Wearable Sensorics for Monitoring Human Fatigue: A Review in Respect to a Smart Safety Helmet

Grigorij E. Rego; Vyacheslav M. Dimitrov; Dmitry B. Chistyakov; Dmitry G. Korzun, Anatoly V. Voronin
Petrozavodsk State University
Petrozavodsk, Russia
regoGr@yandex.ru, {dimitrov, chistyak, dkorzun}@cs.petrsu.ru, voronin@petrsu.ru

***Abstract*—Monitoring a person's functional state directly during work requires a high level of accuracy in the assessments obtained. At the same time, there are limitations regarding power consumption, cost, ergonomics, and the frequency of signal deviations. In this study, we present our review of possible biosignals and sensor modalities. The reference scenario is human fatigue monitoring for workers in industry using a personal digital mHealth assistant based on non-medical wearable devices. The problem is selecting complementary channels and devices without confusing a modality's potential with a complete system's demonstrated capabilities. The results comprise a modality-to-observation map, indicative five-domain scores, a candidate cardiac–respiratory–thermal–inertial–environmental baseline, and an evidence-linked implementation comparison. A smart safety helmet illustrates the architecture for a 12-hour indoor shift with local operation and an author-defined EUR 1000 complete-kit budget. The comparison identifies cloud-access restrictions, operating-time shortfalls, and unresolved cost or protective-integration evidence. The contribution is a traceable connection from biosignal selection to scenario requirements and functional allocation.**

I. Introduction

Digitalization of occupational safety shifts the safety control from occasional medical examinations to continuous assessment of the "Worker–Task–Environment" interaction. A digital mHealth assistant collects physiological, motor, and contextual data to generate warnings without replacing a medical decision, e.g., see [1]–[3].

As a reference mHealth scenario we consider human fatigue monitoring [4]. The problem is how to select complementary biosignals and integrate available devices into practical assistance. Measurement quality, power demand, cost, ergonomics, and data accessibility must be considered together; favorable properties of a sensing principle alone do not establish a usable configuration.

Smart safety helmets provide a concrete integration example. Campero-Jurado et al. presented an industrial helmet prototype with environmental sensing and risk analysis [5]. Dhole et al. combined helmet-based electroencephalography (EEG), an inertial measurement unit (IMU), and communication with a local server for drowsiness and fall detection [6]. These studies establish prior designs, but not the suitability of every subsequent assembly.

This focused review connects the general selection of biosignals and a candidate modular baseline to site allocation and documented implementation evidence. Its scientific value is in exposing where a plausible channel combination still lacks the access, operating-time, or protective-integration evidence required for deployment. The smart-helmet example makes these gaps explicit while retaining the broader personal-assistance architecture.

The rest of the paper is organized as follows. Section II considers the case of human fatigue monitoring and the smart-helmet architecture. Section III reviews possible biosignals and sensor modalities to use in fatigue assistance. Section IV discusses the modular sensory system and implementation evidence. Section V summarizes the key findings of our review study.

II. Digital mHealth Assistance

A. Personal assistance and the general use scenario

Let us consider a reference scenario of digital mHealth assistance when human fatigue is monitored and evaluated during a person's work activity in real time. Note that we focus on the case when sensed data and their evaluation are confidential, owned and controlled by the person within this design. Information goes to external systems only if allowed by the person (e.g., based on an agreement between employee and employer).

The digital assistant needs to evaluate multiple metrics (indexes) based on sensed data for various biosignals. For each metric, its observed current value and retrospective statistics are integrated with the other metrics to form a complete picture: a digital model of the person's health. Then the digital model is subject to retrospective, diagnostic, predictive and other analytics by appropriate experts; the assistant itself provides non-diagnostic feedback.

mHealth application development needs a complete service system with

1) sensors for the human body activity to be monitored,
2) layout design to integrate the sensors in a wearable system (e.g., as a bionic suit),
3) data processing algorithms to run on edge devices (e.g., smartphone-driven service).

Its design requires not only informative sensors and suitable algorithms but also cost-effectiveness and the ability to be an element of a product system, not only a prototype for experiments (maturity level).

