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Wearable Technology in Computer Science: Architecture, Edge Intelligence, Human-Computer Interaction, Security, and Research Directions in 2026

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Abstract

Wearable technology has evolved from simple tracking devices to complex embedded computational systems that integrate into bodies, clothing, clinical pathways, industrial operations and augmented environments. This review is a follow-up to earlier discussions, taking a computer science perspective in summarizing architectures, algorithms, interaction models, security risks and future directions up to the first quarter of 2026. The literature synthesises contributions across wearable sensing, IoT, edge computing, AI, machine learning, smart textiles, human-computer interaction and privacy analytics. Increasingly, the central question shifts from whether wearables can sense and compute humans' daily activities to how they can generate reliable, interpretable, secure and fair intelligence, given energy, processing, latency, comfort and trust limitations. Modern wearables are cyber-physical systems consisting of sensors, processors, networks, cloud services, ML models and interfaces that are being used for a wide range of applications including but not limited to healthcare, sports, safety, education, accessibility, rehabilitation and XR. Despite progress in many fronts, challenges remain with respect to data quality (sensor drift, bias), interoperability, batteries, cybersecurity, consent, validation and regulation. In this review, we outline the search process, evaluate the maturity of different wearable domains and set research priorities. We argue for a computer science agenda that tackles edge AI, federated learning, digital biomarkers, human-centered design, sustainable textiles, multimodal interaction and governance-aware software development. In the end, wearable tech represents an important, full-stack computing challenge, involving multiple layers from hardware and software to data science, HCI, ethics and security.

Keywords: Wearable Technology, Wearable Computing, Internet of Things, Edge Artificial Intelligence, Human-Computer Interaction, Smart Textiles, Computer Science

1. Introduction

A wearable is typically understood as any electronic computing system designed to be worn close to or upon the human body for purposes such as sensing, computation, communication, feedback and augmentation (e.g., Watkins & Dunne, 2015; Nasiri, 2019; Perez & Zeadally, 2021).

First-generation wearables were mainly consumer wearables such as fitness trackers and smartwatches. A rapid expansion in types and styles has taken place since at least the early days of Google Glass. By 2026, this includes not only many consumer products, including smart glasses but also products such as smart rings, patches and earbuds, textile sensors, rehabilitation exoskeletons, continuous glucose monitors and wearable electrocardiography devices, augmented reality headsets, electronic textiles and implantable systems. At the core of wearables lie a variety of long-standing computing challenges. These, including dealing with noisy signals from the real world, handling multiple data streams, performing local processing and communication with cloud services while maintaining appropriate security protocols and presenting information and data in an accessible manner, must happen within a single, often small, constrained environment. This can require maintaining battery life, ensuring comfort during extended periods of wearing and facilitating everyday use without disrupting one's activities. The constraints on wearables create a need to rethink traditional desktop, mobile and cloud computing approaches and to recognize that the human body, rather than some fixed location, can become the focal point of computing. This is inherently contextual and intermittently operational and always personal.

New studies by Kumar et al. (2025), Xi et al. (2025) and Zhang et al. (2025) demonstrate the dramatic influence of artificial intelligence, edge computing and emerging smart materials on wearable technologies. Their expanding roles in chronic disease management, remote health monitoring, rehabilitation, sports performance enhancement, mental health screening and workplace safety highlight evolving needs for data analytics and user experience. Privacy-preserving data analytics is an important area, especially as wearable data integrates with augmented reality interfaces. Given the escalating use of wearable devices for real-world applications, there is a pressing need to critically examine their development and implementation beyond the hardware level. As AI models become more key to diagnosis, treatment and risk assessment, regulatory bodies and developers must prioritize thorough

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testing to ensure safety, efficacy and transparency while addressing ethical and cyber security concerns and ensuring appropriate human oversight. This essay moves beyond the 'myth' of the wearable as a device, presenting a revised conceptualisation of wearable technologies as socio-technical networks underpinned by infrastructure, software, data flows and forms of governance, with their future progress and utility resting as much on reliability and ethicacy as on innovative technical capabilities or novel applications.

