The need for data harmonization, multimodal integration and multi-objective loss functions to identify longitudinal changes in aging

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Table of Contents

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Abstract

Age-related cardiovascular changes, such as arterial stiffening, increased blood pressure, and decreased heart rate variability, contribute to a higher risk of cardiovascular diseases (CVDs), including hypertension, heart failure, atrial fibrillation and stroke. Detecting these changes early is essential for timely intervention and improved outcomes, but current monitoring methods often fall short in detecting subtle age-related changes before overt disease symptoms appear. Non-invasive tools like photoplethysmography (PPG), integrated into wearable devices, offer a promising approach for continuous cardiovascular monitoring. However, significant challenges remain in developing generalizable models that can handle diverse and noisy physiological data from various devices and populations. Addressing these limitations requires advanced, multimodal frameworks that harmonizes data from diverse sources and leverages state-of-the-art deep learning techniques to detect age-related cardiovascular changes.

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1 Introduction

Age-related cardiovascular changes, such as arterial stiffening, increased blood pressure, and decreased heart rate variability, contribute to a higher risk of cardiovascular diseases (CVDs), including hypertension, heart failure, atrial fibrillation and stroke. Detecting these changes early is essential for timely intervention and improved outcomes, but current monitoring methods often fall short in detecting subtle age-related changes before overt disease symptoms appear. Non-invasive tools like photoplethysmography (PPG), integrated into wearable devices, offer a promising approach for continuous cardiovascular monitoring. However, significant challenges remain in developing generalizable models that can handle diverse and noisy physiological data from various devices and populations. Addressing these limitations requires advanced, multimodal frameworks that harmonizes data from diverse sources and leverages state-of-the-art deep learning techniques to detect age-related cardiovascular changes.

2 The cardiovascular system changes with age

As people age, the cardiovascular system experiences progressive structural and functional changes that contribute to an increased risk of cardiovascular diseases (CVDs). Key cardiovascular changes include arterial stiffening, increased systolic blood pressure, decreasing heart rate variability (HRV), and elevated pulse wave velocity [1, 2]. These physiological changes increase the likelihood of adverse cardiovascular outcomes, including stroke, heart failure (HF), hypertension (HTN), and atrial fibrillation (AF) [3, 4]. Given the importance of early detection and intervention, there is a critical need for advanced tools that can detect and monitor these cardiovascular changes before they manifest as overt disease [5]. The challenge is that subtle, longitudinal cardiovascular changes associated with aging can be difficult to detect with infrequent measurements taken using standard monitoring tools like blood pressure cuffs or electrocardiograms (ECGs) in the clinic [6]. Continuous monitoring tools are therefore critically needed to identify at-risk individuals and provide a window for early therapeutic intervention.

