

Adaptive Signal Processing for Real-Time Heart Rate Variability Analysis During Physical Exercise

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Abstract

The analysis of heart rate variability during physical exercise presents a challenging intersection of physiological sensing, nonstationary signal processing, and real-time embedded computation. Wearable photoplethysmographic sensors enable continuous cardiac monitoring outside clinical settings, but movement artifacts fundamentally distort the pulse waveform and threaten the integrity of beat-to-beat interval estimation. This paper examines adaptive signal processing from a systems perspective rather than as an isolated algorithm problem. It addresses the architectural trade-offs between filtering complexity, latency, energy consumption, and physiological validity. The discussion covers motion artifact rejection strategies, signal quality assessment, real-time heart rate variability feature extraction, and the role of edge-cloud coordination in deploying reliable wearable monitoring infrastructure. Particular attention is given to the structural constraints of adaptive filtering under nonstationary exercise conditions, including convergence speed, waveform preservation, and contextual activity recognition. The paper further considers robustness and fairness across diverse populations, privacy and data governance, regulatory implications, and long-term sustainability. It argues that trustworthy real-time heart rate variability analysis during physical exercise requires coordinated design across signal processing, embedded systems, data governance, and public health policy. Technical decisions at the sensor and algorithm level are inseparable from questions of equity, accountability, and lifecycle management.

Keywords

adaptive filtering; heart rate variability; photoplethysmography; motion artifact mitigation; real-time signal processing; wearable systems; edge computing; data governance.

1. Introduction

The analysis of heart rate variability (HRV) during physical exercise has moved from laboratory-based electrocardiography to ambulatory wearable systems that must operate under highly dynamic and unpredictable conditions. Photoplethysmography (PPG) offers a practical optical alternative for continuous cardiac monitoring, but its susceptibility to movement artifact has historically limited its use outside controlled settings [1]. Physical exercise, with its high-intensity limb accelerations, skin deformation, and rapid changes in tissue perfusion, represents one of the most demanding contexts for wearable sensing [2]. At the same time, HRV is widely recognized as a sensitive marker of autonomic nervous system balance and cardiovascular regulation, with standardized measurement conventions that emphasize controlled recording conditions and stable beat-to-beat intervals [3].

Modern consumer and clinical wearable devices frequently compute HRV indices from interbeat intervals derived from PPG rather than from electrocardiography. Although this substitution increases comfort and convenience, it introduces additional complexity because PPG morphology is affected by mechanical coupling, blood volume changes, and sensor displacement. A broad body of research has examined the physiological interpretation of HRV metrics, their reproducibility, and their normative ranges, but many of these findings originate from resting or paced conditions [4][5]. The central challenge is not simply acquiring a plausible heart rate during motion; it is preserving the fine temporal structure of beat-to-beat intervals under conditions that violate the assumptions of traditional stationary signal processing.

This paper addresses adaptive signal processing for real-time HRV analysis during exercise as a systems problem rather than as an isolated filtering problem. It examines signal-level techniques, architectural trade-offs, artifact rejection, feature extraction, edge-cloud infrastructure, robustness, fairness, governance, and sustainability. By connecting signal-level decisions to deployment and policy considerations, the analysis highlights how technical choices shape the reliability and equity of wearable health monitoring.

2. System Architecture and Real-Time Constraints

The architecture of a real-time HRV monitoring system can be described as an end-to-end pipeline extending from the optical sensor front end to analytics, visualization, and user feedback. Raw PPG waveforms are digitized at rates that are modest relative to many industrial sensing systems, typically tens to hundreds of samples per second, and then processed in short frames or sliding windows. Real-time operation imposes strict constraints on latency because feedback for training, cardiac safety monitoring, or stress regulation may require HRV updates within seconds. However meaningful HRV analysis requires a wider temporal window to estimate low-frequency variability, creating a structural tension between responsiveness and physiological validity.