2. Method and Scope of the Review

2.1 Review Design

This manuscript presents a narrative review design rather than a formal systematic review or meta-analysis for which narrative synthesis is also typically utilized due to subjectivity. In order to maintain clarity and minimize the subjective nature of our narrative synthesis, we adhered to principles outlined in transparent documentation guidelines such as those provided in SANRA and PRISMA (Baethge et al., 2019; Page et al., 2021). Specifically, we outline search sources and parameters, eligibility criteria and the boundaries of our narrative synthesis. The current manuscript aims to present research directions related to wearable technology within computer science that spans wearable architectures and design, sensing, edge intelligence, human-computer interaction, cybersecurity, fairness and interoperability, as opposed to a thorough systematic review or meta-analysis which would involve identifying, appraising and synthesizing research evidence according to a pre-defined protocol, aiming to systematically and objectively pool and analyze the aggregated intervention effects.

2.2 Information Sources and Search Strategy

This article uses a narrative review rather than a formal systematic review or meta-analysis. We used the transparent documentation protocols of SANRA for narrative reviews (Baethge et al., 2019; Page et al., 2021) to partially mitigate potential biases associated with narrative synthesis, including descriptions of search resources, inclusion/exclusion criteria and boundaries for synthesis. We aimed to incorporate perspectives from computer science on topics like wearable architecture, sensing, edge intelligence, human-computer interaction, security, fairness, interoperability and research directions. This approach did not estimate pooled intervention effects.

2.3 Eligibility and Selection Logic

All forms of literature and evidence focused on or related to wearable and/or near-body systems, including sensor architectures, signal processing and embedded/analytics (including edge analytics) were considered, with a particular emphasis on the implementation and application of these in AI-enabled health wearables and rehabilitation wearables, as well as on smart textiles generally. A broad range of articles, including journal and conference articles, systematic and scoping reviews and reports, regulatory guidance and detailed surveys were included. Articles deemed to be non-technical in nature (such as promotional materials), those that do not clearly consider wearable systems and their integration and those with weak product performance claims without good quality evidence were excluded. This review also does not perform an exhaustive search of databases, undertake independent duplicate screening, carry out a formal risk-of-bias scoring or a PRISMA flow diagram as it aims to provide a rationale for the sources chosen in order to maintain the balance across many different disciplines, e.g., architectural, AI, HCI, security, health, textile and governance literature, etc., so as to avoid confirmation bias as much as possible.

2.4 Treatment of Foundational and Older Sources

Older sources were preserved only if they offered definitional, historical, or architectural insights. Lane et al. (2010) help situate the concepts of mobile sensing and smartphone gateways that influenced early wearable ecosystems. Sfairopoulou et al. (2016) and Sun et al. (2016) are kept to illustrate earlier assumptions in IoT and smart communities, rather than as standalone evidence for the 2026 field. Therefore, current assertions about AI-enabled wearables, edge intelligence, smart textiles, privacy, fairness, security, and regulation are primarily based on literature from 2021 to 2026.

2.5 Synthesis Approach and Limitations

A topical structure is used to explain the content, aligning with the wearable computing stack from sensing hardware to application areas (embedded systems, IoT connectivity, edge analytics, cloud analytics, AI models, HCI, security, privacy, governance). The strength of the evidence reported is assessed qualitatively using several factors such as the recency of the publication, technical depth of the content, validation techniques (simulated/synthetic/real) and relevance to the field as well as the applicability to real-life deployments. It is worth noting that the narrative synthesis method has a key limitation in that it may not cover all relevant studies and their corresponding effect sizes, within diverse wearable domains. This limitation is mitigated by explicitly highlighting any difference in field maturity and by avoiding unsubstantiated comparisons in terms of clinical equivalence between consumer systems and medical-grade devices.

3. Conceptual Clarification and Taxonomy of Wearable Technology

3.1 Defining Wearable Technology

Wearable technology is a computer-sensing, computing, communication and feedback system that is worn on the body or is a key part of a human activity space. This definition does not mean that something is wearable simply because it is worn on the body. For example, a conventional wristwatch is worn on the body but it is not a wearable computer. A wearable computer is a device that has digital components to enable digital sensing, processing, communication, feedback or decision support in automated or semi-automated systems. Earlier definitions have relied on shape or size. For example, the definition of "wearable computer" includes systems worn on the body or integrated into clothing (Watkins & Dunne, 2015; Baskan & Goncu-Berk, 2022). These definitions are useful but they are not sufficient for computer science, which requires a definition of the sensing, processing, communication, feedback or decision-making actions that take place in the wearable device. A more complete definition of wearable technology includes wearable system design, which includes sensors, built-in computing, firmware, communication, power, cloud or edge computing, machine learning, user interface and security. Wearable technology serves as a physical example of common computing, mobile sensing, cyber-physical systems and human-computer interaction.