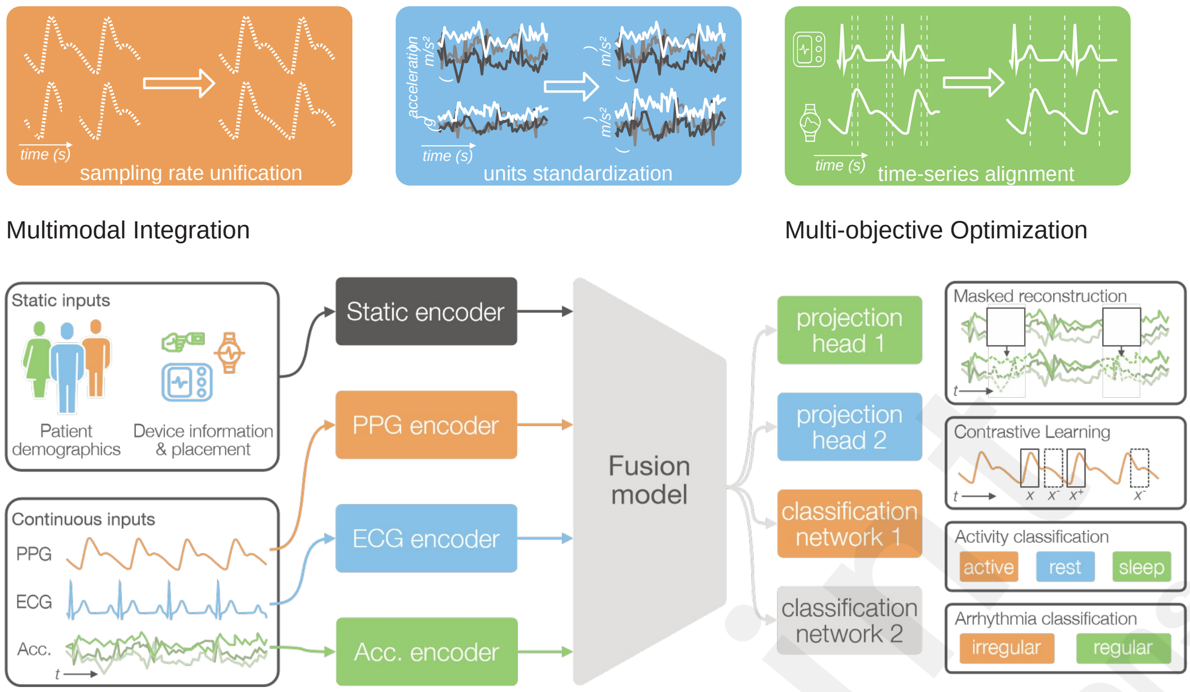

Figure 1: The roles of data harmonization, multimodal integration and multi-objective optimization in creating generalizable models.

3 PPG signals reflect changes in the cardiovascular system

Photoplethysmography (PPG) is a non-invasive optical technique that measures changes in blood volume in the microvascular bed, typically through light absorption at the skin surface [7, 8]. PPG has become widely adopted in wearable devices such as smartwatches and fitness trackers due to its simplicity and ease of integration into everyday settings [9]. Importantly, PPG signals can provide insights into key cardiovascular parameters, including heart rate, heart rate variability, and vascular health markers like pulse wave velocity (a surrogate marker for arterial stiffness) [10]. The ability of PPG to reflect real-time cardiovascular dynamics makes it a promising tool for monitoring age-related cardiovascular changes [11, 12]. For example, changes in PPG waveforms can indicate alterations in arterial compliance or peripheral vascular resistance, which are commonly observed in older adults as a result of arterial stiffening [13]. By capturing these subtle changes in vascular tone and heart rate dynamics, PPG offers the potential to detect early cardiovascular changes that might precede clinical symptoms.

4 Current approaches to interpreting PPG signals

To date, most PPG interpretation methods rely on traditional signal processing techniques. These include feature extraction methods that analyze various aspects of the PPG waveform (e.g., peakto-peak intervals, amplitude) and time-domain or frequency-domain analysis to derive parameters like HRV [11]. While these approaches are effective for basic cardiovascular monitoring, they are less suited for detecting the complex, multi-faceted changes in cardiovascular function associated with aging. For instance, traditional methods often focus on short-term HRV or pulse characteristics, missing broader trends that could signal early cardiovascular deterioration. There is increasing interest in using machine learning methods to enhance the robustness of PPG signal interpretation. For example, deep learning models have shown promise in detecting specific cardiovascular conditions, such as AF, from PPG signals with high accuracy [14]. However, these models require large amounts of clean, annotated data and are typically trained to detect specific disease states, limiting their ability to generalize to broader, age-related cardiovascular changes. Furthermore, the reliance on single, well-curated datasets poses a challenge in real-world applications, where PPG signals are often noisy and collected under suboptimal conditions [9]. Additionally, many existing models are application-specific and fail to generalize across different types of wearable devices [15]. These limitations highlight the need for new approaches that can generalize across different populations, devices, and environments while being robust to the noise and variability inherent in real-world data collection.

5 The need for large, diverse and harmonized datasets

Most existing PPG datasets are collected from young, healthy individuals in controlled conditions, limiting the generalizability [16]. To develop robust models capable of detecting cardiovascular changes in older adults, it is essential to utilize diverse datasets that reflect the variability found in the real-world populations. The integration of multi-modal data, such as PPG, ECG, and motion sensors, is vital to capturing the complex interactions between physiological systems. Harmonizing diverse datasets is necessary to ensure standardization and compatibility. Recent studies provide frameworks for addressing these challenges [17]. Harmonization of sleep and circadian data through standardization of sampling rates and alignment of time-series data has been shown to improve cross-study comparisons and reduce noise and variability [18]. The development of pipelines such as MASH have addressed issues of inconsistent data notations and varying sampling rates across multimodal datasets, facilitating the alignment of diverse datasets collected from different devices [19]. Furthermore, the importance of modular and flexible data preprocessing pipelines has been emphasized, demonstrating that scalable harmonization can be achieved through frameworks that enable seamless integration of new datasets [20]. These advancements in data harmonization techniques provide a foundation for the integration of diverse datasets in cardiovascular monitoring research.