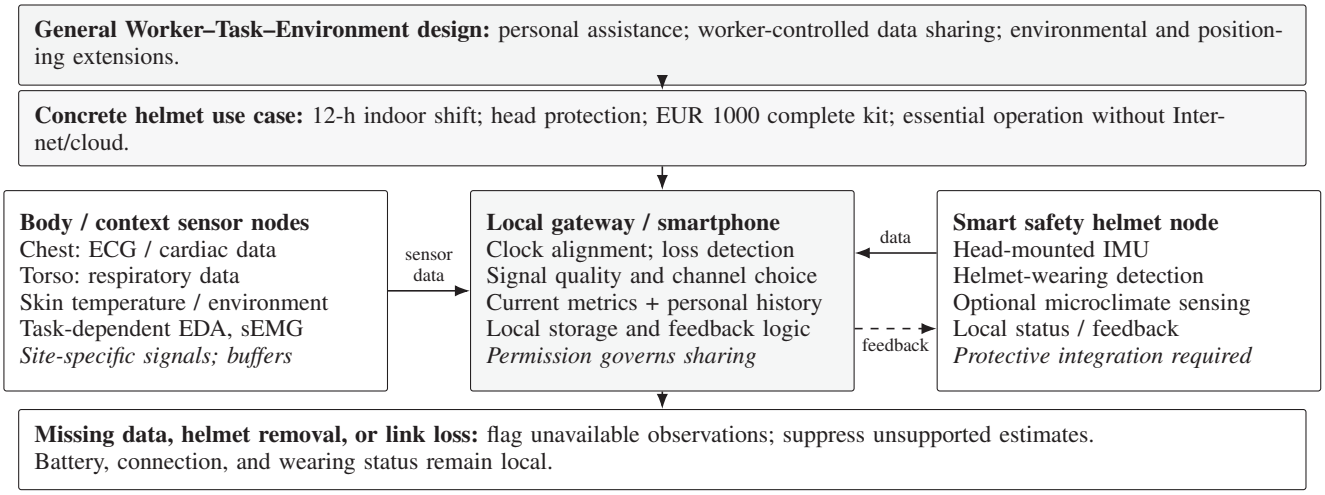


Fig. 1. Modular mHealth assistance with a local smart-helmet implementation. Solid arrows carry data or status; dashed arrows carry feedback. The boxes summarize the allocation and failure handling described in Section II. ECG: electrocardiography; EDA: electrodermal activity; sEMG: surface electromyography; SQI: signal quality index.

B. A concrete smart-helmet use case

The scenario is indoor manual handling and inspection requiring protective headgear during a 12-hour shift, including work and rest. Acquisition, time alignment, storage, and essential feedback must operate without external Internet or cloud services. Authorized Bluetooth Low Energy (BLE) and wired links are permitted. This scenario-specific requirement does not prohibit separately authorized data sharing in the general design.

The EUR 1000 initial budget covers the *complete per-worker kit*: protective helmet, electronics, body-worn sensors, gateway, mounts, accessories, and mandatory first-year software. Shared components count once. Taxes and delivery are excluded unless stated; unknown mandatory costs prevent budget confirmation. Both the budget and shift duration are author-defined.

C. Functional allocation and data continuity

Figure 1 separates three parts. The proposed *smart safety helmet* combines head-motion sensing, helmet-wearing detection, and local feedback; optional air-temperature and relative-humidity sensing describes its microclimate. *Body-worn nodes* provide chest cardiac, torso respiratory, skin-temperature, and task-dependent physiological measurements at their appropriate sites. Relocating a body sensor to a helmet does not preserve implementation equivalence.

A belt-worn or smartphone-based *local gateway* aligns clocks, detects packet loss, assesses signal quality, and stores and processes observations. Keeping its processor and battery off the helmet limits head-borne hardware by design.

Helmet removal, disconnection, and link loss must produce a data-unavailable state. Local battery, connection, and wear-status indications remain available by design; missing physiological data suppress unsupported estimates. Buffering supports later analysis but cannot restore a missed real-time observation. Quality-based channel selection, discussed in Section III-A, requires an appropriate alternative measurement rather than unsupported filling of missing estimates.

D. Protective function and measurement-site constraints

The helmet remains personal protective equipment (PPE), requiring hazard-appropriate protection, correct fit, and manufacturer-compatible accessories [7]; attachment approval, head-borne mass, and suspension clearance must be assessed. Wear status does not prove correct fit. A stationary unworn helmet or isolated acceleration transient cannot establish worker immobility or a fall. These are proposed requirements, not demonstrated properties of an assembled prototype.

III. Human Activity and Fatigue: Possible Biosignals and Sensor Modalities to Analyze

A biosignal (biological signal) is a specific physical or electrical manifestation of an organism's vital activity that can be measured and recorded using instruments. Let us review some promising biosignals (physiological, motor, and some others) to sense at relatively low cost using consumer electronics (non-medical devices) in real time. Table I maps candidate channels to observable outputs, body sites, and interpretation limits. "Baseline" denotes a design choice, not proven fatigue-detection sufficiency; helmet-wearing detection is a status channel rather than a biosignal.

A. Cardiac Activity

The electrocardiogram (ECG) biosignal is a direct source for obtaining the time intervals (R-R intervals) between two adjacent R-waves. Such an interval shows the duration of one cardiac cycle. Chest straps, textile electrodes, and patches support stable detection of R-waves.

The photoplethysmogram (PPG) biosignal records the pulse wave, which is a consequence of cardiac contraction. Smartwatches, fitness bands, and smart rings are the most ubiquitous

