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*Review*

# Wearables for Telemonitoring in ATTR-Amyloidosis: Current Perspectives

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**Abstract**

Wearable sensors enable continuous recording of electrocardiographic, photoplethysmographic, and inertial signals and have accelerated the development of digital biomarkers in cardiovascular medicine. Transthyretin amyloidosis (ATTR) is a progressive multisystem disease characterized by arrhythmia, conduction disturbances, hemodynamic impairment, autonomic dysfunction, and gait abnormalities, making it theoretically suitable for multimodal wearable monitoring. This review summarizes current knowledge on wearable applications in ATTR, evaluates the plausibility of extrapolating signal-based biomarkers from related cardiovascular and neurological cohorts, and outlines methodological and implementation challenges. ATTR-specific data remain limited to small observational studies, mainly on long-term rhythm monitoring and supervised functional assessment. More comprehensive findings support the extraction of metrics such as atrial fibrillation burden, activity patterns, gait variability, and heart rate variability. However, ATTR-related structural remodeling and high arrhythmia burden may distort conventional digital biomarkers, necessitating disease-specific preprocessing and prospective validation. Wearable monitoring in ATTR is technically feasible and biologically plausible but remains investigational. Before routine integration into care pathways can be recommended, standardized, phenotype-stratified studies are needed that link wearable-derived characteristics to assessed clinical outcomes.

**Keywords:** transthyretin amyloidosis; wearables; sensors; telemonitoring; heart failure; neuropathy; atrial fibrillation; gait analysis

## 1. Introduction

Over the past two decades, wearable sensor technologies have evolved from consumer fitness devices to clinically relevant platforms for continuous physiological monitoring (1–3). In cardiovascular medicine, wearables now enable high-resolution capture of electrocardiogram (ECG) signals, photoplethysmographic (PPG) waveforms, pulse oximetry, inertial motion data, acoustic signatures, and behavioral patterns under real-world conditions. This technological maturation has

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driven the development of digital biomarkers, which represent quantifiable, sensor-derived characteristics reflecting underlying biological processes (4). Large-scale investigations such as the Apple Heart Study have demonstrated the scalable detection of atrial fibrillation (AF), while more recent approaches, including the VAMP-HF pilot study, have explored acoustic features from the voice as indicators of heart failure (HF) decompensation (5,6). Complementary findings from telemonitoring studies suggest that continuous remote monitoring not only documents disease status but can also influence outcomes (7). Research on digital biomarkers has now expanded beyond rhythm detection to include activity entropy, gait variability, autonomic indices, sleep disturbances, and multimodal signal integration (4).

Transthyretin amyloidosis (ATTR) is a progressive protein folding disorder characterized by the extracellular deposition of transthyretin fibrils in multiple organ systems. Amyloid formation results either from destabilizing mutations in hereditary ATTR (ATTRv) or from age-related tetramer instability in wild-type ATTR (ATTRwt). The resulting involvement of multiple organ systems includes restrictive cardiomyopathy (ATTR-CM), infiltration of the conduction system, autonomic dysfunction, and progressive peripheral polyneuropathy (ATTR-PNP) (8,9).

ATTR is particularly well suited for digital phenotyping because the disease biology develops gradually across multiple physiological domains. In ATTRwt, restrictive cardiomyopathy typically manifests as heart failure with preserved ejection fraction (HFpEF), AF, conduction disturbances, and chronotropic incompetence, which are detectable in cardiopulmonary exercise testing (CPET) (10). In ATTRv, mutation-specific phenotypes (e.g. TTR-p.Val50Met) often include progressive sensorimotor neuropathy and autonomic impairments that occur either before or together with cardiac involvement (11,12). These manifestations correspond to measurable disturbances in electrical stability, hemodynamics, autonomic regulation, and motor function.

Before obvious clinical deterioration becomes apparent, the progression of ATTR is often accompanied by subtle physiological changes such as increasing arrhythmia burden, decreasing physical activity, altered autonomic variability, emerging gait asymmetry, or early fluid retention (13–15). Despite the availability of disease-modifying ATTR therapies, clinical monitoring remains largely episodic. Such transitional stages are difficult to detect during clinical visits but are theoretically accessible through continuous time series derived from wearable sensors in at risk patients.