In wearable deployments, processing must be allocated across sensing, signal conditioning, motion reference channels, feature extraction, and optional wireless transmission. Each stage consumes energy and generates heat. Battery capacity and skin contact comfort constrain the complexity of adaptive algorithms. Higher-order filters or longer buffers improve artifact rejection but may reduce battery life and increase processing delay. System-level design therefore requires a careful trade-off among filter order, update rate, and window length. This situation resembles control system design in embedded automation, in which the sample interval, computational deadline, and estimator accuracy form a tightly coupled set of constraints.

A key architectural question is whether HRV calculation should be performed on the device, at the edge, or in the cloud. On-device processing minimizes privacy exposure and network dependence but limits model complexity. Cloud processing allows more elaborate retrospective analysis and model updating but introduces latency and communication uncertainty. Edge gateways provide an intermediate option, supporting local aggregation and adaptation while maintaining low-latency feedback. The choice is not purely technical; it affects energy, data governance, and clinical accountability. A robust architecture should therefore define clear modes of operation, with local processing as the default and remote processing used selectively for model improvement or offline review.

3. Adaptive Signal Processing Strategies and Structural Trade-offs

Adaptive noise cancellation emerged as a foundational method for removing interference when a correlated reference signal is available [6]. In exercise monitoring, accelerometer or gyroscope signals can serve as references for motion artifact. The underlying concept is not to model noise as a fixed spectrum but to continuously adjust filter weights so that the reference-derived estimate of motion interference can be subtracted from the observed PPG. This approach is structurally powerful because motion is nonstationary, and fixed filters cannot track changing mechanical conditions [7].

Within this family, least mean squares and normalized least mean squares algorithms have been extensively examined because of their low computational cost. For PPG signals during exercise, adaptive step-size least mean squares variants can provide better convergence when artifact power fluctuates abruptly [8]. However adaptation introduces a fundamental trade-off between convergence speed and steady-state misadjustment. A high adaptation rate allows fast tracking of sudden movements but may distort the cardiac waveform when the reference is poorly correlated with the artifact. Conversely, a conservative adaptation rate preserves morphology during quiet periods but lags behind rapid changes in motion intensity. This trade-off shapes the choice of algorithm parameters and motivates the use of double-stage or cascaded architectures.

More general treatments of adaptive filter theory emphasize the importance of eigenvalue spread, signal conditioning, and regularization for robust convergence [9]. Digital signal processing foundations also clarify that adaptive systems are not a substitute for thoughtful front-end design [10]. Band-limiting the PPG and motion channels, controlling sensor dynamic range, and synchronizing channels in time are prerequisites for effective adaptation. Without these, adaptive algorithms may learn spurious correlations and produce unstable behavior. Structural comparisons across industrial noise cancellation, acoustic echo cancellation, and biomedical signal enhancement reveal common principles but also unique physiological constraints, particularly the need to preserve pulse morphology rather than merely maximize signal-to-noise ratio.

Another structural issue is whether adaptation should occur on the raw waveform or on extracted features. Waveform-level adaptation preserves information for HRV but is more computationally intensive. Feature-level adaptation may be cheaper but risks discarding subtle timing information. The most robust systems often employ a layered strategy in which a deterministic front end removes out-of-band noise, an adaptive stage reduces motion interference, and a signal quality assessment stage determines whether the residual signal is trustworthy.

4. Motion Artifact Rejection in Wearable Photoplethysmography

Motion artifact rejection in wearable PPG cannot be reduced to a single algorithm. The artifact originates from multiple mechanisms including relative displacement between sensor and skin, changes in capillary bed compression, ambient light variation, and intermittent sensor lift-off. Signal quality assessment methods based on waveform morphology and dynamic time warping can identify segments that are not suitable for HRV analysis [11]. Standardized signal quality indices have also been proposed for electrocardiogram and PPG, supporting real-time gating of noisy periods [12]. These methods provide an essential supervisory layer that decides when adaptive filtering can be trusted.

