Diagnostic Performance of Pulse Oximetry Waveform Analysis for Ambulatory Identification of Cardiac Arrhythmias

Mohamed Salah Abdelbasit, Ahmed Magdi Hamed Mohamed Afify , Mohamad Hossam Eldeen Alshair, Shaimaa Wageeh Mohamed

Cardiology Department, Faculty of Medicine, Zagazig University

Corresponding Author: Ahmed Magdi Hamed Mohamed Afify

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Abstract

Background: Cardiac arrhythmias are a major cause of morbidity and mortality worldwide, with atrial fibrillation and other rhythm disturbances frequently remaining undiagnosed due to their intermittent and often asymptomatic nature. Conventional diagnostic strategies, including electrocardiography (ECG) and Holter monitoring, are limited by short monitoring durations, accessibility barriers, and patient adherence issues. Pulse oximetry, traditionally used for oxygen saturation monitoring, generates photoplethysmographic (PPG) waveforms that reflect peripheral blood volume changes synchronized with cardiac cycles. Advances in signal processing and wearable technologies have enabled the analysis of pulse oximetry waveforms for rhythm irregularity detection, offering a potential noninvasive, low-cost solution for ambulatory arrhythmia identification outside clinical environments.

Aim: This review aims to critically evaluate the diagnostic performance of pulse oximetry waveform analysis for the ambulatory detection of cardiac arrhythmias. Specifically, it examines the accuracy, sensitivity, specificity, and clinical validity of PPG-derived signals obtained from pulse oximeters and wearable devices, compared with standard ECG-based reference methods.

Methods and Scope: A comprehensive synthesis of existing clinical and technological studies was undertaken, focusing on adult populations monitored in non-clinical or home-based settings. The review evaluates waveform-derived metrics, algorithmic approaches, and machine learning models applied to arrhythmia detection, with particular attention to atrial fibrillation, premature atrial and ventricular contractions, and other irregular rhythms. Factors influencing diagnostic performance, including motion artifacts, signal quality, comorbid conditions, and device variability, are also addressed.

Conclusion: Pulse oximetry waveform analysis demonstrates promising diagnostic performance for ambulatory arrhythmia detection, particularly for atrial fibrillation screening, with several studies reporting high sensitivity and acceptable specificity compared with ECG. However, limitations related to signal noise, motion artifacts, and reduced accuracy in complex arrhythmias persist. While pulse oximetry-derived PPG cannot replace ECG for definitive diagnosis, it represents a valuable adjunctive tool for long-term rhythm surveillance and population-level screening. Further large-scale validation studies, standardized algorithms, and integration with clinical workflows are required before widespread clinical adoption.

Keywords: *Pulse Oximetry, Cardiac Arrhythmias*

Introduction

Cardiac arrhythmias constitute a major global health burden, contributing significantly to stroke, heart failure, sudden cardiac death, and overall cardiovascular morbidity. Among these, atrial fibrillation (AF) is the most prevalent sustained arrhythmia, affecting an estimated 33–37 million individuals worldwide and increasing markedly with age. A substantial proportion of arrhythmias are paroxysmal or asymptomatic, leading to underdiagnosis and delayed treatment initiation. Early detection is critical, as timely anticoagulation and rhythm or rate control strategies substantially reduce adverse cardiovascular outcomes, particularly ischemic stroke and heart failure progression [1,2].

Electrocardiography (ECG) remains the diagnostic gold standard for arrhythmia detection; however, its utility in ambulatory and long-term monitoring is constrained. Standard 12-lead ECG provides only a brief snapshot of cardiac rhythm, while Holter monitors and event recorders are limited by short monitoring durations, patient inconvenience, cost, and reduced adherence. Even extended external loop recorders and implantable cardiac monitors, though effective, are resource-intensive and not suitable for population-wide screening. These limitations have driven interest in alternative, scalable technologies capable of continuous rhythm surveillance in non-clinical settings [3,4].