Unlike acute inflammatory or ischemic cardiomyopathies, ATTR progresses slowly with cumulative structural remodeling. This temporal profile creates a convergence between the biology of the disease and digital capabilities: wearable sensors can longitudinally capture electrical, mechanical, and behavioral signals that evolve in parallel with pathophysiological changes. However, to translate this potential into clinical utility, sensor-derived features must be explicitly mapped to disease-relevant biological domains.

In ATTR, four interconnected pathophysiological axes are particularly well suited for longitudinal digital phenotyping: electrical instability and conduction disturbances, autonomic dysfunction, hemodynamic impairments and fluid dynamics, and peripheral neuropathy and motor dysfunction (8). These axes interact dynamically with each other: electrical instability can exacerbate hemodynamic impairments, autonomic dysregulation can modulate rhythm patterns, and neuropathy can alter activity metrics that influence cardiac interpretation. Consequently, ATTR provides a compelling framework for multimodal sensor fusion rather than isolated parameter monitoring (see Graphical Abstract).

This review summarizes current findings on wearable sensor technologies in ATTR amyloidosis, defines potential digital biomarkers at the signal and feature level, and proposes a disease-specific conceptual framework for integrating multimodal data from wearable devices into longitudinal ATTR management. By positioning ATTR as a multisystem model for digital phenotyping, we aim to outline both the opportunities and methodological requirements necessary to advance wearable device monitoring from feasibility to clinically actionable disease surveillance.

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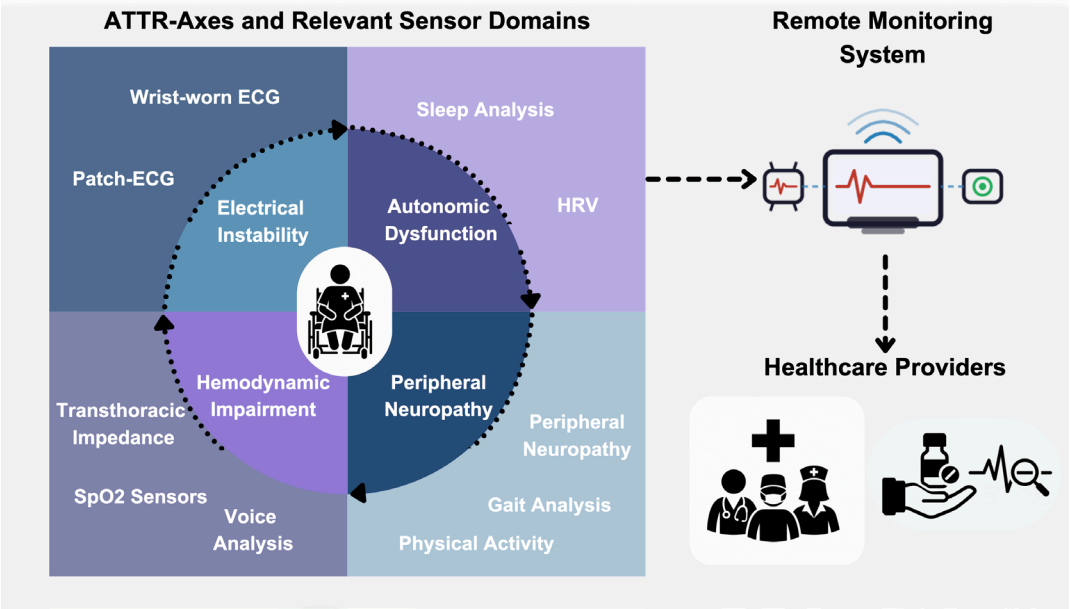


**Figure 1.** Graphical Abstract depicting the proposed ATTR-Axes and their association to Sensor Domains.

## 2. Categories and Technology of Wearable Devices

Wearable monitoring platforms can be categorized according to their primary sensing modality and the physiological signal they capture. In the context of ATTR, three sensor classes are particularly relevant: electrocardiographic monitors, photoplethysmography sensors, and inertial measurement units (IMU).

