Received: 12 September 2025 | Revised: 31 December 2025 | Accepted: 27 January 2026 | Published online: 13 February 2026

REVIEW

Journal of Optics and Photonics Research
2026, Vol. 00(00) 1–9
DOI: 10.47852/bonviewJOPR62027646

BON VIEW PUBLISHING

Photonics in Smart Clothing for Personalized Medicine

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Abstract: The implementation of mobile health (m-Health) technologies into personalized healthcare systems requires substantial financial investment and the engagement of diverse social resources. Mobile systems integrated into smart clothing represent one of the key directions for the future development of healthcare, particularly with the emergence and deployment of high-speed 5G/6G networks. Underpinning this transition from traditional treatment models—based on diagnosis, medical history, and test results—is the concept of disease prevention and real-time early intervention. Prototypes of m-Health systems developed over the past decade, leveraging photonics and flexible electronics, open new frontiers in healthcare delivery. 5G/6G technologies enhance the efficiency of m-Health in smart clothing through features such as massive multiple-input multiple-output data transmission, secure communication protocols, wireless charging, and energy-efficient operational modes. Smart clothing equipped with embedded multispectral sensors, combined with big data analytics and m-Health systems, enables continuous health monitoring, facilitating timely detection and prevention of diseases. This review-conceptual article presents key aspects of designing prototypes of smart clothing based on thin-film micro- and nanoelectronics. It addresses scientific, technical, and social dimensions of implementing these solutions, including the development and investigation of multispectral sensors, aimed at enhancing healthcare system efficiency, improving patients' quality of life, and laying the foundation for future personalized medicine.

Keywords: m-Health, smart clothing, thin-film technologies, organic light-emitting diodes (OLEDs)

1. Introduction

The formation of a new paradigm in digital healthcare, centered on a personalized approach to the patient, is transforming not only medical practice but also adjacent sectors—the economy, governance systems, education, and social infrastructure. At the core of this transformation is a shift in focus from reactive treatment to proactive health management: early diagnosis, risk prediction, preventive interventions, and personalized therapy—collectively enhancing the efficiency of medical care and improving population quality of life. Simultaneously, systems for training healthcare professionals are being advanced through the digitalization of clinical knowledge storage, transmission, and application.

This article presents a conceptual review of the ongoing digital transformation in healthcare and focuses on the key aspects of designing prototypes of smart clothing based on thin-film micro- and nanoelectronics.

The digital transformation of healthcare underpins the formation of a "super-intelligent society," in which the physical and digital worlds are integrated through cyber-physical systems [1]. In this model, the human body and the surrounding environment become continuous sources of data, transmitted in real time via high-speed networks (5G/6G) into the digital domain as big data streams. Artificial intelligence (AI) analyzes this data, identifies hidden patterns, predicts health status dynamics, and generates personalized recommendations or control interventions, promptly feeding them back into the physical space—to the patient or healthcare provider.

One of the key elements of this ecosystem is remote diagnostics. It fundamentally transforms the traditional model of clinical interaction, which relies on episodic visits, medical history collection, and laboratory tests [2, 3]. Instead, digital medicine focuses on continuous monitoring, early detection of deviations, and timely preventive intervention—even before clinical symptoms appear.

Understanding the underlying causes and directions of these changes enables the development of scientifically grounded, technologically adaptive, and clinically effective strategies for implementing digital solutions—both into everyday medical practice and into the system of continuous professional education for healthcare professionals.

2. Remote Diagnostics and Real-Time Health Status Assessment

The rapid development of information technologies in healthcare has facilitated the creation of high-precision diagnostic systems capable of long-term monitoring and recording of biomedical signals. Initially, such systems were designed for stationary use, where they provided continuous patient observation and enabled in-depth real-time analysis of physiological data [4].

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However, obtaining objective and multidimensional information on the population's health status remains a resource-intensive process [5, 6]. As an alternative, methods for real-time health status assessment are gaining increasing adoption—less costly yet highly effective when integrated with intelligent decision-support systems. These automated solutions are successfully applied in preventive screening departments [7] and enable the detection of pathological changes at preclinical, asymptomatic stages [8].

Real-time assessment can be either comprehensive or specialized (focused).

