Can Consumer Wearables Provide Usable Signals? A Multimodal Data Quality Assessment in Real-World Stroke Rehabilitation

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Abstract. Commercial wearables enable continuous tracking of physiological parameters. However, the exported data may be incomplete or affected by artifacts. In stroke rehabilitation, previous work has mainly focused on improving motor function, such as gait and grip, using activity assessment with lab-graded devices. In contrast, the quality of multimodal consumer wearable data remains underexplored. In this work, we examined consumer-wearable-derived physiological data collected from stroke patients undergoing rehabilitation. We computed retention and artifact occurrence after preprocessing across multiple data streams, including smartwatch-derived signals such as electrocardiography, heart rate, skin temperature, steps, and continuous glucose monitoring. The data quality varied across signals. Many signal streams had moderate artifact rates, including non-wear periods, sensor artifacts, and modality-specific signal characteristics, limiting direct interpretation. All data streams showed sufficient retention after preprocessing. These findings show that commercial wearable data require preprocessing and quality assessment before being used for clinical interpretation or downstream computational analysis.

Keywords: Wearable Sensing · Commercial Sensors · Stroke Rehabilitation

1 Introduction

Health-related data recording is no longer limited to research or specialized devices. Most commercially available smartwatches support personal health tracking, and in 2025, an estimated 454.69 million smartwatches were in use worldwide [27]. Their user-friendliness and ability to collect physiological data under

real-world conditions make them relevant for clinical research. However, commercial devices often do not provide raw signals, and proprietary preprocessing, including smoothing, quantization, missing-data handling, and device-specific algorithms, may influence exported data. These signals can still contain artifacts, noise, or preprocessing-related errors. Therefore, researchers must assess temporal coverage, sampling regularity, missingness, quantization, plausibility, and signal-specific artifacts before interpreting wearable-derived biomarkers, especially in clinical settings involving vulnerable groups such as stroke patients. While gait and step-count data can reflect a stroke patient's functional improvement, physiological parameters such as heart rate, skin temperature, and glucose can provide complementary information about the patient's general health status and well-being [20,24,30,47]. In this work, we analyze commercial wearable physiological signals collected in the ongoing stroke rehabilitation study, Sensor-S, across clinical and outpatient settings [1,25,42]. Unlike previous Sensor-S publications, which introduced the study design and technical infrastructure, this paper focuses on the practical usability of the preprocessed physiological signals. We examine artifact patterns, preprocessing outcomes, and signal-specific failure modes to address the following research question: To what extent do commercial wearable signals remain usable in real-world stroke rehabilitation, and which failure modes limit downstream biomarker extraction?

2 Related Work

Stroke rehabilitation studies often focus on motor skills and mobility, using wearables such as inertial measurement units (IMUs), accelerometers, and surface electromyography (sEMG) sensors [6]. Studies on hand function often combine assistive devices, wearables, and games to improve grip strength or finger mobility [36,38,41], while gait studies mainly address rehabilitation training strategies and gait analysis [36,43,44]. However, these studies often do not address broader aspects of patient well-being or biomarkers such as heart rate and skin temperature. Real-world wearable data can support stroke rehabilitation research [41]; however, they are prone to artifacts and therefore require systematic quality assessment [18,32]. Existing frameworks quantify data completeness, on-body time, data loss, compliance, and modality-specific artifacts for individual devices such as the Empatica E4 [5]. Other recommendations emphasize reporting sampling frequency, filtering algorithms, firmware, aggregation mechanisms, outcomes of interest, and consistency checks [14,18]. However, many recommendations remain difficult to apply to consumer devices, which often provide only processed data and limited information about filtering or aggregation methods.

3 Data Collection of the Sensor-S Study

The Sensor-S study analyzes the effect of wearables on patient engagement in stroke rehabilitation. Patients randomly assigned to the intervention group receive a Samsung Galaxy Watch 6, two IMUs, a Dexcom G7 sensor for continuous

glucose monitoring (CGM), and a smartphone with the D4L Collect app. They wear the smartwatch during the 14-day intervention and the Dexcom G7 sensor for 10 days. The Dexcom G7 continuously records interstitial glucose (IGLU), reflecting glucose in the interstitial fluid surrounding tissue cells. The Samsung Galaxy Watch 6 records daily steps, heart rate (HR), skin temperature, and electrocardiograms (ECGs).