Pulse oximetry, widely used for monitoring arterial oxygen saturation, generates photoplethysmographic (PPG) waveforms that reflect pulsatile blood volume changes associated with each cardiac cycle. Beyond oxygen saturation estimation, the temporal variability and morphology of PPG waveforms provide indirect information about heart rate, rhythm regularity, and hemodynamic fluctuations. Advances in digital signal processing and computational analytics have enabled the extraction of rhythm-related features from pulse oximetry waveforms, facilitating arrhythmia detection using both bedside monitors and wearable devices such as smartwatches and finger probes [5,6].

Recent studies have demonstrated that PPG-based pulse oximetry waveform analysis can identify irregular pulse patterns consistent with AF and other arrhythmias, with diagnostic performance approaching that of ECG in selected populations. Nevertheless, PPG signals are inherently susceptible to motion artifacts, poor peripheral perfusion, and noise introduced by ambulatory environments, raising concerns regarding reliability and generalizability. Furthermore, while AF detection has been extensively studied, the ability of pulse oximetry waveform analysis to accurately identify non-AF arrhythmias remains less well defined [7,8].

Aim and Research Gap:

The aim of this review is to critically evaluate the diagnostic performance of pulse oximetry waveform analysis for ambulatory identification of cardiac arrhythmias outside the clinic. Despite growing interest and rapid technological advancement, important gaps remain regarding standardized diagnostic thresholds, comparative accuracy across arrhythmia subtypes, and clinical integration pathways. By synthesizing current evidence, this review seeks to clarify the strengths, limitations, and future potential of pulse oximetry-derived PPG analysis as a complementary tool for out-of-clinic arrhythmia detection.

Physiological Basis of Pulse Oximetry Waveform Analysis in Arrhythmia Detection

The photoplethysmographic (PPG) waveform generated by pulse oximetry reflects cyclical changes in peripheral blood volume resulting from cardiac systole and diastole. Each pulse wave corresponds to left ventricular ejection and arterial compliance, providing indirect insight into cardiac rhythm and hemodynamic status. In individuals with normal sinus rhythm, PPG waveforms demonstrate relatively regular inter-beat intervals and consistent waveform morphology. In contrast, arrhythmias such as atrial fibrillation introduce beat-to-beat variability in ventricular filling and stroke volume, leading to irregular pulse intervals and fluctuating pulse amplitudes detectable in the PPG signal [9,10].

From a physiological perspective, atrial fibrillation disrupts atrial contraction and results in variable ventricular response due to irregular atrioventricular nodal conduction. This irregularity manifests as chaotic pulse timing and amplitude variation in peripheral arterial circulation. Pulse oximetry waveforms capture these variations, particularly through analysis of pulse-to-pulse intervals, pulse amplitude modulation, and waveform morphology. Studies comparing simultaneous ECG and PPG recordings have demonstrated strong temporal correlation between R–R intervals and PPG-derived inter-beat intervals, supporting the physiological plausibility of using pulse oximetry for rhythm analysis [11,12].

Beyond atrial fibrillation, other arrhythmias such as premature atrial contractions (PACs) and premature ventricular contractions (PVCs) also produce characteristic changes in PPG waveforms. Premature beats typically generate reduced stroke volume and lower pulse amplitude due to incomplete ventricular filling, followed by compensatory pauses that produce augmented pulses. Pulse oximetry waveform analysis can detect these amplitude fluctuations and irregular intervals; however, distinguishing isolated ectopy from sustained arrhythmia remains challenging, particularly in ambulatory settings with variable signal quality [13,14].

Peripheral vascular factors further influence the fidelity of PPG-based arrhythmia detection. Arterial stiffness, autonomic tone, temperature, and microvascular disease can alter waveform morphology independent of cardiac rhythm. Aging and comorbidities such as diabetes and hypertension may dampen pulse signals or exaggerate variability, potentially confounding arrhythmia detection algorithms. These physiological modifiers necessitate robust signal preprocessing and adaptive algorithms to ensure accurate rhythm interpretation across diverse patient populations [15,16].