Comprehensive assessment covers multiple physiological systems (cardiovascular, respiratory, nervous, etc.) and includes a set of complementary methods grouped by functional profiles.

Specialized assessment focuses on a specific area—for example, cardiological or neurological status—and employs targeted diagnostic techniques.

Each method included in either type of assessment analyzes from one to five key indicators. These indicators are quantitatively measured based on the patient's primary data and then converted into qualitative interpretations—in the form of scales, recommendations, preliminary conclusions, or diagnostic hypotheses. The combination of quantitative and qualitative results, supplemented with explanations and recommendations, forms a "health passport"—a personalized digital patient profile [9].

The final diagnosis and prescription of therapeutic or preventive measures remain the physician's prerogative; however, automation and standardization of initial assessment significantly facilitate their work and improve diagnostic accuracy. Advances in computational technologies and AI algorithms promote wider adoption of such systems in routine clinical practice [10].

Simplified versions of diagnostic platforms have found application in outpatient and home-based care, enabling patient monitoring outside clinical settings [11]. Simultaneously, there is a growing demand for centralized expert centers capable of processing data from remote patients, especially in conditions of limited access to in-person consultations [12]. Telemedicine solutions enable 24/7 remote consultations, while data analysis modules can operate either autonomously or as part of integrated medical platforms [13].

Despite progress, most existing systems still rely on population-based norms and insufficiently account for individual patient characteristics [14]. This significantly limits their effectiveness within the framework of personalized medicine [15]. Thus, the key challenge for the future is the development of intelligent remote diagnostic systems capable of continuous real-time monitoring, adaptation to individual user parameters, and multifactorial analysis incorporating both internal (physiological, genetic) and external (environmental, behavioral) influences [16].

Modern remote diagnostics represent a transitional stage toward full-fledged digital medicine. Current protocols are often focused on locally addressing identified problems, without systematic analysis of the body's dynamic state [17]. Performing comprehensive, multi-stream diagnostics of "phase states" in a hospital setting remains technically challenging [18], making the development of remote intelligent systems with large-scale integration of biomedical data especially promising.

3. Personalized Medicine

Personalized medicine is an integrative approach to healthcare delivery based on the unique biological, physiological, and genetic characteristics of each patient. It involves the development of individualized strategies for prevention, diagnosis, treatment, and monitoring, grounded in genomic data, biomarkers, and analysis of disease predisposition.

This approach facilitates the transition from a reactive healthcare model—where treatment begins after symptoms appear—to a proactive one, in which early risk detection and disease prevention take priority. The goal of personalized medicine is to enhance treatment efficacy, improve patients' quality of life, and optimize the healthcare system as a whole [19, 20].

The key objectives of this field include disease prevention, adaptation of therapy and rehabilitation to individual patient characteristics, improvement of quality of life, and resolution of socioeconomic challenges within the healthcare sector. Underlying this concept is a simple yet fundamental idea: it is easier to prevent a disease than to treat it.

The development of personalized medicine aims to enhance the effectiveness of medical care for each individual and improve the overall health of society. All objectives stem from the core principle—prevention. This includes preventing the majority of diseases, personalizing therapy, improving quality of life, and addressing systemic healthcare challenges. Their implementation is made possible through the integration of information technologies with advances in modern medicine.

A new class of medical-biological systems based on advanced digital technologies is emerging. These systems enable active interaction among wearable biosensors, pharmaceuticals, and the patient's body, as well as deep integration with biomedical databases, global positioning systems, and neural network algorithms. Real-time information exchange with medical centers allows for prompt treatment adjustments and risk prediction.

Moreover, implementing such systems does not necessarily require expensive stationary or mobile diagnostic complexes. It is sufficient to establish specialized centers operating on the basis of widely available communication networks and GPS technologies. The limitations of current mobile solutions are not insurmountable—they merely define the direction for further development.