4 Methods

4.1 Step Data Processing

The Samsung Galaxy Watch 6 reports cumulative step counts for each day. We processed step data separately for each day. First, we applied a physiological boundary check. As stroke patients may not be able to walk, we set the minimum step count to 0 and the maximum to $18,000$ steps [45]. The smartwatch identifies non-wear periods and encodes them with the placeholder value "2147483646". We also excluded these non-wear episodes. We only included days with valid step data. In the exported data, timestamps appeared to reflect the service's step-count updates rather than the actual times at which individual steps occurred. Therefore, step cadence and checks for rapid step accumulation within short time intervals could not be calculated. We therefore analyzed steps only at the daily level and calculated features such as minimum, maximum, and mean daily steps across multiple days.

4.2 Skin Temperature Data Processing

The Samsung Galaxy Watch 6 samples skin temperature continuously with one value per minute (0.0167 Hz). We first applied a physiological boundary check. Skin temperature values outside the range of $[25, 40]\,^{\circ}\mathrm{C}$ were marked as invalid [5]. Next, we applied a Savitzky-Golay filter to smooth the temperature signal and reduce noise while preserving the signal shape [23]. We then detected remaining outliers using Z-scores with a cutoff of 3. Data points marked as invalid were removed. Resulting smaller gaps were interpolated using shape-preserving piecewise cubic Hermite interpolation (PCHIP). To quantify signal quality, we calculated artifact and retention rates using the number of invalid (N_{valid}), clean (N_{clean}), and raw data (N_{raw}) points:

$$\text{Artifact Rate} = \frac{N_{\text{invalid}}}{N_{\text{raw}}} \tag{1}$$

$$\text{Retention Rate} = \frac{N_{\text{clean}}}{N_{\text{raw}}} \tag{2}$$

The cleaned signal was then used to calculate statistical features, such as slope, minimum, maximum, and mean skin temperature.

4.3 Heart Rate Data Processing

The Samsung Galaxy Watch 6 provides HR values derived from the photoplethysmography (PPG) signal [40]. Samsung provides derived HR at 1 Hz. The values were stored as integer beats per minute (bpm) and exhibited a step-like pattern, suggesting interpolation or forward-filling during device preprocessing. We processed the signal separately for each day. First, we excluded data points outside the physiological range $[30, 240]$ bpm [16] and non-wear periods. Next, we assessed implausible rises and falls in HR using the Acar method. Here, HR_k denotes the current HR measurement at time point k, and $\overline{HR}_{9,k}$ denotes the mean of the preceding nine valid HR measurements:

$$\text{Acar:} \quad |HR_k - \overline{HR}_9| \leq 0.20 \cdot \overline{HR}_9 \tag{3}$$

We removed invalid data points and then applied median absolute deviation (MAD) outlier detection further to clean the signal [31]. Small resulting gaps were interpolated using PCHIP. To evaluate signal quality, we calculated the artifact rate and retention rate. The cleaned signal can be used to calculate statistical features, such as mean HR. To evaluate signal quality, we calculated the artifact rate and retention rate. The cleaned signal can be used to calculate statistical features, e.g., mean HR.

4.4 Electrocardiography Data Processing

In the Sensor-S study, patients recorded a 30-second ECG every second day by touching the watch button with the index finger of the opposite hand. The Samsung Galaxy Watch 6 samples the ECG at approximately 500 Hz. Each recording was processed individually. Wearable ECG recordings can contain motion artifacts, powerline noise, baseline drift, and electromyography (EMG) noise [26]. First, we detected larger segments dominated by motion artifacts or EMG noise, which mainly affect high-frequency components, using a short-time Fourier transform (STFT)-based approach [21]. We computed the STFT using 0.2 s Hamming windows with 50% overlap. For each window Z_{xx}, we calculated the spectral power S_{xx} as

$$S_{xx} = |Z_{xx}|^2. \tag{4}$$

We summed the power above a high-frequency cutoff of 40 Hz to obtain the high-frequency energy for each time window. We then calculated the median and MAD of the high-frequency energy and defined an adaptive threshold as

