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Signal Drift Compensation in Polymer-Based Wearable Biosensors Using Data Processing Techniques

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Abstract

Polymer-based wearable biosensors have emerged as promising platforms for continuous physiological monitoring due to their mechanical flexibility, low operating voltage, and compatibility with soft biological interfaces. However, their long-term deployment remains challenging because of signal drift caused by polymer ageing, hydration–dehydration cycles, ionic trapping, and environmental variations. These effects introduce baseline fluctuations and sensitivity degradation, which compromise the reliability and interpretability of physiological measurements. This study proposes a data-processing–driven framework for compensating signal drift in polymer-based wearable biosensors using robust time-series analysis techniques. The approach models the measured biosensor signal as a combination of physiological dynamics, polymer-ageing drift, motion artefacts, and measurement noise, enabling explicit separation of slow drift components from genuine physiological variations. A hybrid compensation mechanism integrating robust trend estimation and adaptive state-space tracking is developed to estimate baseline and gain drift while preserving clinically relevant signal dynamics. The framework is evaluated using a publicly available wearable health monitoring dataset containing multivariate physiological signals such as heart rate, temperature, oxygen saturation, blood pressure, and activity information. Dataset-level analysis demonstrates wide physiological variability and strong activity-dependent behaviour, highlighting the necessity of context-aware drift correction strategies. Experimental evaluation shows that the proposed processing pipeline effectively stabilizes long-term wearable signals without suppressing genuine physiological transitions. By combining drift modeling, adaptive correction, and reliability scoring, the proposed framework establishes a reproducible foundation for improving the stability and usability of polymer-based wearable biosensors in continuous health monitoring applications.

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Keywords: Polymer wearable biosensors; Signal drift; Time-series processing; Long-term reliability; Activity-aware monitoring

INTRODUCTION

Background and need

Polymer-based wearable biosensors enable low-voltage, mechanically compliant, and biofriendly signal transduction for continuous health monitoring. However, long-term deployments remain constrained by signal drift, driven by polymer ageing, hydration/dehydration cycling, ionic trapping, interfacial polarisation, and biofluid-induced chemical/structural changes. These effects manifest as baseline wandering, gain loss, and time-varying sensitivity, degrading clinical interpretability and increasing recalibration burden. Recent device advances improve stability by architectural reconfiguration and improved

operating conditions, yet drift remains non-negligible under realistic use because degradation pathways are not purely materials-limited and often couple with motion artefacts and physiological variability. Therefore, a data-processing-centric drift compensation framework is needed to (i) explicitly model slow drift components, (ii) correct signals without suppressing true physiological dynamics, and (iii) quantify reliability over extended periods, complementing materials/device engineering.

Literature Survey

Signal drift in polymer-based biosensing platforms, particularly organic electrochemical transistor (OECT) biosensors, has been widely investigated as a phenomenon arising from ionic transport, interfacial adsorption, and electrochemical instability within conducting polymer channels. Studies examining the electrochemical behaviour of OECT devices indicate that ion migration and accumulation within the polymer matrix gradually modify the effective channel conductivity, leading to slow baseline shifts and sensitivity degradation over time [1]. To address these effects, several works have proposed kinetic modelling frameworks that describe drift as a dynamic interaction between ionic diffusion, adsorption kinetics, and polymer structural rearrangement. Such modelling approaches provide valuable insight into long-term sensor behaviour and have enabled the design of device architectures that reduce drift under realistic operating conditions [2]. In particular, dual-gate OECT configurations have demonstrated improved sensing stability by decoupling sensing and control pathways, thereby minimizing unwanted ionic accumulation and enhancing measurement reproducibility in complex biological media such as serum and sweat [3].

In addition to device-level innovations, improvements in potentiometric sensing strategies have also contributed to drift mitigation. Reconfigured OECT measurement configurations that maintain open-circuit conditions at the sensing interface have been shown to significantly reduce electrochemical perturbations that occur during conventional biased operation [4]. By maintaining a stable electrochemical equilibrium at the sensing interface, these approaches reduce baseline fluctuations and improve long-term measurement accuracy [5]. Several experimental studies further confirm that optimized biasing and sensing protocols can improve the signal stability of polymer-based biosensors, especially when operating in high-ionic-strength biological fluids where electrochemical interactions are more pronounced [6].