Particular attention must be paid to improving methods of real-time mobile diagnostics. This includes:

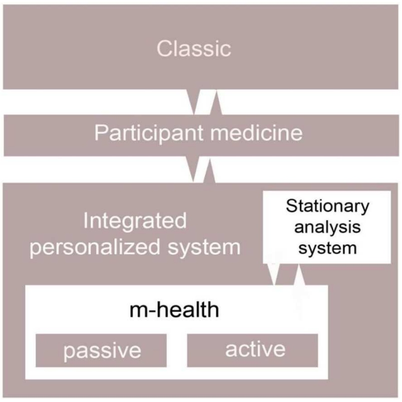
1) Precise spatiotemporal contextualization of biomedical signals (e.g., accounting for geolocation and time of day);
2) Optimization of data processing using multi-threaded architecture;
3) The ability to flexibly configure the system according to the patient's specific clinical profile.

Widespread implementation of personalized medicine is already capable today of fundamentally transforming approaches to the diagnosis and treatment of cardiovascular diseases and oncology, including by reducing the number of errors and ineffective prescriptions. The structural diagram of this transformation is presented in Figure 1.

The classical model of healthcare delivery is undergoing a profound transformation under the influence of information technologies and a shift in focus from disease to the patient as an integrated biosocial system. The scientific foundation for these changes lies in advances in molecular medicine, genomics, proteomics, metabolomics, targeted drug delivery systems, and the development of interdisciplinary competencies.

The traditional "physician–patient" model is gradually giving way to participatory medicine, in which the patient becomes an active participant in the process—from making specific decisions to shaping the overall strategy for monitoring their own health. Information technologies accelerate this transformation, reshaping the very paradigm of healthcare at the level of fundamental scientific principles, terminology, and practices shared by the professional community.

Figure 1
Structural diagram of integrated personalized medicine



The current advancement of personalized medicine is directly linked to the implementation of new classes of biomedical systems based on cutting-edge digital technologies. These systems enable continuous interaction among wearable biosensors [21], pharmacological agents [22], and the patient's body, as well as integration with biomedical databases, GPS, and neural network platforms. Data exchange with clinics and analytical centers occurs in real time.

The operation of such systems is supported by mobile applications, cellular networks, satellite navigation (GPS), and wireless data transmission technologies—Wi-Fi, Bluetooth, and NFC (Near Field Communication) [23].

4. Integrated Inclusive System Based on Big Data

One of the key directions in modern technological development is the integration of big data analytics into various sectors, with healthcare being one of the most promising and in-demand segments [24]. The potential of big data is particularly evident in biomedical research, where data volumes reach extraordinary scales [25].

For example, whole-genome sequencing generates massive datasets containing information on millions of genetic segments. These data are extremely complex to process, store, transfer between research centers, and migrate to digital media. Under these conditions, traditional analytical methods become ineffective [26]. Addressing these challenges requires high-performance computing systems and advanced intelligent analytics algorithms—capable of uncovering hidden patterns, generating predictions, and adapting to growing data volumes.

The synergy of genomic technologies and powerful computational solutions paves the way for breakthroughs in personalized medicine. According to expert estimates, big data can effectively address three key challenges:

1) Continuous monitoring of treatment progress and patient health dynamics,
2) Prediction of potential complications based on historical and real-time data,
3) Prevention of epidemics through real-time analysis of global trends and local outbreaks.

Analysts note a steady increase in the number of projects aimed at developing next-generation medical information systems. Such platforms must not only process petabytes of data but also ensure continuous, instant access to personal medical information—from anywhere in the world and at any time. This is especially critical in the context of global mobility and the expansion of telemedicine.

Growing interest in big data in healthcare is also driven by a fundamental transformation in the physician–patient relationship. Modern medicine increasingly focuses on the patient as an active participant in the care process: the emphasis is shifting toward prevention, early risk detection, and personalized diagnostic and therapeutic strategies. Big data is becoming the technological foundation upon which this new, inclusive, and human-centered model of healthcare is built.

5. Mobile Health Technologies

Mobile health (m-Health) technologies represent one of the most promising areas of digital transformation in medicine [27]. They offer a broad spectrum of capabilities that, in the near future, will become an integral part of everyday clinical practice and preventive healthcare [28].

Against the backdrop of aging populations and the rising prevalence of chronic non-communicable diseases, healthcare systems worldwide are facing increasing pressure [29]. In this context, technologies capable of enhancing the efficiency of diagnosis, treatment, and continuous patient monitoring—as well as optimizing the allocation of medical resources—are especially in demand.