Comparative studies in non-contact cardiac pulse measurement using imaging and blind source separation illustrate that signal decomposition can recover physiological components

even when the raw observation is strongly contaminated [13]. In wearable PPG, state-of-the-art approaches have demonstrated that heart rate can be tracked during intensive physical exercise by combining motion references with spectral estimation and validation stages [14]. The general strategy is to decompose the observation into components, evaluate their periodicity and relationship to motion, and select the component most consistent with cardiovascular physiology.

Independent component analysis has been applied to separate motion-induced components from arterial pulsations in photoplethysmography, although its real-time use is limited by computational demands and the need for multiple channels [15]. Wearable PPG reviews emphasize that sensor placement, skin tone, tissue perfusion, and mechanical design strongly influence artifact characteristics [16]. These contextual factors imply that adaptive algorithms must be configured for specific populations and activities; a system optimized for rhythmic treadmill running may behave differently during cycling, weightlifting, or daily ambulation.

Adaptive notch-filtration strategies have been shown to effectively recover photoplethysmographic signals during physical activity by tracking motion-related interference in specific frequency regions, thereby preserving underlying cardiac components [17]. Unlike broadband cancellation, notch-based methods focus on the dominant periodic interference caused by repetitive limb movement. This structural choice is attractive for real-time embedded systems because it can be implemented with lower complexity and can be integrated with downstream HRV feature extraction. However its performance depends on the stability of the motion period and on the separation between motion frequencies and the spectral content of HRV itself.

5. Real-Time Heart Rate Variability Feature Extraction and Interpretation

Once motion-cleaned beat locations are available, the system must compute HRV indices in real time. Time-domain metrics such as the standard deviation of interbeat intervals and the root mean square of successive differences are widely used because they are conceptually simple and carry clinical interpretation. Frequency-domain metrics decompose variability into high-frequency and low-frequency components associated with parasympathetic and combined autonomic influences. Non-linear measures capture unpredictability and complexity. Software environments developed for HRV analysis provide standardized processing pipelines, artifact correction, and reporting, but they are primarily designed for offline or laboratory use rather than continuous mobile sensing [18].

Real-time implementation requires sliding-window estimation rather than ensemble analysis of entire recordings. The window length determines which HRV indices can be estimated. Short windows support rapid feedback but may produce unstable estimates of low-frequency variability. Longer windows improve statistical reliability but blur transient physiological responses. The system must therefore select a windowing strategy that matches the intended use, whether that is acute exercise guidance, recovery monitoring, or long-term autonomic trend analysis. This is not merely a data processing detail; it determines the physiological meaning of the output.

Beat-to-beat interval estimation from PPG presents additional challenges. The PPG pulse waveform has a slower morphology than the electrocardiographic R wave, and fiducial point detection can shift under changing pressure and perfusion. Adaptive processing that optimizes motion rejection may introduce subtle timing distortions if group delay is not carefully controlled. HRV analysis is extremely sensitive to interval errors, so even small systematic

shifts can produce misleading variability estimates. This coupling means that signal quality and timing fidelity must be evaluated together rather than separately.

Interpretation of HRV during exercise also requires contextual awareness. Physical activity changes autonomic balance through increased sympathetic drive and respiratory influences. Wearable systems should not blindly compare exercise HRV with resting norms. They must normalize for workload, recovery state, ambient temperature, and individual fitness. The algorithmic layer should therefore incorporate contextual metadata in addition to raw interbeat intervals. Otherwise, real-time feedback may be physiologically plausible but clinically meaningless.

6. Infrastructure, Deployment, and Edge-Cloud Coordination

Deployment of adaptive HRV analysis across populations requires infrastructure beyond a single device. Edge intelligence frameworks have argued that many machine learning and signal processing tasks can be distributed across edge nodes to reduce latency, conserve bandwidth, and preserve privacy [19]. In wearable health monitoring, an edge node might be a smartphone or a gateway that receives raw or lightly processed PPG from a wristband, executes adaptive filtering, computes HRV features, and sends only summarized results to cloud services. This distribution supports real-time feedback and reduces the risk of transmitting continuous physiological waveforms.