*Electrocardiographic Monitoring Devices*

Wearable ECG systems record cardiac electrical activity using single-lead or multi-lead configurations and have demonstrated high diagnostic accuracy for arrhythmia detection, particularly atrial fibrillation (AF) (5,16–19). These systems can be broadly divided into consumer-grade wrist-worn devices and medical-grade patch-based monitors.

Wrist-worn devices incorporate dry electrodes into the device casing and typically record short-duration single-lead ECGs (e.g., 30 seconds) upon user activation. The Apple Watch (Apple, Cupertino, USA) was among the first consumer devices to receive regulatory clearance (FDA and CE marking) for AF detection using a single-lead ECG configuration (20). Similar capabilities have since been integrated into other smartwatch platforms. These systems are optimized for intermittent rhythm assessment and event-triggered recording (17).

Patch-based ECG monitors provide continuous rhythm surveillance over extended periods, typically up to 14 days. The Zio Patch (iRhythm Technologies, San Francisco, USA), an FDA-cleared adhesive single-lead ECG device, demonstrated superior arrhythmia detection compared with conventional 24-hour Holter monitoring, largely attributable to prolonged recording duration (19). Continuous ECG patches enable extraction of time-series features beyond binary arrhythmia detection, including AF burden, heart rate variability (HRV), ectopy frequency, and conduction trend analysis.

Smartphone-connected electrode systems, such as KardiaMobile (AliveCor, Mountain View, USA), use handheld electrodes to acquire single-lead ECGs on demand. Clinical trials have demonstrated their utility in AF screening and increased likelihood of capturing transient arrhythmias during symptomatic episodes (18,21,22). For ATTR populations, prolonged rhythm monitoring is particularly relevant given the high prevalence of atrial fibrillation, cardiac arrhythmia necessitating pacemaker implantation and progressive conduction disease (15).

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*Photoplethysmographic Sensors*

Photoplethysmography is a non-invasive optical sensing technique that estimates cardiovascular dynamics by detecting changes in light absorption related to pulsatile blood flow (23–25). An LED emits light into the tissue, and a photodetector measures variations in reflected or transmitted light intensity corresponding to the cardiac cycle. The choice of LED is determined by it's emitted wavelength, with blood oxygen saturation typically requiring both infrared (~850 nm) and red wavelength (~660 nm) emitting diodes (26). Broadly PPG can be classified into either transmissive, with the photodetector located on the opposite side of the LED and skin tissue in-between both, or reflective type, with the LED and photodetector being located next to each other on top of a section of skin tissue. Such PPG sensors are widely integrated into wrist-worn devices and enable passive, continuous acquisition of heart rate, pulse rate variability, peripheral oxygen saturation ($SpO_2$), respiratory rate (derived), and sleep-related physiological patterns.

Unlike ECG devices, PPG operates without user activation, allowing uninterrupted background monitoring. Advanced signal processing enables extraction of pulse morphology features, inter-beat intervals, and pulse transit dynamics. Models for deriving these metrics from the sensor readings are subject of ongoing research and are being expanded into new readings such as blood pressure (27). However, PPG-derived metrics are susceptible to motion artifacts, low peripheral perfusion, and irregular rhythm disturbances, which complicate the use in elderly patients and in conditions such as ATTR-CM. Infiltrative cardiomyopathy and vasomotor instability may alter waveform morphology, necessitating ATTR-specific artifact filtering and quality-index–based preprocessing.

Despite these limitations, the unobtrusive and passive nature of PPG makes it attractive for long-term monitoring in older populations, including patients with ATTR amyloidosis.

*Activity Trackers and Inertial Measurement Units*

Activity monitoring devices typically rely on micro-electromechanical system (MEMS) accelerometers, often combined with gyroscopes and magnetometers, to capture three-dimensional movement patterns (28,29). Raw acceleration vectors are processed using algorithmic models to derive step count, distance travelled, energy expenditure and sedentary time.