$$\text{threshold} = \text{median} + k \cdot \text{MAD}. \tag{5}$$

Here, k controls the strictness of the threshold. Windows above this threshold were marked as potential artifacts and removed As ECG polarity can vary with watch orientation and handedness, QRS complexes may appear inverted. We therefore detected R-peaks in both the original and inverted signal. We defined a 0.5 s window around detected R-peaks and calculated the median peak amplitude, prominence, and gradient to compute a polarity score. Together with signal

skewness, this score determined the ECG polarity. A human expert evaluated the polarity classification. We removed powerline noise using empirical mode decomposition combined with a three-level Coiflet 4 discrete wavelet transform (DWT) [2]. We then applied the SWT-LT denoising framework proposed by Berwal et al.[4], which combines stationary wavelet decomposition, adaptive thresholding, QRS preservation, and low-pass filtering to suppress high- and low-frequency motion artifacts. We modified the framework by replacing the median filter with baseline wander removal using a level 9 DWT with the biorthogonal wavelet bior3.7 [26]. We also replaced the original Haar wavelet in SWT-LT with Symlet 6 (sym6). To evaluate signal quality, we calculated the artifact rate and retention rate. In the cleaned ECG signal, we detected R-peaks and estimated the heart rate. Based on the intervals between consecutive R-peaks, we computed heart rate variability (HRV), which quantifies beat-to-beat variation in cardiac rhythm. We included the mean normal-to-normal interval (MeanNN), the standard deviation of normal-to-normal intervals (SDNN), the root mean square of successive differences (RMSSD), high-frequency power (HF), and the long-term Poincaré plot descriptor SD2 (SD2), which can be suitable for ultra-short HRV recordings [7,11,34,37]. Further statistical ECG features can also be calculated from the cleaned signal.

4.5 Interstitial Glucose Data Processing

The Dexcom G7 samples interstitial glucose every five minutes. First, we removed the warm-up period for each CGM wear [13]. To obtain a numerical signal for filtering and outlier detection, we excluded non-numeric values reported by Dexcom as "low" or "high" and values outside $[20, 400]$ mg/dL. We then checked for implausible rises and falls in interstitial glucose. After discussion with clinical experts, we analyzed glucose changes separately during daytime and nighttime, as postprandial times were not available [9,15]. If the change between two consecutive measurements exceeded the time-specific threshold, we removed the affected value and interpolated small gaps using PCHIP. Next, we analyzed trend-line outliers to identify abrupt patterns that may indicate pressure-related artifacts. As interstitial glucose measurements can exhibit short-term oscillatory noise [10], we detected artifacts using first-order differences and a MAD-based threshold. Values exceeding the threshold were removed, and the resulting small gaps were interpolated using PCHIP. For the cleaned signal, we calculated the artifact rate and retention rate. In addition to classifying glucose values into clinically relevant hypo-, in-, and hyperglycemic ranges [3], we calculated biomarkers such as the low blood glucose index (LBGI) [12,28], high blood glucose index (HBGI) [29], mean amplitude of glycemic excursions (MAGE) [46], glucose management indicator (GMI), coefficient of variation (CV) [33], time in range, hypoglycemia and hyperglycemia (TIR); and average daily risk range (ADRR) [29].

5 Results

Figure 1 shows the raw noisy ECG and the processed ECG. Figure 2 visualizes the raw HR with a plateau-like artifact indicating non-wear periods and the processed HR. Additional examples (Fig. 4 and 6) presenting the raw and processed signals, a visualization of the ECG preprocessing (Fig. 7), and potential biomarkers (Fig. 5) are provided in the appendix. Table 2 reports retention and artifact rates for ECG, HR, and skin temperature. Table 1 summarizes potential biomarkers and their main limitations.

Table 1: Overview of calculated ECG and interstitial glucose biomarkers and their main limitations.

Signal	Biomarkers	Main Limitations and Robustness
ECG	HF, MeanNN	Most robust ECG-derived HRV features
ECG	RMSSD, SDNN, SD2, HR	Highly sensitive to missed or falsely detected R-peaks
IGLU	GMI, ADRR	Robust requires sufficient CGM wear time
IGLU	MAGE, CV, HBGI, LBGI, TIR	Robust, requires careful interpretation of real-world glucose traces
Other	Statistical features	Limited clinical relevance

Table 2: Data quality metrics by signal across both phases (for each phase see Appendix Table 3). Values are reported as mean ± standard deviation (minimum, maximum), and n is the number of days with recordings.