TABLE I. SENSING MODALITIES, PROPOSED ALLOCATION, AND LIMITS OF INTERPRETATION

Modality	Observable output	Proposed location / role	Interpretation or integration condition
ECG	ECG waveform; R–R intervals	Chest; baseline candidate	Contact and event detection; not a direct measure of fatigue
Photo-plethysmography (PPG)	Optical pulse waveform; pulse intervals	Wrist or dedicated head-contact site; alternative	Each site requires its own evidence; pulse intervals are not assumed equivalent to R–R intervals
Respiratory inductance plethysmography (RIP)	Thoracoabdominal motion; respiratory rate	Torso; baseline candidate	Garment fit and calibration; respiratory rate does not specify tidal volume
Skin temperature	Peripheral skin temperature	Skin-contact node; contextual, general baseline	Distinct from core body temperature and under-helmet air temperature
Electrodermal activity (EDA)	Skin conductance and its changes	Wrist or other justified skin site; optional	Electrode conditions, movement, and thermal effects must be reported
IMU	Acceleration and angular velocity	Helmet; baseline, with optional body node	Head motion is not trunk posture; orientation requires an algorithm
Helmet-wearing detector	Contact/proximity indication	Helmet interface; baseline	Wear status is not correct fit and is not a physiological signal
sEMG	Muscle electrical activity	Selected muscle; task-specific	Electrode geometry, contact, and task-specific fatigue interpretation
EEG	Scalp electrical potentials	Dedicated electrodes; research extension	Motion artifacts and suspension clearance; no assumed PPE compatibility
Video-based eye tracking	Eye images, gaze and eyelid measures	Head-mounted module; optional	Optical access, privacy, operating time, and protective eyewear compatibility
Environmental / microclimate sensing	Local temperature, humidity or a defined exposure variable	General-context node or qualified helmet location	Ambient, under-helmet, and skin measurements are different quantities
Acoustic / biochemical sensing	Respiratory sounds or a specified analyte	Microphone, patch or mask; extension	Noise, sampling matrix, calibration and analyte specificity

category of wrist-worn or finger-worn PPG sensing devices. Also, smart earbuds and hearables are in-ear devices to capture PPG from the blood vessels in the ear canal or earlobe.

A single-channel ECG can provide better R–R interval measurements than PPG since it is less sensitive to vasoconstriction and optical interference [8]. PPG is often easier to use and more ergonomic due to small size and low cost, although more sensitive to movement, cold, and contact. Multi-channel recording can improve the result, but a Signal Quality Index (SQI) is needed to evaluate each channel independently, and the system can selectively ignore "bad" signals and prioritize "good" ones [9]. An IMU can serve as a motion reference for PPG quality control.

ECG-derived R–R intervals support heart rate variability (HRV) and rhythm analysis. Polar H10 validation concerns rest and incremental exercise [10]; it does not validate helmet-contact PPG or establish equivalence between pulse and R–R intervals.

B. Breath or Respiration

The respiration biosignals reflect physical load, heat stress, and hyperventilation. Possible measurement approaches are respiratory inductive plethysmography (RIP), strain gauges, bioimpedance, accelerometry, and acoustics [11], [12].

The chest strap can provide a stable waveform by measuring the movement of the chest. Proper fitting becomes the most critical factor for accurate measurements. Similarly, strain-gauge sensing uses stretchable or mechanical strain sensors (placed on chest or abdomen) to measure torso expansion and contraction.

Bioimpedance respiration (or impedance pneumography) estimates breathing rate and volume from changes in electrical impedance across the chest (or other body parts). Strategic electrode placement and managing the electrode-skin interface are the most critical factors for accurate measurements.

Chest-mounted inertial measurement units (IMUs) monitor respiration by tracking the periodic mechanical expansion, contraction, and angular inclination of the thorax. An IMU measures absolute inertial motion, and the respiratory signal is masked by locomotor dynamics of the human body, such as walking, running, or changing postures.

The acoustic measurements estimate breathing rate by the acoustic vibrations and sound envelopes generated by airflow in the upper airways; cough is another observable output. The acoustic design is cost-effective. Advanced signal-processing algorithms are needed to isolate breathing sounds from competing acoustic data (e.g., background noise).

A promising direction is “smart masks”, which are at an early development phase. A face mask can be equipped with a respiration-monitoring device to estimate breathing rate, volume, and signal patterns from airflow, temperature changes, and mechanical expansion, with output-specific calibration. This function differs from the biochemical mask discussed below.

RIP captures thoracoabdominal motion and supports respiratory rate and variability measurements. Walking validation of Hexoskin [13], other respiratory sensors [12], and integrated non-invasive devices [11] provide distinct evidence. Respiratory rate, tidal volume, and minute ventilation require separate assessment.

C. Skin Electrodermal Activity, Temperature, and Biochemistry

The electrodermal activity (EDA) biosignal reflects changes in the electrical properties of the skin due to the activity of the sweat glands under the control of the autonomic nervous system [14]. Another name for this biosignal is the galvanic skin response (GSR).

EDA is studied for mental health and stress tracking, including burnout and depression-related detection applications. These broader applications are not treated here as stand-alone diagnostic capabilities. Sweat gland density varies across the human body, and the place to attach sensors is important. For instance, finger electrodes provide a strong signal but are not suitable for the activity with manual labor, and wrist electrodes are more acceptable. Also, sweat sensors are limited by their dependence on sweating conditions and calibration [15].

The skin temperature biosignal reflects changes in peripheral (skin) temperature rather than direct internal core body temperature [16]. Consumer wearables track relative changes or deviations from the individual person’s baseline, not absolute clinical fevers. For instance, tracking baseline skin temperature variations overnight can evaluate wellness trends.

