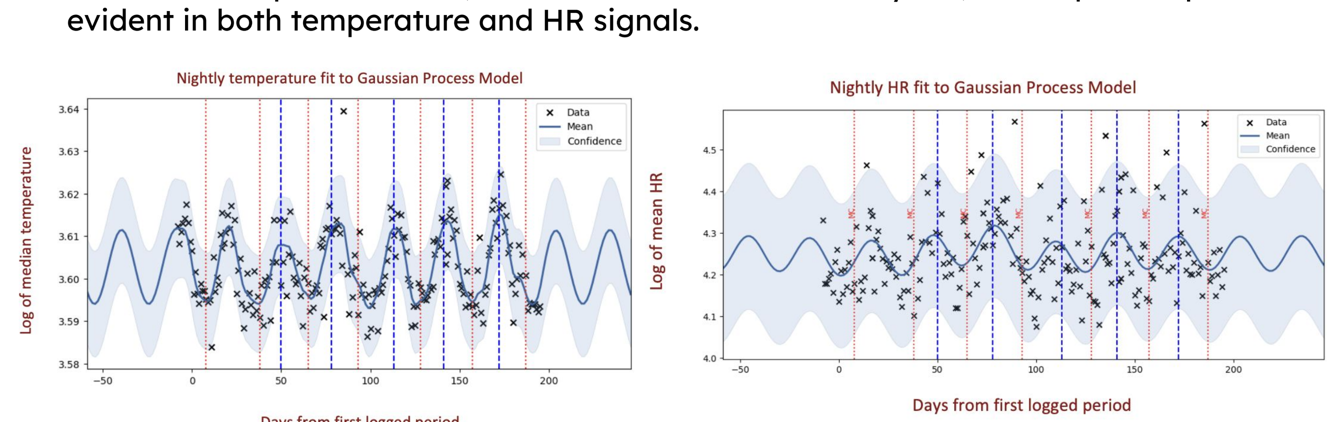
Figures 5a-b. GP fits for nightly temperature (left, a) and heart rate (right, b) aligned to menstrual cycle logging across an individual patient. Black points represent observed nightly values, dark blue lines indicate the GP mean, and shaded regions show 95% confidence intervals. Red and blue vertical lines mark logged menstrual cycle events. The models capture smooth, non-linear variation across cycles, with repeated patterns evident in both temperature and HR signals.



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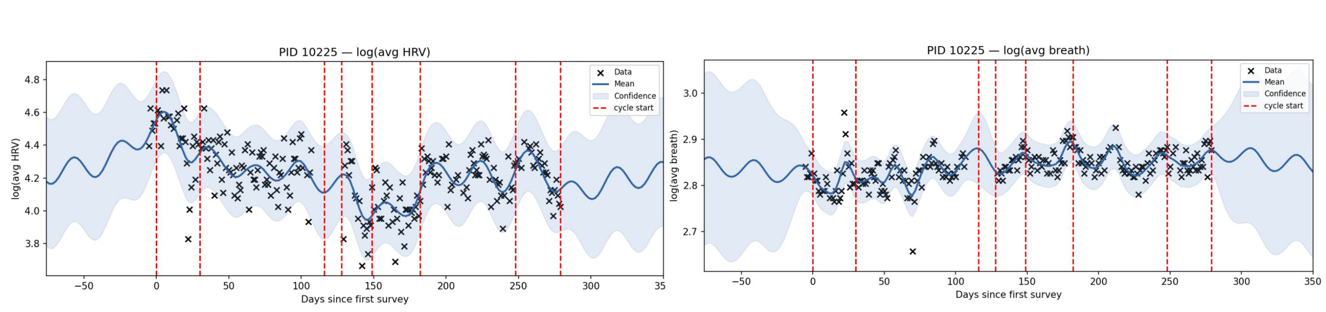

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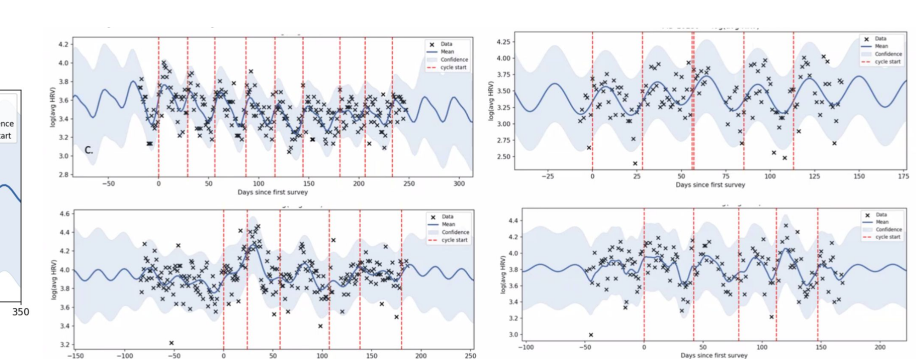