Research-grade devices such as the ActiGraph platform (Ametris, Pensacola, USA) have been widely used in cardiovascular and neurological studies (30). However, consumer-grade accelerometer-based wearables increasingly demonstrate sufficient signal fidelity for longitudinal monitoring applications. More sophisticated signal processing modalities, allow for a detailed segmentation of body position and movement information, with consistently lower computational cost allowing their implementation in wearable devices (31).

Beyond general activity tracking, wearable inertial measurement units (IMU) incorporate accelerometers, gyroscopes and magnetometers to enable detailed and quantifiable gait analysis (2). Activity measurement systems comprise 2 – 8 wearable IMU wearable sensors and are commonly placed at the lower limbs, waist, or lumbar (L4) region to capture temporal and spatial gait parameters (2,32). Extractable features include stride length, cadence, gait variability, step asymmetry, turning stability, and postural sway. Commercial systems such as LEGSys (BioSensics, Newton, USA) have demonstrated feasibility in differentiating neurological gait phenotypes in real-world settings (33). For ATTRv amyloidosis, where progressive sensorimotor polyneuropathy is common, IMU-derived gait variability and asymmetry indices represent particularly promising candidate digital biomarkers for at-home disease monitoring.

To contextualize the technical characteristics of the main wearable sensor modalities relevant for ATTR monitoring, Table 1 summarizes the signal characteristics, and disease-specific issues of ECG-, PPG-, and IMU-based systems. This comparison shows that each modality captures different physiological dimensions and has different susceptibility to artifacts and disease-related signal distortions.

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**Table 1.** Technical Comparison of Major Wearable Sensor Modalities Relevant to ATTR Monitoring.

| Parameter | Electrocardiography | Photoplethysmography | Accelerometry/Gyroscope |
|---|---|---|---|
| **Primary Measured Signal** | Cardiac electrical potential difference | Optical pulse waveform (blood volume changes) | Linear acceleration and angular velocity |
| **Signal Domain** | Bioelectrical | Optical / Hemodynamic | Mechanical / Kinematic |
| **Core Extractable Features** | RR intervals, PR/QRS duration, AF burden, HRV | Pulse rate variability, $SpO_2$, pulse morphology, sleep-related metrics | Step count, stride length, gait variability, asymmetry index, fall detection |
| **Strengths** | Gold standard for arrhythmia detection; direct electrical measurement | Passive continuous monitoring; integrated in consumer devices | Objective functional assessment; sensitive to motor decline |
| **Key Limitations** | Limited leads in wearables; motion artifacts; electrode-skin dependency | Motion artifacts; low perfusion sensitivity; AF reduces accuracy | Algorithm-dependent feature derivation; placement-sensitive |
| **ATTR-Relevant Applications** | AF burden tracking, conduction trend monitoring, autonomic HRV analysis | Resting HR trends, autonomic modulation | Neuropathy progression, activity decline, fall risk |
| **Continuous Monitoring Capability** | Intermittent active (wrist-worn device) or continuous passive (patch) | Continuous passive | Continuous passive |

Legend: HRV = Heart rate variability, $SpO_2$ = peripheral oxygen saturation, AF = atrial fibrillation, ATTR = transthyretin amyloidosis, HR = Heart rate

## 3. Evidence of Wearables in ATTR-Amyloidosis

The evidence for monitoring ATTR amyloidosis using wearables remains sparse and heterogeneous, with most data coming from small observational cohorts or sub-studies embedded in clinical trials. Existing data can be grouped into three domains: early detection, rhythm monitoring, and functional assessment. A broader evidence base from heart failure and neurological populations provides biological plausibility and methodological templates but does not replace ATTR-specific validation.

*Early Diagnosis of ATTR-CM*

Despite increasing awareness and improved diagnostic pathways, cardiac amyloidosis remains substantially underdiagnosed. Artificial intelligence (AI) models trained on 12-lead ECG and echocardiographic data have demonstrated promising performance in detecting cardiac amyloidosis in tertiary cohorts (34–36). However, these approaches depend on clinical acquisition infrastructure and specialist interpretation.

