

Managing Data Integrity in Medical Wearables

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Summary:

The shift to wearable medical monitoring introduces critical challenges in data integrity. This talk examines integrity across technical, temporal, and clinical dimensions. We propose addressing these gaps through uncertainty quantification, multimodal sensor fusion, and automated edge-based quality control. By prioritizing integrity-by-design, mHealth systems can deliver the trustworthy, actionable insights necessary for clinical adoption and remote healthcare.

Keywords: wearables, mHealth, Endotrain, quality, sensor fusion, checklist

Introduction

The transition of medical monitoring from controlled clinical environments to the unconstrained environments of everyday life via wearables is revolutionizing healthcare. However, this shift to remote, unsupervised settings introduces a significant challenge: uncertainty regarding the integrity of the generated data. For a wearable device to be clinically actionable, the data it produces must be more than just available; it must be trustworthy, precise, and contextually relevant.

In this special session, we explore the multiple dimensions and mechanisms of data integrity in mobile health (mHealth) systems, drawing specifically on medical time series from wearable sensors. We emphasize the intersection of signal processing, clinical validation, and the practical deployment of health technologies in resource-constrained or mobile settings.

Background

In the context of medical wearables, data integrity is a multidimensional construct requiring cross-domain expertise. This extends beyond the traditional definition of integrity as a security concept (e.g., the C-I-A triad), which focuses on preventing unauthorized modification. To ensure a correct diagnosis or treatment delivery, data must satisfy several criteria:

Technical Integrity (Signal Quality): This refers to the physical fidelity of the data. Wearables are prone to motion artifacts, sensor displacement, and environmental noise. High technical integrity requires sophisticated signal-quality algorithms

to distinguish physiological processes from noise.

Temporal Integrity: Data must be accurately timestamped and synchronized. In multi-sensor arrays (e.g., matching heart rate with SpO₂), a lag of even a few seconds can lead to incorrect clinical interpretations. This is particularly challenging in body area networks or where devices are orchestrated across multiple sites and time zones.

Contextual Integrity: Data is only actionable if the context in which it was collected is known. For instance, a heart rate of 120 beats per minute has different clinical implications depending on whether the user is hiking or sleeping.

Completeness: Integrity is compromised by data gaps. These can often be caused by battery failures, connectivity issues, or synchronization errors.

Consistency: Consistency ensures that data remains unaltered and reproducible across platforms and during cloud transfers.

Clinical Integrity (Accuracy): The degree to which the wearable's digital output matches the "gold standard" clinical measurement. This involves objective and transparent validation against traditional medical devices.

Usability: A lack of usability in a medical system is a significant source of data integrity issues. With medically untrained users, poor interface design or ergonomic discomfort can lead to improper sensor placement and subsequent data degradation.

Approach

Our research group's approach focuses on making health monitoring smarter rather than just more frequent. We tackle the integrity gap through several methodological pillars:

Estimating uncertainty: We have introduced several metrics that allow us to quantify the severity of an integrity breach and to estimate the usefulness of the data for a given task. These metrics are highly application-specific. For example, a signal quality index (SQI) may be tuned to detect photoplethysmography distortions that prevent respiratory rate estimation while still allowing for reliable heart rate tracking [1]

Reliability through context-aware filtering: Sensor fusion enables systems to distinguish physiological anomalies from environmental noise. By fusing multimodal streams (physiological, environmental, and inertial), systems can increase specificity. While machine learning approaches for multimodal fusion show high potential, the challenge remains in obtaining robust, in-the-wild ground-truth labels.

Automated Quality Control and closed-loop feedback: Real-time algorithms at the edge can detect and flag low-quality data at the point of recording. By integrating these checks into a feedback loop, the system can alert users to adjust their devices immediately, preventing extensive data gaps. A practical example of this is the use of automated image quality checks in wound self-assessment [2].

Integrity-by-design: Maintaining integrity despite varying user expertise is a design-phase requirement. We advocate integrating ethics consultations and usability assessments early in the development of mHealth platforms [3], particularly for vulnerable users or in low-resource settings, and using quality checklists to help implementers anticipate challenges without requiring exhaustive multi-domain knowledge [4].

Conclusion

Managing data integrity goes beyond administrative data management plans or adherence to FAIR Data Principles [5]. It is an indispensable pillar of mobile health. As we move toward more autonomous medical systems, the quantity of data is never a substitute for quality. Future developments will likely focus on Explainable AI (XAI) to provide transparent justifications for including or excluding data, further bridging

the gap between wearable technology and clinical trust.

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