It is expected that the integration of mobile solutions into clinical practice will significantly accelerate and improve the accuracy of medical interventions [30]. Automated remote monitoring of physiological parameters, combined with diverse mobile hardware–software systems, will substantially reduce the workload on medical staff—particularly in outpatient care and post-hospitalization monitoring [31].

Main application areas of m-Health technologies:

Analytics—collection and analysis of data from mobile devices and sensors to improve healthcare management and clinical decision-making.
Access to care—creation of digital platforms for patient–physician interaction, specialist knowledge exchange, access to up-to-date treatment information, and delivery of mobile telemedicine services.
Self-monitoring and prevention—use of fitness trackers, activity sensors, apps for visualizing physical activity and recovery processes, and services aimed at disease prevention through promotion of a healthy lifestyle.
Solutions for the pharmaceutical industry—“smart” inhalers and medication containers, platforms for monitoring treatment adherence, analytics for drug development and optimization, and systems to combat counterfeit products.
Tools for healthcare institutions—diagnostic software (for detecting diseases and injuries), mobile patient support applications, and clinical decision-support systems for physicians.

Equipment Requirements.

Although mobile technologies are most commonly associated with consumer devices—smartphones and tablets—their use in healthcare facilities requires compliance with specific standards. One key requirement is equipment resistance to aggressive disinfectants, essential for preventing nosocomial infections.

An example of compliance with these requirements is the rugged mobile devices from Motorola Solutions—smartphones, tablets, and data collection terminals designed for operation in extreme conditions. These devices are already successfully deployed across various industries, including healthcare, demonstrating their reliability, functionality, and adherence to medical standards [32].

6. Smart Clothing, Photonics, and Mobile Health Technologies

Modern technologies are ushering in a qualitatively new stage in the digitalization of healthcare, rapidly evolving and transforming approaches to diagnosis, treatment, and prevention. Ignoring this trend may result in the loss of strategic advantage for both public institutions and private companies operating in sectors adjacent to healthcare. This refers to personalized m-Health, based on the principle of continuous real-time monitoring of physiological parameters.

Within the framework of m-Health technologies and through the use of smart clothing, it becomes possible to measure a wide range of biometric parameters—from heart rate to blood oxygen levels and physical activity.

For instance, the study by Sobotnicka et al. [33] focuses on implementing a virtual care model in primary healthcare settings. Remote patient monitoring was conducted using the S-Patch EX biosensor to detect clinical signs of cardiovascular diseases. Results showed that arrhythmia was detected with significantly higher probability in the remote monitoring group compared to the standard observation group.

The article by Hassain et al. [34] presents a concept of digital sensing modules for noninvasive and continuous monitoring of critical physiological parameters—cardiovascular, respiratory, and musculoskeletal activity. The proposed solutions integrate advanced technologies: electrocardiography, impedance cardiography, electromyography, and Doppler flowmetry for blood flow assessment.

An innovative IoT-based (Internet of Things) development [35]—Smart Medicine Box—is designed for medication management and health monitoring of elderly patients. The device features medication intake reminders and ensures safety, efficacy, and data protection. Built on affordable components—Arduino Nano, Wi-Fi module, and a sensor suite (temperature, pulse oximeter, accelerometer)—it transmits data wirelessly to the cloud, enabling continuous monitoring and early detection of emergencies. The use of the HTTPS protocol (via the ESP8266 module) ensures secure data transmission, while the SIM800L module provides backup communication in case of power failure or network outages.

Photonic technologies are increasingly being employed for health status data collection [36, 37]. Unlike traditional electronics, where electrical current serves as the information carrier, photonics utilizes photon flow. This enables higher signal processing speeds and a greater degree of component miniaturization.

As discussed, both electronic and photonic pathways offer distinct advantages for integration into smart clothing. A comparative analysis of their core principles, capabilities, and limitations is presented in Table 1.

