

POTENTIAL FOR CONTACTLESS VITAL SIGN MONITORING AND ARTIFICIAL INTELLIGENCE APPLICATIONS IN CRISIS SITUATIONS

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Vital signs monitoring is essential for detecting medical conditions such as cardiovascular disease, sleep disorders, and other physiological anomalies. It plays a critical role in civilian and military healthcare, offering the ability to analyse and predict adverse outcomes in diverse environments. This literature review explores recent advancements in contactless vital sign monitoring technologies, focusing on their applications, effectiveness, and integration in real-world medical scenarios. The review examines modern sensor technologies and artificial intelligence (AI) applications in systems such as remote photoplethysmography (rPPG), thermal imaging, and radar-based monitoring. Emphasis is placed on machine learning-enhanced signal processing and the capacity of these technologies to operate without physical contact. Contactless systems enable real-time, long-term monitoring of patients without the need for direct human supervision. These systems have demonstrated significant potential in environments like emergency departments, mass casualty incidents, and home care, where they assist in patient sorting, early warning, and outcome prediction. When integrated with AI, these technologies reduce decision-making time, increase accuracy, and may prevent misdiagnosis. They are especially beneficial for solitary patients and overburdened healthcare workers. The integration of contactless vital sign monitoring systems with AI offers a promising future in healthcare. Such technologies can enhance clinical efficacy, improve patient safety, and potentially allow one healthcare professional to manage more patients effectively, raising effectiveness and economic productivity. As automation advances, these systems may become indispensable in reducing the workload and error rates associated with vital sign monitoring. Huge potential for use is possible in the Military Medicine and MASCAL-related environments, and further research is needed.

Keywords: contactless triage, automatic vital sign control systems, military medicine, MASCAL.

INTRODUCTION

Modern healthcare is increasingly embracing non-invasive technologies for patient monitoring. One of the most promising developments in this field is the emergence of contactless vital sign monitoring, which allows for real-time measurement of physiological parameters such as heart rate (HR), respiratory rate (RR), body temperature, and oxygen saturation (SpO₂) without physical contact.

The COVID-19 pandemic further accelerated interest in remote and hygienic monitoring solutions. This literature review aims to analyse the current state of research on contactless vital sign monitoring, highlighting existing methods, their advantages and limitations, and directions for future development.

In this publication, we want to analyse existing technologies for vital sign control systems and human search and control

systems to establish a connection in this field of technologies and their possible ways of use in modern medical approaches in civil, military, and other forms of use. One of the goals is to analyse the existing models of human detection and health condition analysis systems, identify and recommend optimal technical solutions and their combinations for implementation and future use. The common goal is to find and show the most effective ways of use based on the existing technology presence.

METHODOLOGY

- Databases searched: PubMed, Scopus, Researchgate
- Search terms used: “contactless vital sign monitoring” (“remote photoplethysmography”, “thermal imaging in healthcare”, “radar technology use in medicine”)
- Inclusion criteria: peer-reviewed articles published between 2000 and 2025, studies focusing on non-invasive monitoring technologies
- Exclusion criteria: studies not available in English, articles lacking empirical data

TECHNOLOGICAL FOUNDATIONS OF CONTACTLESS MONITORING

Optical methods (Remote Photoplethysmography – RPPG). One of the most studied approaches is remote photoplethysmography (rPPG) using standard RGB cameras. rPPG can estimate pulse rate by detecting subtle changes in skin colour due to blood flow. While effective under controlled conditions, this method is sensitive to lighting variations and subject motion.

Introduction to PPG and rPPG. Photoplethysmography (PPG) is a non-invasive optical technique that measures blood volume changes in the microvasculature by analysing light absorption in tissue. In clinical practice, PPG underlies familiar devices like pulse oximeters and finger clip heart rate sensors. Remote photoplethysmography (RPPG) extends this principle by capturing the same pulse-induced colour changes without direct contact, using a regular camera and ambient or infrared light (Haugg *et al.*, 2022).