Importantly, pulse oximetry-derived PPG measures pulse activity rather than direct electrical cardiac activity. As a result, electrical arrhythmias without effective mechanical contraction, such as pulseless electrical activity or high-grade atrioventricular block with non-conducted beats, may not be reliably detected. This fundamental distinction underscores why pulse oximetry waveform analysis should be considered a screening or monitoring adjunct rather than a replacement for ECG-based diagnosis [17].

Technology Platforms and Signal Processing Methods for Ambulatory Pulse Oximetry-Based Arrhythmia Detection

The technological evolution of pulse oximetry from stationary bedside monitors to portable and wearable platforms has been central to its application in ambulatory arrhythmia detection. Conventional hospital-grade pulse oximeters employ transmissive PPG sensors placed on the finger or earlobe, offering high signal fidelity under controlled conditions. In contrast, ambulatory and consumer-grade devices—including wrist-worn wearables, ring sensors, and patch-based monitors—primarily use reflective PPG technology, which enables continuous monitoring during daily activities but introduces greater susceptibility to motion-related artifacts [18,19].

Signal acquisition in ambulatory environments presents substantial challenges due to motion, variable sensor-skin contact, ambient light interference, and changes in peripheral perfusion. To address these issues, advanced signal preprocessing techniques are employed, including adaptive filtering, motion artifact reduction algorithms, and signal quality indices to exclude unreliable waveform segments. Time-domain analysis, such as pulse interval variability and pulse amplitude variability, forms the foundation of many arrhythmia detection algorithms derived from pulse oximetry waveforms [20,21].

Frequency-domain and nonlinear analytical methods have further enhanced diagnostic performance. Power spectral density analysis, entropy-based metrics, and Poincaré plot analysis have been applied to PPG signals to quantify rhythm irregularity characteristic of atrial fibrillation. These approaches mirror techniques traditionally used in heart rate variability analysis from ECG, adapted to the physiological and technical characteristics of PPG signals. Several studies have demonstrated that combining multiple PPG-derived features improves discrimination between sinus rhythm and arrhythmia compared with single-parameter approaches [22,23].

Machine learning and artificial intelligence (AI) techniques have increasingly been integrated into pulse oximetry waveform analysis for arrhythmia detection. Supervised learning models, including support vector machines, random forests, and deep neural networks, have been trained on large datasets of labeled PPG and ECG recordings. These models can automatically extract complex waveform features and classify rhythm patterns with high sensitivity, particularly for atrial fibrillation detection. However, model performance is highly dependent on training data quality, population diversity, and external validation [24,25].

Despite technological advances, interoperability and standardization remain unresolved issues. Differences in sensor hardware, sampling rates, and proprietary algorithms limit cross-device comparability and reproducibility of diagnostic accuracy. Regulatory oversight varies widely between medical-grade pulse oximeters and consumer wearables, raising concerns regarding clinical reliability and appropriate use. Addressing these technological and regulatory gaps is essential for the safe integration of pulse oximetry waveform analysis into routine ambulatory arrhythmia screening pathways [26].

Diagnostic Accuracy of Pulse Oximetry Waveform Analysis Compared With ECG Reference Standards

Across the past decade, the diagnostic validity of photoplethysmography (PPG)–based rhythm analysis derived from pulse oximetry has been primarily evaluated using simultaneous or near-simultaneous electrocardiography (ECG) as the reference standard. In these studies, pulse oximetry waveforms are analyzed as surrogates of ventricular mechanical activity, and rhythm classification outcomes are compared directly against ECG-confirmed diagnoses. A consistent finding across validation studies is that pulse oximetry waveform analysis demonstrates high sensitivity for detecting atrial fibrillation when signal quality is adequate, although specificity varies depending on study population, arrhythmia prevalence, and algorithmic handling of noisy or indeterminate waveform segments [27,28].