EDA interpretation must specify the output, tonic/phasic separation, electrode location, and recording conditions, including movement and thermal effects. Autonomic reactivity is contextual, not a specific fatigue diagnosis. Skin-mountable patches [16] and low-power environmental instruments [17] measure different quantities; ambient and under-helmet air temperatures must also be distinguished from skin temperature.

Sweat metabolites [15] and battery-free exhaled-breath condensate sensing [18] require distinct sampling matrices, analytes, calibration, selectivity, drift assessment, and task-relevant interpretation. These are biochemical extensions, not established fatigue labels; a sensing mask is not automatically compatible protective equipment.

D. Inertial Measurement Units and Electromyography

The IMU signal combines accelerometers and gyroscopes to measure linear acceleration, angular velocity, and algorithm-derived orientation in three-dimensional space. Such human body activity can be tracked as motion, posture, tilts, and falls [19]. Gait analysis supports recognition of walking patterns based on continuous data tracking. Activity classifiers require training on real operations.

Algorithms combine sensed data from both accelerometers and gyroscopes (sensor fusion). Gyroscopes track fast, smooth turns but drift over time. Accelerometers correct tilt angles using gravity, balancing each sensor’s weaknesses. Optionally, magnetometers measure magnetic fields like a compass to find absolute heading or North to stabilize rotation errors.

Wearable electromyography (EMG) monitoring systems capture the electrical activity of skeletal muscles using skin-conformal or textile surface sensors (sEMG) combined with wireless microcontrollers for real-time health, sports, and human-computer tracking [20]. The skin preparation requirements and material properties of conventional wet gel electrodes present severe bottlenecks for continuous, day-long wearable EMG monitoring. While these electrodes remain the medical gold standard for short-term static tests, their contact quality can deteriorate during prolonged daily activities.

A chest accelerometer alone is not a full IMU. An eight-IMU occupational system illustrates multi-segment assessment [19]; helmet-only data describe head motion, not trunk posture or indoor position. Construction-relevant sEMG studies [20] and channel documentation [21] require implementation-specific interpretation: muscle, electrode geometry, skin preparation, adhesion, and duration must be specified.

E. Electroencephalography and Oculography

The EEG biosignal measures the electrical activity of neurons in the brain, considering direct electrical brainwave fluctuations (such as Alpha, Beta, and Theta waves) [22]. EEG applications include monitoring central disorders of hypersomnolence, tracking neurological baselines, and research on early screening for neurodegenerative patterns. Novel trends include cognitive wellbeing (managing burnout, optimizing deep-work schedules, and neurofeedback training) and industrial safety (tracking alertness and fatigue levels for workers). In real-life settings, brainwaves are measured in tiny micro-volt signals, and even minor disruptions can mask actual neural activity. Dry electrodes are one proposed integration option.

The electrooculography (EOG) biosignal tracks eye movements and blinks by measuring the natural electrical potential difference between the cornea and the retina [23]. Blinking and eye movement (pupil) are associated with wakefulness. EOG signals have a higher voltage than brainwave EEG signals, making them easier to filter and analyze.

The video-oculography (VOG) biosignal uses head-mounted infrared cameras and IMUs to record and quantify eye and head movements in real time [24]. Infrared cameras capture high-resolution digital images of the eyes (often at 100 to 250 frames per second) to track pupil or corneal reflections. IMUs measure the head rotation and heading velocity alongside eye coordinates to map combined gaze and head movement in space.

TABLE II. INDICATIVE MODALITY-LEVEL SCORES FOR CONFIGURING A SENSORY SYSTEM (1–5)

Modality	Measurement	Energy efficiency	Cost	Integration	Raw-data access
ECG	5	3	3	4	4
PPG/SpO_2	3	5	5	5	3
Breathing (RIP)	4	4	4	3	4
Acoustic	3	5	5	4	3
Temperature	3	5	5	5	5
EDA	3	5	4	4	4
IMU	5	5	5	5	5
EMG	4	3	3	3	3
EEG	3	2	2	3	4
Oculomotor	4	3	2	3	3
Biochemistry	3	3	2	3	2

Reading guide: larger values indicate more favorable expected characteristics. These modality-level author judgments are not experimental device grades and are not summed. Scenario-specific operating-time and cost codes are defined separately in (1).

Video-oculographic test–retest and pre/post-exercise evidence [24] is measurement-specific. Eyelid measures include PERCLOS (percentage of eyelid closure); lighting, optical access, and privacy constrain deployment. Eye cameras are not EOG recorders, and drowsiness is not general fatigue [6]. EEG electrodes, eyewear, visors, and helmet suspension require a compatible arrangement, making these channels optional in the helmet configuration.

F. Environmental sensors

Electrochemical cells are used for wearable environmental gas monitoring (CO, H_2S, O_2, NO_2) [17]. Other environmental characteristics can be used to describe the context (e.g., noise, lighting, temperature, vibration).

The context can be extended with determining geographical coordinates and tracking the position of objects in space. Global Navigation Satellite System (GNSS) determines the coordinates of an object outdoors where satellite reception is available. A real-time local positioning system (RTLS) tracks the movement of objects or people inside buildings and in restricted areas.

Integrated sensing of noise, lighting, vibration, and GNSS/RTLS supports industrial EHS (Environmental Health and Safety) and connected-worker technology.