Table 1
Key technological comparisons between electronic and photonic smart textiles

Criterion/aspect	Electronic (traditional/flexible) technologies	Photonic technologies
Principle of operation	Based on measuring electrical signals (ECG, EMG, impedance).	Based on optical methods (spectroscopy, tomography).
Main diagnostic methods	Electrocardiography (ECG), impedance cardiography (ICG), electromyography (EMG).	Photoplethysmography (PPG/rPPG), optical coherence tomography (OCT), fluorescence spectroscopy, multispectral imaging.
Integration into fabric	Printed circuits, conductive threads, thin-film flexible sensors (based on ALD—atomic layer deposition).	Thin-film organic light-emitting diodes (OLEDs), fiber optics, vertical-cavity surface-emitting lasers (VCSELs), nanosystems for spectral analysis.
Advantages	- Relative technological maturity. - Well-developed signal analysis methods. - Effective for monitoring electrophysiological processes.	- High signal processing speed. - High degree of component miniaturization. - Noninvasiveness and capability for contactless measurements (rPPG). - Capability for deep tissue probing (OCT). - Broad spectrum of analyzable parameters (oxygenation, tissue composition, blood flow).
Disadvantages/limitations	- Sensitivity to electromagnetic interference. - Usually require skin contact. - Limited information on the biochemical composition of tissues.	- Complexity of processing optical data (scattering in tissues). - Higher cost of components (e.g., VCSEL). - Dependence on medium transparency/properties.
Application examples in smart clothing	- Electronic vest with sensors for nanorobot navigation and diagnosis of motor impairments. - S-Patch EX sensor for detecting arrhythmias. - Systems with ECG/EMG sensors.	- DermaGlow—a wearable multispectral skin analyzer. - VCSEL-based systems for wearable tomography (“patch”). - Mobile applications with rPPG (e.g., “comestai”) for measuring pulse and SpO_2 via camera.
Role in personalized medicine	They provide continuous monitoring of physiological functions (heart rhythm, muscle activity, respiration).	They allow tracking of biochemical and morphological changes in tissues (metabolism, microcirculation, pigmentation), which is critical for early diagnosis.
Development prospects (synergy)	Development toward flexibility, stretchability, and energy efficiency (e.g., through ALD technologies).	Scaling power and efficiency (VCSEL), creation of integrated photonic chips for wearable diagnostics.

A notable example is presented in the work by Zuccotti et al. [38], which combines data from reference devices with remote photoplethysmography (rPPG). Using a smartphone's front-facing camera and the "comestai" application, facial video recordings are captured to extract vital signs. Results confirm that such contactless mobile applications can become an accessible and convenient tool for everyday health monitoring.

Traditionally, optical spectroscopic devices such as commercial colorimeters have been used to assess skin condition. However, they are expensive, do not support continuous monitoring, and exhibit variable accuracy depending on skin tone. The article by Hamid et al. [39] presents a solution to this problem—DermaGlow, a wearable multispectral system designed for low-cost, noninvasive, and continuous monitoring of melanin, erythema, and skin tone—regardless of skin pigmentation.

Fluorescence spectroscopy methods enable the detection of pathological processes in biological tissues associated with shifts in metabolic homeostasis and biochemical alterations [40].

Recent advances in imaging—particularly in optical coherence tomography (OCT/OCTA) and adaptive optics—allow for the identification of microvascular and neurostructural changes with micrometer-level resolution. However, the true breakthrough lies in the integration of AI. Deep learning models trained on large retinal datasets have already achieved, and in some cases surpassed, expert-level performance in diagnosing diabetic retinopathy [41, 42], age-related macular degeneration, and detecting markers of cardiovascular risk [43, 44].

Further development of photonics is linked to scaling the power and efficiency of semiconductor lasers, especially vertical-cavity surface-emitting lasers (VCSELs) [45]. In biomedical applications, such lasers enable deeper tissue penetration—in OCT systems, visualization depths exceeding 3 mm are achievable with resolutions below 5 µm [46].

A study by Zhang et al. [47] presents a programmable multi-element infrared VCSEL source on a chip—a compact photonic module for rapid raster scanning. The technology enables continuous reconstruction of dynamic objects with 100 µm resolution and frame rates exceeding 15 Hz—applicable to both moving objects and stationary objects with changing optical properties. Integration of the multi-point VCSEL source with CMOS (complementary metal–oxide–semiconductor) cameras represents a key step toward developing wearable, monolithic "skin patch"-type imaging devices for mobile patients.

