

Continuous Electrocardiogram Monitoring with a Loose T-Shirt

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Abstract

Loose-fitting clothing is an ideal form factor for unobtrusive electrocardiogram (ECG) monitoring but has long been deemed unviable due to severe motion artifacts caused by fabric shifting. We present a hardware-software co-design that enables continuous cardiac tracking within a standard, loose t-shirt. Physically, the shirt's weight presses a thin sensor against the skin, trapping perspiration to form a stable fluidic anchor via capillary pull and negative pressure, while a structural kirigami pattern mechanically absorbs lateral shear. Computationally, a hybrid electrode simultaneously captures ECG and capacitive micro-motion variances to adaptively filter noise during activity. In a pilot study with six participants, the system achieved a 92.7% full waveform detection rate at rest ($r = 0.89$) and an 84.5% R-peak detection rate during walking with a 4.58 bpm heart rate mean absolute error. Participants preferred the shirt over commercial patches and chest straps, demonstrating the feasibility of continuous ECG monitoring in a loose-fitting shirt.

CCS Concepts

• **Human-centered computing** → **Ubiquitous and mobile devices**; • **Applied computing** → **Health care information systems**; • **Hardware** → **Sensor devices and platforms**.

Keywords

Smart Clothing, Wearables, Continuous Electrocardiogram, Motion Artifact Mitigation

ACM Reference Format:

Ho Man Colman Leung, Kyle Tong, Ming Gong, [†]Nam Bui, and Xia Zhou. 2026. Continuous Electrocardiogram Monitoring with a Loose T-Shirt. In *Hot Topics in Mobile and Wireless Systems for Health (MobiDx '26)*, October 26–30, 2026, Austin, TX, USA. ACM, New York, NY, USA, 9 pages. <https://doi.org/10.1145/3842657.3842785>



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MobiDx '26, Austin, TX, USA

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ACM ISBN 979-8-4007-2974-4/2026/10

<https://doi.org/10.1145/3842657.3842785>

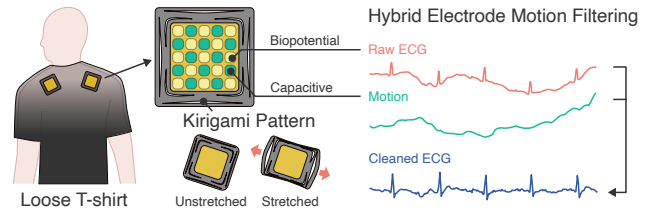


Figure 1: System Overview. Kirigami design for electrode stabilization with a hybrid electrode for motion filtering.

1 Introduction

Continuous electrocardiogram (ECG) monitoring enables early detection of cardiovascular anomalies missed during standard clinical windows [22]. Moving ECG tracking into everyday life requires embedding dry electrodes into wearables that balance signal quality with user comfort. While adhesive patches and tight athletic straps provide stable contact, they cause skin irritation and are too restrictive for continuous everyday wear [3, 9, 14, 21, 50].

Loose-fitting clothing is an ideal form factor for unobtrusive health tracking. However, common daily movements subject the skin-electrode interface to severe shearing and liftoff, resulting in motion artifacts that distort the signal beyond the capabilities of basic filters or advanced decomposition techniques. Consequently, loose clothing has long been deemed unviable for reliable biopotential measurement [45].

To resolve the tradeoff between comfort and signal quality, we introduce a hardware-software co-design for continuous ECG monitoring in loose-fitting t-shirts that directly targets the primary sources of noise: perpendicular macro-motions, lateral macro-motions, and micro-motions (Figure 1). Physically, the shirt's weight presses a thin, flexible sensor against the upper back, trapping perspiration to form a gel-free fluidic anchor to the skin. Mechanically, a structural kirigami pattern absorbs lateral shear forces to decouple the electrode from fabric shifting. Computationally, an interleaved hybrid electrode simultaneously captures ECG and capacitive micro-motion variances, driving a context-aware software pipeline to adaptively filter mechanical noise during physical activity while preserving waveform geometry at rest.

Evaluating the system on six participants across five two-minute activities, we achieved a 92.7% full waveform detection rate with strong morphological correlation ($r = 0.89$)

against a research-grade ground truth at rest. During walking, the system achieved an 84.5% R-peak detection rate and a heart rate Mean Absolute Error (MAE) of 4.58 bpm. Paired with user preference $\geq 4.83/5.0$ over commercial patches and chest straps, our system demonstrates the feasibility of continuous monitoring with a standard loose shirt.

