

Wearable Biosensors for Early Detection of Clinical Deterioration: A Clinical Paradigm Shift from Episodic Snapshot Screening to Continuous AI-Driven Predictive Surveillance

Fasiha Malek¹, Parimalkumar M. Chaudhary²

¹Nursing Tutor, School of Nursing, P. P. Savani University, Surat, India
Email: [fasiha.malek\[at\]pppsu.ac.in](mailto:fasiha.malek[at]pppsu.ac.in)

²Lecturer, School of Nursing, P P Savani University, Surat, India
Corresponding Author Email: [parimal.chaudhary\[at\]ppsu.ac.in](mailto:parimal.chaudhary[at]ppsu.ac.in)
Orcid ID: 0009-0000-7711-1305

Abstract: *Clinical deterioration in hospitalized patients, particularly those residing in general medical-surgical wards, frequently goes undetected until an irreversible critical event occurs. This operational latency leads to avoidable Intensive Care Unit (ICU) admissions, prolonged hospital lengths of stay, and increased inpatient mortality. The traditional architecture of acute nursing care relies heavily on episodic, manual vital sign examinations performed every four to six hours. However, physiological decompensation typically manifests subtle, multi-parametric signatures hours before overt clinical collapse. Wearable biosensors offer an innovative, non-invasive solution by enabling high-fidelity, real-time tracking of foundational physiological indicators. This comprehensive paper provides an analytical breakdown of the clinical drivers of continuous monitoring, evaluates the technical architecture of medical-grade wearable sensors, reviews the machine learning predictive models powering early warning detection, examines clinical ecosystem expansion via 'Hospital-at-Home' initiatives, identifies operational barriers like alarm fatigue, and delineates a roadmap toward a highly proactive, predictive model of inpatient medicine.*

Keywords: Wearable Biosensors, Clinical Deterioration, Remote Patient Monitoring, Artificial Intelligence, Predictive Analytics, Continuous Physiological Monitoring, Early Warning Systems, Digital Health, Medical-Surgical Nursing, Patient Safety

1. Introduction

1) The High Stakes of 'Failure to Rescue'

In contemporary acute care environments, the general medical-surgical ward represents a critical vulnerability point in patient safety frameworks. While these universal units house the vast majority of hospitalized individuals, they operate with significantly lower nurse-to-patient staffing ratios than intensive care units (ICUs) or step-down progressive intermediate care units. Consequently, patient surveillance in general wards is heavily restricted to episodic, manual vital sign checks executed by a clinician or nursing assistant at standardized clinical intervals typically once every four to twelve hours [1].

This intermittent oversight model creates extensive visual and operational gaps. Physiological deterioration is rarely an instantaneous, spontaneous occurrence; instead, it is a gradual, progressive trajectory driven by homeostatic breakdown. Peer-reviewed clinical investigations consistently establish that up to 80% of patients who experience in-hospital cardiac arrests or unexpected, emergency ICU transfers display documented, verifiable physiological deviations including progressive tachypnea, uncompensated tachycardia, or acute micro-temperature alterations—up to eight hours prior to catastrophic collapse [2]. When these subtle, physiological warning signals pass unnoticed or fail to trigger dynamic escalation protocols, the resulting clinical end-state is defined as a 'Failure to Rescue'

(FTR). FTR remains a principal contributor to preventable inpatient mortality worldwide [3].

The institutional challenge lies squarely in the structural limitations of legacy Early Warning Scores (EWS), such as the Modified Early Warning Score (MEWS) and the National Early Warning Score 2 (NEWS2). While these standardized scoring tables successfully organize clinical escalation when a threshold is breached, they remain fundamentally dependent on the snapshot cadence of manual vitals collection. If a patient develops systemic occult sepsis or progressive hypoxemic respiratory failure immediately following a standard morning assessment round, their physiological breakdown will proceed completely unmonitored for hours until the next scheduled intervention block [4].

Medical-grade wearable biosensors completely bridge this operational data gap. By altering the clinical surveillance paradigm from isolated, reactive snapshots to an unceasing, high-density real-time data stream, wearable devices empower healthcare institutions to remove systemic blind spots. Shifting to constant wireless telemetry both within physical facilities and across remote environments marks a milestone in clinical engineering, moving healthcare away from reactive damage mitigation and toward early, preventative clinical rescue [5]. Use the Framingham Legacy to establish the historical baseline of risk prediction. Then, transition into SCORE2, QRISK3, and PREVENT to show the current clinical standards and highlight the gaps your paper aims to fix [17].

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Critical Definition: Failure to Rescue

A 'Failure to Rescue' occurs when subtle signs of degradation are missed over an extended multi-hour window. Continuous biosensors change the timeline, allowing teams to intervene during sub-clinical phases before major biological failure occurs.