Environmental sensors require their own validation and do not replace required exposure instruments. The indoor scenario does not require GNSS; an RTLS is a separately assessed local subsystem. Selected exposure or positioning nodes enter the same full-kit assessment as other modules.

IV. MODULAR SYSTEM

A. Modality-level configuration and the candidate baseline

Consumer electronics covers a large niche of health-oriented sensors, and the niche is growing fast. Nevertheless, specialized scenario-oriented solutions are still occasional. Mature devices exist for individual channels, but the reviewed examples do not establish a single device that provides ECG, respiration, EDA, EEG, environmental context, and open access to raw data.

In particular, chest straps (Polar [35], Actiheart [36]) and patches (VitalPatch [37], BioButton [38]) provide examples of cardiac monitoring. Example devices for EEG are BrainBit [39], EMOTIV [40], OpenBCI [41]; for EDA, Empatica [42] and Shimmer [43]; for oculomotorics, Tobii [44] and Pupil Labs [33].

As a consequence, the system must be modular, i.e., configured from several devices. Table II shows our indicative scores (from 1 to 5) for the sensory system configuration: higher values mean better expected measurement, lower power demand or cost, easier integration, or fewer raw-data restrictions. These qualitative author judgments describe configuration trade-offs, not fatigue-classification accuracy or experimentally calibrated device grades, and must not be summed into a universal ranking.

For the fatigue case, the proposed minimally sufficient system is formed by ECG or quality-controlled PPG, respiration, skin temperature, an inertial module, and environmental sensors. Such parameters as EDA, EMG, EEG, and oculomotor activity are proposed to increase specificity in the baseline scenario. This composition and the added-channel benefits are hypotheses, not experimentally established results. In the helmet scenario, the exact skin-temperature and environmental modules remain task-dependent selections.

B. Evidence and implementation-level assessment

A modality specifies a measurement principle; an implementation additionally specifies device, location, acquisition settings, firmware, software, and transfer route. The V3 framework separates verification, analytical validation, and clinical validation [45].

This focused narrative review uses modality reviews, methodological chapters, primary studies, and official product/interface documentation. Selection is purposive, without exhaustive market coverage, independent double screening, hardware trials, or an expert panel. Records distinguish output,

TABLE III. SELECTED IMPLEMENTATIONS: CITED DOCUMENTATION AND SCENARIO-SPECIFIC EVIDENCE GAPS

Implementation	Measurement evidence / output	Operating time	Cost evidence	Integration with helmet-based system	Local data access and interpretation
Polar H10	R–R interval validation at rest / exercise [10]; exported ECG and acceleration [25]	General 400-h specification; selected streaming mode unresolved [26]	Complete-kit C: unresolved	Chest node; not a helmet IMU	Local ECG at 130 Hz and acceleration via SDK. Internal recording is not ECG storage [25]
Hexoskin Smart	Walking validation of earlier implementation [13]; current garment/recorder requires version matching	Smart recorder: 36 h stated; concurrent streaming-mode evidence unresolved [27]	Mandatory SDK fee not public [28]	Torso garment; independent of head mounting	Android SDK provides licensed sample-level data streaming; free BLE route exposes processed values [28]
EmbracePlus / Care	PPG, EDA, skin temperature, acceleration listed [29]; performance requires output-specific evidence	Selected mode: unresolved in comparison	Complete-kit C: unresolved	Wrist node, not a helmet sensor	Documented sample-level data access is via cloud download; does not meet the selected local-access requirement [29]
Xsens DOT	Inertial data; no transfer of body-site validation to head placement	Up to 8 h continuous; nominal $q_T = 2$ [30]	Complete-kit C: unresolved	Helmet attachment requires separate approval	SDK/local recording documented; standard operating time below 12 h [30]
Shimmer3R EMG	Two sEMG channels [21]; earlier Shimmer-based results do not validate every 3R mode	Mode-specific hours unresolved; battery capacity is not operating time	EUR 680 unit only; accessories/software extra [21]	Selected muscle; electrodes and cabling	Local recording and streaming documented; complete software/operating configuration remains to be specified [21]
BrainBit Flex4	Four EEG channels at 250 Hz [31]; no exact-scenario performance established	12 h stated; nominal $q_T = 3$, no margin [31]	Complete-kit C: unresolved	EEG cap; helmet compatibility unresolved	BLE and SDK documented; interface availability is not whole-shift validation [31]
Pupil Labs Neon	Eye video / derived ocular outputs; required endpoint must be specified [32]	4 h at 200 Hz or 8 h at 30 Hz; $q_T = 1$ or 2, respectively [32]	From EUR 6250; academic EUR 5515 [33]. $q_C = 1$ for any kit including it	Head-worn frame; selected PPE combination unresolved	Local API available [34]; listed configuration exceeds budget and falls short of the operating-time requirement
Proposed smart safety helmet node	Head-mounted IMU, wear-status sensing and local feedback: design allocation, not measured performance	12 h is a requirement, not a result	No complete bill of materials; C unresolved	Manufacturer-compatible assembly and protective assessment required	Local interface, buffering and status outputs are requirements, not demonstrated features

Interpretation: nominal operating-time grades apply only to the stated operating conditions. "Unresolved" denotes insufficient applicable evidence. No row establishes that a complete EUR 1000 helmet-based kit meets all requirements. A helmet IMU and a torso accelerometer observe different locations.

setting, source, and limitations; independent measurements, developer studies, specifications, and proposals are not interchangeable. Missing studies do not imply poor performance, and validation is not transferred across hardware revisions without justification. Listed specifications and prices reflect the cited documentation snapshot, not newly verified quotations; omission is not an exclusion verdict.