Our key contributions are as follows:

- We propose a motion decoupling interface that adheres an electrode to the skin via the shirt's natural weight and fluidic suction from trapped perspiration, paired with a structural kirigami pattern to decouple the sensor from fabric shear.
- We develop a hybrid electrode design that simultaneously captures ECG and capacitive micro-motion variances to drive a context-aware software pipeline that adaptively suppresses mechanical noise.
- We conduct a feasibility evaluation with six participants in five activities, demonstrating a 92.7% full waveform detection rate at rest ($r = 0.89$), an 84.5% R-peak detection rate during walking.

2 Related Work

Prior mobile health research struggles to balance signal quality with user comfort. Wrist photoplethysmography (PPG) maximizes comfort but lacks the cardiac waveform morphology that diagnosis requires [8, 37], while ambulatory ECG captures it using bulky hardware and irritating adhesives [9, 14, 21]. To bridge this gap, recent works integrate dry electrodes into chest straps [50], clothing [7, 39], furniture [3, 46], car seats [20], and necklaces [48]. However, these systems rely on tight pressure or stationary postures to maintain contact. If clothing is slightly loose, fabric shifting induces motion artifacts that overwhelm the ECG signal.

Once these artifacts are introduced, existing filtering techniques struggle to resolve them. Bandpass filtering fails when motion noise overlaps the ECG spectrum [2], while decomposition methods like Discrete Wavelet Transform [23] and Empirical Mode Decomposition [24] suffer from mode mixing during movement. Hardware-assisted filtering also presents trade-offs: accelerometers [4, 6] capture global body movement rather than localized fabric shifting, while impedance-based tracking [18, 40] requires active current injection. This injection causes leakage, demanding high sampling rates, and added complexity elevates power consumption.

Consequently, loose-fitting clothing remains unviable as neither standard sensing architectures nor filtering algorithms can tolerate the extreme dynamics of fabric shifting.

3 Background and Challenges

ECG measures the heart's electrical activity by detecting differential surface voltages caused by cardiac depolarization

and repolarization [13, 30, 42]. The resulting waveform provides critical metrics like heart rate via the RR interval [36] and breathing rate via thoracic baseline variations [32]. Transitioning this monitoring to everyday life requires prioritizing user comfort. While clinical monitors and tight athletic straps are too constrictive for continuous wear, integrating dry electrodes into a loose-fitting t-shirt requires zero behavior change or skin preparation. However, without conductive gel to bridge microscopic air gaps, the dynamic movement of loose clothing results in a highly fluctuating skin-electrode impedance [16] due to macro-motion and micro-motion, two distinct mechanical phenomena that introduce layered signal acquisition challenges.

Macro-Motions. These large-scale displacements present the primary challenge during daily wear (e.g., walking, reaching). They subject the electrode to mechanical forces that disrupt the already-weakened interface. Lateral shear forces drag the electrode across the skin, introducing baseline wander. Simultaneously, perpendicular forces lift the electrodes from the skin, widening the air gaps beyond the range of biopotential conduction and breaking the electrical circuit. Mitigating macro-motion requires localized mechanical intervention to stabilize the fabric and prevent contact loss.

Micro-Motions. Even with mechanical stabilization against liftoff, the interface remains susceptible to subtle displacements induced by respiration, postural shifts, or transient fabric twitching. These microscopic movements constantly modulate residual air gaps and contact pressure at the skin, dynamically altering interface impedance and injecting signal distortion. However, from an electromagnetic perspective, these shifting micro-gaps alter the localized capacitance between the electrode and the skin. Therefore, while micro-motions disrupt resistive biopotential measurements, they simultaneously produce a corresponding capacitive variance that can be tracked [10].

4 System Design

Our hardware-software co-design (Figure 2) mitigates motion artifacts by addressing three specific challenges: physically anchoring against perpendicular macro-motions, mechanically absorbing lateral macro-motions, and computationally filtering micro-motions.