2) The Tech Stack: Medical-Grade Wearables and Form Factors

Diverging completely from consumer-oriented fitness trackers engineered for general wellness or recreational metrics, clinical-grade wearable biosensors must adhere to strict regulatory testing, validation, and compliance metrics (such as United States FDA 510(k) clearance or European CE Mark certification). These systems must maintain measurement precision, verify high artifact rejection capabilities during movement, achieve robust biocompatibility, and safely stream end-to-end encrypted biometrics across hospital corporate networks.

Form Factors and Spatial Architectures

Medical wearables have transitioned from heavy, wire-tethered tracking consoles to ultralight, low-profile, ergonomic layouts designed for seamless clinical application. The leading configurations currently deployed in active clinical ecosystems include:

- 1) **Adhesive Torso Patches:** These single-use or extended-wear disposable hydrogel mechanisms are affixed directly over the left pectoral or upper sternal body surfaces. They integrate micro-electronics, ultra-low-power microchips, miniature solid-state accelerometers, and cutaneous biopotential electrodes.
- 2) **Clinical Smart Rings:** Slipped over the patient's digit, these designs leverage miniaturized multi-wavelength photoplethysmography (PPG) to track vascular blood volume fluctuations, capturing dense cardiovascular signatures with zero impact on user mobility.
- 3) **Advanced Optical Wristbands:** Advanced wristbands built specifically for hospital-grade telemetry. They

deploy custom optical rings to counteract severe motion artifacts, which frequently render basic consumer smartwatches useless in active clinical settings.

Pioneering Commercial Clinical Solutions

A highly specialized suite of medical platforms has established a presence within international healthcare networks:

- 1) **VitalConnect VitalPatch:** A thin, flexible biosensor patch adhered directly to the patient's chest. It records single-lead raw ECG data, continuous heart rate, heart rate variability (HRV), respiratory rate via impedance pneumography, skin temperature, and body tilt/posture for fall detection, running continuously for up to 14 days [6].
- 2) **BioIntelliSense BioButton:** A small, coin-sized sensor that adheres to the upper chest, providing non-invasive tracking of resting heart rate, respiratory rate, skin temperature, and activity levels. Its power profile enables a 30-day wear cycle without battery maintenance, optimizing it for perioperative and long-term sub-acute observation [7].
- 3) **Philips Biosensor BX500:** A single-use patch designed to communicate natively with existing Philips IntelliVue patient monitoring consoles. It focuses exclusively on continuous heart rate and respiratory rate tracking, providing an affordable option for medical-surgical ward retrofits [8].
- 4) **Masimo SafetyNet:** Leveraging a wireless, tetherless pulse oximeter module (Radius PPG), this system streams constant peripheral oxygen saturation (SpO₂), pulse rate, and respiration rate directly into automated cloud interfaces for real-time tracking [9].

Physiological Modalities and Clinical Significance

Table 1 outlines the core biometric targets tracked by current clinical wearables along with their underlying measurement technologies and specific clinical implications.

Physiological Parameter	Measurement Technology	Clinical Significance for Early Detection
Heart Rate & ECG Metrics	Biopotential Electrodes / Multi-wavelength PPG	Detects occult tachyarrhythmias, early compensatory tachycardia indicating hypovolemia, occult hemorrhage, or systemic infectious shock.
Respiratory Rate (RR)	Impedance Pneumography / Acoustic / Accelerometry	The single most sensitive predictor of acute metabolic and respiratory distress; early primary indicator for pneumonia and sepsis [10].
Oxygen Saturation (SpO ₂)	Transmissive / Reflective Photoplethysmography	Identifies silent hypoxia profiles, progressive respiratory breakdown, and sleep architecture desaturations.
Core/Skin Temperature	Solid-State Digital Thermistors	Highlights early febrile or hypothermic shifts associated with localized infections, systemic sepsis, or circulatory shock.
Heart Rate Variability (HRV)	R-R Interval Micro-analysis Algorithms	Directly measures autonomic nervous system strain; a sudden degradation in HRV indicates high systemic stress and impending collapse.

3) The Power of 'Early': AI, Predictive Analytics, and Clinical Deterioration

The raw computational output of an active continuous biosensor patch is immense: a single adult patient monitored across a standard 24-hour hospitalization block generates millions of digital data packets. Routing these high-volume raw text telemetry feeds directly to floor nurses or attending physicians would cause operational paralysis. Consequently, the utility of wearable biosensing systems depends on advanced edge computing and cloud-based Artificial Intelligence (AI) algorithms capable of converting raw

biological signals into highly filtered, actionable, and predictive clinical metrics.