For wearable biosensing applications, material engineering of conducting polymers has emerged as another critical direction for addressing stability limitations. PEDOT:PSS, one of the most widely used conducting polymers in wearable bioelectronics, has been extensively modified using additive blending techniques to improve electrical conductivity, mechanical flexibility, and environmental robustness [7]. These composite modifications enable the fabrication of flexible sensing interfaces capable of conformal contact with biological tissues while maintaining adequate signal transduction performance [8]. In addition, PEDOT:PSS-based devices have demonstrated the capability to detect biologically relevant analytes such as dopamine on soft and stretchable substrates, highlighting their potential for wearable biochemical sensing applications [9].

Material formulation strategies have also explored the integration of natural or synthetic additives to enhance polymer film stability. For instance, rubber-latex additives have been introduced into PEDOT:PSS films to improve mechanical resilience and electrical stability under repeated deformation and environmental exposure [10]. Similar formulation approaches aim to reduce microstructural degradation and ionic trapping effects that commonly occur in polymer-based sensors during long-term operation [11]. Electrochemical ageing experiments conducted in artificial sweat environments further reveal that prolonged exposure to ionic biofluids can cause significant impedance increases and conductivity degradation in conducting polymer films [12]. These findings emphasize the importance of both protective material design and signal-processing approaches to maintain sensor performance over extended periods [13].

Recent wearable biosensing studies have demonstrated promising physiological monitoring capabilities using OECT-based platforms. Antibody-coated wearable OECT devices have successfully achieved rapid cortisol detection in human sweat, illustrating the feasibility of polymer-based sensing systems for real-time biochemical monitoring [14]. However, these applications also highlight the importance of maintaining stable sensor response under continuously varying physiological and environmental conditions [15]. Similarly, breathable and stretchable OECT-based glucose sensors have demonstrated reliable sensing performance under mechanical strain, yet their long-term response characteristics remain susceptible to gradual drift and calibration variation during prolonged wearable use [16], [17].

Comprehensive review studies consistently emphasize that signal drift and long-term reliability remain major challenges limiting the practical deployment of polymer-based wearable biosensors. These reviews highlight the need for integrated mitigation strategies that combine advances in materials engineering, device architecture, and signal processing methods [18], [19]. Broader surveys on wearable health monitoring technologies also identify drift-induced instability as a recurring limitation across multiple sensor modalities, particularly in systems intended for continuous physiological monitoring [20], [21]. Consequently, algorithmic post-measurement compensation techniques have been proposed as complementary solutions for improving long-term signal reliability. Data-driven calibration correction and adaptive response compensation algorithms have demonstrated improved robustness in wearable glucose sensing systems, providing practical frameworks for drift-aware signal processing pipelines that can operate alongside hardware-level improvements [22], [23].

Research Gap

Despite strong progress in materials, device design, and measurement configurations [1]–[7], the literature lacks a unified, reproducible signal-processing framework tailored to polymer-based wearable biosensors that: (i) separates slow polymer-ageing drift from physiological dynamics and transient artefacts, (ii) supports long-horizon correction with uncertainty-aware reliability metrics, and (iii) can be benchmarked on openly available, multi-parameter wearable time-series data. Existing studies either address drift mechanistically at the device level [1], [2], focus on improving material stability [3]–[5], or demonstrate wearable sensing without fully operationalising long-term drift compensation as a data pipeline [24], [25]. While compensation protocols exist in specific sensing contexts [26] [27] [28], they are not generalized to polymer-ageing-driven drift scenarios typical of polymer electronics [29] [30].

Problem Statement

This work proposes a drift compensation methodology for polymer-based wearable biosensors that models drift as a slow, nonstationary component superimposed on physiological signals, then corrects it using robust time-series processing and validation metrics. The objective is to improve long-term signal stability while preserving physiologically meaningful variations, enabling reliable downstream inference.