Signal	n	Retention Rate	Artifact Rate
ECG	95	0.933 ± 0.021 (0.750, 0.967)	0.103 ± 0.121 (0.000, 0.625)
Heart rate	567	0.990 ± 0.060 (0.376, 1.000)	0.126 ± 0.325 (0.000, 1.000)
Skin temperature	594	0.826 ± 0.356 (0.000, 1.000)	0.301 ± 0.365 (0.000, 1.000)
IGLU	320	0.964 ±0.152 (0.160, 1.000)	0.035 ±0.151 (0.000, 0.840)

6 Discussion

The ECG examples (Fig. 1 and 7) illustrate why preprocessing and quality control are necessary before deriving biomarkers from wearable ECG recordings. In the raw ECG signal in Fig 1 of patient 56, the signal has an elevated baseline drift and is corrupted by noise, masking the Q and ST-wave structures, limiting direct interpretation. After preprocessing, the QRST complex is reconstructed, facilitating R-peak detection and subsequent analysis. A second example (Fig. 7) shows inverted polarity, motion artifacts, and residual noise. If such artifacts are not corrected, peak detection methods may misidentify Q- or S-wave structures as R-peaks. Artifacts may also mask true R-peaks, resulting in missed detections and artificially prolonged RR intervals. These errors affect time-domain HRV (e.g., RMSSD, SDNN, and SD2) and HR estimates, as illustrated by the implausible HR drop in Fig. 1 of patient 44. The HRVs' HF and MeanNN remained stable, underscoring the importance of signal-specific preprocessing and quality

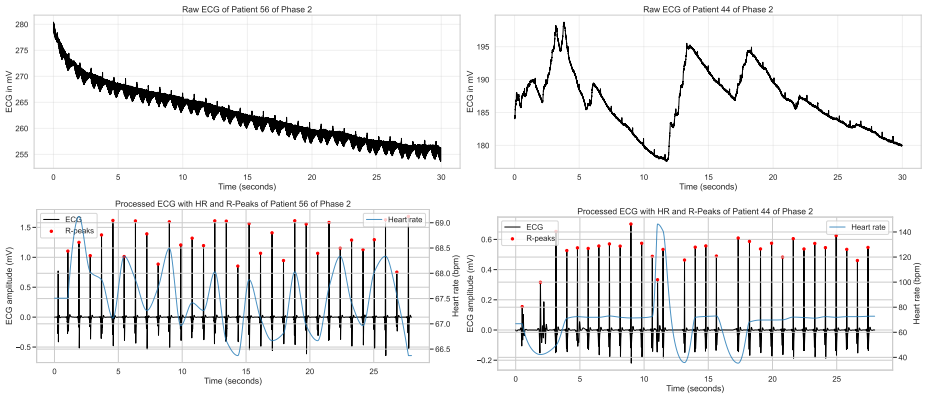

Fig. 1: The upper graphs show the raw ECG signal of patient 56 and patient 44 in the second phase. The lower graphs show the processed ECG signals for each patient, respectively.

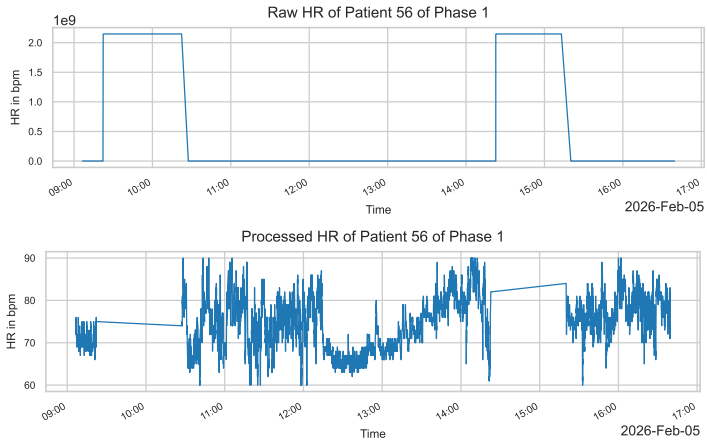

Fig. 2: Raw (upper image) and processed heart rate (lower image) from patient 56 in Phase 1. The raw signal includes two non-wear periods, visible as plateaus, which were removed during preprocessing.