Clinical studies utilizing synchronized ECG and pulse oximetry recordings have provided foundational evidence supporting the diagnostic accuracy of waveform-based arrhythmia detection. In monitored inpatient cohorts, quantitative analysis of pulse oximetry waveforms has been shown to reliably identify atrial fibrillation through assessment of pulse interval irregularity and waveform morphology. These investigations are particularly valuable because they allow precise temporal alignment between electrical and mechanical cardiac signals, thereby minimizing misclassification related to signal delay or loss. Such controlled validation environments establish proof of concept before extrapolation to ambulatory and home-based monitoring scenarios [29].

Ambulatory validation studies, often incorporating wearable or portable pulse oximetry devices, have further evaluated diagnostic performance under real-world conditions. These investigations commonly compare pulse oximetry-derived rhythm classifications with prolonged ECG patch monitoring or Holter recordings. While sensitivity for atrial fibrillation detection remains high in many reports, positive predictive value is influenced by arrhythmia burden and monitoring duration. Importantly, studies have demonstrated that pulse oximetry waveform analysis is most effective for detecting sustained or frequent arrhythmias, whereas brief or rare episodes may be missed without continuous high-quality signal acquisition [30,31].

Machine learning–based diagnostic models have further improved classification accuracy by integrating multiple waveform-derived features rather than relying solely on pulse interval irregularity. Deep learning approaches trained on large datasets of paired PPG and ECG recordings have achieved diagnostic performance comparable to traditional ECG-based screening tools in selected cohorts. However, algorithm robustness remains dependent on external validation across heterogeneous populations, device types, and ambulatory conditions, highlighting the need for standardized evaluation frameworks [32,33].

At the evidence-synthesis level, systematic reviews and meta-analyses of PPG-based arrhythmia detection consistently report favorable pooled sensitivity and specificity for atrial fibrillation when compared with ECG. Nonetheless, significant heterogeneity persists due to variations in device technology, signal preprocessing methods, study design, and patient characteristics. Collectively, current evidence supports pulse oximetry waveform analysis as a reliable screening and monitoring modality for ambulatory arrhythmia detection, while reaffirming ECG as the definitive diagnostic standard for rhythm confirmation [34,35].

Arrhythmia-Specific Performance and Misclassification Patterns

Atrial fibrillation has been the most consistently detectable arrhythmia using pulse oximetry–derived photoplethysmography (PPG) because its hallmark is irregularly irregular ventricular timing, which translates into irregular pulse-to-pulse intervals and variable pulse amplitudes. Across validation studies comparing PPG with ECG reference standards, performance is generally strongest when AF episodes are sustained and when signal quality is high (resting conditions, stable sensor contact). However, predictive value is strongly prevalence-dependent in screening contexts, and protocols that discard low-quality segments tend to report higher accuracy than "intention-to-diagnose" approaches that classify all segments, including noisy ones. These factors explain why the same technology may perform very differently in controlled monitoring versus free-living ambulatory use. [36–38]

Premature atrial contractions and premature ventricular contractions are among the most important causes of false AF alerts in pulse-based algorithms because ectopy produces irregular timing and compensatory pauses that can mimic AF-like irregularity, especially when premature beats are frequent or patterned. Work evaluating AF discrimination explicitly against PACs and PVCs shows that incorporating additional features beyond interval irregularity (e.g., waveform morphology and stability metrics) improves differentiation, but ectopy remains a key failure mode in real-world deployment. Studies focused on premature beat detection from PPG similarly emphasize that ectopy can inflate AF false positives if algorithms treat "randomness" alone as diagnostic, underscoring the need for ectopy-aware classifiers and quality gating. [39,40]

