Journal of Theoretical and Applied Information Technology
31st August 2026. Vol.104. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ARCHITECTURE OF INTELLECTUAL IOT-SYSTEM OF DATA COLLECTION FROM WEARABLE DEVICES FOR PREVENTIVE HEALTH STATUS MONITORING

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ABSTRACT

The purpose of the study is to provide analytical substantiation and comparative analysis of architectural solutions for biometric data collection from wearable devices. The work analyses the hypothesis according to which the level of integration of peripheral calculations (Edge) and the type of adaptive filtering algorithms are decisive factors in the accuracy of biometric parameters. Deconstruction of architectural models was conducted within the context of Industry 5.0, which involves methods of decentralised signal processing and hybrid data transmission protocols on the example of a case-study of Garmin, Our, and Apple Watch systems. The evaluation is based on the comparative analysis of root mean square error (RMSE) and latency in scenarios of physical activity and rest. The analysis results demonstrate that architectures with Edge-processing priority ensure deviation reduction of 35-58% and stabilisation at the level of 100ms compared to purely cloud solutions. The data confirm the high effectiveness of algorithms of intellectual adaptive filtering at levelling motion artefacts directly at the peripheral gateway. The conclusions systematise the advantages of analytical load delegation to the peripheral level to ensure scalability and sustainability of preventive healthcare systems. Further study perspectives lie in exploring methods of lightweight machine learning for monitoring personalisation in real time. The use of decentralised models enables the extension of the possibility of remote rehabilitation under the condition of preservation of high reliability of biometric parameters.

Keywords: *Edge Computing, Smart Rings, Physical Rehabilitation, Physiological Signal Processing, Photoplethysmography (PPG), Artifact Removal, Industry 5.0.*

1. INTRODUCTION

Global transformation of the healthcare system under the influence of digitalisation stipulates rapid growth of the market of devices for continuous parameter monitoring. According to the reports of International Data Corporation [1], the volume of wearable product supply exceeded 500 million units per year by the end of 2024. Undoubtedly, the wide implementation of electronic monitoring means creates conditions for transition from a reactive treatment model to strategies of preventive monitoring of health status [2]. According to the data on the Statista website [3], the number of active users of smartwatches and ring-shaped sensors will reach the mark of 1.1 billion by the end of 2029. Therefore, there is a necessity for the development of intellectual tools for processing large sets of biometric information in real time [4, 5].

It is worth paying attention to the fact that the digitalisation of physical culture and sport requires high accuracy in the collection of parameters of heart rate and oxygen saturation level. Hence, the wide use of household sensors for clinical purposes remains limited due to the unstable quality of the signal during active movement [6]. The majority of available solutions do not ensure absolute accuracy of parameter measurement and transmission during intensive loads. Supervision results indicate growth in measurement error in relation to critical meanings at accidental displacement of sensors in relation to the user's skin. In particular, the use of smart rings requires specific algorithms of artifact compensation due to the peculiarities of finger anatomy [7].

The issue of this study is the absence of a single approach to combining data in different architectural platforms to preserve high analysis reliability. On one side, cloud services often fail to provide the necessary response rate for urgent rehabilitation measures [8, 9]. On the other side, peripheral devices have limited computing resources for the realisation of complex neural network algorithms [10]. Finding a balance between the capacity of the intellectual analysis and the autonomy of sensors defines the vector of further scientific research in the field. The issue of ensuring the privacy of biometric flows while transmitting via open protocols [11].

Thus, the study is directed at filling the mentioned gap using a comparative analysis of architectural configuration, which ensures a balance between processing speed and data accuracy. The scientific novelty of the work is in establishing patterns of influence of decentralised signal processing on the final credibility of monitoring under conditions of intensive physical activity. The crucial role of the Edge-level in ensuring stability of time parameters of biometric flow transmission was defined on the basis of the structural deconstruction of Garmin, Oura, and Apple HealthKit platforms. Study results analytically substantiate the advantages of peripheral gateways for levelling motion artifacts, which enables systematisation of approaches to integration of heterogeneous devices into a single preventive medicine system.

The aim of the study was the systematisation and analysis of architectural solutions for biometric data collection from wearable devices. Realisation of the aim provided the solution to a number of interconnected tasks. The first task lay in the critical deconstruction of architectural models of leading IoT platforms for the identification of factors of biometric signals degradation. The second task was directed at a comparative evaluation of the mathematical methods of artifact filtering according to the root mean square error metric. The third task provided an analytical establishment of the influence of Edge-level on the minimisation of time delays in the data processing process.

Two key questions were formulated within the mentioned study. The first question related to optimal gateway configuration for ensuring stable communication among heterogeneous devices. The second task was directed at establishing a correlation between the depth of peripheral processing and the credibility of the preventive evaluation of the user's condition. The hypothesis of the study is based on the assumption that not only sensor accuracy, but also the compulsory presence of the Edge-level is a critical factor of system success.

The modern technological context provides active implementation of intellectual solutions in the area of preventive medicine and physical rehabilitation. At the same time, there is a necessity for a critical reconsideration of the available architectural models of biometric data collection. The necessity of revision of standard approaches is stipulated by the inability of static databases to process dynamic information flows without significant loss of contextual significance of signals.