Gravity-Assisted Interface for Perpendicular Macro-Motion. Mitigating macro-motion requires an anatomical placement that resists perpendicular liftoff. We strategically position thin, non-porous flexible electrodes on the upper back (Figure 2a), a more stable contact zone than the anterior chest, where posture often causes loose clothing to drape away from the skin. This establishes a horizontal bipolar lead mirroring a standard anterior Lead I [26]. Prior work

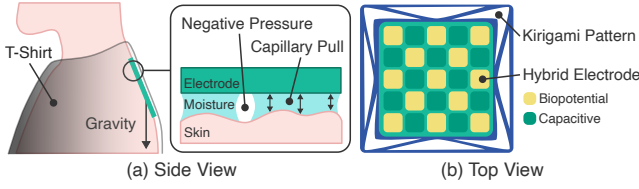


Figure 2: System design. (a) Side view: the shirt presses the sensor against the skin, where trapped moisture provides capillary adhesion and a negative-pressure seal. (b) Top view: a kirigami frame for motion decoupling surrounds the hybrid electrode grid.

establishes that posterior placement preserves Lead I morphology at reduced amplitude [49]. We confirmed this on our hardware with a 10 s simultaneous recording from one participant using wet Ag/AgCl electrodes at both sites, obtaining a Pearson correlation of $r = 0.98$ (Appendix A). This configuration preserves the essential cardiac morphology and rhythm information for detecting conditions like atrial fibrillation (AFib), bradycardia, and tachycardia [34, 43].

Beyond placement, the interface leverages the clothing’s weight and fluid dynamics to physically stabilize contact. The shirt’s natural drape continuously presses the sensor against the skin, displacing air and trapping natural perspiration. This moisture forms microscopic liquid bridges that draw the substrate and epidermis together via capillary forces [15, 38]. By preventing air reentry, this fluidic layer induces a localized vacuum [5]. Ultimately, gravity resists perpendicular liftoff, while this fluidic seal anchors against sliding without the need for adhesive.

Kirigami Decoupling for Lateral Macro-Motion. To prevent shifting clothing from dislodging the sensor, the interface uses a kirigami structure to mechanically absorb lateral shear forces (Figure 2b). Kirigami uses geometric incisions to transform rigid materials into compliant architectures [33, 47]. We cut two concentric rings of slits, offset so the outer ring is interrupted at the corners and the inner ring at the edge midpoints. All load therefore passes through the strips between them, which buckle and twist out-of-plane so that the frame shears while the sensing island remains undeformed (Figure 2b, bottom). By localizing strain within these strips, the structure attenuates fabric tension before the electrode, with residual micro-motion remaining.

Hybrid Electrode and Filtering for Micro-Motion. To filter the remaining noise from perpendicular micro-motions that bypass the kirigami structure, the system pairs an interleaved electrode design (Figure 2b) with a context-aware filtering pipeline (Figure 3). Subtle out-of-plane shifts from respiration or posture modulate the skin-electrode distance and induce localized electrochemical artifacts. To physically capture this noise, we split the electrodes into two networks:

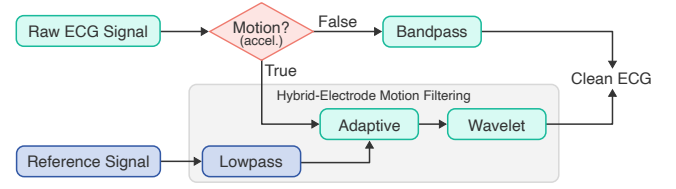


Figure 3: Context-aware filtering pipeline. Motion detection selects between a bandpass filter at rest and the Hybrid-Electrode Motion Filter during movement.



Figure 4: Implementation of the proposed system. (a) Hybrid electrode integrated into a stretchable kirigami pattern. (b) Inside view of the prototype showing two sensing electrodes and the central bias electrode. (c) Exterior back view showing the data acquisition system (DAQ).

an exposed active layer to record the biopotential, and a dielectric-isolated reference layer that measures the capacitive variance representing this perpendicular variation. This dual-channel data then feeds into a context-aware adaptive filtering pipeline. To prevent adaptive filters from introducing mathematical artifacts when the reference channel lacks dominant noise [41], the system uses a simple bandpass filter during stationary periods and only triggers the three-stage pipeline during active motion. First, the reference signal undergoes low-pass filtering to extract the low-frequency drift motion and reject any biopotential leakage [11]. A normalized least-mean-squares (NLMS) adaptive filter then uses this reference to dynamically estimate and subtract localized micro-motions from the ECG [44]. Finally, Discrete Wavelet Transform (DWT) decomposition [1] removes any residual high-frequency artifacts to yield the restored ECG signal.

5 Implementation

We built our prototype using commercially available materials and off-the-shelf hardware (Figure 4). The system comprises three primary modules: (1) the textile sensing interface, (2) the data acquisition hardware, and (3) the signal processing pipeline.