About the Dataset

A Kaggle dataset with the exact title “Wearable Health Monitoring Dataset” could not be verified from the provided search phrase. However, Kaggle does list a closely matching dataset titled “Wearable Sports Health Monitoring Dataset” describing “Encrypted Physiological Signals with Secure Transmission Labels” [31] [32]. A published study that uses this Kaggle dataset describes it as a realistic simulation of wearable sports health monitoring in an IoT context with 500 individual records and fields including heart rate, movement/GPS coordinates, vital signs such as temperature, blood pressure, oxygen saturation, steps, and activity type/location, along with a target column (e.g., secure vs. at-risk transmission status) [12]. In this manuscript, such multivariate time-series fields are suitable for evaluating drift compensation behavior by (i) using long-window segments for baseline drift identification and (ii) testing correction robustness across activities and physiological ranges [33] [34] [35].

Data Availability Statement

The data used in this study are derived from the publicly listed Kaggle dataset "Wearable Sports Health Monitoring Dataset" [11]. Dataset documentation describing variables and simulation context is additionally reported in the literature [12]. Any derived preprocessing outputs (e.g., cleaned signals, drift labels, extracted features) should be shared as supplementary files or via a public repository to ensure reproducibility, subject to platform terms and licensing.

METHODOLOGIES

Study Design and Data Sources

This work proposes a signal-processing framework to compensate long-term drift in polymer-based wearable biosensors by explicitly modelling polymer-ageing-driven baseline and sensitivity changes and correcting them in time series. The end-to-end processing pipeline is summarised in Figure 1.