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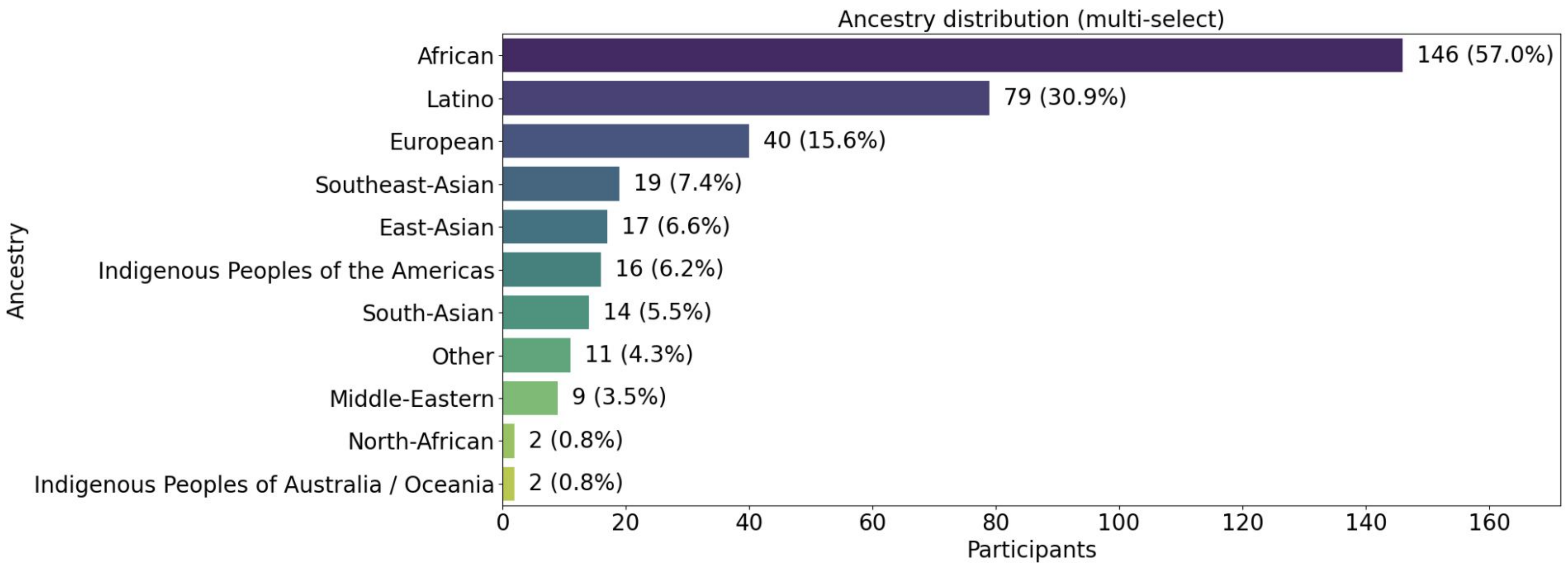
Things I wanted to include but no room:

Ancestry distribution



Next Steps

For next steps, I am hoping that we can extend in three directions. 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. Second, 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. Third, 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. Goal also to annotate unannotated cycles and predict (various).

Actual statistical tests

```
Overall paired t-test (Oura vs Survey): t=-4.688, p=4.686e-06, n=235

=== GLOBAL TESTS on delta (Oura - Survey age) ===
```

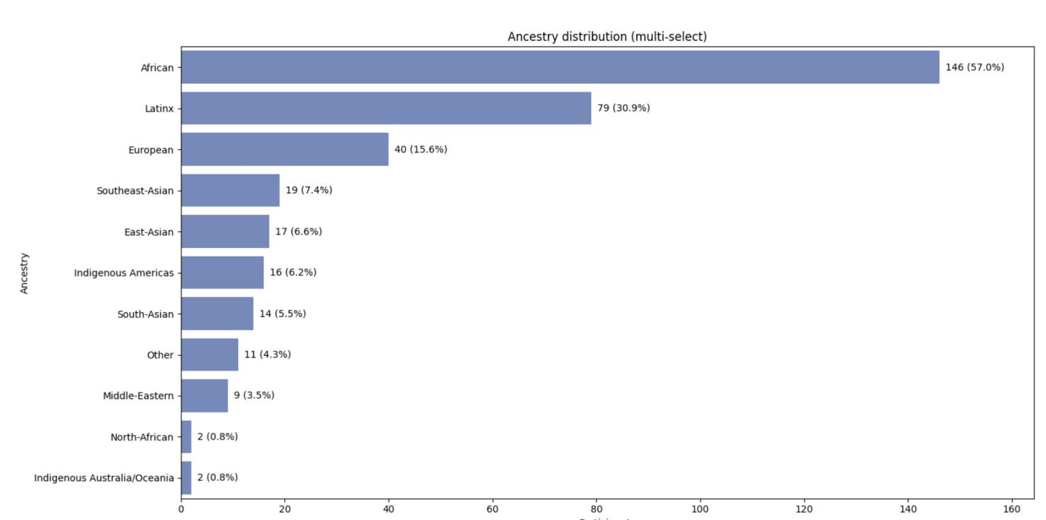
	group	k	n	anova_p	kw_p	sig_flag
0	address	10	101	0.275323	0.163996	No
1	ancestry	10	325	0.001927	0.004036	Yes
2	education_label	5	234	0.001923	0.011987	Yes
3	income_label	4	234	0.085390	0.088138	No
4	normalized_pigment	10	114	0.679516	0.646727	No