To expand screening accessibility, Sangha et al. evaluated an AI algorithm trained on single-lead wearable ECG data to identify ATTR-CM (37). Using noisy real-world wearable recordings, the model achieved a sensitivity of 85% and specificity of 80% (AUROC 0.90, 95% CI 0.88–0.92). Although preliminary and derived from selected cohorts, this study demonstrated that diagnostic signal features characteristic of ATTR-CM may be extractable even from consumer-grade, real-world ECG data.

However, implementation in screening programs requires external validation in populations with varying disease prevalence, as the positive predictive value and associated costs are highly dependent on prevalence. In addition, the performance of the model must be evaluated under real-world signal variations, including motion artifacts and arrhythmic disturbances. At present, portable ATTR screening should be considered hypothesis-generating rather than clinically established.

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*Arrhythmia Detection in ATTR-amyloidosis*

Atrial fibrillation and conduction abnormalities are highly prevalent in ATTR-CM and are associated with increased morbidity and hospitalization risk (13,24). Non-sustained ventricular tachycardia also occurs frequently and may contribute to sudden cardiac death risk (38). Current expert consensus recommends ambulatory rhythm monitoring, with prolonged monitoring considered in selected patients (39).

Wearable ECG systems offer extended monitoring durations compared to conventional 24-hour Holter recordings. In a retrospective study of 38 ATTR-CM patients undergoing 14-day patch-based ECG monitoring, AF was detected in 21.3% and non-sustained ventricular tachycardia in 81.6% of patients (16). Detection rates exceeded those observed in a stroke-evaluation control cohort, highlighting the high arrhythmic burden in ATTR-CM.

Although limited by small sample size and retrospective design, this study supports the feasibility of long-term wearable rhythm surveillance in ATTR-CM. Similarly, implantable loop recorder case series have demonstrated a high frequency of actionable arrhythmic events over extended follow-up (40), underscoring the clinical relevance of continuous rhythm assessment. Evidence from non-ATTR populations further supports prolonged wearable monitoring. In comparative studies, extended patch monitoring detected significantly more arrhythmic events than short-term Holter recordings, largely due to longer recording duration (19,41). Large-scale smartwatch studies have further demonstrated scalable AF detection in general populations (5).

Whether these detection rates translate into ATTR-CM and lead to improved outcomes remains to be proven. Importantly, beyond binary arrhythmia detection, the wearable ECG enables quantification of AF burden and longitudinal RR variability trends, which may be more meaningful in progressive infiltrative cardiomyopathies.

*Wearable based Functional Assessment*

Functional limitation is central in ATTR-CM and typically assessed with NYHA class and the 6-minute walk test (6MWT) (42–45). However, episodic testing may fail to capture day-to-day variability or gradual decline.

A substudy within ATTRibute-CM investigating the use a wearable Opal V2C System (APDM Wearable Technologies, Portland, USA) to conduct a 6MWT, demonstrated high concordance between wearable-derived and conventionally measured 6MWT distance ($r = 0.998$, 95% CI 0.992–0.999) (46). However, measurements were obtained under controlled clinical conditions, thus performance and adherence in unsupervised at-home settings remain to be established. Given the relevance of 6MWT as a trial endpoint (47), home-based assessment could become attractive if robustness to real-world variability is demonstrated.

*Neuropathy and Gait Monitoring in ATTRv*

Hereditary ATTR often manifests as progressive sensorimotor polyneuropathy (PNP) (12). Traditional assessment relies on clinical scales and neurophysiological tests, which are episodic and examiner-dependent. To date, no ATTR specific evidence exists on the use of wearables to monitor progression or treatment related remission of neuropathy. Nonetheless, small studies in diabetic neuropathy, which presents overlapping features with ATTR-PNP, exhibited the feasibility and usefulness of wearable vibration or electrical stimulation systems to improve plantar sensation and motor function (48,49). Another interesting but yet explorative research field, with potential transferability to ATTR-PNP, resembles the application of pedobarography enabled by in-sole pressure and temperature sensors to identify early deterioration in plantar sensation (50,51).