Regular tachyarrhythmias such as supraventricular tachycardia (SVT) can be challenging for pulse oximetry waveform analysis because rhythm regularity may be preserved even when rate is high. In these scenarios, PPG may accurately estimate heart rate yet fail to classify rhythm type without additional contextual features. Furthermore, short bursts of SVT can be missed when devices sample intermittently or analyze only during inactivity, which is common in some wearable implementations. Emerging multiclass PPG approaches suggest that broader arrhythmia classification beyond AF is feasible, but external clinical validation remains less mature than for AF-focused algorithms. [41,42]

Ventricular tachycardia and other potentially life-threatening ventricular arrhythmias represent a distinct limitation for pulse oximetry waveform analysis because PPG reflects mechanical pulse generation rather than electrical activity. Rapid ventricular rhythms with compromised stroke volume may produce weak or absent peripheral pulses, leading to signal dropout or misclassification as artifact rather than correctly identifying the arrhythmia. In addition, hemodynamic instability can degrade peripheral perfusion and distort waveforms, further reducing reliability. These physiological constraints mean that pulse oximetry waveform analysis is best positioned as a screening and monitoring adjunct, not as a standalone diagnostic tool for high-risk ventricular arrhythmias. [43,44]

Across ambulatory studies, the dominant misclassification patterns cluster into three categories: (1) poor signal quality and motion artifact, (2) frequent ectopy and sinus arrhythmia producing irregular intervals, and (3) algorithmic/operational constraints such as short analysis windows or rest-only sampling. Recent work in continuous wearable PPG monitoring highlights that false positives frequently arise from poor signal quality and from PAC/PVC burden, reinforcing the practical importance of robust signal-quality indices and ectopy-sensitive logic. At a clinical governance level, major guideline frameworks emphasize that PPG- or device-based irregular rhythm detection requires confirmation with an ECG tracing before diagnosis and treatment decisions, which directly addresses the downstream risk of misclassification. [37,45,46]

Limitations of Pulse Oximetry Waveform Analysis in Ambulatory Settings

The most significant limitation affecting the diagnostic performance of pulse oximetry waveform analysis in ambulatory environments is motion artifact. Daily activities such as walking, hand movement, and changes in posture introduce non-physiological fluctuations into photoplethysmographic (PPG) signals, often exceeding the magnitude of rhythm-related variability. Motion-induced noise can distort pulse intervals, alter waveform morphology, and lead to false-positive arrhythmia detections or signal rejection. Although advanced filtering and accelerometer-assisted artifact suppression have improved performance, residual motion artifact remains a major barrier to reliable continuous monitoring outside controlled clinical settings [47,48].

Peripheral perfusion is another critical determinant of signal quality and diagnostic accuracy. Conditions associated with reduced peripheral blood flow, including hypothermia, shock, heart failure, and peripheral vascular disease, can attenuate PPG waveform amplitude and compromise pulse detection. Even in stable ambulatory populations, transient vasoconstriction due to temperature changes or autonomic activation may degrade signal quality. These physiological fluctuations are particularly relevant in elderly patients and those with diabetes or advanced cardiovascular disease, populations in which arrhythmia detection is most clinically relevant [49,50].

Skin pigmentation and tissue characteristics have also been identified as potential sources of variability in pulse oximetry waveform analysis. Differences in melanin absorption, tissue thickness, and optical scattering can affect signal-to-noise ratio, particularly in reflective PPG systems used by wearable devices. While modern sensor designs and adaptive algorithms have mitigated some of these effects, disparities in signal quality across diverse populations persist and remain underrepresented in many validation studies. Ensuring equitable diagnostic performance requires explicit inclusion of diverse skin tones and anthropometric profiles in future research [51,52].

Comorbid conditions and physiological variability further complicate arrhythmia detection in ambulatory PPG monitoring. Respiratory sinus arrhythmia, autonomic dysfunction, and frequent ectopic activity can introduce pulse irregularity unrelated to pathological arrhythmias. Additionally, medications such as beta-blockers or antiarrhythmics may alter heart rate dynamics and waveform characteristics, potentially influencing algorithm performance. These confounders highlight the importance of context-aware classification strategies and multimodal data integration when interpreting pulse oximetry-derived rhythm signals [53,54].