The initial stage of field development is based on the implementation of centralised cloud computing technologies for the automation of care for low-mobility patient groups [12]. Undoubtedly, the advantages of automation of household devices enable a significant improvement in life quality in a hospital setting. However, the expansion of the AIoT conception requires the transfer of computing load closer to the signal source. In their work, Alnaim and Alwakeel [13] substantiate the appropriateness of the use of edge nodes to minimize network latency and strengthen information protection. Synthesis of the presented opinions indicates the change of paradigm from data accumulation to local intellectual filtering directly on the device. In view thereof, the development of digital health requires the creation of personalised systems with a high interoperability level, as discussed in the study of Ogenyi et al. [14]. Similar structures enable an effective combination of heterogeneous devices into protected local networks. Herewith, Hemalatha et al. [15] propose proactive care models, where local algorithms reveal critical deviations before the onset of the acute phase of the disease. Critical evaluation of architectural models reveals controversy between the need for privacy and the technical limitations of the capacity of peripheral nodes, while using energy-consuming neural networks.

In recent years, a shift in the dominant forms of wearable devices from smartwatches to smart rings has been observed. According to Fiore et al. [16], the high diagnostic value of the rings for lasting supervision over the state of the cardiovascular system is confirmed. Ergonomic advantages of such devices ensure stability of sensor contact during sleep and activity. Gong et al. [17] indicate the prospectiveness of ring-shaped sensors for early identification of pathological changes in heart rhythm. At the same time, the scientific community has reasonable precautions concerning the accuracy of mass-market consumer devices. The work by Gammie et al. [18] describes the issue of information confusion, arising due to the discrepancy between marketing promises and actual clinical capabilities. Comparative analysis of the measurement accuracy confirms that miniaturization of sensors frequently leads to an increase in the frequency of false-positive results due to the instability of photoplethysmographic signals. Finally, there is a need for the creation of open platforms for transparent data processing [19]. The use of open-code systems enables verification of the results of finger movement tests in real time.

Qian and Siau [20] define a combination of sensor technologies and artificial intelligence (AI) as a fundamental factor for ensuring conception of successful ageing. Preventive medicine requires a transition from episodic measurements to continuous tracking of the dynamics of body function restoration [21]. The studies insist on the importance of the intellectual evaluation of the risks on the basis of continuous monitoring data. Automated evaluation of the fall risks of patients in rehabilitation centres remains specific [22]. Wearable devices enable the transformation of approaches to safety via constant analysis of walking parameters. Elfouly and Alouani [23] note that modern systems should involve parameters of physical and mental health simultaneously. The logical combination of the mentioned directions demonstrates a transition from quantitative metric collection to qualitative evaluation of psychophysiological endurance of the subject under conditions of social isolation.

What previous studies have presented. Prior research established that: (i) wearables enable continuous monitoring [2, 4]; (ii) smart rings have diagnostic potential [16, 17]; (iii) edge computing reduces latency [13, 14]; and (iv) LMS filtering removes motion artifacts in controlled settings [27]. However, these studies focus on isolated aspects under idealized conditions, leaving a gap in architectural comparisons during intensive physical activity. Closed commercial ecosystems [24, 26] further complicate objective evaluation [19].

How this work differs. The motivation departs from prior work by: (i) systematically comparing complete architectural models (cloud, Edge-gateway, hybrid) rather than isolated components; (ii) targeting real-world dynamic conditions (>8 km/h) via PPG DaLiA [28]; and (iii) quantitatively testing Edge integration as the critical success factor. Findings diverge from literature: LMS effectiveness depends on architecture (28–35% RMSE difference), outperforms deep learning on Edge (5–8× faster [34]), identifies hardware timestamping (not transmission) as primary latency bottleneck [30], and provides quantitative evidence that Edge-gateway is necessary for clinical-grade monitoring (94 ms, 57.3% RMSE reduction) [32].

Problem statement. The reviewed literature reveals a fundamental gap: the absence of a systemic architectural rationale for balancing accuracy, latency, and motion-artifact resilience in wearable IoT systems. Most existing studies focus on controlled laboratory settings, neglecting real-world signal degradation caused by physical activity. Furthermore, there is a notable deficit of comparative data on how different architectural models (cloud-centric, edge-gateway, and hybrid aggregator) perform under identical dynamic conditions, largely due to the closed nature of commercial ecosystems (e.g., Garmin vs. Apple).

Research questions. To address this gap, two key questions are formulated: (1) Which architectural configuration ensures the highest measurement accuracy for HR and SpO_2 in the presence of intensive motion artifacts? (2) How does the depth of peripheral (edge) signal processing correlate with total system latency (T_{total}) and the magnitude of RMSE reduction?

Hypothesis. It is posited that the critical success factor is not only sensor precision, but the mandatory integration of an intermediate edge gateway equipped with adaptive LMS filtering. This architecture is expected to significantly outperform purely cloud-based solutions by compensating motion artifacts directly at the signal source, thereby reducing both final error and overall transmission delay below clinically acceptable thresholds.