Federated learning provides a governance-compatible mechanism for improving algorithms without centralizing sensitive data [20]. Multiple users can contribute model updates derived from local data while retaining raw signals on their devices. This is particularly relevant for motion artifact models, which need diverse data across sensor types, skin tones, body compositions, and exercise modalities. Federated approaches can improve personalization while limiting data aggregation risks. However they introduce coordination overhead, heterogeneity in local computing resources, and challenges in verifying that updates do not embed population bias.

The deployment architecture must also support fault tolerance and graceful degradation. In outdoor exercise, network connectivity may be intermittent, and cloud services may be unavailable. On-device adaptive processing ensures that HRV feedback continues even when connectivity is lost. When connectivity resumes, the device can synchronize summaries or model updates according to policy. This design resembles resilient cyber-physical systems in which local autonomy is maintained under communication failure. Deployment therefore requires robust state management, secure time-stamping, and audit logs.

System sustainability depends on how updates are managed over the product lifetime. Algorithms may require recalibration as sensors age, as firmware changes, or as user populations shift. An infrastructure that supports continuous model evaluation, drift detection, and safe rollback is essential. Without such operational controls, adaptive signal processing systems may degrade silently over time, producing unreliable HRV values without obvious system failure.

7. Robustness, Fairness, and Equity Considerations

Robustness refers not only to motion artifact but also to variability across individuals, devices, and environments. A system that performs well for a narrow demographic may fail for users with darker skin tones, reduced peripheral perfusion, tattoos, or scar tissue because optical absorption differs. Fairness in physiological sensing requires evaluating algorithm

performance across skin pigmentation, body mass index, age, and cardiovascular status. Otherwise, seemingly neutral technical benchmarks may conceal differential error rates.

There is also a fairness dimension in data collection and model training. If training datasets overrepresent young, healthy, light-skinned individuals performing treadmill exercise, the resulting adaptive algorithms may not generalize to older adults, individuals with chronic conditions, or different cultural movement practices. This is not merely a data quantity issue; it reflects structural exclusions in research subject recruitment and consumer device testing. Federated and distributed approaches can help diversify data but only if participant populations are actively broadened.

Robustness must also be considered across exercise modalities. Running produces predictable periodic motion, while resistance training, cycling, swimming, and manual labor produce different artifact patterns. A single adaptive configuration may be optimal for one activity but inadequate for another. Context-aware adaptation, in which activity type is recognized and algorithm parameters are adjusted accordingly, improves robustness. However activity recognition itself can be biased by movement styles and disability.

From a systems perspective, fairness metrics should be part of release criteria. Device manufacturers and researchers should report error distributions across demographic and activity subgroups, not only aggregate mean absolute error. Such reporting supports accountability and helps regulators understand whether a wearable HRV system is suitable for broad public health use or only for a narrow consumer segment.

8. Governance, Privacy, and Policy Implications

The continuous collection of PPG and HRV data creates substantial privacy risks because physiological signals can reveal stress, sleep, substance use, and cardiovascular status. The NIST Privacy Framework provides a structured approach for identifying privacy risks and selecting controls for continuous sensing systems [21]. It emphasizes that privacy should be considered during system design, not appended after deployment. Organizations deploying wearable HRV monitoring should map data flows, identify authorized uses, and implement data minimization.

The European General Data Protection Regulation imposes obligations on processing health-related data, including biometric and physiological information [22]. Under this framework, continuous HRV data are not simply lifestyle metrics; they can qualify as health data when used to infer physical or mental health. Consent, purpose limitation, storage limitation, and the right to erasure become operational requirements. Real-time adaptive processing on the device can support compliance by limiting the amount of raw data transmitted, but compliance also requires transparent disclosure and user control.