Three dimensional camera-based gait analyses have been able to distinguish asymptomatic carriers from symptomatic ATTRv patients and to detect longitudinal changes in specific gait parameters such as toe-off time and pelvic rotation which were undetected by traditional visual observation (13,52). However, these systems require a sophisticated and expensive laboratory

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infrastructure. Wearable IMU offer the possibility of quantifying gait variability, asymmetry, and falls at home. Although ATTR-specific studies on wearable devices are lacking, neurological populations such as Parkinson's disease and multiple sclerosis patients have demonstrated the feasibility and correlation with clinical motor scales (2,53–56). Fall detection is another relevant application. Automated fall detection systems are highly sensitive but can suffer from a high false positive rate (57). In ATTR, falls can be caused by both neuropathy and conduction-related syncope, suggesting that multimodal integration (portable gait pattern analysis and ECG) could improve etiological differentiation.

The TelePD study will be the first to examine the feasibility of wearable socks for measuring gait and balance data at home, as well as the response to balanced telerehabilitation compared to unsupervised exercises (58). This study will provide valuable insights into the use of wearables during remote treatment and their reliability as a tool for physicians to track therapy success.

*Exploratory Digital Biomarkers*

Wearable-derived HRV and sleep metrics may reflect autonomic dysfunction, and studies have demonstrated predictive value of HRV measurements for sudden cardiac death (59,60). However, in ATTR interpretation can be confounded by atrial fibrillation, ectopy, and conduction disease, necessitating further research including ATTR populations. In HF, early detection of deteriorating heart function is essential to prevent hospitalization or further adverse outcomes. Remote monitoring approaches that monitor fluid changes by thoracic impedance systems or voice biomarkers captured with a smartphone have shown promise in broader HF cohorts (6,61), but remain unvalidated in ATTR.

## 4. Why Extrapolation from Adjacent Diseases Is Plausible - But Requires Validation

ATTR progresses slowly with incremental deterioration often preceded by subtle changes in arrhythmic burden, resting heart rate, activity tolerance, autonomic regulation, and motor stability (mostly in ATTRv). These processes evolve longitudinally and may be detectable through continuous physiological sampling in at-risk cohorts rather than episodic clinical encounters. The availability of disease-modifying therapies increases the need for dynamic monitoring of progression and therapeutic response. Wearables offer biologically coherent measurement domains: validated AF detection is directly actionable in ATTR-CM (5,16,62), may potentially detect subtle fluid status changes prior to HF decompensation (6), and accelerometer-based physical activity or gait metrics align with known disease trajectories. Evidence supporting the clinical value of these domains, albeit to varying degrees, has been established across a number of pathophysiologically adjacent disease states (Table 2).

**Table 2.** Monitoring Domains and its relevance to ATTR-Amyloidosis and Evidence in comparable diseases.

| Monitoring domain | Sensor type | ATTR relevance | Comparable Diseases with Evidence for the Use of Wearables | Evidence level |
|---|---|---|---|---|
| **Arrhythmia** | ECG patch / Watch | High | Atrial Fibrillation, Heart Failure, Ischemic Heart Failure | High |
| **Physical Activity** | Accelerometer | High | Heart Failure, Multiple Sclerosis, Parkinsons‘ Disease, Alzheimers | Moderate |
| **Neuropathy (Gait, Balance)** | IMU / in-shoe | High (ATTRv) | Multiple Sclerosis, Parkinsons‘ Disease | Moderate |
| **Autonomic** | HRV, Sleep Tracker | Moderate | Risk stratification, Epyleptic seizures | Low to Moderate |
| **Heart Failure Decompensation Detection** | Voice Recording, | High | Heart Failure | Low |

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| | | | | |
|---|---|---|---|---|
| **Fall Detection** | Thoracic impedance Wearable Button, Accelerometer | Moderate | Multiple Sclerosis, Parkinsons' Disease | Moderate to High |

Legend: ATTR = transthyretin amyloidosis, ECG = electrocardiography, AF = atrial fibrillation, ATTR = transthyretin amyloidosis, HRV = heart rate variability

However, extrapolation from HF or neurological cohorts assumes that signal-disease relationships remain stable in the context of infiltrative cardiomyopathy, conduction disease and peripheral neuropathy. ATTR-specific structural remodeling may distort conventional digital biomarkers (e.g., HRV interpretation in the presence of AF or conduction delay; PPG waveform instability in low-perfusion states). Therefore, wearable-derived metrics in ATTR must be regarded as biologically plausible but unvalidated until prospective studies demonstrate reproducible associations with clinically adjudicated endpoints.