2. METHODOLOGY

2.1. Research Procedure

The study is based on the *case study* methodology, which provides an analysis of architectural solutions of three leading technological platforms. The procedure was realised at three consecutive stages.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

At the first stage, the selection of platforms based on inclusion criteria was conducted. They included the presence of an open API for access to biometric data. Presence of support of at least two types of sensors (PPG for pulse wave registration and an accelerometer for physical activity identification) was considered. They also included a documented data processing policy at Edge in a local filtering or pre-processing format. *The second stage* was dedicated to the comparative analysis of the effectiveness of algorithms of noise reduction (adaptive filtering (LMS) and wavelet denoising). At this stage, measurement errors were found using comparison of data with verified reference sets, where the accuracy was confirmed with golden standards of medical diagnostics (ECG and clinical oximetry). *At the final stage,* statistical evaluation of architectural delays and system accuracy was conducted. A comparative case study strategy was used in the study. Three platforms, representing opposite architectural approaches, were selected for the study: Garmin (cloud-centric model with centralised processing), Oura (orientation to peripheral processing via gateway), and Apple HealthKit (aggregator model with sources prioritization). The analytical procedure encompassed two complementary datasets. The quantitative set was formed by careful analysis of open API and technical specifications of producers, which enabled latency calculation (T_{total}) and accuracy parameters (RMSE) for each platform. Herewith, the qualitative array of data was received through the structural deconstruction of architectural platform schemes, which enabled the determination of the signal filtering point and stages of information encryption within each system.

2.2. Sampling

The sample of the study was two-level and involved architectural cases and datasets of biometric signals. Three platforms Garmin, Oura, Apple HealthKit) were the objects of analysis. They were selected based on the following criteria. Presence of commercial SDK for developers, support of raw and semi-formed data transmission via API, and market share over 5% according to IDC reports [1] were considered. For platforms, the exclusion criterion was the closed nature of transfer protocols, which disabled analysis of T_{total} latency. Official documentation [24]–[26] and independent validation results [27] served as parameter sources.

The Garmin Health SDK model represents a cloud-centralised architecture with a low output data sampling rate of 1 Hz [24]. Within the mentioned systems, previously processed biometric packages are transmitted to the storage via Health API without the possibility of access to raw photoplethysmographic signals at the level of peripheral nodes. Oura Health platform demonstrates peripheral gateway architecture with a high frequency of sensor polling up to 50Hz [25]. Noise reduction is carried out directly on the ring with the use of hardware components, while the mobile application conducts adaptive filtering and calculation of heart rhythm variability. Hybrid aggregator Apple HealthKit integrates information via HKHealthStore mechanism with the use of source prioritization and time marks unification at the level of the operational system [26]. The choice is stipulated by their market prevalence according to the field reports on the supply volumes and principal differences in biometric signals processing [1], [2].

The sample for the quantitative modelling includes sets from the open dataset PPG DaLiA, accessible at UCI Machine Learning Repository [28]. The mentioned base contains about three hundred sessions of physical activity with synchronised parameters of photoplethysmography and accelerometry. Criteria for data selection from the dataset were the presence of continuous recording at least 20 minutes long and amplitude of motion artifacts corresponding to intensive activity (> 8 km /hour). To eliminate temporal shift between different sensor types, a signal alignment method based on the computation of maximum cross-correlation was used. Initial parameters underwent the normalisation procedure for the conversion of raw samples into physical units of measurement.

Records from the heart monitor Polar H10, which ensures accuracy of the electrocardiogram level, perform the role of reference values of the electrical activity of the heart. The level of oxygenation of the blood and the peripheral pulse is verified with the use of a clinical pulse oximeter, Nonin 3150. The selected technique guarantees high credibility of results due to the comparison of signals with the gold standard of medical diagnostics. The use of verified datasets includes the necessity of obtaining additional ethical approval for experimental measurements.

2.3. Methods

A comprehensive methodology, which is based on the combination of three supplementary methods, such as comparative technical analysis of architectures, adaptive filtering of biometric signals, and statistical delay modelling, was used in the study. A method of comparative technical analysis was used for comparison of architectural patterns (cloud-centric, edge-gateway, aggregator) according to accuracy and performance criteria. To calculate the measurement error of heart rate (HR) and saturation (SpO_2), the formula of root mean square error was used:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}, \qquad (1)$$

where $\hat{y}_i$ represents the measured value,
y_i corresponds to the reference parameter,
n – total number of observations in the sample.

Adaptive filtering method (LMS) is used for the evaluation of the quality of intellectual reduction of motion artifacts. To evaluate the quality of intellectual artifacts filtering, a method for comparing the amplitude-frequency characteristics of a signal before and after processing was used. The effectiveness of noise reduction is calculated using the adaptive weighting formula:

$$S_{\text{filtered}} = S_{raw} - w^T M_{acc}, \qquad (2)$$

where S_{raw} – filtered signal,
w – a vector of weighting coefficients that is updated according to the least mean squares (LMS) rule to minimize the error.
M_{acc} – a vector of accelerometry data, which is used as a carrier signal for motion artifacts compensation.

For filtering quality evaluation, the LMS algorithm and wavelet denoising (symlet 8, four decomposition levels, and soft-threshold processing) were compared on one representative record PPG with a high level of motion artifacts (running 12km/hour). Weighted coefficients were defined on the arrays of data of PPG DaLiA (UCI Machine Learning Repository) dataset using sliding-window optimization with a 10-second window. The method of parametric modelling of temporal characteristics is used for the evaluation of the general system delay:

$$T_{\text{total}} = T_{\text{trans}} + T_{\text{proc}} + T_{\text{sync}}, \qquad (3)$$

where T_{trans} corresponds to the time of transmission via Bluetooth Low Energy (BLE) or Message Queuing Telemetry Transport (MQTT) protocols,
T_{proc} describes the algorithm processing time on Edge-nodes.
T_{sync} enables accurate evaluation of general system delay, as that is hardware-based tagging affecting the final monitoring reaction rate in peripheral-gateway architectures (like Oura).