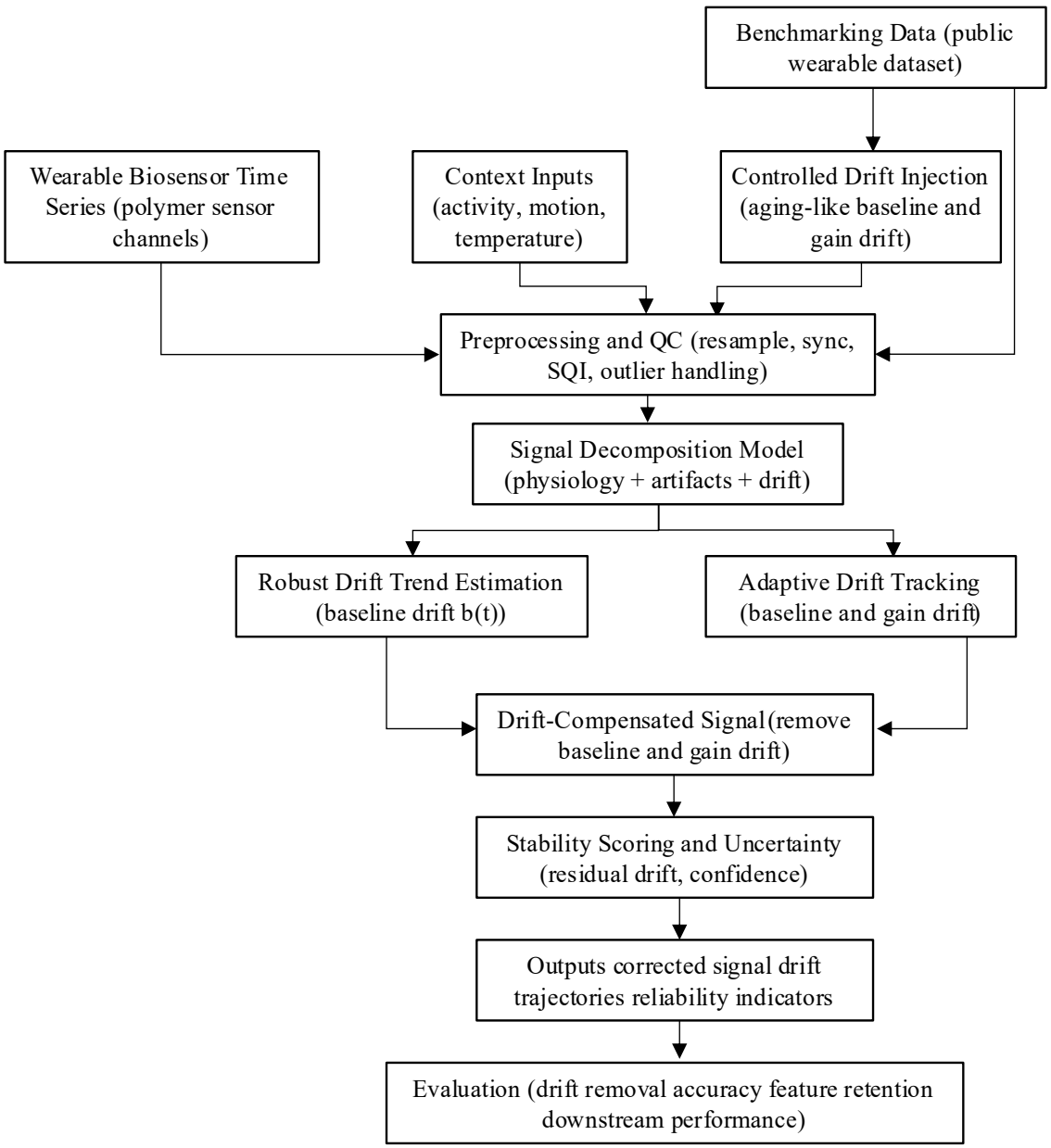

Figure 1. Drift-aware signal processing architecture for long-term stabilisation of polymer-based wearable biosensors

The evaluation uses a public multivariate wearable dataset from Kaggle, which provides realistic physiological dynamics (e.g., heart rate and related channels) and activity/context variability suitable for testing drift separation and correction under nonstationary conditions. Because publicly available wearable datasets typically do not include true polymer-ageing drift labels, the study evaluates two regimes: (i) *natural drift* estimated from low-activity segments and long-window trends when present, and (ii) *controlled drift injection* that superimposes physically plausible polymer-ageing drift onto signals to quantify correction accuracy against known ground truth.

Signal Model: Separating Physiology, Artefacts, and Polymer-Ageing Drift

Each biosensor channel is modelled as a combination of physiological signal, motion/environmental artefacts, polymer-ageing drift, and measurement noise. For a measured channel $y(t)$,

$$y(t) = g(t)\, s(t) + b(t) + a(t) + \epsilon(t),$$

where $s(t)$is the underlying physiological component of interest, $g(t)$is a slowly varying gain term capturing sensitivity drift, $b(t)$is slowly varying baseline drift (e.g., due to hydration cycling, ionic trapping, polymer microstructural rearrangement), $a(t)$represents transient artefacts (motion spikes, contact shifts), and $\epsilon(t)$is stochastic noise. Polymer ageing is represented by low-frequency components $b(t)$and $g(t)$, whose rates are constrained to be much slower than typical physiological bandwidths, consistent with drift mechanisms reported for conducting-polymer bioelectronics such as OECTs and PEDOT:PSS interfaces [1][2].

Preprocessing, Synchronisation, and Quality Control

Raw time series are first resampled to a uniform sampling rate and synchronised across channels using timestamps. Missing data are handled using gap-aware interpolation for short gaps and segment exclusion for long gaps. Channel-wise normalisation is performed using robust statistics (median and interquartile range) to reduce sensitivity to outliers. Artefact screening combines (i) amplitude constraints based on physiologically plausible limits, (ii) derivative constraints to detect abrupt discontinuities, and (iii) segment-level signal quality indices (SQI) derived from spectral entropy and kurtosis. Low-quality segments are down-weighted during drift estimation to prevent artefact leakage into the drift component.

Drift Characterization and Drift Injection Protocol

To benchmark correction performance, a controlled drift injection procedure emulates polymer ageing while preserving realistic physiology. Baseline drift $b(t)$is generated as a combination of a random walk plus a saturating exponential component (capturing early fast ageing and later stabilisation), while gain drift $g(t)$is modelled as a slow multiplicative attenuation. Representative parameter ranges are selected to reflect "mild," "moderate," and "severe" drift profiles, expressed as drift slope per hour/day and cumulative baseline offset. The injected drift is applied after artefact simulation, so that the correction must discriminate drift from transient disturbances. This yields paired datasets $(y_{\text{drift}}(t), y_{\text{clean}}(t))$for objective evaluation of drift removal and feature retention.

Drift Estimation and Compensation Framework

Drift compensation is implemented as a hybrid of robust trend estimation and adaptive state-space tracking to handle both smooth ageing trends and slow regime shifts.