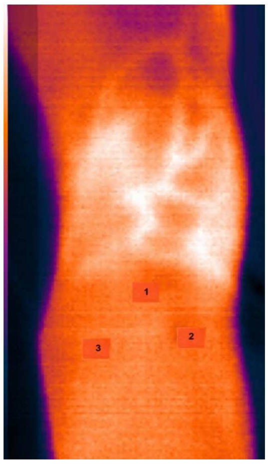
Traditionally, medical practice has evolved within a static model, assuming patient isolation in hospitals, clinics, or rehabilitation centers. However, as a biosocial system, a human being continuously interacts with a changing external environment. Therefore, transitioning to a dynamically adaptive model of medical intervention—one oriented toward the patient's natural living conditions—is no longer merely possible, but essential [48].

Effective implementation of such a model requires continuous assessment of external and internal factors affecting the body, incorporating real-time geospatial parameters. It is precisely these requirements that modern m-Health solutions integrated into smart clothing are designed to meet.

Today, the most promising technologies include thin-film and aerosol coatings, including organic light-emitting diodes (OLEDs) fabricated via atomic layer deposition (ALD). These heterogeneous functional systems are capable of performing both diagnostic and therapeutic functions.

Prototypes of m-Health systems based on flexible micro- and nanoelectronics have already been developed (Figure 2) [49].

Figure 2
Placement of active thin-film biosensors (1, 2, 3) for remote monitoring of the knee joint (infrared image, 7.2–13 µm, copyright image)



The device architecture is based on nanostructured films deposited via ALD onto flexible polymer substrates—such structures are considered the foundation for personalized wearable electronics, such as electronic vests [50].

The m-Health hardware–software platform is implemented as an information architecture with remote web access, providing a unified interface for interaction in both local and global computing environments.

The operation of ALD-based structures (particularly OLED components) is supported by self-learning algorithms based on artificial neural networks. Integration of heterogeneous sensor systems with neural network algorithms enables automatic classification of physiological parameters, adaptive filtering, recognition, and interpretation of biomedical signals and images. This, in turn, allows for the construction of predictive health models with continuous real-time data updates.

7. Smart Clothing Prototypes by the Kosh-Kort Engineering and Technology Group

The noninvasive diagnostic technology implemented in smart clothing was developed based on an inertial thermophotogrammetric stereoscopic visualization system. Initially, this system was used to identify archaeological objects in soil and to study human physical fields. Following the successful demonstration of multispectral technologies on historical and cultural heritage objects, it was proposed to adapt them for medical purposes—specifically, for tracking the trajectory of a medical nanorobot prototype being developed by the Kosh-Kort engineering and technology group. An electronic vest with embedded components served as the platform for reference measurements. This prototype was designed to provide high-precision 3D navigation and control of the nanorobot's movement inside the human body. As part of the research, an original design for the nanorobot's outer shell was also developed.

The vest was developed at the Laboratory of Information Technologies in Humanities and Natural Sciences of Saratov State University (led by Rustam Singatulin) in collaboration with the Department of Medical Devices and Technologies at Saratov State Technical University (led by Piter Plotnikov).

The vest operates on the principle of stereophotogrammetric methods, enabling measurement of the patient's body position across various spectral ranges. External webcams operating in infrared and visible spectra, along with specialized software algorithms, are used for this purpose (Figure 3). The technology has been successfully applied in diagnosing: motor impairments following stroke and traumatic brain injury, degenerative and hereditary neurological disorders, cardiological pathologies (as a visual diagnostic tool), musculoskeletal pain syndromes, and other deviations.

The first-generation diagnostic system prototype (2012–2016) enabled automatic spatial orientation of camera-captured objects (body or body parts) within a coordinate system by matching them with reference fragments from a database. This was achieved using stereo-matching algorithms capable of analyzing images with varying geometries.

The system was designed to detect the following types of motor patterns:

1) Typical—smooth, occurring during continuous movement;
2) Suboptimal—compensatory synkineses in the spine and limbs;
3) Atypical—accompanied by extraneous movements, distorted trajectory, or altered velocity;
4) Other deviations in motor activity.