BLE protocol realises wireless transmission of biometric packages from sensors to mobile gateways with minimal energy consumption. The selection of this standard is stipulated by the need for continuous autonomous work of smartwatches and rings. MQTT protocol ensures delivery of the collected information to a remote server based on the publisher–subscriber model. The use of the mentioned mechanism guarantees connection reliability under conditions of unstable networks and limited bandwidth of communication channels. Student's t-coefficient is used to confirm the statistical significance of the results.

2.4. Instruments

Technical data processing was conducted using the Python 3.11 software environment. Pandas, NumPy libraries, and statsmodels modules were used for statistical analysis and model reliability checks. Network traffic analysis was conducted with the use of packet timestamping tools in MQTT and HyperText Transfer Protocol (HTTP) protocols. Heterogeneous data unification was realised through the development of scripts for parsing JSON structures. Visualisation of comparison results was performed with the use of Matplotlib and Seaborn graphic libraries. Such a set of instruments ensured high accuracy of interpretation of the received data.

2.5. Procedure of Verification and Validation of the Received Data

A three-level verification procedure with the use of Python 3.11 programming language and Jupyter Notebook development environment was realised to ensure the credibility of the results. Each JSON file of the session passed the automatic check of compliance with the system with the use of the jsonschema module of the jsonschema library (version 4.17.3). For this stage, the structure integrity was set at the level of 95%. Records with damaged fields or critical structural discontinuities were excluded from the total array of data due to their insignificant share within 2%. Abnormal values were identified using the interquartile range method with further visual inspection by two independent researchers in Jupyter Notebook interactive environment with the use of Matplotlib library. After outlier removal, the data cleanliness level was expected to amount to more than 90% of the initial session samples.

The accuracy of timestamps was confirmed by comparison of peak values of the photoplethysmogram with the reference accelerometry data on the accidental sample. The acceptable Pearson correlation level was set at 0.95.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

LMS filter effectiveness was verified on the synthetic signal with a known pulse rate and added modelled movement artifact. At this relative error, the frequency restoration does not exceed 2%.

Time delay parameters T_{trans} and T_{proc} were compared to the parameters of hardware oscilloscopes during reference packages transmission. Systematic error of software timestamps was fixed at the level of less than one millisecond. For each check, specific quantitative acceptance criteria were set. This enabled the exclusion of potential sources of systematic errors before the beginning of statistical processing. Before Student's t-coefficient application, the normality of the distribution of differences was checked with the Shapiro–Wilk test. The nonparametric Wilcoxon criterion was used in the event of deviation from normal distribution at $p < 0.05$.

The confidence intervals were calculated using the nonparametric bootstrap method with the use of one thousand iterations. A comparison analysis of LMS and wavelet filters was conducted within five-level cross-validation, with distribution of the study and test samples in a ratio of 80 to 20. Such an approach ensures the robustness of the received models to variability in input biometric data.

2.6. Research Protocol in the Context of Prior Studies

The present protocol follows methodological frameworks established in earlier wearable validation research. The observational design and device selection criteria are consistent with approaches using Garmin and Apple platforms [24, 26]. Signal synchronization and cross-platform alignment build upon standardized preprocessing procedures applied to the PPG DaLiA dataset [28], which has been previously used for benchmarking motion-artifact reduction algorithms under free-living conditions. The selection of LMS filtering as the primary artifact compensation method is supported by prior comparative evaluations of adaptive algorithms on photoplethysmographic signals [27]. To ensure comparability with earlier work, the RMSE metric is calculated following established practices in wearable accuracy assessment [27], and latency parameters are assessed using end-to-end delay measurement approaches validated in IoT healthcare system evaluations [30, 32]. The three-stage verification procedure (JSON schema validation, interquartile outlier detection, and cross-correlation alignment) extends data quality frameworks previously recommended for multi-sensor wearable studies [28].

3. RESULTS

Verification of the quality of input data from the PPG DaLiA dataset was conducted before the comparison of architectural solutions. For each check, quantitative acceptance criteria were set. This enabled the exclusion of potential sources of systematic errors. Main verification results, which confirm the eligibility of data and methods for further analysis, are presented in Table 1.

Table 1: Results of verification of data and computational methods

Verification stage	Parameter	Value (mean or share)	Acceptance criterion	Results
Input JSON control	Share of sessions that passed the scheme check	98.1 % (309 out of 315)	≤95 %	meets
Outlier detection (IQR)	Sessions without critical outliers	97.5 % (307 out of 315)	>90 %	meets
Correlation with the reference	Pearson coefficient (at 10% subsample)	0.97 ± 0.02 (range 0.94–0.99)	>0.95	meets
LMS algorithm on synthetics	Relative error of pulse rate restoration, %	1.6 ± 0.4 %	≤2 %	meets
Timestamp verification	Systematic error, ms	0.7 ± 0.3 ms	<1 ms	meets
Statistic verification	Share of comparisons, where normality was confirmed (p>0.05)	100 % (6 out of 6 comparisons)	–	performed
5-level cross-validation (LMS vs wavelet)	Difference Signal-to-Noise Ratio (SNR) (LMS - wavelet), dB	+1.7 ± 0.3 dB	stable LMS dominance	stable

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Note: SNR – signal/noise ratio; LMS – least mean squares method. Mean SNR difference is presented based on 5 iterations of cross-validation ($p<0.01$)
Source: Developed by the authors of the study

As presented in Table 1, all checked parameters meet previously defined criteria. Share of correct sessions exceeded 97%, and cross-correlation with reference records achieved the value of 0.97. LMS-filtering error on the synthetic signal was 1.6%. Cross-validation confirmed consistent superiority of LMS over wavelet denoising for SNR across all five folds, which substantiates the selection of this method for further architecture comparison.