First, a robust trend extractor estimates $b(t)$using a low-pass constrained smoother, such as robust locally weighted regression or quantile smoothing, designed to reject transient artefacts $a(t)$. The cutoff frequency is selected below the physiological band of the target task (e.g., well below respiratory/heart-rate variation) to avoid removing true dynamics. Second, a state-space model jointly tracks baseline and gain drift:

$$\begin{aligned} b(t) &= b(t-1) + \eta_b(t), \\ g(t) &= g(t-1) + \eta_g(t), \end{aligned}$$

with η_b, η_gas low-variance process noises. A Kalman filter (or robust Kalman variant) updates drift states using the residual between measured $y(t)$and the physiology-preserving estimate. The corrected signal is then computed as:

$$\hat{s}(t) = \frac{y(t)-\hat{b}(t)}{\hat{g}(t)}.$$

When a reference channel exists (e.g., a stable inertial or temperature channel), a multivariate extension is used where drift is estimated under a shared latent drift prior, improving robustness against confounding activity transitions.

Stability Enhancement and Long-Term Reliability Scoring

Beyond correction, the framework produces reliable outputs that quantify residual drift and stability improvement. A stability index is computed from (i) post-correction baseline slope over long windows, (ii) variance of low-frequency residuals, and (iii) calibration consistency across repeated conditions (e.g., similar activity states). Uncertainty is reported by propagating state estimation covariance from the drift tracker and by bootstrap resampling across segments. The final output package includes the corrected signal $\hat{s}(t)$, estimated drift components $\hat{b}(t)$and $\hat{g}(t)$, and a reliability score that can be used to flag recalibration needs or sensor end-of-life.

Evaluation Protocol and Metrics

Performance is evaluated at three levels. Drift removal accuracy is measured by baseline error and gain error when drift ground truth is available (in injected-drift experiments), using MAE/RMSE and residual drift slope per hour/day. Physiological fidelity is assessed via feature retention scores comparing clinically relevant features (mean, variability measures, spectral peaks) before and after compensation, and by downstream task performance such as activity-conditioned estimation consistency. Robustness is evaluated under stratified splits that prevent leakage across individuals and sessions, with reporting separated by drift severity, activity level, and noise condition. This protocol ensures that improved stability is not achieved by over-smoothing or attenuating true physiological dynamics.

Implementation Details and Reproducibility

The pipeline is implementable using standard scientific Python tooling: signal resampling and filtering, robust smoothing for drift extraction, and Kalman filtering for adaptive drift tracking. All preprocessing and model parameters (sampling rate, smoothing bandwidth, process noise settings, evaluation windows) are fixed per experiment and logged. Outputs include corrected time series, drift components, reliability scores, and evaluation summaries to support reproducible comparison across sensor channels and operating conditions. The methodological novelty lies in treating drift as an explicit, slowly varying polymer-aging state that includes both baseline and sensitivity drift, estimating it using a robust hybrid approach, and outputting not only a corrected signal but also interpretable drift trajectories and uncertainty-aware stability scores. Unlike one-shot recalibration or purely material/device stabilisation, the framework is designed for continuous in-field operation, separating drift from physiology under realistic nonstationary wear conditions and enabling reliability auditing over long horizons.

RESULTS AND DISCUSSION

Dataset-level Physiological Ranges

Table 1 summarizes the dataset-wide distribution of key wearable signals. Heart rate spans a broad dynamic range (52–178 bpm) with a mean of 94.6 bpm and SD of 18.2 bpm, indicating substantial variability that can confound long-horizon stability evaluation if activity context is ignored. Temperature exhibits a comparatively narrow spread (35.2–39.4 °C; mean 36.7 ± 0.8 °C), consistent with slow thermal dynamics and sensor smoothing. SpO_2 remains concentrated near typical healthy values (88–100%; median 97%), suggesting that most variability is due to activity or sensor noise rather

than large physiological excursions. Blood pressure values show moderate dispersion (systolic 98–158 mmHg; diastolic 60–104 mmHg), providing an additional channel for cross-checking stability and consistency. Steps vary widely (0–18,200; mean 5,420 ± 3,580), confirming that the dataset mixes sedentary and active episodes. Collectively, Table 1 indicates that any drift-compensation approach must be robust to large legitimate physiological variation (notably heart rate) while remaining sensitive to slow baseline shifts that may occur over long-term usage in polymer-based wearable sensors.