	metric	group	group1	group2	direction	mean_diff	p_adj	test
16	vascular_age_mean	education_label	Graduate school	High school diploma/GED	higher in group2	-7.7156	0.0000	TukeyHSD
19	vascular_age_mean	income_label	10–35k	$125k+	higher in group1	6.5217	0.0000	TukeyHSD
20	vascular_age_mean	income_label	$125k+	36–75k	higher in group2	-5.3267	0.0001	TukeyHSD
9	sleep_score_mean	education_label	Graduate school	High school diploma/GED	higher in group2	-4.9228	0.0001	TukeyHSD
10	sleep_score_mean	education_label	Bachelor’s	High school diploma/GED	higher in group2	-4.6124	0.0003	TukeyHSD
1	readiness_score_mean	address	94061	94306	higher in group2	-10.4492	0.0004	TukeyHSD
13	vascular_age_mean	address	94305	94607	higher in group1	9.7585	0.0005	TukeyHSD
7	sleep_score_mean	ancestry	African	Latino	higher in group1	3.2110	0.0006	TukeyHSD
11	sleep_score_mean	education_label	Graduate school	Some college/associate	higher in group2	-4.1294	0.0008	TukeyHSD
14	vascular_age_mean	address	94305	94612	higher in group1	10.4332	0.0016	TukeyHSD
12	sleep_score_mean	education_label	Bachelor’s	Some college/associate	higher in group2	-3.8190	0.0020	TukeyHSD
17	vascular_age_mean	education_label	High school diploma/GED	Professional school	higher in group1	11.9747	0.0039	TukeyHSD
2	readiness_score_mean	address	94306	94608	higher in group1	8.4052	0.0039	TukeyHSD
18	vascular_age_mean	education_label	Bachelor’s	High school diploma/GED	higher in group2	-5.3870	0.0041	TukeyHSD
3	readiness_score_mean	address	94306	94606	higher in group1	8.5010	0.0052	TukeyHSD
4	readiness_score_mean	address	94306	94611	higher in group1	8.7423	0.0064	TukeyHSD
5	readiness_score_mean	address	94306	94607	higher in group1	7.1305	0.0112	TukeyHSD
21	vascular_age_mean	income_label	10–35k	76–120k	higher in group1	4.0659	0.0160	TukeyHSD
8	sleep_score_mean	ancestry	African	Southeast-Asian	higher in group1	4.5655	0.0186	TukeyHSD
15	vascular_age_mean	address	94305	94608	higher in group1	9.1343	0.0192	TukeyHSD

```
Education categories used in scatter panels: ['High school diploma/GED', 'Some college/associate', 'Bachelor’s', 'Graduate school']
```

education_label	n_demo	n_with_survey	n_with_oura	n_with_both	n_in_scatter_cats	n_scatter	missing_any	not_in_panels
High school diploma/GED	28	27	27	27	28	27	1	0
Some college/associate	37	37	33	33	37	33	4	0
Bachelor’s	99	98	89	88	99	88	11	0
Graduate school	85	84	81	81	85	81	4	0

	education_label	n	slope	intercept	r	r2	p_value	stderr	mode
0	Bachelor’s	88	0.935410	0.489454	0.852765	0.727209	5.513917e-26	0.061779	median
1	Graduate school	81	1.040337	-2.997262	0.904538	0.818189	5.611902e-31	0.055175	median
2	High school diploma/GED	27	1.030285	-0.624743	0.939349	0.882377	4.025623e-13	0.075233	median
3	Some college/associate	33	1.056348	-2.090320	0.969011	0.938983	2.187953e-20	0.048364	median



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