Overcoming the Flaws of Population-Wide Early Warning Scores

Traditional early warning scores like NEWS2 operate on basic static threshold tables. For instance, if an absolute heart rate measurement exceeds 110 beats per minute, the scoring engine assigns a fixed categorical value of 2 points. This approach overlooks the patient's baseline variations. A baseline heart rate of 105 beats per minute may represent a stable, compensated state for a geriatric patient with permanent, rate-controlled atrial fibrillation, yet that exact

same value indicates severe clinical breakdown for a young post-operative patient whose pre-surgical baseline rested at 55 beats per minute.

AI-driven predictive surveillance engines address this by calculating a patient's personalized physiological baseline in real time. By deploying machine learning (ML) architectures, the software models the individual's normal circadian rhythms and positional deviations (e.g., physiological pulse attenuation during deep sleep, benign cardiovascular acceleration during brief physical

therapy). As a result, the algorithm flags anomalies based on variations from the patient's personalized historical data signature, rather than relying on rigid population averages [11].

Visualizing Multi-Parametric Drift

Figure 1 illustrates how continuous biosensors detect subtle deviations across multiple physiological metrics concurrently, generating an early warning hours ahead of episodic manual assessments.

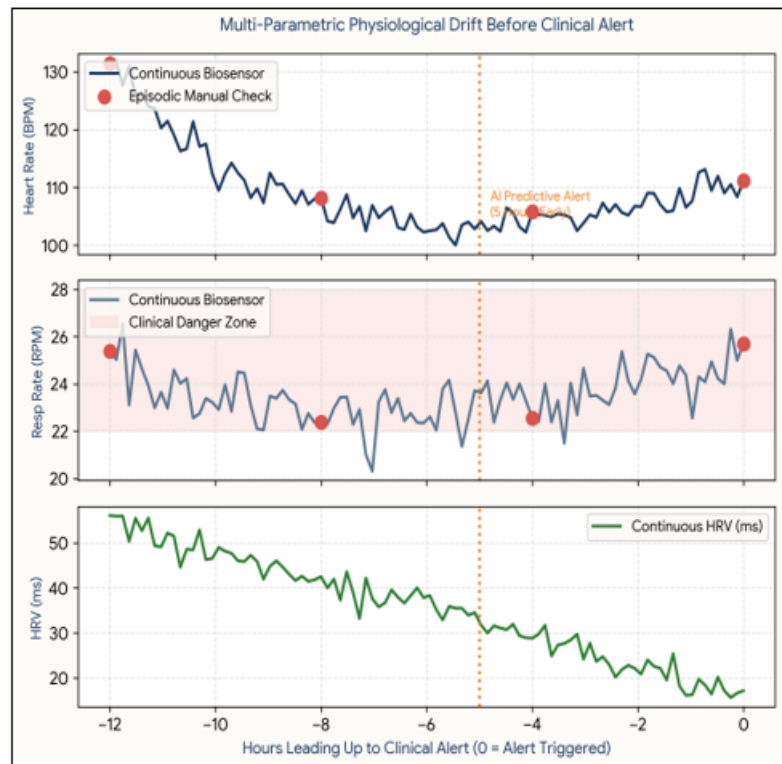


Figure 1: Comparison of Continuous Biosensor Streams vs. Intermittent Manual Checks in a Decompensating Inpatient

Multi-Parametric Trend Analytics & Sepsis Interventions

Advanced early detection frameworks rely heavily on identifying subtle correlations across multiple metrics over time. A minor, statistically small increase in respiratory rate combined with a slow decline in heart rate variability and an incremental climb in skin temperature will prompt a high-priority alert for systemic inflammatory response syndrome (SIRS) or early-stage infectious sepsis- even when every single biometric value, evaluated independently, sits comfortably within normal 'green' boundaries on a standard paper chart.

This predictive alert window is essential for timely clinical outcomes. In critical conditions like septic shock, each hour of delayed antibiotic administration increases patient mortality by approximately 7.6% [12]. Machine learning predictive biosensing systems routinely uncover sub-clinical indicators of systemic infection 12 to 24 hours before the patient exhibits an explicit fever spike or symptomatic hypotension, giving medical teams a wide window to secure laboratory blood cultures, begin targeted empiric fluid resuscitation, and deliver early antibiotics [11].

4) Clinical Settings and the 'Hospital-at-Home' Paradigm

The rollout of wearable biosensing technology is fundamentally changing the layout of modern hospital networks, allowing intensive, high-fidelity monitoring to move beyond standard critical care environments.