6 Modern neural network architectures for multimodal data

Recent advances in deep learning offer significant potential for improving cardiovascular monitoring, particularly through attention-based and deep state space models [21, 22]. These models have shown considerable promise in handling multi-modal, sequential data such as health timelines, but have not yet incorporated PPG, ECG, or motion data. Modern architectures are well-suited to processing long sequences of data, allowing for the detection of temporal patterns and trends in cardiovascular signals that may indicate early deterioration [23]. Their ability to integrate multi-modal inputs enables them to learn from the complex interactions between different types of physiological signals, providing a comprehensive view of cardiovascular health. Furthermore, these architectures can process multiple high-frequency signals, such as PPG and ECG, simultaneously. These signals, though rich in cardiovascular information, are susceptible to noise, and traditional models often treat them independently, missing critical interactions [16]. Recent advances in self-supervised learning offer the potential to design architectures that can integrate multiple high-frequency signals, enhancing the model's ability to distinguish between artifacts and true physiological changes [24]. By incorporating motion sensor data alongside PPG and ECG signals, the model can better interpret physiological states and detect subtle cardiovascular changes in older adults, even in noisy, real-world conditions [15].

7 The need for a multi-objective loss function

In machine learning, the loss function is a critical component that directs how models learn from data. For complex applications such as detecting cardiovascular changes using multi-modal, noisy data, conventional loss functions that focus purely on accuracy or classification often fall short [25, 26]. Multi-objective loss functions offer a powerful solution by enabling models to optimize multiple objectives simultaneously, such as imputing missing data, handling noise, and learning from diverse signals like PPG, ECG, and motion data [27]. By guiding the model to predict missing signals or adjust for signal quality variations, multi-objective loss functions will it possible to detect cardiovascular deterioration more accurately, even in challenging real-world scenarios. Advanced loss functions that balance tasks like imputing missing data and detecting subtle cardiovascular changes will significantly improve model performance across heterogeneous datasets, ultimately enhancing personalized care for older adults.

Recent advancements in multi-task learning have provided valuable frameworks for addressing complex, multi-objective optimization problems. The concept of framing multi-task learning as a multi-objective optimization problem, utilizing Pareto optimality, has been introduced as a method to balance competing objectives without compromising performance on individual tasks [27]. This approach is particularly relevant in cardiovascular monitoring, where multiple tasks such as autoregressive prediction of PPG/ECG signals, cross-modality predictions, and classification must be optimized simultaneously. Building on this foundation, frameworks for dynamically balancing tasks during training have been developed, enabling models to adapt and prioritize tasks based on their relative importance [27, 28]. This adaptive capacity is crucial when dealing with varied data types and the complex nature of cardiovascular changes. Furthermore, the significance of loss functions that capture interactions between tasks has been emphasized, offering strategies for refining multi-objective optimization approaches [29]. These developments in multi-task learning and multi-objective optimization provide a robust theoretical foundation for designing complex loss functions capable of handling the multifaceted challenges inherent in cardiovascular monitoring using multi-modal data.

8 Conclusion

The growing burden of age-related cardiovascular diseases highlights the urgent need for advanced tools that can detect and monitor subtle, longitudinal changes in cardiovascular function. While photoplethysmography (PPG) holds great promise for non-invasive, continuous monitoring, existing approaches fall short in their ability to generalize across diverse populations, devices, and realworld conditions. The future of cardiovascular health monitoring relies on a concerted effort to harmonize data across multiple sources and modalities, integrating diverse datasets that reflect the true variability of the human population.

To make meaningful progress in this field, researchers and industry stakeholders must prioritize three key areas:

1. Data Harmonization: Without standardization and harmonization, the wealth of data collected from wearables, healthcare systems, and diverse populations remains underutilized. Collaborative efforts across disciplines are needed to establish common frameworks for integrating multimodal physiological data, such as PPG, ECG, and motion sensors. These frameworks must ensure compatibility across devices and environments, enabling more robust models that generalize to real-world scenarios.

2. Multimodal Integration: Cardiovascular changes do not occur in isolation. Integrating multiple physiological signals—PPG, ECG, and others—provides a more comprehensive picture of cardiovascular health. Advanced deep learning models, particularly those using modern architectures like attention-based and state-space models, are well-positioned to capture the complex interactions between these signals. However, future research must prioritize models that can learn across multiple modalities, handle noisy data, and address the unique challenges of older populations.

3. Multi-Objective Loss Functions: In real-world applications, the challenges of noisy data,missing signals, and high variability must be met with sophisticated loss function designs that balance multiple objectives. Multi-task learning and multi-objective optimization frameworks offer a promising path forward by enabling models to learn from diverse data types while prioritizing key health metrics. Implementing these techniques will pave the way for the early detection of cardiovascular changes, personalized care, and more effective interventions for aging populations.

This is a critical juncture in cardiovascular research and health monitoring. By advancing in these three areas, we can create the infrastructure needed for scalable, real-time monitoring solutions that empower healthcare providers to intervene earlier and more effectively. The integration of data harmonization, multimodal learning, and advanced loss functions has the potential to transform cardiovascular care, improving outcomes for millions of older adults worldwide.

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Supplementary Files

Figures

The roles of data harmonization, multimodal integration and multi-objective optimization in creating generalizable models.