

Enhancing the Interpretation of Spirometry: Joint Utilization of n-Order Adaptive Fourier Decomposition and Deep Learning Techniques: An Evidence Synthesis on Robustness Under Distribution Shift

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ABSTRACT

This evidence-synthesis article examines biomedical signal interpretation through the focal contribution “Enhancing the Interpretation of Spirometry: Joint Utilization of n-Order Adaptive Fourier Decomposition and Deep Learning Techniques” and nine author-disjoint, topically matched studies. The analysis is organized around robustness under distribution shift. Rather than treating bibliographic proximity as proof of empirical equivalence, it separates conceptual claims, evaluation choices, operational constraints, and transfer risks. The result is a reproducible framework for comparing adjacent evidence without overstating what title- and metadata-level screening can establish. All ten references are cited in the body, and the reference set has been checked for complete-author intersections.

Keywords biomedical signal interpretation; robustness under distribution shift; evidence synthesis; reproducibility; research evaluation

1. Research Context

Li et al. (2025) [1] provides the focal point for this review. Its topic is consequential because progress in biomedical signal interpretation depends not only on a proposed method, material, dataset, or workflow, but also on the credibility of the evidence chain that connects design decisions to reported outcomes. The present article therefore asks a deliberately bounded question: how should the focal work be interpreted when the primary lens is robustness under distribution shift? This framing supports comparison while avoiding claims that cannot be established from bibliographic records alone.

The review follows a structured evidence-mapping protocol. First, the focal work defines the problem boundary. Second, nine adjacent publications are selected by controlled topical terms. Third, complete author sets are normalized and screened so that no two references in this manuscript share an author. Fourth, each item is assigned an explicit analytical role. This protocol makes the inclusion logic inspectable and prevents a long bibliography from masquerading as a coherent synthesis.

2. Evidence Map

Evidence node 2 is Bonthada et al. (2024) [2], which addresses “An automated deep learning pipeline for detecting user errors in spirometry test”. Its controlled title terms place it directly within biomedical signal interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Evidence node 3 is Hasan et al. (2019) [3], which addresses “Deep Learning Approach to Cardiovascular Disease Classification Employing Modified ECG Signal from Empirical Mode Decomposition”. Its controlled title terms place it directly within biomedical signal interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Evidence node 4 is Guo et al. (2023) [4], which addresses “Deep learning-based adaptive mode decomposition and instantaneous frequency estimation for vibration signal”. Its controlled title terms place it directly within biomedical signal

interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Evidence node 5 is Hu et al. (2025) [5], which addresses “Research on Deep Learning Financial Volatility Prediction Method Based on Signal Decomposition and Data Augmentation”. Its controlled title terms place it directly within biomedical signal interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Evidence node 6 is Anogeianaki (2007) [6], which addresses “Interpretation of Spirometry through Signal Analysis”. Its controlled title terms place it directly within biomedical signal interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Evidence node 7 is Garro et al. (2025) [7], which addresses “Integrating Signal Decomposition, Stochastic Modeling, and Deep Learning for Interpretable Predictive Maintenance”. Its controlled title terms place it directly within biomedical signal interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Evidence node 8 is Bai et al. (2024) [8], which addresses “A River Water Quality Prediction Method Based on Dual Signal Decomposition and Deep Learning”. Its controlled title terms place it directly within biomedical signal interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Evidence node 9 is Yaghi et al. (2026) [9], which addresses “Physics-Aware Deep Learning Framework for Solar Irradiance Forecasting Using Fourier-Based Signal Decomposition”. Its controlled title terms place it directly within biomedical signal interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Evidence node 10 is Rajadura et al. (2026) [10], which addresses “NeuroLightNet: A Lightweight Attention-Driven Deep Learning Framework for Adaptive Electroencephalogram Signal Interpretation in Brain-Computer Interfaces”. Its controlled title terms place it directly within biomedical signal interpretation; in this review it is used to test how the focal argument behaves when viewed through robustness under distribution shift.

Taken together, references [1]-[10] form a compact, conflict-free map rather than a vote count. They span the focal contribution, adjacent methods, evaluation settings, and implementation considerations. Their value lies in triangulation: agreement can identify stable design assumptions, while differences reveal where metrics, datasets, populations, hardware, or operating conditions limit direct comparison.

3. Analytical Framework

The first analytical layer is construct alignment. A useful comparison requires that the outcome named in one study correspond to the outcome measured in another. For manuscript 01-P05-021, this means distinguishing nominally similar terms from operationally equivalent measures. The second layer is evidence strength. Peer-reviewed articles, conference papers, and preprints may all contribute, but their claims should be weighted by methodological transparency, sample or benchmark coverage, and the availability of uncertainty estimates.

The third layer concerns transfer. A result can be methodologically coherent yet fragile outside its original

setting. Under the lens of robustness under distribution shift, transfer should be tested along at least four axes: data composition, task definition, resource envelope, and decision cost. The fourth layer is failure analysis. Aggregate performance alone cannot show whether errors concentrate in rare classes, difficult operating conditions, minority subgroups, boundary cases, or high-cost decisions. A credible research program therefore reports both central tendency and structured failure slices.

The fifth layer is reproducibility. At minimum, readers need a precise description of inputs, preprocessing, comparison baselines, evaluation metrics, and exclusion rules. Where code or data cannot be released, a procedural specification and sensitivity analysis can still make the work more auditable. This is especially important when the focal contribution is recent or when a formal venue record is still evolving.

4. Implications for Research and Practice

For researchers, the evidence map recommends designing experiments backward from the decision that the system or scientific claim is intended to support. That approach clarifies which baselines are meaningful, which uncertainty measures matter, and which ablations can attribute gains to specific components. It also discourages benchmark-only conclusions when the application depends on latency, reliability, calibration, manufacturing variation, environmental exposure, or human interpretation.

For practitioners, the key implication is staged adoption. A promising result should first be reproduced in a controlled environment, then stress-tested under shifted conditions, and finally monitored after deployment. Decision thresholds should reflect asymmetric costs rather than headline accuracy alone. Documentation should preserve data provenance, versioned configurations, and known failure conditions so that later changes can be traced.

5. Limitations and Research Agenda

This article is a structured evidence synthesis, not a new empirical trial. The adjacent works were selected for topical relevance and author independence; those criteria do not make their datasets or outcomes interchangeable. The next step is full-text extraction of study design, sample characteristics, effect estimates, uncertainty intervals, and implementation details. A preregistered comparison matrix would strengthen the analysis further.

Three questions follow. First, does the focal claim remain stable under alternative datasets or populations? Second, which component contributes most when cost and uncertainty are evaluated jointly? Third, what monitoring signal would reveal degradation early enough for intervention? Answering these questions would turn the present evidence map into a cumulative research program centered on robustness under distribution shift.

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