The vest's configuration included a mobile device with 3G/4G, GLONASS (Global Navigation Satellite System), and GPS support, embedded sensors, LED markers, and other electronic components. Power was supplied by silver-zinc batteries (SZD-12). Key advantages of the prototype include low cost, high measurement accuracy, process automation, ease of use, and real-time diagnostic capability.

In the second and third generations of smart clothing, textile materials from Shaoxing Yunjia Textile Product Co., Ltd. were used as the base. In the latest developments—particularly in the creation of a smart jumpsuit—experimental fabrics based on hybrid carbon fiber were employed, using a production technology originally developed in the USSR (the Union of Soviet Socialist Republics).

The newest next-generation prototype is designed for operation on 5G/6G networks and is fully personalized for each user. The methodology for designing clothing with integrated wearable technologies is developed individually, taking into account the specific anatomical and physiological parameters of each person. The heterogeneous m-Health system, combined with a neural network, automatically selects classification features based on personalized biometric data. The process of applying functional coatings via ALD is carried out using a self-learning system comprising a user model, a neural network, and a 3D printer.

Figure 3
Personal remote noninvasive escort system of the first generation (2016). Patient visualization on the map and in web-escort mode (copyright image)

The smart jumpsuit consists of five functional layers:

1) Shielding layer—fabric with silver fibers to protect against external electromagnetic interference.
2) Cotton layer—ensures comfort and hygiene.
3) Contact layer—contains OLEDs for visualization and feedback.
4) Compensating (centering) layer—stabilizes sensor positioning relative to the body.
5) Perforated layer—provides ventilation and heat dissipation.

During operation, the system generates a three-dimensional data array reflecting the user's movement dynamics and physiological parameters. Remote visualization is performed in real time, and 3D identification of individual characteristics enables the construction of predictive health models with continuous adjustment [51]. In addition, the system supports collaborative research and facilitates the implementation of group synchronous learning methods using immersive technologies.

Currently, the engineering and technology group "Kosh-Kort" is conducting validation of the prototype, its scalability, and clinical trials. A fully functional smart clothing prototype is expected to be presented at one of the Asian technology exhibitions in 2027–2028.

8. Conclusion

The market for inclusive m-Health systems based on thin-film nanotechnologies and photonics demonstrates dynamic and sustained growth. The integration of big data analytics technologies with wearable medical solutions—particularly smart clothing—opens fundamentally new possibilities for personalized approaches to health, prevention, and recreation. These solutions contribute not only to treatment but also to the active improvement of quality of life, especially within the context of an emerging high-tech society.

AI plays a pivotal role in this process. Thanks to AI, it becomes possible to efficiently process vast volumes of medical data, automatically generate preliminary diagnostic hypotheses, and deliver personalized recommendations—tailored to the unique parameters of each patient. Feedback to the physical environment is implemented through two pathways: via informational alerts to physicians and patients and through automated control of therapeutic and diagnostic devices—for example, medication dosing or adjustment of physical activity levels.

Such systems operate 24/7, providing continuous monitoring and support. They are easily integrated into both local applications (e.g., on the patient's smartphone) and large-scale digital healthcare platforms—ranging from regional electronic registries to global biomedical databases.

Particular importance is now placed on developing intermediate systems—solutions positioned between the patient and the clinic. These are designed to provide personalized diagnostics, prevention, rehabilitation, and dynamic adjustment of treatment programs—even before acute conditions arise. This direction is becoming a priority within the transition from reactive to proactive medicine.

Future development prospects are tied to the deep integration of m-Health systems with medical and biological data processing centers. Such integration lays the foundation for next-generation global biomedical resources—capable of accounting not only for an individual's genetic and physiological characteristics but also their behavioral patterns, geolocation, social context, and real-time dynamics of change. It is upon this foundation that the medicine of the future will be built—personalized, predictive, preventive, and fully human-centered.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Irina Veshneva: Methodology, Software, Validation, Formal analysis, Writing – review & editing. **Rustam Singatulin:** Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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How to Cite: Veshneva, I., & Singatulin, R. (2026). Photonics in Smart Clothing for Personalized Medicine. *Journal of Optics and Photonics Research.* https://doi.org/10.47852/bonviewJOPR62027646