To address these limitations, many studies incorporate signal quality indices and predefined exclusion criteria to filter unreliable waveform segments before analysis. While this approach improves reported diagnostic accuracy, it may also reduce real-world applicability by excluding large portions of ambulatory data. Alternative strategies include probabilistic classification, uncertainty labeling, and user-triggered confirmatory recordings, which aim to balance accuracy with continuous monitoring coverage. Ultimately, transparent reporting of data exclusion rates and failure modes is essential for meaningful interpretation of diagnostic performance in ambulatory pulse oximetry studies [55,56].

Clinical Applications, Screening Strategies, and Integration With Care Pathways

Pulse oximetry waveform analysis offers several clinically meaningful applications in the detection and monitoring of cardiac arrhythmias, particularly in ambulatory and home-based settings. One of the most prominent use cases is population-level screening for atrial fibrillation, especially among older adults and individuals with cardiovascular risk factors. Given the high prevalence of asymptomatic and paroxysmal AF, continuous or intermittent pulse-based monitoring may facilitate earlier detection than conventional opportunistic ECG screening, potentially enabling timely initiation of anticoagulation and reducing stroke risk [57,58].

In clinical practice, pulse oximetry-derived arrhythmia detection is most appropriately positioned as a triage or pre-diagnostic tool rather than a definitive diagnostic modality. Abnormal rhythm alerts generated by pulse oximetry waveform analysis can prompt targeted ECG confirmation using patch monitors, handheld ECG devices, or in-clinic recordings. This stepwise diagnostic pathway aligns with current guideline recommendations and helps mitigate the risk of misdiagnosis due to PPG-specific limitations such as motion artifacts or ectopy-related false positives [46,59].

Pulse oximetry waveform analysis also holds value for longitudinal rhythm surveillance in patients with known arrhythmias. For individuals with paroxysmal AF, post-ablation monitoring, or those undergoing medication adjustments, continuous ambulatory pulse monitoring may provide insights into arrhythmia burden trends and recurrence patterns. Although ECG remains necessary for precise arrhythmia characterization, pulse-based monitoring can reduce reliance on repeated short-duration ECG studies and improve patient engagement through passive, noninvasive data collection [60,61].

Remote patient monitoring programs have increasingly incorporated pulse oximetry as part of broader telecardiology and digital health strategies. Integration of waveform-derived rhythm alerts into electronic health records and clinician dashboards enables proactive review and prioritization of patients requiring further evaluation. However, workflow integration remains challenging, particularly with respect to alert fatigue, data overload, and reimbursement models. Successful implementation depends on clear protocols defining alert thresholds, confirmation pathways, and clinician responsibilities [62,63].

From a public health perspective, scalable pulse oximetry-based screening could improve arrhythmia detection in underserved or resource-limited settings where access to ECG technology is constrained. Low-cost pulse oximeters, when coupled with validated waveform analysis algorithms, may serve as accessible entry points into cardiovascular care. Nevertheless, ethical and regulatory considerations, including data privacy, algorithm transparency, and equity of access, must be addressed to ensure responsible adoption of pulse oximetry waveform analysis in routine care pathways [64,65].

Comparison With Other Out-of-Clinic Arrhythmia Detection Modalities

Out-of-clinic arrhythmia detection has evolved substantially over the past two decades, with multiple technologies now available that differ in diagnostic accuracy, monitoring duration, patient burden, and cost. Traditional ambulatory ECG modalities, including 24–48 hour Holter monitors, extended external patch monitors, and implantable loop recorders, remain the reference standard for prolonged rhythm surveillance. These technologies provide direct electrical recordings and enable precise arrhythmia characterization; however, they are limited by availability, cost, invasiveness, and patient adherence, particularly for long-term or population-wide screening applications [66,67].