Textile Sensing Interface. The 7.0×7.0 cm hybrid electrodes are fabricated from flexible printed circuit boards (FPCBs) with an Electroless Nickel Immersion Gold finish for stable surface conductivity (Figure 4a). These FPCBs are

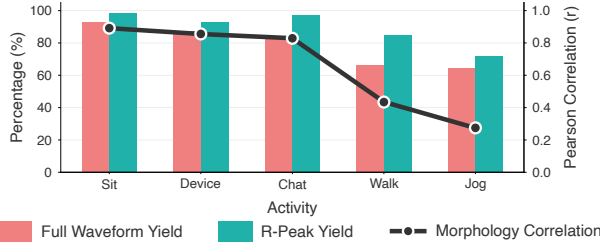


Figure 5: Signal integrity and peak yield across activities. Grouped bars compare the Full Waveform Yield to the R-Peak Yield, while the overlaid line tracks the Pearson correlation (r) of the waveform morphology.

bonded to a spandex substrate and patterned into the 9.5×9.5 cm kirigami geometry, whose 3 mm-wide strips span 18–21 mm. Two electrodes span the upper back 18 cm apart, forming a horizontal bipolar lead with a central fabric bias electrode for common-mode rejection. The array is sewn into a size Large 100% cotton t-shirt to reproduce everyday loose drape (Figure 4b).

Data Acquisition Hardware. The electrodes are connected to an OpenBCI acquisition system [35] (Figure 4c). The hardware’s analog front-end digitizes both the biopotential and the capacitive reference channels, wirelessly streaming the raw data at 250 Hz to a host computer. The incoming stream is visualized in real time for signal quality monitoring and logged for offline processing. Motion state is determined from the board’s onboard accelerometer.

Signal Processing Pipeline. Within the software pipeline, the reference channel is first low-pass filtered at 0.5 Hz to isolate mechanical drift. Both channels are then processed through an NLMS adaptive filter (10 taps, $\mu = 0.1$), followed by a DWT using a Daubechies 4 (db4) mother wavelet to extract the cleaned ECG waveform. Finally, we use NeuroKit2 [27] to compute physiological metrics: heart rate (HR) and heart rate variability (HRV) derived from the QRS complexes, alongside breathing rate (BR) via ECG-derived respiration algorithms.

6 Preliminary Feasibility Evaluation

We conducted a pilot user study to evaluate our system’s performance during simulated daily activities. Six participants (5M/1F, age 24–36, BMI 18.7–25.7 kg/m²) without known heart disease wore our custom t-shirt and completed five consecutive 2-minute activities modeling daily behaviors: sitting stationary, using a device while seated, chatting while standing, walking continuously, and jogging in place. The shirt recorded posterior ECG alongside a ground-truth Lead I from a second OpenBCI system, using wet Ag/AgCl electrodes at the forearm to avoid interfering with the posterior sensor. Streams were aligned by shared-host timestamps.

Evaluation Metrics. We evaluate three dimensions:

- **Waveform Morphology:** Three metrics against the ground truth: (1) *Coverage*, the percentage of matched heartbeats for *R-peaks* (100 ms window [31]) and *All Peaks* (sequential P, R, T; 120 ms for P/T to accommodate posterior vector shifts [29]). (2) *Structural Similarity*, the Pearson correlation over a 500 ms PQRST window (150 ms pre-, 350 ms post-R-peak) [19]. (3) *Temporal Error*, the mean absolute alignment error across matched peaks.
- **Signal-to-Noise Ratio (SNR):** In-band noise variance (dB), from subtracting an ensemble-averaged heartbeat template from each 500 ms window [25].
- **Vital Sign Accuracy:** Mean Absolute Error (MAE) for heart rate (HR) and breathing rate (BR), plus the HRV metrics RMSSD and SDNN over sliding windows.

6.1 System Performance Across Activities

We applied the evaluation framework to our multi-activity dataset to quantify the system’s robustness.

Waveform Morphology Accuracy. As shown in Figure 5, the context-aware pipeline captures clean ECG geometry during stationary states (Sitting, Using Devices, Chatting). During Sitting, the system achieves an R-Peak Yield of 98.2%, a Full Waveform Yield (complete PQRST complex) of 92.7%, and a strong morphological correlation ($r = 0.89$) against the ground truth.