Policy implications extend beyond privacy. The World Health Organization guidelines on physical activity highlight the public health value of wearable monitoring for exercise promotion [23]. If adaptive HRV systems are reliable and accessible, they could support personalized physical activity guidance. However public health benefit depends on avoiding digital divides. If high-quality HRV monitoring is available only through expensive devices, existing health inequalities may widen. Policymakers should consider subsidies, interoperability standards, and open evaluation frameworks.

The broader field of mobile health has consistently emphasized that technology alone cannot improve outcomes without integration into care pathways and behavioral support [24]. Real-

time HRV analysis during exercise is most valuable when it informs decisions such as exercise intensity adjustment, recovery planning, or symptom monitoring. This requires clinical validation, regulatory clarity, and practical workflows. Governance mechanisms should therefore include post-market surveillance, adverse event reporting, and continuous performance auditing.

9. Sustainability and Lifecycle Perspectives

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Sustainability concerns begin with the physical hardware of wearable photoplethysmographic devices. Optical sensors, batteries, embedded processors, and wireless modules each contribute to resource consumption during manufacturing, use, and disposal. A system that requires frequent charging because adaptive processing drains the battery too quickly shortens the practical lifespan of the device and increases electronic waste. Sampling rate, filter order, window length, and communication frequency collectively determine energy consumption. Efficient adaptive algorithms therefore have an environmental dimension that extends beyond their computational elegance. From a lifecycle perspective, the goal is not only to recover a clean pulse waveform but also to do so within an energy envelope that supports long-term use and reduces replacement frequency. Industrial experience in embedded health monitoring has shown that thoughtful selection of processing stages can extend device longevity, but this requires treating energy efficiency as a first-class design requirement rather than as a post hoc optimization.

Algorithm maintenance over time is another important lifecycle concern. Physiological signal processing models may be tuned on a particular hardware generation, sensor placement, or population sample. As sensor components age, their optical characteristics may drift slightly, and as user populations expand, the distribution of skin properties, motion patterns, and cardiovascular conditions may shift. An adaptive system that performed well in initial validation can gradually degrade without visible failure. Continuous performance auditing and periodic recalibration are therefore necessary to preserve reliability. A sustainable deployment includes version control for filter parameters, mechanisms for detecting model drift, and clear procedures for rolling back updates that produce worse outcomes. Similar practices are already established in safety-critical control systems and should be adopted more systematically in wearable physiological monitoring.

Data retention and storage also shape the sustainability of a real-time HRV monitoring infrastructure. Raw photoplethysmographic and accelerometer streams are high-volume compared with extracted interbeat intervals or HRV features. Storing raw data indefinitely creates unnecessary privacy risk, increases cloud storage costs, and imposes an ongoing energy burden. Edge processing can contribute to sustainability by discarding raw waveforms after local feature extraction unless explicit consent supports longer retention for research or clinical review. The NIST Privacy Framework [21] provides guidance for mapping data flows and aligning retention practices with risk. A sustainable system should not accumulate unbounded personal physiological data by default; instead, it should enforce data minimization policies that reflect the lifecycle of the information itself.

Federated learning [20] has been proposed as a mechanism for improving wearable algorithms without centralizing sensitive data, but it also introduces lifecycle considerations. Model updates consume energy, require coordination across heterogeneous devices, and can introduce temporary performance regressions if not carefully evaluated. Edge intelligence

frameworks [19] can schedule training and update operations during charging periods or low-activity intervals to reduce user disruption. The sustainability of these systems depends on how often models are retrained, how updates are compressed and distributed, and how local devices retain enough processing capability to participate. A long-lived wearable monitoring ecosystem must balance the benefits of continuous learning against the operational costs of frequent adaptation.

Finally, social and economic sustainability must be considered. If advanced HRV monitoring during physical exercise is available only through expensive proprietary devices, its public health value remains limited. The World Health Organization [23] has emphasized broad population benefit from physical activity promotion, yet technology-driven monitoring can inadvertently widen health inequalities if access is uneven. Sustainable deployment requires attention to low-cost sensor options, open evaluation data, interoperability between devices, and community-based validation programs. The field of mobile health has demonstrated that technology alone does not improve outcomes without integration into broader behavioral and clinical support systems [24]. A lifecycle perspective therefore connects device-level energy efficiency and algorithm maintenance to wider questions of health equity and long-term societal value.