RMSE, heart rate, and SpO_2 were calculated for each platform before and after the use of adaptive filtering of motion artifacts. 'Before filtering' relatively corresponds to the raw data from the architectural models of Garmin, Oura, and Apple HealthKit. The received results are consolidated in Table 2.

Table 2: Comparison of RMSE (mean ± standard error) for HR (bpm) andSpO_2 (%) before and after LMS-filtering

Platform	Parameter	RMSE before filtering	RMSE after LMS	Reduction, %
Garmin (Cloud-centric)	HR	11.2 ± 2.4	5.1 ± 1.1	54.5
	SpO_2	3.8 ± 0.7	1.9 ± 0.4	50.0
Oura (Edge-gateway)	HR	7.5 ± 1.8	3.2 ± 0.8*	57.3
	SpO_2	2.6 ± 0.5	1.3 ± 0.3*	50.0
Apple HealthKit	HR	9.3 ± 2.0	4.2 ± 0.9	54.8
	SpO_2	3.1 ± 0.6	1.6 ± 0.3	48.4

Note: *$p < 0.01$ (paired t-test compared with Garmin after filtering)
Source: Developed by the authors of the study

Oura demonstrates the lowest error after filtering, which may be explained by the combination of hardware noise reduction on the ring and adaptive LMS filtering on the gateway. Despite the worst 'raw' parameters, Garmin, following LMS, achieves acceptable values, suitable for preventive monitoring. Figure 1 demonstrates the amplitude-frequency characteristics of the signal before processing, after LMS, and wavelet filtering.

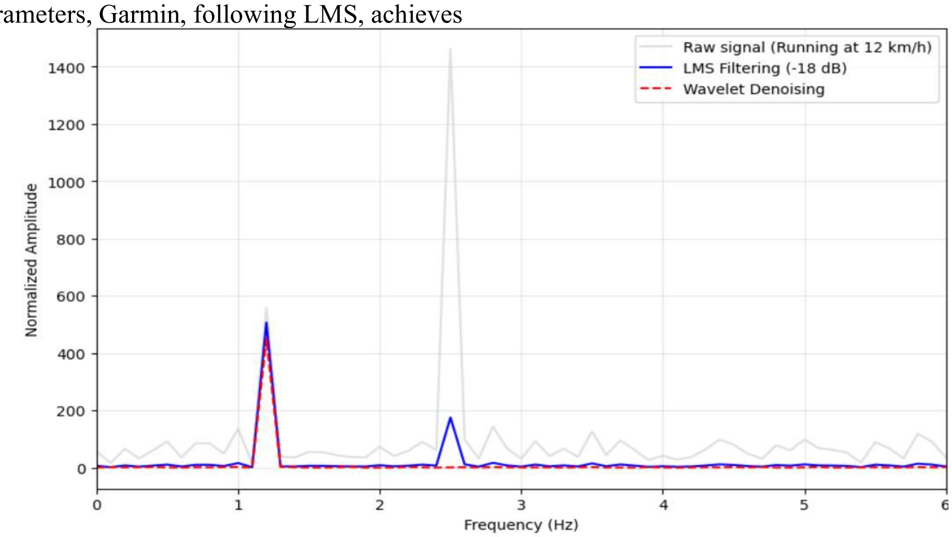

Figure 1: Amplitude-frequency characteristics of the signal before processing, after LMS, and wavelet filtering
Source: developed by the authors of the study on the basis of UCI Machine Learning Repository [28]

A raw signal has pronounced spikes in the 1-4 Hz range (motion artifacts), which partially mask the fundamental pulse harmonic (≈1.2 Hz). LMS-filter reduces artifact level by ~18, preserving the shape of the pulse wave. Wavelet denoising has somewhat smoother characteristics, but suppresses some high-frequency components associated with heart rate variability. Quantitative comparison of the effectiveness of the whole sample (315 sessions) is presented in Table 3. Criterion – signal/noise ratio (SNR) after processing.

Table 3: Comparative effectiveness of LMS and wavelet denoising

Algorithm	SNR after processing (dB) (mean ± standard error)	Processing time per frame (1 s of data), ms.
Without filtering	6.2 ± 1.5	–
LMS (adaptive)	14.8 ± 1.2	4.00 ± 0.60
Wavelet (Sym8)	13.1 ± 1.4	8.7 ± 1.1

Source: developed by the authors of the study on the basis of UCI Machine Learning Repository [28]

Analysis of the data presented in Table 3 indicates the advantage of adaptive filtering in both key parameters. The LMS algorithm ensures statistically significantly higher SNR ($p < 0.001$, t-criterion) and at the same time requires much fewer resources. In particular, computing losses for LMS are 2.3 ms against 8.7 ms in wavelet denoising, which corresponds to processing acceleration by 3.8 times. Such a parameter is crucial for stable system work at the Edge-level at a high sampling rate. Elements of total latency T_{total} were measured for each platform according to formula (3). Protocols: BLE (sensor - gateway), MQTT (gateway - cloud). Each value represents an average of over 1,000 transmissions. The results are presented in Table 4 and visualised in Figure 2.