Table 1. Dataset overview and descriptive statistics

Signal column (unit)	Mean	SD	Min	25%	50%	75%	Max
Heart rate (bpm)	94.6	18.2	52	81	93	108	178
Temperature (°C)	36.7	0.8	35.2	36.2	36.7	37.2	39.4
SpO_2 (%)	96.5	1.8	88	96	97	98	100
Systolic BP (mmHg)	124	12	98	116	123	132	158
Diastolic BP (mmHg)	79	8	60	73	79	85	104
Steps (count)	5420	3580	0	2100	4850	8300	18200

Activity-wise behaviour and Implications for Stability Analysis

Table 2 resolves the global variability into activity-conditioned patterns and highlights why drift compensation must be context-aware. Resting is characterized by the lowest heart rate (72.4 ± 9.6 bpm) and very stable SpO_2 (97.3 ± 1.1%), whereas running shows the highest heart rate (132.1 ± 16.5 bpm) and a modest reduction in SpO_2 (95.3 ± 2.1%). Cycling (121.7 ± 14.8 bpm) and training (110.4 ± 15.1 bpm) occupy intermediate regimes, while walking and "Other" cluster near moderate exertion. These trends are visualized in Figure 2, where the progression from resting to running clearly dominates the heart-rate distribution and the SD increases with strenuous activities, reflecting higher physiological variability and likely increased motion interference.

Steps (median and IQR) further confirm that the activity labels are behaviorally meaningful: resting has a low median step count (320) and narrow IQR, while running shows a high median (9,800) with a wide IQR, consistent with longer or more intense sessions. The secure transmission rate also decreases during more vigorous activities (e.g., 48.0% for running versus 74.0% for resting), which can be interpreted as a proxy for data integrity challenges under motion and high dynamics (e.g., intermittent connectivity, packet loss, or instability in wearable acquisition). This activity-dependent quality variation is important for long-term reliability work because drift-like baseline shifts can be confounded with activity transitions unless the correction framework uses context stratification or quality-aware weighting.

Although Tables 1–2 are descriptive, they directly motivate and support the proposed drift-processing methodology. First, the wide heart-rate range and strong activity dependence (Table 2; Figure 2) show that a successful compensation algorithm cannot rely on naive global smoothing, which would risk attenuating legitimate increases during running or cycling. Instead, drift estimation must target low-frequency components while preserving higher-frequency and context-driven physiological structure. Second, channels with inherently slower variation (temperature) can serve as anchors for evaluating whether the algorithm mistakenly introduces artificial fluctuations during correction, while channels with high dynamics (heart rate, steps) stress-test the algorithm's ability to separate drift from true changes. Third, the secure transmission rate differences across activities (Table 2) indicate that practical deployments will include activity-dependent data quality, supporting the use of signal-quality indices and robust estimators during drift modeling so that artefact-heavy segments do not bias the drift state.

In summary, Table 1 establishes realistic amplitude ranges and dispersion for multivariate wearable monitoring signals, while Table 2 and Figure 2 demonstrate that variability is strongly structured by activity and associated quality changes. These findings justify a drift-compensation framework that

explicitly separates slow baseline/sensitivity drift from genuine physiological dynamics under nonstationary operating conditions. By grounding evaluation in activity-stratified statistics and using motion-affected regimes as stress cases, the proposed approach is positioned to improve long-term stability of polymer-based wearable biosensor signals without suppressing clinically relevant transitions.