Inpatient General Medical-Surgical Units

Historically, the implementation of comprehensive telemetry monitoring was constrained by physical infrastructure costs and wired hardware requirements; continuously tracked beds were strictly limited to physical ICU or step-down rooms. Flexible wireless patches remove these operational barriers. Patients residing on lower-acuity floors can move around freely, which reduces the risk of deep vein thrombosis (DVT), addresses functional deconditioning, and boosts patient satisfaction, while remaining under constant surveillance. If a patient's respiratory drive fails while walking, the centralized monitoring interface alerts nearby staff immediately, enabling rapid deployment of rapid response teams before full cardiorespiratory collapse occurs.

The Integration of 'Hospital-at-Home' Models

One of the most notable expansions of biosensor deployment is the clinical development of Hospital-at-Home (HaH) initiatives. Traditionally, patients requiring continuous clinical oversight for conditions like acute congestive heart failure exacerbations, severe chronic obstructive pulmonary disease (COPD) flares, or stable bacterial cellulitis were forced to remain within high-cost, acute inpatient beds.

Utilizing medical-grade wearables, these patients can be safely discharged back to their home settings equipped with a connected biosensor patch, a secure cellular transmission hub, and a peripheral pulse oximeter. The biosensor continuously uploads physiological data back to a central hospital clinical command deck managed by specialized virtual care teams [13].

If a home-based patient with heart failure experiences progressive nocturnal tachypnea along with fluid retention, the analytics system detects the subtle shift overnight. The virtual team receives a preventative notification, allowing a clinician to modify the patient's oral medications over the phone the following morning. This early management approach avoids an emergency department revisit and subsequent hospital re-admission, lowering total system expenses, preserving physical hospital beds for critical cases, and improving patient experience metrics [14].

5) Technical, Operational, and Human Obstacles

While the clinical benefits of wearable biosensors are clear, broad adoption across global healthcare infrastructure faces several technical, operational, and human challenges.

Alarm Fatigue and Motion Artifact Filtering

The primary operational barrier introduced by non-invasive constant monitoring is alarm fatigue. In modern medical centers, floor nurses deal with hundreds of acoustic notifications per shift from infusion devices, telemetry systems, and patient call lights. Incorporating millions of data points from wearable sensors could worsen this challenge if data processing algorithms are not carefully calibrated.

Because unconstrained patients actively move, shower, and change positions, wearables are highly susceptible to motion artifacts- spurious electrical deviations caused by kinetic activity rather than real physical changes. For instance, rapid upper-limb motion during tooth brushing can mimic ventricular tachyarrhythmias on an unrefined signal processing system, generating a false high-priority emergency alarm. If clinicians are repeatedly interrupted by false positive notifications, they rapidly become desensitized, lower alert volumes, or experience cognitive fatigue, undermining the core safety purpose of the monitoring infrastructure [15]. Implementing advanced multi-stage signal validation and context filtering is critical to ensure only true physiological decline triggers clinical alerts.

EHR Interoperability and Standardized Workflows

For wearable architecture to perform effectively, it cannot operate inside isolated vendor software silos. Data streams must integrate directly with institutional Electronic Health

Record (EHR) platforms like Epic, Oracle Health (Cerner), and MEDITECH.

Injecting second-by-second raw vital sign feeds directly into an EHR database would crash data architectures and overwhelm clinical documentation. Consequently, solutions must be built to store raw biometric data in secure cloud repositories while sending only high-level summary trends, validated periodic averages, and filtered AI notifications into the EHR workflow using standardized protocols like the Fast Healthcare Interoperability Resources (FHIR) standard [16].

Biocompatibility and Patient Adherence

Human elements play a significant role in actual clinical effectiveness. Geriatric or cognitively impaired patients may find continuous patches uncomfortable and pull them off prematurely. Furthermore, chemical medical adhesives worn over multiple days can cause skin tears, allergic contact dermatitis, or localized moisture lesions, especially in frail, geriatric populations. Developing hypoallergenic, breathable materials and simple application protocols is essential for sustaining long-term patient compliance.

2. Conclusion and Future Directions

Wearable biosensors represent a fundamental evolution in inpatient surveillance, replacing traditional episodic vital checks with continuous, proactive oversight. By closing the observational windows common to lower-acuity units, these devices equip clinical teams with the data required to mitigate 'Failure to Rescue' events. Powered by predictive machine learning models, healthcare systems can transition from reactive crisis intervention to early management of sub-clinical physiological shifts.

Looking forward, next-generation clinical wearables will integrate more advanced diagnostic targets, including continuous non-invasive blood pressure estimation models and real-time interstitial fluid biomolecule profiling (such as continuous lactate and glucose sensing). As clinical evidence grows and enterprise interoperability scales, continuous biosensing is positioned to become a standard of care, ensuring that whether a patient is located in an intensive care suite, a general medical ward, or their own home, they remain under the protection of a continuous, intelligent digital watchman.

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