control before interpreting derived biomarkers (see Tab. 1). In the continuous HR data, non-wear periods and extreme values can obscure the amplitude and temporal structure of the physiological signal, as well as potential artifacts (see Fig. 2). Wrist-measured skin temperature is influenced by both physiological and external factors, including ambient temperature, movement, and changing environmental conditions [8]. Thus, abrupt changes should therefore be interpreted cautiously (see Fig.6). Nevertheless, the recorded signals showed acceptable artifact and retention rates on average (see Tab. 2). The skin temperature had the

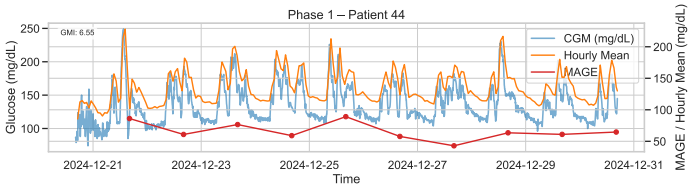

Fig. 3: The plot shows the IGLU after preprocessing for patient 56, including the GMI, MAGE, and mean hourly glucose.

lowest retention rate and the highest artifact rate, with only 82.6% of the signal usable and 30.1% artifacts on average, indicating that the selected preprocessing pipeline produced signals suitable for the subsequent analyses. The results also suggest that data from commercial devices can reach sufficient quality for stroke rehabilitation studies involving patients with potential cognitive impairment or motor limitations [39,43]. This aligns with previous work highlighting the potential of commercial wearable devices in clinical studies [5,22,19]. Several limitations remain. HR and HRV metrics from short wearable ECG recordings were sensitive to missed or falsely detected R-peaks. Step data provided useful information on physical activity, but smartwatch-derived timestamps limited the analysis to the daily level, preventing cadence-based analyses and checks for short-term step artifacts. IGLU signal and IGLU-derived biomarkers were generally applicable, but their interpretation was limited by the absence of meal timing and corresponding blood glucose reference measurements, which would help distinguish physiological glucose changes from sensor-related artifacts. Elevated glucose values also require careful interpretation, as stroke patients often have risk factors associated with impaired glucose regulation [17,35]. Overall, commercial wearable devices can be used to collect HR, skin temperature, ECG, and IGLU data in real-world clinical studies, provided adequate preprocessing and quality assessment are in place.

7 Conclusion and Future Work

This work presented a preprocessing and quality-control workflow for multimodal wearable sensor data collected from older stroke patients in a real-world rehabilitation setting. Consumer-grade wearable devices can support downstream biomarker extraction, but only after extensive data cleaning, artifact handling, and modality-specific plausibility checks. Valid biomarker extraction remains challenging. IGLU-derived metrics can be calculated using established definitions, but real-world glucose traces require additional preprocessing decisions partly informed by clinical expertise. ECG-derived metrics were sensitive to missed or falsely detected R-peaks, short recordings, and implausible RR intervals. Future studies should evaluate whether the proposed pipelines generalize to other consumer smartwatches with similar modalities. Studies using CGMs should collect meal information and blood glucose samples when possible.

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Disclosure of Interests. The authors declare no conflict of interest.

A Appendix

A.1 Examples of Raw Signals in Comparison to the Preprocessed Signal and Biomarkers

The Figures 4, 6, and 7 present the raw and the processed signal. The Figure 5 shows the biomarker ADRR.