Researchers first demonstrated the feasibility of RPPG in the early 2000s, and subsequent studies in 2008–2012 showed that vital signs like heart rate could be accurately extracted from ordinary face video under ambient lighting. RPPG is appealing because cameras are now built into most laptops and smartphones, making contactless monitoring widely accessible (Haugg *et al.*, 2022).

SCIENTIFIC BASIS OF RPPG TECHNOLOGY

Principle of operation. RPPG relies on physiological phenomena: blood volume oscillations during the heartbeat change the skin's optical properties. Subtle changes in skin

colour, invisible to the naked eye, can be detected by a high-resolution camera. In practice, the green colour channel provides the strongest signal, due to haemoglobin's absorption characteristics (Khanam *et al.*, 2021).

Signal processing and algorithms. Modern RPPG relies heavily on advanced algorithms. Techniques such as Independent Component Analysis (ICA) and Principal Component Analysis (PCA) help separate pulse signals from noise (Khanam *et al.*, 2021). The CHROM method, among others, enhances signal quality. Deep learning models have further improved RPPG performance by learning pulse extraction patterns directly (Saikevičius *et al.*, 2025).

RPPG – PERFORMANCE AND RECENT ACHIEVEMENTS IN MEDICINE

Accuracy of vital sign measurements. Studies report that RPPG can measure heart rate with clinical-grade precision under controlled and even clinical settings. For instance, a 2020–2021 hospital study of 963 patients found excellent agreement between RPPG respiratory rate and standard monitors (Allado *et al.*, 2022). In a neonatal ICU study, RPPG heart rates showed a Pearson correlation of ~0.99 with ECG readings (Khanam *et al.*, 2021).

Expanded vital parameters. Researchers have extended RPPG to estimate blood oxygen saturation (SpO₂), and even blood pressure using machine learning models. Although these capabilities are emerging, initial studies demonstrate promising accuracy, especially with deep learning enhancements (Schiavo *et al.*, 2022).

Telemedicine and remote patient monitoring. RPPG enables vital sign assessment during virtual visits (Schiavo *et al.*, 2022). During the COVID-19 pandemic, RPPG technology was integrated into telemedicine workflows to measure heart rate and breathing rates remotely (Allado *et al.*, 2022). The U.S. Veterans Affairs successfully piloted an RPPG “Vitals” tool built into its video platforms, confirming ease of use and clinical value (Garvin *et al.*, 2024).

Clinical monitoring in hospital settings. In hospitals, RPPG reduces the need for physical sensors, improving patient comfort and infection control. In NICUs, RPPG systems monitored premature infants' vitals without skin-contact devices, preventing skin injuries (Khanam *et al.*, 2021). Clinical pilot studies have shown that contactless systems could detect early deterioration on hospital wards (Saikevičius *et al.*, 2025).

Emergency and triage applications. In emergency departments, RPPG-based systems provided rapid, contactless vital sign measurements during triage, with results comparable to standard methods. RPPG's potential for mass casualty and infectious disease scenarios is under active development (Schiavo *et al.*, 2022).

Patient screening and preventive medicine. RPPG can be used for large-scale cardiovascular screening, stress detec-

tion, and infectious disease monitoring (Allado *et al.*, 2022). Mobile health apps already leverage smartphone cameras to offer heart rate and breathing checks, broadening the RPPG's preventive health role (Schiavo *et al.*, 2022).

THERMAL IMAGING

Infrared thermography is employed to measure body temperature and respiratory rate. It was shown that thermal cameras can effectively detect fever and monitor breathing patterns (Chai *et al.*, 2020). However, these systems often require calibration and stable ambient temperatures.

Introduction to medical thermal imaging. Thermal imaging, or infrared thermography (IRT), is a non-contact imaging technique that visualises temperature distributions on the skin surface by detecting emitted infrared radiation. Renewed interest in medical thermography has surged from 2020 onward due to technological advancements and the global demand for non-invasive monitoring during the COVID-19 pandemic. Modern IRT devices offer high spatial and thermal resolution, affordability, and portability, enabling real-time clinical application (Lahiri *et al.*, 2020).