However, intense physical activity introduces step impacts, baseline wander, and electromyographic (EMG) noise. During Walking and Jogging, the Full Waveform Yield drops to 65.9% ($r = 0.43$) and 64.5% ($r = 0.27$), respectively, as mechanical noise swamps low-amplitude P and T waves. Despite this peripheral wave corruption, the architecture successfully isolates high-amplitude R-peaks, maintaining an R-Peak Yield of 84.5% during Walking and 71.7% during high-impact Jogging. This motion degradation may stem from suboptimal fit, since all participants wore the same shirt size. We analyze the relationship between user Body Mass Index (BMI) and performance in Section 6.2 and propose mitigation strategies in the Discussion.

Waveform Timing Precision. Reliable rhythm assessment requires temporal precision in peak detection. During Sitting, our system achieves accurate peak alignment, tracking R-peaks with a MAE of 5.38 ms and subtler P and T waves with sub-10 ms precision (Table 1; Appendix C). In dynamic states, mechanical noise obfuscates lower-amplitude wave boundaries, increasing P and T wave alignment errors to over 44.0 ms. Conversely, R-peak errors remain tightly bounded at 12.0 ms during Walking and 15.7 ms during Jogging. Detected R-peaks therefore remain accurately localized. The residual error in interval-based metrics arises from missed beats rather than mislocalized ones.

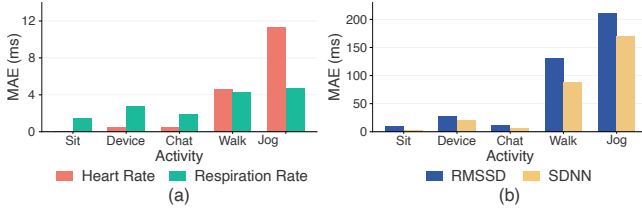


Figure 6: Vital signs accuracy across activities. (a) Cardiorespiratory Rate Errors: MAE for heart rate (HR) and breathing rate (BR). (b) Heart Rate Variability Error: Autonomic tracking errors reported as MAE for RMSSD and SDNN.

Noise Suppression and SNR. To evaluate signal quality, the post-processed SNR was calculated across all activity protocols (Table 1). During stationary activities, the system maintains stable SNR: Sitting achieves 6.23 dB, while Using Devices and Chatting settle at 2.64 dB and 2.19 dB, owing to minor postural adjustments and localized muscle contractions. Dynamic movement introduces low-frequency voltage swings from heel-strikes and torso motion that exceed the amplitude of the ECG peaks, dropping the walking SNR to -5.78 dB. During Jogging, sensor displacement and EMG interference push it to -7.42 dB, placing the noise floor above the underlying biopotential signal power.

Vital Sign Inference. We evaluated vital sign accuracy using MAE across activities (Figures 6a and 6b). Stationary states yield negligible baseline errors, achieving an HR MAE of 0.03 bpm, BR of 1.44 bpm, RMSSD of 8.98 ms, and SDNN of 3.50 ms during sitting. Minor postural shifts introduce marginal fluctuations, keeping HR errors below 0.51 bpm and HRV errors small relative to reported short-term ranges [28]. Motion artifacts expand HR errors to 4.58 bpm during walking, well within the ≤ 10 bpm industry threshold [17], though exceeding it during jogging (11.38 bpm). BR demonstrates resilience, peaking at 4.25 bpm during walking and 4.75 bpm during jogging, indicating that low-frequency thoracic modulation remains extractable even when high-frequency morphological features are corrupted. Additionally, HRV metrics severely degrade during movement, with RMSSD MAE climbing to 130.90 ms during walking and 211.30 ms during jogging. Because RMSSD relies on the squared differences of successive intervals, minor temporal jitter or missed R-peaks rapidly compound the error. To help mitigate these errors, we outline potential physical stabilization strategies in §7.

6.2 Impact of User BMI on System Performance

Because all participants wore the same shirt size, BMI acts here as a proxy for clothing and sensor fit. Our kirigami decoupling mechanism requires physical freedom to deform

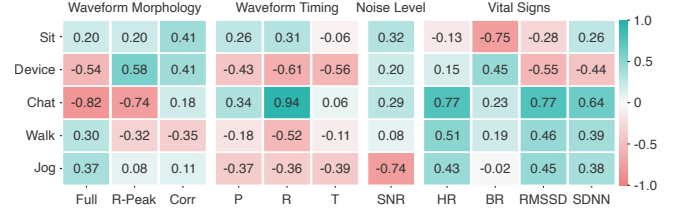


Figure 7: Correlation between user BMI and system performance across activities (red: negative; green: positive). Abbreviations: Full: Full ECG Yield; R-Peak: R-Peak Yield; Corr: Morphology Correlation; P/R/T: peak timing delays; SNR: Signal-to-Noise Ratio; HR/BR: Heart/Breathing Rate; RMSSD/SDNN: HRV parameters.