The five implementation domains are measurement performance, operating time, complete-kit initial deployment cost, integration, and local data access. Measurement performance remains descriptive without justified reference values and acceptance limits. Modality-level scores in Table II cannot substitute for these checks.

Sample-level data may already be filtered or downsampled [45]; derived heart rate, intervals, and scores are distinct outputs. Software development kits (SDKs) and application programming interfaces (APIs) provide access routes, while device timestamps alone do not establish cross-device synchronization.

C. Scenario-specific scoring rules and mandatory constraints

Let T be operating time in the selected acquisition mode, C the complete-kit initial deployment cost, and $T_0 = 12$ h and $B = 1000$ euros the scenario requirements. Define $r_T = T/T_0$ and $r_C = C/B$. Optional reporting codes are

$$q_T = \begin{cases} 1, & r_T < 0.5, \\ 2, & 0.5 \le r_T < 1, \\ 3, & 1 \le r_T < 1.5, \\ 4, & 1.5 \le r_T < 2, \\ 5, & r_T \ge 2, \end{cases} \quad q_C = \begin{cases} 5, & r_C \le 0.5, \\ 4, & 0.5 < r_C \le 0.75, \\ 3, & 0.75 < r_C \le 1, \\ 2, & 1 < r_C \le 1.25, \\ 1, & r_C > 1.25. \end{cases} \tag{1}$$

Only the scenario boundaries are requirements; the other breakpoints are author-defined, not experimentally optimized. Source values and units remain available, and ordinal codes

are not summed. "Up to" operating time supports at most a nominal grade for the stated mode.

Mandatory access, operating time, budget, and PPE requirements receive separate *supported*, *contradicted*, or *unresolved* statuses. Contradiction excludes that configuration; unresolved evidence prevents verified suitability. Missing evidence is not a low score, and favorable cost cannot compensate for mandatory failures. All mandatory kit items are needed to establish $C \leq B$; one mandatory component above B excludes the configuration.

D. Documented comparison and results

Table III compares specific configurations, grouping multisensor platforms rather than counting each channel as a separate device. Product/interface documentation is not itself validation of fatigue detection or protective compatibility. The comparison yields three findings.

First, channel availability does not ensure the required access route: EmbracePlus uses cloud retrieval, whereas Hexoskin separates free processed values from licensed sample-level streaming [28], [29]. Cloud buffering is not local signal access.

Second, general battery life cannot be assigned to every acquisition mode. The reviewed H10 documentation does not establish its general operating time for simultaneous ECG and acceleration streaming [25], [26]; the standard DOT and Neon durations are below the shift requirement [30], [32]. Extra power or replacement defines another configuration, requiring reassessment of mounting, interruptions, and cost.

Third, helmet integration adds the protective and status requirements in Section II to the physiological-channel selection. Neither body-worn validation nor the prior helmet prototypes establish compliance of this particular assembly. The table therefore exposes missing integration evidence rather than identifying a deployment-ready kit.

E. Sensitivity, limitations, and future work

The exclusions are insensitive to internal grade boundaries: 8 hours remains below 12, cloud-only retrieval fails local access, and Neon's academic price exceeds the kit budget [29], [30], [33]. Changing the scenario itself can change eligibility. This is a logical sensitivity check, not a statistical experiment.

Heterogeneous validation, incomplete mode descriptions, changing products, and an untested assembly limit the comparison. Without a complete bill of materials, protective assessment, or full-shift test, minimality, optimality, affordability, and deployment readiness remain unestablished.

Future tests must address protective compatibility, simultaneous-streaming duration, timing error, work/rest data availability, and wear-status detection. Fatigue interpretation requires independent task and participant outcomes. The role of data processing algorithms to run on edge devices is the subject of further research, together with personalized longitudinal models, SQI-based channel choice, testing additional-channel benefits, and a separate evaluation of entropy features.

V. Conclusion

This paper reviewed the latest results for the problem of digital mHealth assistance based on tracking biosignals of human activity in real time. We considered the selection problem of biosignals to use and consumer electronics sensors to integrate into a wearable system. The resulting synthesis links a candidate modular baseline and qualitative trade-offs to measurement sites, a smart-helmet architecture, and configuration-specific evidence.

For the stated shift, local-access restrictions, operating-time shortfalls, and unresolved complete-kit costs or protective integration prevent confirmation of a fully compliant assembly. These findings do not invalidate the proposed biosignal combination; they identify the evidence required to move from channel selection to deployment.

The scientific significance is a traceable distinction between useful observations, candidate configurations, and verified capabilities. Neither the baseline's minimum sufficiency nor a functioning fatigue detector is claimed as an experimental result. Full-system and fatigue-outcome validation remain the next step.