Scientific basis of thermal imaging technology. IRT measures the infrared radiation naturally emitted by the skin, which correlates closely with underlying blood flow and metabolism (Lahiri *et al.*, 2020). Since human skin behaves nearly like a blackbody radiator, with emissivity close to 0.98, it enables accurate thermal mapping. Thermal cameras capture this radiation in the 8–14 μm wavelength range, translating it into false-colour thermograms for medical interpretation (Czaplik *et al.*, 2021). Advances in Artificial Intelligence (AI) and image processing have improved the diagnostic utility of thermal patterns, allowing detection of subtle physiological changes (Sun *et al.*, 2023).

IRT – PERFORMANCE AND RECENT ACHIEVEMENTS IN MEDICINE

Fever detection. During the COVID-19 pandemic, IRT was deployed globally for mass fever screening in public spaces. Thermal screening systems demonstrated sensitivities up to 92% when targeting the inner canthus for core temperature approximation, although specificity remained lower due to environmental factors. ISO and IEC standards were updated to guide accurate deployment (ISO/IEC, 2022).

Respiratory monitoring. IRT can measure respiratory rate by tracking thermal fluctuations around the nostrils during inhalation and exhalation. Studies report correlations ($r \approx 0.99$) between thermal-derived respiratory rates and reference methods. AI-enhanced models achieve 98–99% accuracy in respiratory rate estimation under controlled conditions (Abbas *et al.*, 2021).

Wound healing and burn assessment. IRT provides early detection of infection and poor perfusion in chronic wounds and burns. In burn depth estimation, thermography pre-

dicted healing time with ~89% accuracy, achieving ~68% sensitivity and 95% specificity (Renkielska *et al.*, 2006). In diabetic foot care, thermal asymmetry serves as an early indicator of ulceration risk (Lavery *et al.*, 2007).

Oncology and inflammation monitoring. Recent AI-supported thermal imaging systems have achieved 80–90% sensitivity and specificity in breast cancer screening as an adjunct tool (Gutierrez *et al.*, 2024). Dynamic thermography has also been validated for identifying skin cancers and differentiating benign from malignant lesions by analysing thermal recovery curves (Soto and Godoy, 2024).

Telemedicine and remote monitoring. IRT supports remote care via smartphone-connected thermal cameras, allowing patients to monitor wound healing, fever, or inflammation from home. Diabetic foot ulcer prevention systems using at-home thermal scanners are in clinical trials and reduce complications by early detection of inflammatory “hot spots” (Lavery *et al.*, 2007).

Clinical monitoring. Hospitals employ thermal imaging in post-surgical monitoring. For instance, in microsurgical flap monitoring, a 2 °C temperature drop predicted vascular compromise with 88.6% sensitivity and 98.9% specificity, often before clinical signs appear (Singla *et al.*, 2024).

Emergency and triage. IRT enables contactless triage by identifying febrile patients and assessing perfusion status. It is used in emergency departments for early identification of sepsis and vascular injury by assessing peripheral and facial thermal gradients (ISO/IEC, 2022).

Preventive screening. Thermal imaging is used for early cancer screening in underserved populations, particularly for breast and thyroid tumours. Pilot programmes using AI-assisted thermography show promising accuracy in low-resource settings (Soto and Godoy, 2024).

RADAR AND RF TECHNOLOGIES

Millimetre-wave radar can monitor respiratory and cardiac activity through clothing and even walls (Wang *et al.*, 2020). These technologies are particularly promising for use in vehicles, smart homes, and hospital beds.

Introduction to radar-based medical sensing. Radar technologies enable contactless monitoring of physiological parameters by emitting electromagnetic waves and analysing their reflections from the body. These systems can detect sub-millimetre movements of the chest wall due to respiration and micro-vibrations from cardiac activity using Doppler or frequency-modulated continuous wave (FMCW) techniques (Mercuri *et al.*, 2019). Unlike optical or thermal sensors, radar systems are robust to lighting conditions, skin tone, and clothing, making them ideal for continuous and privacy-preserving monitoring (Adib and Katabi, 2013).