during movement, and its effectiveness depends on individual torso dimensions. Our correlation matrix suggests a dual-phase trend between user BMI and system performance (Figure 7). At lower BMIs, the system operates as intended, as a looser fit allows the kirigami pattern to decouple outer fabric motion from the skin-anchored electrodes. At higher BMIs, the increased torso volume appears to trade stationary performance against motion robustness. During stationary periods, the tighter clothing applies greater passive contact pressure, securing the electrode and reducing respiration rate errors ($r = -0.75$, Appendix B).

However, this tighter fit coincides with degraded performance during dynamic movement. We hypothesize that excessive body volume compresses the structural layers together, generating inter-layer friction that pins the kirigami pattern in place, so that gravity and torso extension drag the coupled electrode into a suboptimal position. This accompanies reduced Full ECG Yield ($r = -0.82$) and increased R-wave timing errors ($r = 0.94$). While milder motion such as walking may temporarily break this friction lock and allow the sensor to self-adjust, high-intensity movement overwhelms the interface. During jogging, dynamic shear forces appear to bypass the kirigami structure and map onto the coupled electrode, coinciding with SNR degradation ($r = -0.74$).

6.3 Ablation Study

Empirical results highlight a critical trade-off in physiological signal modeling: aggressive motion artifact mitigation is essential during dynamic states but systematically distorts signals during rest. As shown in Table 1, applying the standalone motion filtering pipeline during the Sitting scenario degrades morphology, dropping signal correlation from 0.890 to 0.751 and inflating heart rate MAE from 0.03 to 0.45 bpm compared to a simple bandpass baseline. Conversely, relying solely on static baseline filtering fails during intense activities like Jogging, yielding an MAE of 32.00 bpm against 11.38 bpm for our context-aware pipeline. Our framework resolves this

dilemma by using real-time inertial data to activate aggressive filtering only when physical artifacts threaten signal integrity, preserving undisturbed signals during rest while mitigating noise during motion.

6.4 Usability

Upon completion, participants evaluated the proposed system via a 5-point Likert scale and open-ended feedback. Quantitative results were uniformly positive: comfort, convenience, and ease of use (Q1–Q3) all received $\geq 4.83/5.0$. All six participants preferred our system over commercial ECG patches (Q4: 4.83/5.0) and chest straps (Q5: 5.0/5.0), rating the overall experience 4.67/5.0 (Q6). Moreover, qualitative feedback echoed these quantitative findings. Users praised the zero-effort, frictionless sensing of an everyday t-shirt that successfully bypasses the skin irritation and physical restriction of traditional monitors. The sole critique noted the data-acquisition module's bulkiness, a footprint addressable through custom PCB miniaturization.

7 Discussion and Future Work

Hardware Optimization. To address the motion-induced degradation observed during dynamic tasks, future iterations will refine both clothing form factor and sensor geometry. First, because our results (Sec. 6.2) suggest that BMI influences motion resilience, fabricating multiple clothing sizes is a straightforward mitigation. Since discrete sizing cannot suit every individual, we will also explore structural designs such as low-friction interlayer linings or localized elastic zoning that let a single size tolerate a wider BMI range without compromising the kirigami mechanism. Fabric weight, weave, and stretch likewise alter drape and transmitted shear, which we will characterize across materials. Second, we will explore multi-electrode clusters and alternative geometries to maintain skin contact during movement, enabling adaptive channel selection that evaluates each element's SNR and routes the most stable channel. Third, we will rebalance the surface area ratios within the hybrid structure: because capacitive components are highly sensitive, reducing their area frees space for biopotential elements, lowering the high contact impedance of dry electrodes [12]. Finally, we will reduce the system's footprint. Miniaturizing the processing unit and integrating its connections into an FPCB replaces loose wires and mitigates cable noise, while the patch devotes 47% of its area to the kirigami frame, making frame miniaturization the clearest route to a smaller sensor. Both improve comfort for long-term wear, which future trials will assess alongside skin tolerance.