Acknowledgment

This research is implemented within the state assignment no. 075-03-2026-472 of the Ministry of Education and Science of Russia (project FSNW-2026-0003).

References

[1] A. Meigal, L. Gerasimova-Meigal, and D. Korzun, "Smartphone-enabled mHealth sensorics for digital assistance of human autonomic resilience to stress," in *Proc. 36th Conf. Open Innovations Association FRUCT*, 2024, pp. 885–891.

[2] J. Moon and B.-K. Ju, "Wearable sensors for healthcare of industrial workers: A scoping review," *Electronics*, vol. 13, no. 19, 2024, Art. no. 3849.

[3] Y. Qian and K. L. Siau, "Advances in IoT, AI, and sensor-based technologies for disease treatment, health promotion, successful ageing, and ageing well," *Sensors*, vol. 25, no. 19, 2025, Art. no. 6207.

[4] K. Kakhi, S. K. Jagatheesaperumal, A. Khosravi, R. Alizadehsani, and U. R. Acharya, "Fatigue monitoring using wearables and AI: Trends, challenges, and future opportunities," *Computers in Biology and Medicine*, vol. 195, 2025, Art. no. 110461.

[5] I. Campero-Jurado, S. Márquez-Sánchez, J. Quintanar-Gómez, S. Rodríguez, and J. M. Corchado, "Smart helmet 5.0 for industrial internet of things using artificial intelligence," *Sensors*, vol. 20, no. 21, 2020, Art. no. 6241.

[6] S. R. Dhole, A. Kashyap, A. N. Dangwal, and R. Mohan, "A novel helmet design and implementation for drowsiness and fall detection of workers on-site using EEG and random-forest classifier," *Procedia Computer Science*, vol. 151, pp. 947–952, 2019.

[7] Occupational Safety and Health Administration, "Head protection: Safety helmets in the workplace," Safety and Health Information Bulletin, Accessed: Oct. 7, 2026. [Online]. Available: https://www.osha.gov/sites/default/files/publications/SAFETY_HELMET_SHIB.pdf

[8] L. Neri *et al.*, "Electrocardiogram monitoring wearable devices and artificial-intelligence-enabled diagnostic capabilities: A review," *Sensors*, vol. 23, no. 10, 2023, Art. no. 4805.

[9] Y. Yu, B. Jain, G. Anand, M. Heidarian, A. Lowe, and A. Kalra, "Technologies for non-invasive physiological sensing: Status, challenges, and future horizons," *Biosensors and Bioelectronics: X*, vol. 16, 2024, Art. no. 100420.

[10] M. Schaffarczyk, B. Rogers, R. Reer, and T. Gronwald, "Validity of the Polar H10 sensor for heart rate variability analysis during resting state and incremental exercise in recreational men and women," *Sensors*, vol. 22, no. 17, 2022, Art. no. 6536.