Scientific basis of radar sensing. Radar sensors transmit radio waves in frequencies ranging from 3 GHz (UHF) to

300 GHz (mmWave) and measure the time delay and phase shift of reflected signals to infer motion and position (Mercuri *et al.*, 2019). In medical applications, radar can detect periodic motion such as heartbeats or respiration by observing frequency modulations in the returned signal (Szmola *et al.*, 2025). Advanced signal processing and AI algorithms are used to extract physiological signals like respiratory rate, heart rate, and even heart rate variability (HRV) (Han *et al.*, 2019).

RADAR TECHNOLOGIES – PERFORMANCE AND PRACTICAL ACHIEVEMENTS IN MEDICINE

Vital sign monitoring. Radar systems have been validated in clinical and real-world settings for continuous measurement of respiratory and heart rates. A 2025 study using a 60 GHz FMCW radar reported over 95% accuracy in detecting respiratory rate compared to capnography, with a mean absolute error < 1 bpm (Szmola *et al.*, 2025). Another 2023 paediatric ICU study found mmWave radar could track respiration with high precision despite motion artefacts (Arasteh *et al.*, 2023).

Sleep and home health monitoring. Radar has been integrated into commercial sleep devices such as Google Nest Hub (2nd Gen), which uses Soli radar to monitor breathing and sleep cycles. Validation against polysomnography showed high accuracy for breathing rate detection and sleep staging (Xu *et al.*, 2023). These systems are increasingly used for unobtrusive overnight monitoring in home environments.

Fall detection and elder care. Radar enables privacy-preserving, always-on monitoring in elder care environments. A 2022 system using ultra-wideband radar achieved 98.7% sensitivity and 99.5% specificity for detecting simulated falls, with successful deployment in long-term care facilities (Maitre *et al.*, 2021). Radar does not capture identifiable images, addressing privacy concerns compared to video surveillance.

Neonatal and ICU monitoring. Radar has been piloted in neonatal ICUs for non-contact vital sign monitoring. Studies demonstrated that mmWave radar could detect breathing and HR in neonates with correlation coefficients > 0.95 compared to ECG and respiratory belts (Arasteh *et al.*, 2023). This reduces skin irritation and sensor detachment, which are common in traditional monitoring.

Imaging and stroke triage (emerging use). Early-stage studies have explored radar for low-resolution brain imaging. A 2024 pilot using RF tomography showed promise for identifying cerebral haemorrhage in pre-hospital stroke triage, potentially offering a portable supplement to CT in rural settings (Origlia *et al.*, 2024).

ARTIFICIAL INTELLIGENCE AND SIGNAL PROCESSING

Machine learning plays a key role in improving accuracy and robustness. It has shown significant growth in recent

years. AI use has demonstrated its efficacy in all fields of IT, finance, analytics, aviation, medicine, military, etc. According to studies, neural networks filter noise, correct for motion, and analyse facial micro expressions to assess stress and fatigue levels (Shu *et al.*, 2018). A combination of AI and existing technologies, as well as new technology implementation, is showing a huge growth in all fields of human life.

Introduction to artificial intelligence. AI and signal processing have revolutionised modern medicine by enabling automated diagnostics, personalised treatments, and contactless physiological monitoring. AI algorithms — especially deep learning models — now assist in interpreting complex biomedical signals and images, detecting patterns invisible to clinicians, and supporting decision-making in real-time (Esteva *et al.*, 2019). Combined with advanced signal processing, AI improves the accuracy, speed, and scalability of medical technologies.

Technological overview. Signal processing in medicine involves extracting, filtering, and analysing physiological data from bio signals such as ECG, EEG, EMG, and medical images. AI techniques, including machine learning (ML) and deep learning (DL), build predictive models from these signals by learning complex nonlinear features (Rajpurkar *et al.*, 2017). Integration of AI with time-frequency analysis, Fourier transforms, and wavelet decompositions enhances detection of anomalies like arrhythmias, epileptic seizures, and pulmonary diseases (Faust *et al.*, 2018).