*Implementation Barriers and Future Directions*

Beyond scientific validation, there are significant structural barriers to implementation in clinical practice. Wearable platforms differ in terms of sensor modality, sampling frequency, preprocessing pipelines, and proprietary algorithms, which limits reproducibility and comparability between studies. Regulatory classification varies by jurisdiction, leading to uncertainty regarding standards of proof and liability in medically complex populations.

Interoperability with electronic health records remains limited, and reimbursement pathways for monitoring rare cardiomyopathies with wearables are poorly defined. Without integration into structured care pathways, there is a risk that continuous data streams will generate an information burden rather than actionable clinical insights.

Importantly, the demographic profile of ATTRwt amyloidosis presents an additional challenge for implementation. Patients tend to be older and may have lower digital literacy, sensory limitations, or lower adherence to device-based self-management strategies. Device usability, passive data collection, minimal user interaction requirements, and caregiver-supported workflows are therefore critical for sustainable adoption in this population.

Future research should combine prospective, phenotype-stratified validations with implementation science approaches anchored in specialized amyloidosis centers. Multimodal sensor fusion, predefined triage algorithms, and cost-benefit analyses will be essential to transition wearable monitoring from feasibility to clinically meaningful integration into ATTR care. Finally, the use of wearables could enable centers with interdisciplinary ATTR-expertise to incorporate scalable remote monitoring for a widespread provision of medical care.

## 5. Conclusions

Wearable sensor technologies offer a biologically coherent framework for early detection and long-term monitoring in transthyretin amyloidosis. The progressive and multisystemic nature of ATTR aligns with domains that can be measured with ECG, PPG, and inertial motion sensors, and early studies demonstrate the feasibility of rhythm and function assessment. However, ATTR-specific validation remains limited, and prospective studies linking wearable-derived features to adjudicated clinical outcomes are needed before routine implementation can be recommended. Furthermore, successful integration must consider the demographics of ATTRwt, where advanced age and limited digital literacy may constrain the use of technology-dependent monitoring strategies.

Wearables should therefore be viewed as a promising but still experimental adjunct to structured multidisciplinary care. Importantly, wearables are intended to complement, rather than substitute, the established clinical methodologies that underpin current ATTR management. Their

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ultimate value depends not only on the accuracy of the signals, but also on validated clinical impact and practical applicability in the patient populations for which they are intended.

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## Abbreviations

The following abbreviations are used in this manuscript:
6MWT – 6-Minute Walk Test
AF – Atrial Fibrillation
AI – Artificial Intelligence
ATTR – Transthyretin Amyloidosis
ATTR-CM – Transthyretin Amyloidosis Cardiomyopathy
ATTR-PNP – Transthyretin Amyloidosis Polyneuropathy
ATTRv – Hereditary Transthyretin Amyloidosis (variant)
ATTRwt – Wild-Type Transthyretin Amyloidosis
AUROC – Area Under the Receiver Operating Characteristic Curve
CE – Conformité Européenne
CI – Confidence Interval
CPET – Cardiopulmonary Exercise Testing
ECG – Electrocardiogram
FDA – Food and Drug Administration
HF – Heart Failure
HFpEF – Heart Failure with Preserved Ejection Fraction

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HRV – Heart Rate Variability
IMU – Inertial Measurement Unit
LED – Light-Emitting Diode
MEMS – Micro-Electromechanical System
NYHA – New York Heart Association
PNP – Polyneuropathy
PPG – Photoplethysmography
$SpO_2$ – Peripheral Oxygen Saturation
TTR – Transthyretin

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