Supplementary Materials

For

Addressing Data Quality Challenges in Observational Ambulatory Studies: Analysis, Methodologies and Practical Solutions for Wrist-worn Wearable Monitoring

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Open Science Statement

All data and corresponding code are openly available through Github and Kaggle datasets.

Github: https://github.com/predict-idlab/data-quality-challenges-wearables
Kaggle datasets: https://www.kaggle.com/datasets/jonvdrdo/mbrain21/data

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S1: Non-wear Detection: Algorithm Comparison

This appendix assesses the performance of our revised non-wear detection algorithm relative to the on-body algorithm of Böttcher et al. via metric-based performance evaluation using a labeled subset of the mBrain data. In order to validate on the mBrain dataset, we first created an annotation dashboard to label the mBrain data retrospectively, as depicted in **Figure XX.** This allows determining performance assessment metrics, which are shown in **Table XX and Table XX**, for ours and Böttcher's algorithm respectively**.** These metrics indicate that our revised algorithm outperforms Böttcher's in both precision and recall, consequently yielding a higher F1-score. Additional data and code specifics can be found in the accompanying [notebook].

Supplemental Figure 1: Screenshot of the annotation dashboard utilized to label off-wrist periods.

Note: Via the "label" selection box, different labels can be assigned to annotations, each with their own color coding. For the shown excerpt, three off-wrist periods (red shaded area) and one sleep period (green shaded area) were annotated. The code for the annotation dashboard can be found [here.]

Supplemental Table 1: Classification report of our non-wear detection algorithm.

	precision	recall	f1-score
Non-wear	0.89	0.98	0.93
on-body	0.98	0.88	0.94
Macro avg	0.94	0.94	0.94

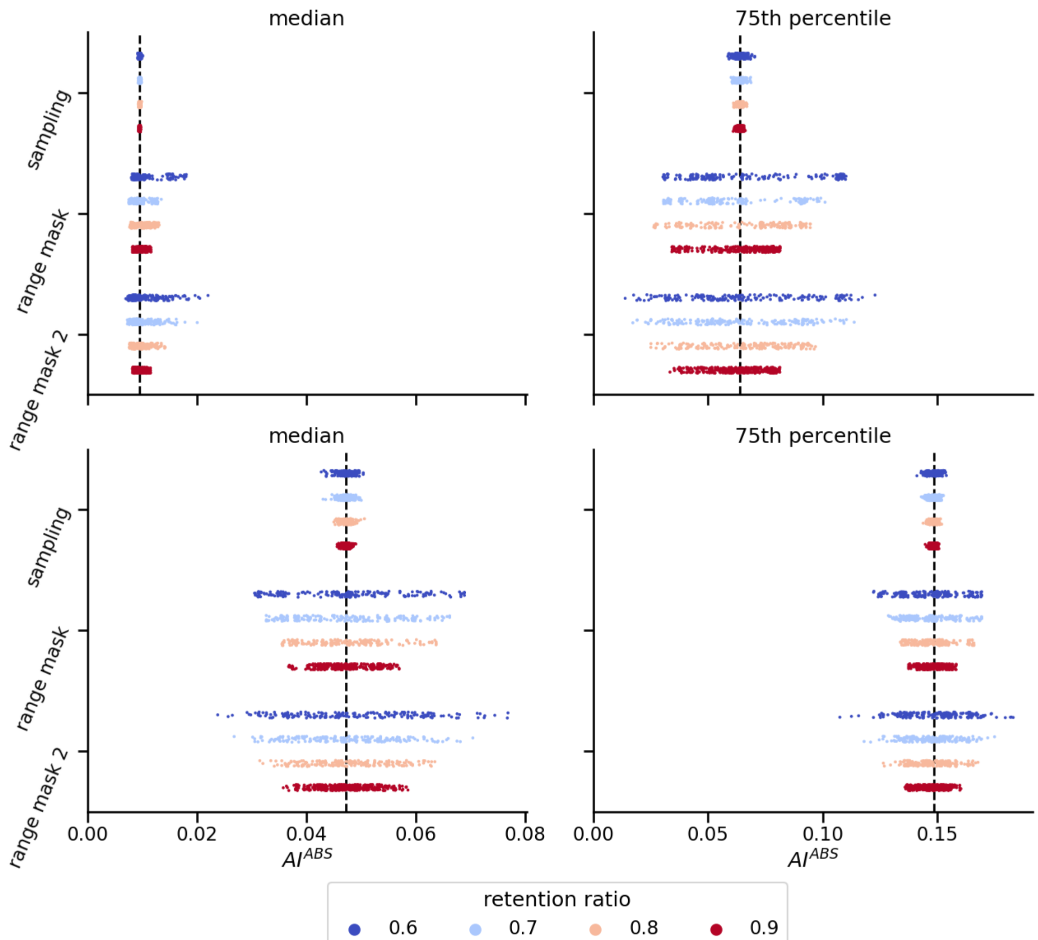
Supplemental Table 2: Classification report of Böttcher's non-wear detection algorithm.

	precision	recall	f1-score
Non-wear	0.45	1	0.66
on-body	1	0.65	0.79
Macro avg	0.73	0.83	0.71

S2: Comparison of Gap Induction Procedures

In Supplemental figure XX, we present a visual comparison of the effects of various gap induction techniques used during bootstrapping. It is evident from the figure that the variability in sampling-based bootstrapping is considerably less than that in block-based bootstrapping (i.e., range mask and range mask 2). This highly reduced variability suggests that sampling-based bootstrapping may not be suitable for assessing metric-gap sensitivity in wearable data. Interestingly, the difference between range mask and range mask 2 is minimal, suggesting that introducing multiple blocks versus a single large block does not notably alter the variability. Implementation details can be found in this notebook.

Supplemental Figure 2: Strip-plot comparison of gap induction procedures (y-axis) for various retention ratios (hue), metrics (columns) and reference series (rows).



Note: Each row in the figure utilizes a distinct reference series. Columns represent different metrics (i.e., 50th and 75th percentiles). The vertical dashed black line indicates the metric value of the gap-free reference series. This visualization was derived by converting the E4 accelerometer data into a second-by-second activity index, AI^{ABS}, following the methodology of Bai et al. (2016). Data retention ratios during gap induction are differentiated by hue. The y-axis labels the used bootstrapping technique: 'sampling' involves random sample removal; 'range-mask' introduces single block-based gaps; and 'range mask 2' introduces multiple block-based gaps.