AI – PERFORMANCE AND RECENT ACHIEVEMENTS IN MEDICINE

Cardiovascular disease detection. AI combined with ECG signal processing enables early detection of arrhythmias, myocardial infarction, and heart failure. A 2022 study using a convolutional neural network (CNN) trained on ECG data achieved 94% sensitivity and 96% specificity in classifying atrial fibrillation (Hannun *et al.*, 2019). AI systems now monitor ECGs in real time in ICUs and wearable devices.

Neurological monitoring (EEG and seizure detection). AI-enhanced EEG analysis is used to detect epileptic seizures and classify sleep stages. Deep learning models using recurrent neural networks (RNNs) have reached > 95% accuracy in seizure detection in clinical trials (Roy *et al.*, 2018). These models reduce false alarms and enable continuous, remote neurological assessment.

Respiratory analysis and COVID-19 screening. Signal processing of respiratory sounds using AI (e.g., CNNs and spectrogram analysis) has been used for COVID-19 diagnosis. A 2020 smartphone-based study reported over 90% accuracy in differentiating COVID-related coughs from other respiratory conditions using acoustic signals and AI (Laquarta *et al.*, 2020).

Medical imaging interpretation. AI-based image recognition systems have dramatically improved the detection of

diseases in X-rays, CTs, and MRIs. In lung cancer screening, AI-aided CT interpretation reached 94.4% sensitivity, outperforming radiologists in some cases (Ardila *et al.*, 2019). Similar systems are used in breast cancer, stroke, and brain tumour diagnostics.

ICU and remote patient monitoring. AI and signal processing are used in ICUs for early warning systems. Predictive analytics platforms process heart rate variability, respiration, and oxygen saturation to detect sepsis or cardiac arrest hours in advance. A 2023 platform using LSTM neural networks predicted ICU deterioration with 85% accuracy (Boussina *et al.*, 2024).

Personalised medicine and risk prediction. AI algorithms process longitudinal patient signal data to predict disease risk. For example, models analysing wearable sensor signals have predicted heart failure onset up to 13 days in advance in high-risk populations (Stehlik *et al.*, 2020). These tools are now being integrated into remote monitoring programmes.

ADVANTAGES AND LIMITATIONS OF CURRENT APPROACHES

Comparing existing remote vital sign monitoring technologies, we found both have advantages and limitations. The following comparison is shown in Table 1. The use of several technologies at the same time is helping to reduce limitations and improve data quality.

PRACTICAL APPLICATIONS

Contactless technologies are currently applied in:

- Public health screening (e.g., COVID-19 fever detection at airports)
- Elderly care and smart homes (fall detection, health tracking)
- Driver monitoring systems (fatigue detection in vehicles)
- Telemedicine (remote monitoring and consultation)
- Military Medicine
- MASCAL

FUTURE DIRECTIONS

Despite promising advances, several challenges remain:

- Improving robustness to lighting and motion conditions
- Standardising validation metrics and protocols
- Developing multimodal systems combining several sensors
- Conducting large-scale clinical trials to validate accuracy

CONCLUSION

Contactless monitoring of vital signs represents a significant innovation in the field of digital health, both in Military Medicine and Civilian Healthcare. Current technologies demonstrate high accuracy in controlled environments and offer the ability to perform fast, objective, and precise contactless triage of patients and casualties. However, broader implementation requires further research into real-world scenarios, signal reliability, and integration with clinical workflows.

Between 2020 and 2025, significant advancements in contactless monitoring technologies, such as remote photoplethysmography (rPPG), thermal imaging, radar systems, and AI-driven signal processing, have transformed the landscape of modern healthcare. These technologies enable passive, non-invasive, and continuous monitoring of vital signs across diverse clinical settings, including telemedicine, intensive care, emergency triage, MilMed, and home-based care.

Remote photoplethysmography and thermal imaging have matured into reliable tools for real-time physiological assessment, supporting applications in fever screening, respiratory monitoring, wound care, and preventive diagnostics. Simultaneously, radar technologies have proven effective in privacy-preserving, contactless detection of respiration, heart rate, and patient movement, making them invaluable in high-acuity and resource-limited environments.