Real-time Processing and Monitoring. We plan to develop a mobile companion application for real-time ECG visualization and automated signal quality assessment. The

application streams data from the sensor's MCU, flagging electrode displacements or motion artifacts as they arise. Building on this, we will extend the pipeline to compute HR, BR, and HRV continuously. The phone's inertial sensors could also supply an additional motion reference for multimodal denoising, complementing our capacitive channel. Whether these computations are best placed on the sensor MCU or the phone, in power, latency, and bandwidth, remains unquantified.

Extensive User Study. We plan to recruit participants from diverse demographics. Future validation will focus specifically on a wide distribution of user BMIs to thoroughly test our sizing against distinct body shapes. We will also introduce longitudinal studies where participants wear the clothing continuously for a full day. This long-term monitoring will allow us to investigate if and when signal degradation occurs over time, verifying system resilience across both stationary intervals and high-intensity activities. We will broaden the activity set beyond walking and jogging to stairs, reaching, driving, and desk work. Exercise ECG, by contrast, warrants a separate pipeline rather than treatment as a harder daily case. Additionally, to ensure clinical viability, we will benchmark our system against FDA-cleared clinical-grade monitors, such as a standard ambulatory Holter system, moving beyond our current forearm-referenced wet electrode baseline, and confirm the upper-back placement against alternative sites across body types. Finally, we will extend validation to cardiac patients, whose abnormal waveforms may interact differently with the pipeline.

8 Conclusion

We introduce a hardware-software co-design for continuous, unobtrusive ECG monitoring within standard, loose-fitting t-shirts. By embedding kirigami-stabilized hybrid electrodes on the upper back, the system mechanically decouples the interface from fabric motion. Paired with a context-aware filtering pipeline, this architecture balances stationary precision with dynamic noise suppression. Evaluated across five activities, the system achieved a 92.7% waveform detection rate ($r = 0.89$) at rest, and an 84.5% R-peak detection rate with a 4.58 bpm heart rate MAE during walking. Strongly preferred by users ($\geq 4.83/5.0$), this zero-effort system demonstrates that continuous ECG monitoring is feasible in a loose t-shirt, a form factor previously deemed unviable.

Acknowledgments

This work is supported by the National Science Foundation (IIS-2202553). The manuscript was edited for grammar with Gemini and Claude.

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A Posterior Placement Verification

Figure 8 shows the simultaneous anterior and posterior recordings underlying the $r = 0.98$ correlation reported in Section 4. Both sites used wet Ag/AgCl electrodes, isolating the effect of placement from that of electrode type.

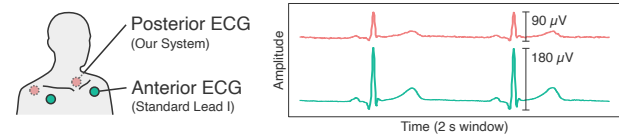


Figure 8: Comparison of raw ECG signals over a 2-second window from the 10-second recording. The posterior signal (top, red) exhibits a smaller amplitude ($90 \mu\text{V}$) than the anterior reference (bottom, green, $180 \mu\text{V}$) because it is aligned away from the heart axis. Despite this reduction, both signals show aligned R-peaks, and the posterior signal preserves the standard PQRST geometry with a correlation of 0.98.

B BMI Correlation Detail

Figure 9 shows the per-participant data underlying the two BMI correlations reported in Section 6.2, with 95% confidence intervals.

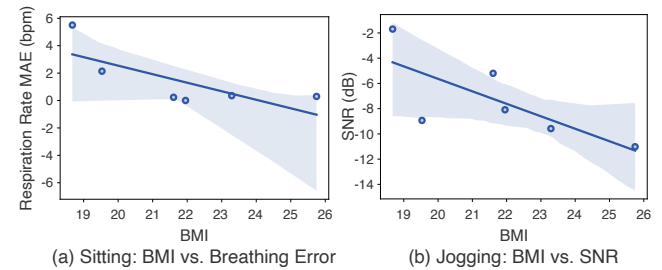


Figure 9: Sensor performance as a function of user BMI during (a) sitting against breathing rate error and (b) jogging against SNR. Shaded regions denote the 95% confidence interval ($N = 6$).