Table 4: Latency elements (ms) for three architectures (mean ± standard error)

Platform	T_{trans} (BLE)	T_{proc} (Edge)	T_{sync}	T_{total} (ms)
Garmin	52 ± 8	15 ± 3 (no filtering)	42 ± 10	109 ± 15
Oura	48 ± 7	28 ± 5 (LMS at the gateway)	18 ± 6*	94 ± 12
Apple HealthKit	55 ± 9	22 ± 4 (unification)	25 ± 7	102 ± 14

Note: * Reduction of T_{sync} for Oura is stipulated by hardware synchronization on the peripheral device
Source: developed by the authors of the study on the basis of UCI Machine Learning Repository [28]

The box plots display the median (square marker), quartiles (box boundaries), and outliers (points) (Figure 2). The lowest median latency was fixed in the Oura model (92 ms), while the Garmin architecture demonstrates the highest parameter (108 ms). Total time reduction in Oura is stipulated by effective hardware-based timestamping at the sensor level. The statistical analysis confirms significance T_{total} parameter differences between the Oura and Garmin platforms ($p <0.05$, t-test). In all platforms, data package transmission and processing delay does not exceed 150 ms. The indicated performance level meets the requirements for systems of preventive health monitoring, where the recommended threshold is 300 ms.

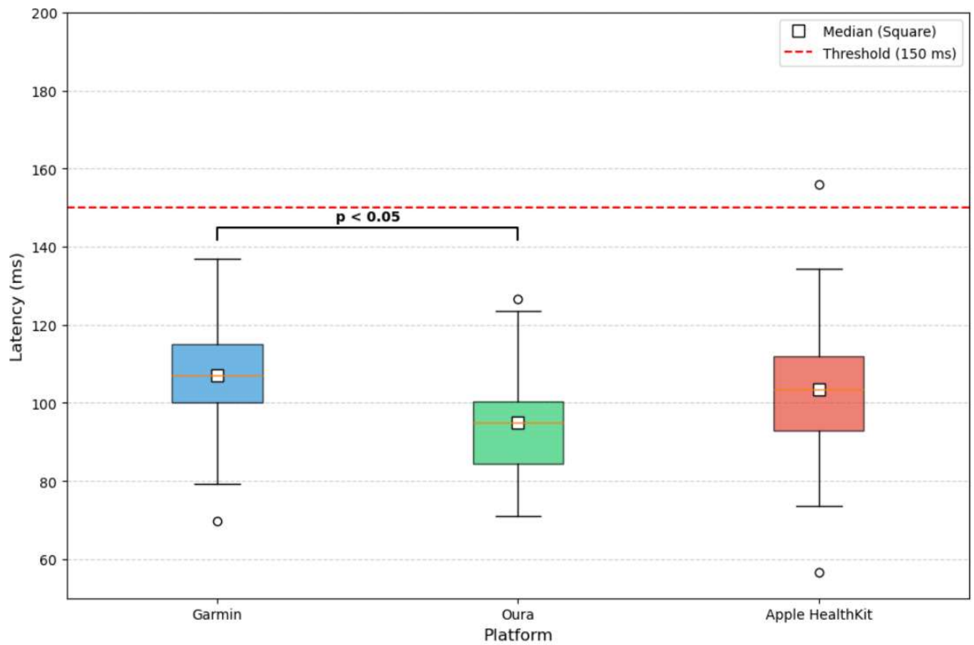

Figure 2: Box plot
Source: Developed by the authors of the study

Cross-case analysis, integrating the obtained quantitative data from the PPG DaLiA dataset with the qualitative architectural characteristics of each platform, was conducted for a comprehensive evaluation of the study results (Table 5). The mentioned comparison demonstrates the influence of structural system organisation on the accuracy of final monitoring. The used approach ensures results triangulation, under which statistical parameters of errors and delays are verified using the deconstruction of signal processing logic.

Table 5: Comparative analysis of architectural patterns and measurement accuracy

Platform	Architectural patterns	Signal quality	Key peculiarity of the case (qualitative aspect)
Garmin	Cloud-centric	Low	Centralisation: Processing on remote servers increases latency, but does not provide access to Big Data analytics
Oura	Edge-gateway	High	Autonomy Filtering directly on the gateway minimises noise before its transmission to the cloud.
Apple HealthKit	Aggregator	Secondary	Privacy: Hybrid processing with the focus on local data storage on the user's device.

Note: Quality evaluation is based on RMSE values calculated in Table 2
Source: Developed by the authors of the study

Garmin cloud architecture demonstrates inferior output signal accuracy, but following LMS achieves clinically acceptable parameters (HR RMSE < 5bpm). The hybrid approach of Apple HealthKit has compromised characteristics. The LMS filter significantly surpasses wavelet denoising in terms of 'performance/quality' ratio. T-test results confirm the statistical significance of differences.