[11] H. C. Ates *et al.*, "Integrated devices for non-invasive diagnostics," *Advanced Functional Materials*, vol. 31, no. 15, 2021, Art. no. 2010388.
[12] A. Ali *et al.*, "A novel wearable sensor for measuring respiration continuously and in real time," *Sensors*, vol. 24, no. 20, 2024, Art. no. 6513.
[13] J. Montes, J. C. Young, R. D. Tandy, and J. W. Navalta, "Reliability and validation of the Hexoskin wearable bio-collection device during walking conditions," *International Journal of Exercise Science*, vol. 11, no. 7, pp. 806–816, 2018.
[14] S. Tonello, N. Berti, M. Guidolin, E. Sardini, and N. F. Lopomo, "Electrodermal activity and sweat rate sensing technologies for occupational health monitoring: A systematic review," *IEEE Access*, vol. 14, pp. 19 337–19 362, 2026.
[15] G. Assalve *et al.*, "Advanced wearable devices for monitoring sweat biochemical markers in athletic performance: A comprehensive review," *Biosensors*, vol. 14, no. 12, 2024, Art. no. 574.
[16] B. B. Manjunath *et al.*, "Battery-free, wireless, and skin-mountable multi-sensory patch for biosignal monitoring," *Sensors and Actuators A: Physical*, vol. 404, 2026, Art. no. 117751.
[17] A. Gazis, I. Papadongonas, A. Andriopoulos, C. Zioudas, and T. Vavouras, "Comprehensive review: Sensor technologies, instrumentation, and signal processing in low-power IoT," *Academia Engineering*, vol. 2, no. 1, 2025.
[18] W. Heng *et al.*, "A battery-free smart mask for long-term exhaled breath biochemical sensing," *Nature Sensors*, vol. 1, no. 4, pp. 328–340, 2026.
[19] S. Baklouti, A. Chaker, T. Rezgui, A. Sahbani, S. Bennour, and M. A. Laribi, "A novel IMU-based system for work-related musculoskeletal disorders risk assessment," *Sensors*, vol. 24, no. 11, 2024, Art. no. 3419.
[20] Y. Gautam and H. Jebelli, "EMG-FLES: Flexible wearable electromyography and edge-AI system for near-real-time muscle fatigue monitoring for construction-relevant tasks," *Sensing and Bio-Sensing Research*, vol. 52, 2026, Art. no. 101029.
[21] Shimmer Research, "Shimmer3R EMG unit," Accessed: Oct. 7, 2026. [Online]. Available: https://www.shimmersensing.com/product/shimmer3-emg-unit/
[22] M. Bisla and R. S. Anand, "Wearable EEG technology for the brain-computer interface," in *Computational Intelligence in Healthcare Applications*, R. Agrawal, M. A. Ansari, R. S. Anand, S. Sneha, and R. Mehrotra, Eds. Academic Press, 2022, ch. 9, pp. 137–155.
[23] I. Rakhmatulin and G. R. Naik, *Signal Processing-Driven AI for Healthcare*, 1st ed. Academic Press, 2026, ch. 12.
[24] B. Šarkić *et al.*, "Portable eye-tracking technology for oculomotor testing: A pre-post exercise and reliability study," *Sports Medicine and Health Science*, 2025, advance online publication. [Online]. Available: https://doi.org/10.1016/j.smhs.2025.07.009
[25] Polar Electro, "Polar H10: Supported data types and recording modes," official Polar BLE SDK documentation. Accessed: Oct. 7, 2026. [Online]. Available: https://github.com/polarofficial/polar-ble-sdk/blob/master/documentation/products/PolarH10.md
[26] ——, "Polar H10 user manual: Technical specifications," Accessed: Oct. 7, 2026. [Online]. Available: https://support.polar.com/e_manuals/h10-heart-rate-sensor/polar-h10-user-manual-english/technical-specifications.htm
[27] Hexoskin, "What is the maximum of data storage for the Hexoskin device?" Accessed: Oct. 7, 2026. [Online]. Available: https://support.hexoskin.com/what-is-the-maximum-of-data-storage-for-the-hexoskin-device
[28] ——, "Hexoskin real-time data streaming options (BLE and SDK)," Accessed: Oct. 7, 2026. [Online]. Available: https://support.hexoskin.com/hexoskin-real-time-data-streaming-options-ble-and-sdk
[29] Empatica, "Raw data: EmbracePlus and the Empatica Health Monitoring Platform," Accessed: Oct. 7, 2026. [Online]. Available: https://www.empatica.com/rawdata/
[30] Xsens, "Xsens DOT: Product specifications and developer resources," Accessed: Oct. 7, 2026. [Online]. Available: https://www.xsens.com/wearables/xsens-dot
[31] BrainBit, "BrainBit Flex4: Technical specifications and software," Accessed: Oct. 7, 2026. [Online]. Available: https://brainbit.com/hardware-solutions/brainbit-flex/
[32] Pupil Labs, "Neon: Technical specifications," Accessed: Oct. 7, 2026. [Online]. Available: https://pupil-labs.com/products/neon/specs
[33] ——, "Neon: Product overview and pricing," Accessed: Oct. 7, 2026. [Online]. Available: https://pupil-labs.com/products/neon
[34] ——, "Neon: Real-time application programming interface," Accessed: Oct. 7, 2026. [Online]. Available: https://docs.pupil-labs.com/neon/real-time-api/
[35] Polar Electro, "Polar H10 heart rate sensor," Accessed: Jun. 22, 2026. [Online]. Available: https://www.polar.com/en/sensors/h10-heart-rate-sensor
[36] CamNtech, "Actiheart 5," Accessed: Jun. 22, 2026. [Online]. Available: https://www.camntech.com/actiheart-5
[37] VitalConnect, "VitalPatch and cardiac monitoring platform," Accessed: Jun. 22, 2026. [Online]. Available: https://vitalconnect.com/cardiac-monitoring/
[38] BioIntelliSense, "BioButton and remote patient monitoring solutions," Accessed: Jun. 22, 2026. [Online]. Available: https://www.biointellisense.com/solutions/at-home-patient-monitoring/
[39] BrainBit, "BrainBit Flex wearable EEG sensor and SDK," Accessed: Jun. 22, 2026. [Online]. Available: https://brainbit.com/
[40] EMOTIV, "EPOC X and Insight EEG headsets," Accessed: Jun. 22, 2026. [Online]. Available: https://www.emotiv.com/
[41] OpenBCI, "Ultracortex and open-source biosensing platform," Accessed: Jun. 22, 2026. [Online]. Available: https://openbci.com/
[42] Empatica, "EmbracePlus continuous health monitoring platform," Accessed: Jun. 22, 2026. [Online]. Available: https://www.empatica.com/embraceplus/
[43] Shimmer Research, "Shimmer GSR+ wearable sensor platform," Accessed: Oct. 8, 2026. [Online]. Available: https://www.shimmersensing.com/product/shimmer3-gsr-unit/
[44] Tobii Pro, "Tobii Pro Glasses 3 and eye-tracking systems," Accessed: Jun. 22, 2026. [Online]. Available: https://www.tobii.com/products/eye-trackers/wearables/tobii-pro-glasses-3
[45] J. C. Goldsack *et al.*, "Verification, analytical validation, and clinical validation (V3): the foundation of determining fit-for-purpose for biometric monitoring technologies (BioMeTs)," *npj Digital Medicine*, vol. 3, 2020, Art. no. 55.