The integration of AI and advanced signal processing further enhances the diagnostic accuracy, responsiveness, and scalability of these systems. By enabling early detection of anomalies and reducing clinical workload, these technologies not only improve patient outcomes but also extend the capacity of healthcare personnel.

Table 1. Comparison of existing remote vital sign technology advantages and limitations

Technology	Advantages	Limitations
rPPG	Low-cost, camera-based, easy to integrate	Sensitive to lighting, motion artefacts
Thermal Imaging	Works in low light, detects fever	Expensive, affected by ambient temperature
Radar	Works through clothes, no lighting dependency	High cost, signal processing complexity
AI	Adaptive, enhances precision	Requires large datasets and computational power

As these tools continue to evolve, they are expected to become foundational elements in the future of automated and intelligent healthcare, supporting safer, faster, and more efficient decision-making across medical domains.

Huge potential for use is possible in the MilMed and MASCAL-related environments, and further research is needed.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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BEZKONTAKTA DZĪVĪBAS PAZĪMJU MONITORINGA UN MĀKSLĪGĀ INTELEKTA PIELIETOJUMA POTENCIĀLS KRĪZES SITUĀCIJĀS

Dzīvības pazīmju noteikšana un monitorings ir būtisks veselības stāvokļa noteikšanai, tostarp sirds un asinsvadu slimību, elpošanas traucējumu un ar miegu saistītu patoloģiju diagnostikā. Tas ieņem nozīmīgu lomu gan civilajā, gan militārajā veselības aprūpē, īpaši vidēs, kurās ātra pacientu novērtēšana, ierobežoti personāla resursi vai bīstami apstākļi apgrūtinā tradicionālu fizisku kontaktu ar pacientu. Šajā literatūras apskatā analizēti jaunākie sasniegumi dzīvībai svarīgo pazīmju bezkontakta monitoringa tehnoloģijās, koncentrējoties uz to klīnisko pielietojamību, efektivitāti un integrāciju reālās medicīniskās situācijās. Apskatā tiek izvērtētas mūsdienīgas sensoru tehnoloģijas un mākslīgā intelekta (MI) risinājumi, tostarp attālināta fotopletizmogrāfija (rPPG), termālā attēlveidošana un uz radaru balstīta monitorēšana. Īpaša uzmanība pievērsta mašīnmācīšanās pastiprinātām signālu apstrādes metodēm, kas ļauj precīzi iegūt fizioloģiskos parametrus bez tieša fiziska kontakta. Šīs tehnoloģijas nodrošina nepārtrauktu reāllaika monitoringu, vienlaikus samazinot nepieciešamību pēc pastāvīgas medicīnas personāla klātbūtnes. Literatūras dati liecina, ka bezkontakta monitoringa sistēmām ir ievērojams potenciāls neatliekamās palīdzības nodaļās, masu cietušo incidentos (MASCAL), kaujas lauka medicīnā un mājas aprūpē. Šādās situācijās tās veicina ātru triāžu, agrīnu klīniskās pasliktināšanās atklāšanu, pacientu prioritizāciju un iznākumu prognozēšanu. Integrējot šīs sistēmas ar MI balstītu lēmumu atbalstu, iespējams samazināt diagnostikas aizkavi, uzlabot mērījumu precizitāti un mazināt cilvēcisko kļūdu risku. Tas ir īpaši nozīmīgs vientuļiem pacientiem un pārslogotam veselības aprūpes personālam. Dzīvībai svarīgo pazīmju bezkontakta monitoringa tehnoloģiju integrācija ar mākslīgo intelektu iezīmē daudzsološu virzienu nākotnes veselības aprūpes sistēmās. Šādi risinājumi var uzlabot klīnisko efektivitāti, paaugstināt pacientu drošību un palielināt veselības aprūpes speciālistu operatīvo kapacitāti, ceļot efektivitāti un ekonomisko produktivitāti. Automatizācijai turpinot attīstīties, šāda veida sistēmas var kļūt par neaizvietojamiem instrumentiem darba slodzes samazināšanai, resursu optimizācijai un medicīnisko iznākumu uzlabošanai gan militārajā, gan civilajā veselības aprūpē.