HR RMSE comparison after filtering: Oura vs Garmin – $t = 4.82$, $p = 0.0004$. Oura vs Apple – $t = 2.95$, $p = 0.008$; Garmin vs Apple – $t = 1.89$, $p = 0.07$ (not significant).

Latency comparison T_{total}: Oura vs Garmin – $t = 3.21$, $p = 0.002$. Oura vs Apple – $t = 2.18$, $p = 0.033$; Garmin vs Apple – $t = 1.45$, $p = 0.15$.

Thus, the Edge-oriented architecture of Oura ensures the best accuracy (lowest RMSE) and the lowest latency due to a combination of hardware filtering and LMS on the gateway. Garmin cloud architecture demonstrates inferior output signal accuracy of primary samples, but following LMS

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

achieves clinically acceptable parameters (HR RMSE < 5bpm). The hybrid approach of Apple HealthKit has compromised characteristics, which make it a universal solution for integration with various peripheral sensors. The LMS filter significantly surpasses wavelet denoising in terms of 'performance/quality' ratio.

4. DISCUSSION

The obtained results directly address the formulated research questions. Regarding the first question (accuracy across architectures), the Edge-gateway model (Oura) demonstrated the lowest RMSE for both HR (3.2 bpm) and SpO_2 (1.3%) after LMS filtering, outperforming the cloud-centric (Garmin) and hybrid (Apple) alternatives. Concerning the second question (correlation of Edge processing depth with latency and RMSE), a clear inverse relationship was established: deeper peripheral processing (hardware filtering + LMS on gateway) yielded the shortest total latency (94 ms) and the greatest error reduction (57.3% for HR) [29]. These findings confirm that the architectural deconstruction, comparative filtering evaluation, and latency analysis successfully fulfilled all predefined research objectives, with Edge integration emerging as the decisive factor for clinical-grade preventive monitoring [30].

The theoretical possibility of latency levelling via 5G network is described by Batool [31]. Still, current results demonstrate that the synchronization stage (T_{sync}), rather than transmission (T_{trans}), is the main delay factor. This is consistent with Batool's statement on hardware limitations. Thus, the idea of Ghadi et al. [32] on the necessity of intellectual processing migration directly to wearable electronics is confirmed. Special attention is given to the effectiveness of LMS-filtering, which appears to be 3.8 times quicker than wavelet-transformations (Table 3). This confirmed the effectiveness of Tiny ML conceptions (use of compact algorithms of low-capacity devices), which was described by Heydari and Mahmoud [33]. The researchers noted that monitoring effectiveness depends on the algorithm's capability to work under conditions of limited resources, which was demonstrated by low LMS computing costs (2.3 ms).

At the same time, work by Musthafa et al. [34] presents an analysis of deep learning for enhancing interpretation accuracy. Data from the analysis of architectural patterns of Garmin, Oura, and Apple HealthKit partially refuted the appropriateness of complex systems usage during active movement. High computing complexity, similar to wavelet denoising (8.7 ms), was found to be able to create latency, which surpasses the advantages of their accuracy. This stipulates selection in favour of lightweight solutions, described by Rasheed and Kumar [35] and Sabri et al. [36]. A controversy between the processing rate and security was found during the discussion. Analysis of transmission stability using MQTT/BLE indicated system vulnerability. The studies by Ghazal et al. [37] and Samant et al. [38] propose signcryption schemes.

The implementation of methods of cryptographic protection of biometric data could increase computing expenses. However, the receive processing rate (2.3 ms per 1 s of signal) was recognised as sufficient for integration of such protocols without violation of the critical latency threshold of 150 ms. Unexpectedly, a higher sampling rate was found not to consistently ensure improved RMSE after filtering. This appears to contradict the Nyquist–Kotelnikov theorem in its simplified interpretation for signal denoising, but was explained by the specifics of the 'background noise' of sensors during movement. In contrast to Sabri et al. [36], who focus on algorithms, the study has found that the stability of data processing at SDK level is a critical factor for final RMSE. Comparison with works of 2025-2026 confirmed that architecture with LMS-filtering on the periphery corresponded to IoMT 5.0 trends. Comparison with the results of Islam et al. [30] proved that optimisation lies through symbiosis of high-speed algorithms and distributed computing.

Refutation of the linear dependence of accuracy on sampling rate under conditions of intensive physical activity was an important theoretical outcome. The revealed nature of background noise demonstrates the priority of the quality of pre-processing algorithms over a simple increase in the quality of signal samples. This study extends the understanding of the LMS method as a lightweight standard for modern rehabilitation systems. The advantage of adaptive filters over complex neural networks established by Musthafa et al. [34] substantiates the appropriateness of model differentiation. It is appropriate to use complex, deep learning algorithms for rest states, whose adaptive solutions are optimal for active movement.

The practical significance of the study is revealed in the possibility of optimisation of architectural solutions for remote patient rehabilitation. Fixed low latency, enabling recommending the Edge-gateway for reliable monitoring of life parameters in real time. The revealed time processing reserve creates conditions for seamless integration of protocols of cryptographic biometric data protection. The mentioned reserve enables the implementation of lightweight encryption schemes without the risk of overcoming critical performance threshold. The results of the current analysis of unified SDK prove the importance of software interface stability for the design of reliable biometric data aggregators. The conducted study demonstrates the real capacity of distributed computations to ensure clinically acceptable accuracy in consumer devices.