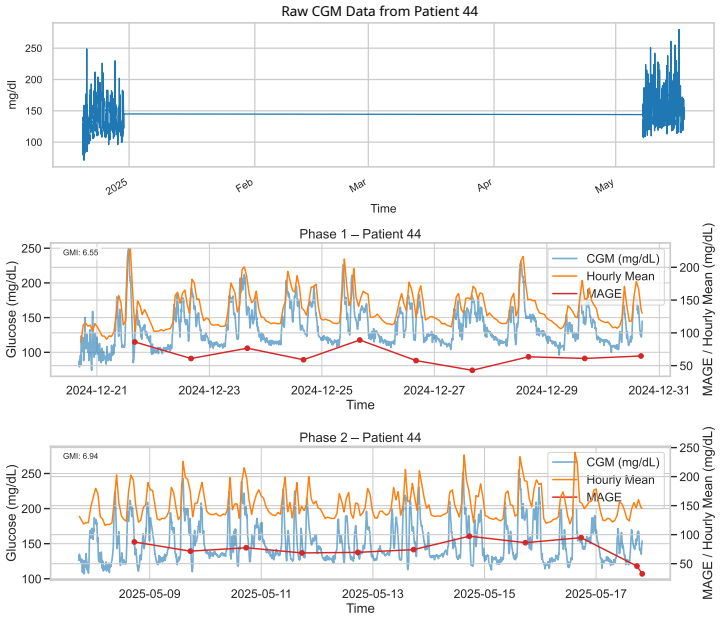

Fig. 4: Raw interstitial glucose and processed interstitial glucose data from one participant in Phase 1 and Phase 2, including glucose management GMI and MAGE. The total wear time was 10 days per phase.

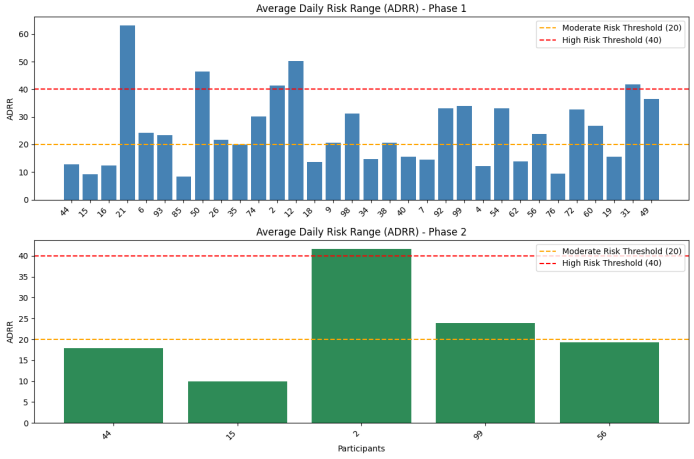

Fig. 5: ADRR Biomarker calculated from IGLU data as an example of possible biomarkers.

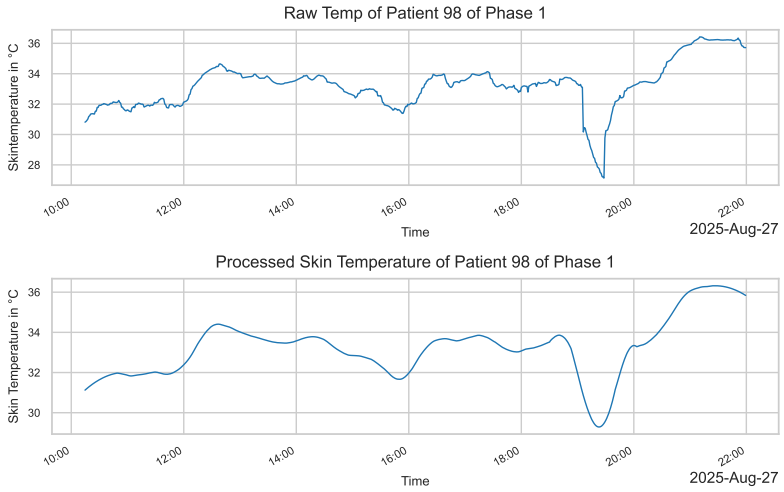

Fig. 6: Raw (upper image) and processed skin temperature (lower image) from patient 98 for one day in Phase 1.

A.2 Artifact and Retention Rate across Study Phases

Table 3 provides an overview of retention and artifact rates across the study phases for each modality individually.