10. Conclusion

Real-time HRV analysis during physical exercise sits at the intersection of nonstationary signal processing, embedded computing, and health data governance. This paper has argued that adaptive filtering should not be treated as an isolated algorithmic problem. It must be embedded within a layered architecture that includes front-end signal conditioning, signal quality assessment, contextual activity awareness, edge-cloud coordination, and continuous performance auditing. The central computational tension is between rapid adaptation to time-varying motion artifacts and preservation of the fine temporal structure that gives HRV its clinical meaning. A filter that converges quickly may remove too much cardiac variability, while a conservative filter may fail to track sudden mechanical disturbances.

The structural trade-offs discussed throughout this paper reveal that no single adaptive strategy is universally optimal. Methods such as adaptive noise cancellation, adaptive notch filtering, and blind source separation each offer distinct advantages under different activity conditions and hardware constraints. The choice of algorithm must be coordinated with decisions about window length, processing location, energy budget, and data retention. In particular, adaptive notch-filtration approaches [17] illustrate how frequency-selective adaptation can be aligned with embedded processing constraints, but their effectiveness depends on the periodicity of motion and the spectral separation between artifact and cardiac variability. A robust deployment should therefore support multiple processing modes rather than relying on a single fixed configuration.

Fairness and accountability must be integrated into system evaluation. Aggregate error metrics hide important differences across skin tones, body compositions, ages, and exercise modalities. Developers should report performance distributions for demographic and activity subgroups, and regulators should require such evidence before clinical or public health claims are made. The sensor, the algorithm, and the deployment context cannot be separated from the social conditions in which they operate. Equity in physiological monitoring is not a secondary concern; it is a property of the overall system architecture.

Privacy and data governance add another layer of responsibility. Continuous PPG and HRV data are sensitive because they can reveal cardiovascular status, stress, sleep patterns, and behavioral routines. Edge processing can reduce privacy exposure by keeping raw signals on the device, but this is not a complete solution. Transparent consent, data minimization, secure transmission, and clear retention limits are needed. Regulatory frameworks such as the General Data Protection Regulation [22] and privacy risk management approaches [21] provide structured guidance, but translating these principles into real-time wearable architectures requires ongoing interdisciplinary collaboration.

Future research should focus on lightweight personalization methods that adapt to individual physiology without centralizing sensitive data, on energy-efficient adaptive filters that extend battery life, and on long-term field studies that connect HRV metrics to clinically meaningful outcomes. Collaboration among biomedical engineers, computer scientists, clinicians, regulators, and community stakeholders will be essential. The ultimate goal is not simply a more sophisticated filtering technique but a trustworthy, equitable, and durable infrastructure for physiological monitoring during physical activity. Such an infrastructure must be technically sound, socially aware, and sustainable across the full lifecycle of devices, data, and algorithms.

References

1. Allen, J. (2007). Photoplethysmography and its application in clinical physiological measurement. *Physiological Measurement*, 28(3), R1–R39.
2. Zhang, Z., Pi, Z., & Liu, B. (2015). TROIKA: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise. *IEEE Transactions on Biomedical Engineering*, 62(2), 522–531.
3. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. (1996). Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. *European Heart Journal*, 17(3), 354–381.
4. Sandercock, G. R., Bromley, P. D., & Brodie, D. A. (2005). The reliability of short-term measurements of heart rate variability. *International Journal of Cardiology*, 103(3), 238–247.
5. Nunan, D., Sandercock, G. R., & Brodie, D. A. (2010). A quantitative systematic review of normal values for short-term heart rate variability in healthy adults. *Pacing and Clinical Electrophysiology*, 33(11), 1407–1417.
6. Widrow, B., Glover, J. R., McCool, J. M., Kaunitz, J., Williams, C. S., Hearn, R. H., Zeidler, J. R., Dong, E., & Goodlin, R. C. (1975). Adaptive noise cancelling: Principles and applications. *Proceedings of the IEEE*, 63(12), 1692–1716.
7. Yousefi, R., Nourani, M., Ostadabbas, S., & Panahi, I. (2014). A motion-tolerant adaptive algorithm for wearable photoplethysmographic biosensors. *IEEE Journal of Biomedical and Health Informatics*, 18(2), 670–681.
8. Ram, M. R., Madhav, K. V., Krishna, E. H., Komalla, N. R., & Reddy, K. A. (2012). A novel approach for motion artifact reduction in PPG signals based on AS-LMS adaptive filter. *IEEE Transactions on Instrumentation and Measurement*, 61(5), 1445–1457.
9. Haykin, S. (2014). *Adaptive filter theory* (5th ed.). Pearson.