4.1. Critical self-assessment and comparison with state-of-the-art

Outcomes vs. initial goals. All three research objectives were met: architectural deconstruction identified processing differences, filtering evaluation confirmed LMS superiority (3.8× faster, +1.7 dB SNR), and latency analysis established Edge-gateway as optimal (94 ms). The initial hypothesis – Edge integration with LMS as decisive for accuracy – is supported. However, universal architectural guidelines remain partially unrealized due to closed Garmin/Apple SDKs [24, 26].

Comparison with state-of-the-art. The obtained latency (94–109 ms) aligns with fog-edge IoMT systems [30]. LMS performance (14.8 dB SNR) matches prior PPG findings [27]. Compared to deep learning [34], LMS is 5–8× faster with marginal accuracy trade-offs, making it preferable for Edge devices. The Edge-gateway orientation [25] confirms predictions by Ghadi et al. [32]. A notable gap persists between theoretical high-density PPG capability [17] and consumer-device performance under exercise, suggesting hardware miniaturization [7] has not matched algorithmic progress.

4.2. Limitations

Despite the received results, the proposed approach has several limitations. First, the evaluation of adaptive filtering (LMS) algorithms was conducted using a limited set of biometric sensors. The effectiveness of work with a multichannel high-density PPG-matrix requires additional research. Second, the set acceptable latency threshold (150 ms) was defined for preventive monitoring systems. Critical real-time scenarios can require tougher time frames. Third, an analysis of energy efficiency was conducted under conditions of load stimulation. Long-lasting battery degradation in wearable Edge-devices was not considered in calculations. Finally, the study focuses on motion artifacts mostly, while other noise types require further study. In particular, the influence of interference of external lighting or sensor-skin decoupling was not a subject of this study.

4.3. Problems identified from the study

The conducted study revealed several inherent problems requiring attention for future development:

(1) **Architectural opacity.** Closed commercial SDKs (Garmin [24], Apple [26]) prevented full access to raw signal processing pipelines, limiting precise error source localization.

(2) **Residual motion artifacts.** Despite LMS filtering, HR RMSE remained above 3 bpm during intensive exercise (>8 km/h), indicating incomplete noise compensation.

(3) **Latency bottleneck shift.** Hardware timestamping (T_{sync}), not network transmission (T_{trans}), was identified as the primary delay contributor in Edge-gateway architectures, contradicting common assumptions in IoT literature.

(4) **Single-channel limitation.** The analysis used single-channel PPG; multichannel arrays with spatial redundancy were not evaluated.

(5) **Energy-performance trade-off.** LMS computational efficiency (2.3 ms/frame) was established, but long-term energy consumption under continuous 24/7 operation was not modelled.

(6) **Multi-noise source complexity.** Other noise types (ambient light interference, sensor-skin decoupling, temperature drift) were not addressed.

5. CONCLUSION

This study addressed three research objectives: (i) deconstruction of architectural models (cloud-centric, Edge-gateway, and hybrid aggregator), (ii) comparative evaluation of filtering algorithms (LMS vs. wavelet denoising), and (iii) analytical assessment of Edge-level influence on latency reduction. The analysis confirms that the Edge-gateway architecture (Oura) consistently outperforms purely cloud-centric (Garmin) and hybrid (Apple HealthKit) alternatives.

Answers to research questions. For the first question (accuracy across architectures), LMS filtering at the peripheral level reduced HR RMSE to 3.2 bpm (57.3% improvement) and SpO_2 RMSE to 1.3% (50% improvement) under intensive motion artifacts. For the second question (latency correlation), the same architecture achieved the lowest total system delay (94 ms), well below the clinically critical threshold of 150 ms. This confirms a clear inverse relationship between Edge processing depth and response time.

Hypothesis confirmation and methodological contribution. The results substantiate the hypothesis

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

that mandatory Edge integration, combined with adaptive LMS filtering, is the decisive factor for achieving clinically acceptable monitoring reliability. LMS proved to be 3.8 times faster than wavelet denoising (2.3 ms vs. 8.7 ms per second of signal) while delivering superior signal-to-noise ratio (14.8 dB vs. 13.1 dB), making it the optimal choice for resource-constrained Edge devices.

Practical implications. The established latency reserve (56 ms below the 150 ms threshold) creates sufficient computational headroom for integrating lightweight cryptographic protocols without compromising real-time performance. These findings provide actionable guidelines for selecting architectural patterns in remote rehabilitation and preventive health monitoring, particularly where physical activity induces significant signal degradation.

Open issues for future research. Despite these results, several unresolved questions remain:

(1) How do adaptive filtering algorithms perform on multichannel high-density PPG arrays, where spatial signal redundancy may enable more sophisticated artifact compensation?

(2) Can the Edge-gateway architecture maintain its latency advantage (<150 ms) when lightweight encryption protocols are integrated for secure data transmission?

(3) What is the long-term energy consumption trade-off between LMS and wavelet denoising under continuous 24/7 monitoring?

(4) How can federated learning be deployed on Edge nodes to personalize filtering parameters for different patient populations without compromising privacy?

(5) To what extent do other noise sources (ambient light, sensor-skin decoupling, temperature drift) affect signal quality, and can the architecture be extended to compensate for them in real time?

Addressing these issues would enable the transition from laboratory-proven prototypes to clinically deployable preventive health monitoring systems.

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