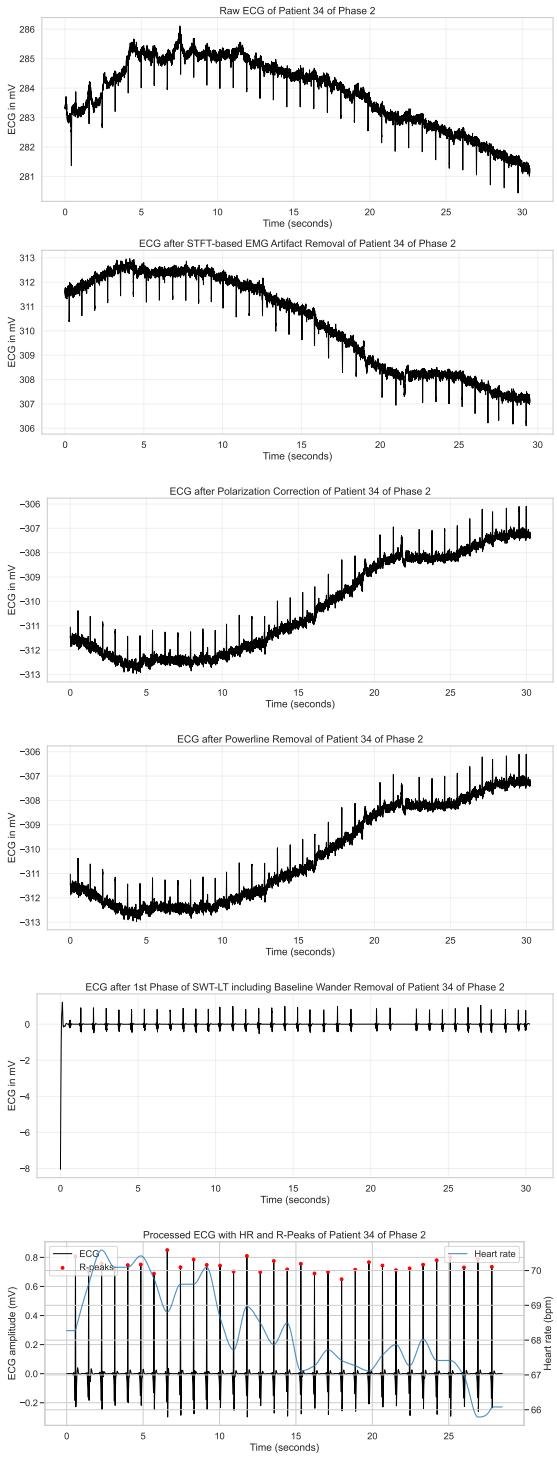

Fig. 7: The figure visualizes the ECG signal of patient 34 in the second phase after each preprocessing step, highlighting the importance of a complete ECG pipeline to reconstruct a noise-free signal for subsequent analysis.

Table 3: Data quality metrics by signal and study phase. Values are reported as mean ± standard deviation (minimum, maximum). N stands for the number of days with recordings.

Signal	Phase	N	Retention Rate	Artifact Rate
ECG	Phase 1	48	0.932 ± 0.029 (0.750, 0.967)	0.103 ± 0.105 (0.000, 0.435)
ECG	Phase 2	47	0.933 ± 0.000 (0.933, 0.934)	0.103 ± 0.136 (0.016, 0.625)
ECG	Overall	95	0.933 ± 0.021 (0.750, 0.967)	0.103 ± 0.121 (0.000, 0.625)
Heart rate	Phase 1	396	0.989 ± 0.063 (0.500, 1.000)	0.170 ± 0.368 (0.000, 1.000)
Heart rate	Phase 2	171	0.994 ± 0.050 (0.376, 1.000)	0.024 ± 0.151 (0.000, 1.000)
Heart rate	Overall	567	0.990 ± 0.060 (0.376, 1.000)	0.126 ± 0.325 (0.000, 1.000)
Skin temperature	Phase 1	421	0.778 ± 0.394 (0.000, 1.000)	0.353 ± 0.394 (0.000, 1.000)
Skin temperature	Phase 2	173	0.942 ± 0.200 (0.000, 1.000)	0.174 ± 0.239 (0.000, 1.000)
Skin temperature	Overall	594	0.826 ± 0.356 (0.000, 1.000)	0.301 ± 0.365 (0.000, 1.000)
IGLU	Phase 1	270	0.958 ± 0.165 (0.160, 1.000)	0.042 ± 0.165 (0.000, 0.840)
IGLU	Phase 2	50	1.000 ± 0.001 (0.999, 1.000)	0.001 ± 0.001 (0.000, 0.001)
IGLU	Overall	380	0.964 ±0.152 (0.160, 1.000)	0.035 ±0.151 (0.000, 0.840)

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