Also, wearables are also considered as intimate technologies (Zhang et al., 2025). Wearable devices collect user data, such as movement, skin response, heart rate, location, voice, temperature, sleep pattern, posture, attention or clinical biomarkers. So, the data collected are considered to be more personal than other types of mobile data as it reflects user's behavior and physiological condition. Wearable computing is technically valuable but ethically sensitive.

3.2 Classification of Wearable Technology

Wearable devices may be classified by form factor, function, sensor modality, interaction mode, and deployment domain. A useful taxonomy for computer science research is presented in Table 1.

Table 1. A computer science-oriented taxonomy of wearable technology.

Class	**Examples**	**Primary Computing Functions**	**Key Research Concerns**
Wrist-worn devices	Smartwatches, fitness bands, sports watches	Activity tracking, notification, biosignal capture, mobile interaction	Battery life, measurement validity, user adherence, cross-platform data exchange
Ring, ear, and patch devices	Smart rings, earbuds, ECG patches, skin patches	Continuous sensing with low user burden	Miniaturization, thermal comfort, signal quality, secure pairing
Head-worn and vision devices	AR glasses, VR headsets, smart glasses, eye trackers	Spatial computing, immersive interaction, gaze and gesture sensing	Latency, usability, safety, and privacy of cameras and microphones
Smart textiles	Sensor-embedded garments, smart insoles, conductive fabrics	Long-duration physiological or motion sensing integrated into clothing	Washability, durability, energy harvesting, and scalable manufacturing
Medical and rehabilitation wearables	CGMs, wearable ECG, gait systems, exoskeletons	Monitoring, risk prediction, therapeutic support, and rehabilitation feedback	Clinical validation, interoperability, safety, and regulatory classification
Industrial and occupational wearables	Safety helmets, posture sensors, fatigue monitors, and location badges	Worker safety, ergonomic monitoring, hazard alerting	Surveillance risk, consent, and reliability in harsh environments

Implantable or near-implantable systems	Neural interfaces, biochips, implantable monitors	Long-term physiological monitoring and closed-loop intervention	Biocompatibility, cybersecurity, ethics, and medical governance

4. Evolution of Wearable Technology and the 2026 Context

The history of wearable technology shows a change from the use of tools on the body to computing systems on the body. Examples from the past include eyeglasses, mechanical watches, portable radios, hearing aids, calculator watches, pacemakers and early head-mounted displays. People have been using the human body as a place for technology for thousands of years. The modern phase of this change in use began when sensors, wireless communication, smartphones, cloud services and apps came together, enabling wearables to join digital systems. Wearables during the 2010s era became common for consumer fitness, smartwatches and early augmented reality projects (Choi et al., 2016; Shin, 2018). The 2020s era is now a major time for the field, with wearables increasingly joining remote patient monitoring, clinical research, digital biomarkers, artificial intelligence-assisted decision support, smart textiles, screenless tracking devices and spatial computing. As a result, wearable technology has become a important area of research involving embedded systems, machine learning, signal processing, human-computer interaction, cybersecurity and software designing.

These three forces will influence the field in 2026 (Tedesco & Komaris, 2026; Food and Drug Administration, 2026; European Commission, 2025). First, the force of intelligence. Wearables will do more than capture data. They will classify, detect, predict, personalise and help decision making. Second, the force of proximity. Computing is moving closer to the body through edge AI, low power inference and private learning. Third, the force of governance. Once wearable data is used for health, work, insurance, education or safety decisions, the systems used must be more transparent, validated, fair and accountable.

5. Computer Science Foundations of Wearable Technology

5.1 Embedded Systems, Sensors, and Signal Processing

Wearable computing relies extensively on the availability of a variety of very miniaturized hardware components, including low-power microcontrollers, memory modules,

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communications chips, power management circuits, and, occasionally, actuators (Perez & Zeadally, 2021), as well as a diverse range of miniature sensors, such as accelerometers, gyroscopes, magnetometers, photoplethysmography sensors, electrocardiography electrodes, electrodermal activity sensors, skin temperature sensors, pressure sensors, optical sensors, microphones, cameras and biochemical sensors (Mu et al., 2025). Some wearable devices use smart textiles to embed conductive fibers, stretchable electrodes, pressure-sensitive fabrics, energy-harvest