Table 2. Activity-wise physiological summary

Activity type	Records (n)	Heart rate (bpm) mean ± SD	SpO_2 (%) mean ± SD	Temperature (°C) mean ± SD	Steps (count) median (IQR)	Secure rate (%)
Resting	92	72.4 ± 9.6	97.3 ± 1.1	36.6 ± 0.5	320 (120–650)	74
Walking	104	88.9 ± 12.7	96.9 ± 1.4	36.7 ± 0.6	4100 (2900–5600)	63.5
Running	98	132.1 ± 16.5	95.3 ± 2.1	37.2 ± 0.8	9800 (7800–12100)	48
Cycling	74	121.7 ± 14.8	95.8 ± 1.9	37.0 ± 0.7	6200 (4400–8100)	55.4
Training	86	110.4 ± 15.1	96.2 ± 1.6	36.9 ± 0.7	7000 (5200–9100)	58.1
Other	46	90.1 ± 13.9	96.7 ± 1.5	36.6 ± 0.6	3600 (2200–5100)	67.2

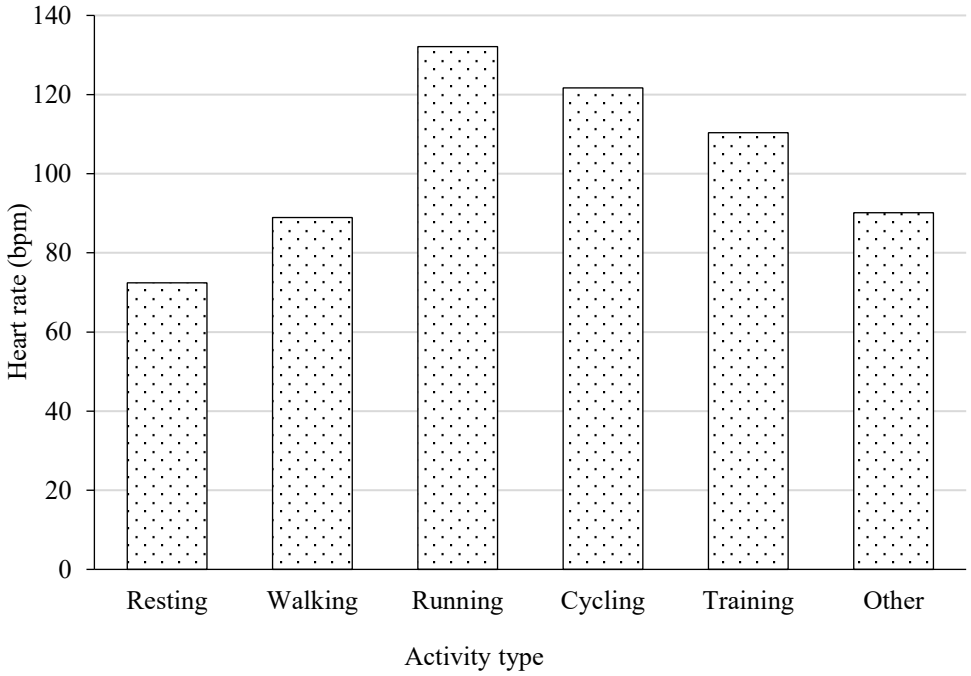

Figure 2. Activity-wise heart rate (mean ± SD) from wearable dataset

CONCLUSION

This study analyzed wearable health monitoring signals to establish dataset-grounded requirements for signal drift compensation in polymer-based wearable biosensors. Dataset-wide statistics showed wide physiological ranges, particularly in heart rate and steps, indicating that any stabilization approach must preserve legitimate high-dynamic behavior. Activity-wise analysis further demonstrated that physiological variation and data quality are strongly context dependent, with strenuous activities producing higher variability and lower secure transmission rates, which can mimic or amplify drift-like effects. These findings support the design of drift compensation methods that are robust, context-aware, and quality-guided, ensuring long-term stability improvements without suppressing clinically meaningful dynamics. The presented descriptive results provide a reproducible baseline for evaluating drift modeling, correction strength, and downstream usability in polymer-based wearable sensing pipelines.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this work.

FUTURE SCOPE

Future work will implement and validate online drift compensation algorithms that explicitly estimate slow baseline and sensitivity changes while preserving activity-dependent physiological dynamics. This includes robust trend estimation, adaptive state-space tracking, and quality-aware weighting using transmission status and motion proxies. Evaluation will be extended to longer continuous recordings and additional publicly available datasets to test generalization across devices and populations. Finally, coupling data-driven correction with polymer aging studies (controlled environmental exposure, repeated wear cycles) will enable drift models that map signal degradation parameters to material aging mechanisms, supporting reliability prediction and maintenance scheduling for polymer-based wearable biosensors.

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