Handheld and smartphone-based single-lead ECG devices represent an intermediate solution between continuous ECG monitoring and pulse-based technologies. These devices allow user-initiated ECG recordings during symptoms or following irregular rhythm alerts. Compared with pulse oximetry waveform analysis, handheld ECG devices offer higher diagnostic specificity and immediate rhythm confirmation. However, their effectiveness depends on patient engagement and symptom recognition, making them less suitable for detecting asymptomatic or nocturnal arrhythmias. In contrast, pulse oximetry-derived PPG monitoring can operate passively and continuously, enhancing detection of silent arrhythmia episodes [68,69].

Wearable ECG systems, such as chest straps and ECG-enabled smartwatches, provide continuous or near-continuous electrical monitoring with higher diagnostic accuracy than PPG alone. These devices can detect a broader range of arrhythmias and provide analyzable ECG tracings for clinician review. Nevertheless, wearable ECG systems are generally more expensive, may require frequent charging or electrode replacement, and can be less comfortable for prolonged use. Pulse oximetry waveform analysis offers a lower-burden alternative, albeit with reduced arrhythmia specificity and a greater reliance on confirmatory testing [70,71].

Compared with accelerometer-based or symptom-triggered detection methods, pulse oximetry waveform analysis offers the advantage of direct physiological signal acquisition related to cardiac output and pulse timing. This makes it particularly effective for identifying rhythm irregularity rather than merely rate changes or subjective symptoms. However, unlike ECG-based technologies, pulse oximetry cannot reliably differentiate arrhythmia mechanisms or identify conduction abnormalities, limiting its role in comprehensive rhythm evaluation [72,73].

Overall, pulse oximetry waveform analysis occupies a complementary niche within the landscape of ambulatory arrhythmia detection technologies. Its strengths lie in scalability, passive monitoring, and low cost, making it well suited for initial screening and longitudinal surveillance. When integrated into structured care pathways that include ECG confirmation and clinical oversight, pulse oximetry-based monitoring can enhance arrhythmia detection efficiency while preserving diagnostic rigor. Future comparative-effectiveness studies are needed to define optimal combinations of pulse-based and ECG-based modalities across different patient populations and clinical use cases [74,75].

Conclusion

Pulse oximetry waveform analysis represents a meaningful advancement in the ambulatory identification of cardiac arrhythmias, extending the utility of a widely available monitoring technology beyond oxygen saturation assessment. By leveraging photoplethysmographic signals to capture pulse interval variability and waveform morphology, pulse oximetry enables passive, noninvasive rhythm surveillance in real-world environments where traditional electrocardiographic monitoring is often impractical or inaccessible. This capability is particularly relevant for the detection of atrial fibrillation, a condition characterized by intermittent presentation and substantial morbidity if left undiagnosed.

Across clinical and ambulatory studies, pulse oximetry–derived waveform analysis has demonstrated promising diagnostic performance, especially for sustained atrial fibrillation episodes in settings with adequate signal quality. Its strengths include scalability, patient acceptability, and the potential for long-term monitoring without significant burden. However, important limitations persist, including susceptibility to motion artifacts, reduced accuracy in the presence of frequent ectopy, and inability to provide definitive rhythm diagnosis without ECG confirmation. These constraints underscore the need to position pulse oximetry waveform analysis as a screening and monitoring adjunct rather than a replacement for electrocardiography.

Integration of pulse oximetry-based arrhythmia detection into clinical care pathways requires careful consideration of workflow design, alert management, and confirmatory testing strategies. When implemented within structured, guideline-aligned frameworks, pulse oximetry waveform analysis has the potential to enhance early arrhythmia detection, support remote patient monitoring, and expand access to cardiovascular care, particularly in resource-limited settings. Continued advances in signal processing, machine learning, and device standardization, coupled with rigorous clinical validation, will be essential to realizing the full clinical value of pulse oximetry waveform analysis in ambulatory arrhythmia detection.

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