C Full Ablation Study

Table 1 provides a comprehensive performance breakdown of different configurations across the evaluated activity scenarios. We benchmark our context-aware architecture against standard baselines including conventional bandpass filtering, wavelet denoising, and adaptive noise cancellation. We also include an ablated variant of our pipeline utilizing motion filtering without context awareness. Performance is evaluated across signal availability (Coverage), structural preservation (Morphology Correlation), window tracking accuracy (Timing MAE), and downstream vital sign inference (HR, BR,

Table 1: Comprehensive Algorithmic Benchmarking and Ablation Matrix Across All Scenarios

Scenario	Pipeline Configuration	Coverage (%)		Morph.	SNR	Timing MAE (ms)			Vital Sign MAE			
		Full	R-Peak	Corr (r)	(dB)	P	R	T	HR (bpm)	BR (bpm)	RMSSD (ms)	SDNN (ms)
Sitting	Bandpass	92.6%	98.2%	0.890	6.20	9.5	5.4	7.7	0.03	1.44	9.0	3.5
	Wavelet	91.1%	98.2%	0.877	5.53	10.5	5.3	7.9	0.03	1.41	9.6	3.8
	Adaptive	88.2%	97.6%	0.729	1.84	12.1	5.1	20.2	0.64	0.98	18.4	13.5
	Ours (<i>Motion Filter Only</i>)	91.7%	97.8%	0.751	7.41	12.0	5.1	20.9	0.45	0.90	15.4	10.9
	Ours (Context-Aware)	92.7%	98.2%	0.890	6.23	9.5	5.4	7.7	0.03	1.44	9.0	3.5
Using Devices	Bandpass	87.3%	93.0%	0.852	2.56	18.8	8.8	11.9	0.49	2.78	27.2	20.2
	Wavelet	86.7%	93.2%	0.836	2.15	19.9	8.8	12.2	0.26	2.17	21.9	14.7
	Adaptive	84.2%	90.9%	0.705	1.74	19.3	8.0	25.7	1.37	2.04	26.1	25.3
	Ours (<i>Motion Filter Only</i>)	86.8%	93.1%	0.713	2.45	19.5	7.9	26.2	0.88	2.06	20.0	17.7
	Ours (Context-Aware)	87.1%	93.0%	0.853	2.64	18.8	8.8	11.6	0.49	2.77	27.2	20.2
Standing	Bandpass	84.5%	96.9%	0.830	2.27	23.4	6.2	15.3	0.51	1.90	11.9	5.8
	Wavelet	84.5%	97.0%	0.819	2.08	24.8	6.2	15.9	0.51	1.73	11.6	5.7
	Adaptive	71.0%	94.6%	0.662	-0.36	29.7	6.9	29.4	1.72	2.07	29.3	25.9
	Ours (<i>Motion Filter Only</i>)	77.8%	96.1%	0.707	1.21	28.0	7.1	29.4	0.85	2.72	22.1	14.6
	Ours (Context-Aware)	84.3%	97.0%	0.831	2.19	23.4	6.2	15.3	0.51	1.85	11.9	5.8
Walking	Bandpass	56.3%	73.0%	0.359	-10.19	40.0	9.3	36.3	15.91	3.45	752.1	506.2
	Wavelet	55.1%	72.4%	0.347	-10.68	41.9	9.4	34.9	17.12	3.23	979.9	694.3
	Adaptive	60.8%	82.8%	0.382	-8.89	44.7	11.8	42.2	6.44	3.81	228.5	155.5
	Ours (<i>Motion Filter Only</i>)	65.7%	83.9%	0.437	-6.61	43.6	12.2	41.6	5.07	4.05	154.7	101.6
	Ours (Context-Aware)	65.9%	84.5%	0.433	-5.78	44.8	12.0	44.5	4.58	4.25	130.9	87.6
Jogging	Bandpass	50.6%	51.6%	0.256	-9.74	46.0	18.0	39.3	32.00	5.02	609.3	471.0
	Wavelet	53.8%	52.1%	0.245	-10.26	45.4	18.4	41.4	31.75	4.56	607.5	466.4
	Adaptive	65.1%	70.7%	0.246	-8.94	43.7	15.5	48.0	12.10	4.85	234.4	184.0
	Ours (<i>Motion Filter Only</i>)	64.0%	71.5%	0.272	-9.18	45.4	15.2	47.6	11.59	5.23	211.1	169.1
	Ours (Context-Aware)	64.5%	71.7%	0.272	-7.42	44.8	15.7	47.7	11.38	4.75	211.3	170.4

RMSSD, and SDNN MAE). For each activity block, the top-performing configuration within each metric is highlighted in bold.

Received 10 July 2026; revised 15 August 2026; accepted 30 August 2026