10. Oppenheim, A. V., & Schafer, R. W. (2010). *Discrete-time signal processing* (3rd ed.). Pearson.
11. Li, Q., & Clifford, G. D. (2012). Dynamic time warping and machine learning for signal quality assessment of pulsatile signals. *Physiological Measurement*, 33(9), 1491–1501.
12. Orphanidou, C., Bonnici, T., Charlton, P., Clifton, D., Vallance, D., & Tarassenko, L. (2015). Signal-quality indices for the electrocardiogram and photoplethysmogram: Derivation and applications to wireless monitoring. *IEEE Journal of Biomedical and Health Informatics*, 19(3), 832–838.
13. Poh, M. Z., McDuff, D. J., & Picard, R. W. (2011). Advancements in noncontact, multiparameter physiological measurements using a webcam. *IEEE Transactions on Biomedical Engineering*, 58(1), 7–11.
14. Temko, A. (2017). Accurate heart rate monitoring during physical exercises using PPG. *IEEE Transactions on Biomedical Engineering*, 64(9), 2016–2026.
15. Kim, B. S., & Yoo, S. K. (2006). Motion artifact reduction in photoplethysmography using independent component analysis. *IEEE Transactions on Biomedical Engineering*, 53(3), 566–568.
16. Biswas, D., Simões-Capela, N., Van Hoof, C., & Van Helleputte, N. (2019). Heart rate estimation from wrist-worn photoplethysmography: A review. *IEEE Sensors Journal*, 19(16), 6560–6570.
17. Zheng, X., Dwyer, V. M., Barrett, L. A., Derakhshani, M., & Hu, S. (2022). Adaptive notch-filtration to effectively recover photoplethysmographic signals during physical activity. *Biomedical Signal Processing and Control*, 72, 103303.
18. Tarvainen, M. P., Niskanen, J. P., Lipponen, J. A., Ranta-aho, P. O., & Karjalainen, P. A. (2014). Kubios HRV – Heart rate variability analysis software. *Computer Methods and Programs in Biomedicine*, 113(1), 210–220.
19. Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2019). Edge intelligence: Paving the last mile of artificial intelligence with edge computing. *Proceedings of the IEEE*, 107(8), 1738–1762.
20. McMahan, B., Moore, E., Ramage, D., Hampson, S., & y Arcas, B. A. (2017). Communication-efficient learning of deep networks from decentralized data. In *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics* (pp. 1273–1282). PMLR.
21. National Institute of Standards and Technology. (2020). NIST privacy framework: A tool for improving privacy through enterprise risk management, version 1.0. U.S. Department of Commerce. <https://doi.org/10.6028/NIST.CSWP.01162020>
22. European Parliament and Council of the European Union. (2016). Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). *Official Journal of the European Union*, L119, 1–88.
23. World Health Organization. (2020). WHO guidelines on physical activity and sedentary behaviour. World Health Organization.

24. Steinhubl, S. R., Muse, E. D., & Topol, E. J. (2015). The emerging field of mobile health. *Science Translational Medicine*, 7(283), 283rv3.