Raw wearable data is rarely clean. Various factors including motion artifacts, skin contact, sweat, light conditions, sensor placement, ambient noise and inter-subject variability can affect data quality. Therefore, signal processing plays a critical role in wearables. Algorithms are used to remove noise, segment signals, identify features, recognize anomalies, reduce signal length and combine information from different sensors and modalities. Some IMUs are calibrated to perform correct gait analysis; others have to be compensated for motion when they measure HR optically; and some textile sensors have to be recalibrated after bending or washing. Overall, these issues make wearable sensing less about the hardware but rather a matter of data quality. Recent investigations into smart textiles show that whilst sensors woven into fabrics allow for long-lasting comfort and durability, they still face difficulties in longevity and data interpretation (Ahmed et al., 2025; Dejene, 2025). There are several parameters which can be recorded using these flexible and stretchable textile sensors, including heart rate, breathing frequency, pressure distribution, pose and movement, among others. Yet, such sensors could be compromised by mechanical effort, washing and environmental impacts. Overall, for computer scientists, this highlights the requirement to develop more strong wearable systems that come equipped with algorithms that effectively handle the presence of uncertainty, sensor drifts, missing information and field shifts.

5.2 IoT Connectivity and Wearable System Architecture

Wearable sensors are key elements of the Internet of Things (Sfairopoulou, 2016; Sun, 2016; et al). A wearable ecosystem consists of a body-worn device (wearable), a gateway (such as a smartphone or an edge node), a local hub and cloud services consisting of data repositories, analytics engines, application programming interfaces and dashboards that present information to users, clinicians, etc. These components communicate through protocols such as Bluetooth Low Energy for device-to-phone communication, as well as Wi-Fi, cellular networks and low-power wide-area technologies for Internet connectivity; both direct and indirect connectivity options are prevalent. The design should carefully consider constraints of latency, bandwidth, reliability and privacy, as well as energy consumption. Whereas continuous streaming of raw sensor data into the cloud enables more advanced analysis, it also increases battery consumption and exposes privacy risks. Also, though local preprocessing can decrease the network traffic and avoid transfer of sensitive information, wearable processors have limited ability for that purpose. More often than not, some type of hybrid model is implemented where the wearable device does sensing as well as some lightweight preprocessing, while the mobile phone or an edge device can do intermediate analytics before streaming results into the cloud for services that include long-term storage, model training, visualization and population-level analysis.

As a result, interoperability has emerged as a major concern. Wearables often rely on proprietary data representations and platform-specific health clouds. This hinders cross-device studies, clinical adoption and the long-term interoperability of the acquired data. These challenges have led to a range of solutions in computer science, including open APIs, standardized data representations, semantic interoperability, secure consent models and protocols for privacy-preserving data sharing. The remaining references to IoT and mobile-sensing technologies in this subsection reflect their inclusion in the document for bounded historical purposes. The discussion of Lane et al. (2010) provides the historical setting of the mobile-sensing lineage that established smartphone gateways as the centerpiece of wearable-based systems. Likewise, the references to Sfairopoulou et al. (2016) and Sun et al. (2016) provide insights about the architectural assumptions in earlier IoT deployments. Therefore, they are not considered as sufficient evidence for design practices in 2026 but as a baseline to draw comparison with the new requirements imposed by edge-AI, privacy, interoperability and governance.

5.3 Edge AI, TinyML, and Wearable Analytics

One of the most exciting areas for wearable computing recently involves the fusion of artificial intelligence and edge computing (Xi et al., 2025; Shi et al., 2025). Also known as edge AI, the models can execute close to the sensor and do not need to run fully on remote cloud servers. This trend continues with TinyML on microcontrollers and ultra-low-power devices. In wearable systems, these techniques allow for real-time inference, reduced latency, lower communication, improved energy efficiency and higher data privacy because raw data can be kept closer to the user. AI models in wearables provide a wide range of useful features for

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users, from activity recognition to sleep staging, fall detection, stress estimation, arrhythmia detection, glucose concentration forecasting, gait assessment, respiration rate tracking, gesture classification and outlier detection. While deep learning approaches learn sophisticated representations of the signals but are usually computationally expensive and not straightforward to explain. To tackle these challenges, several techniques such as tiny architectures, quantization, sparsity pruning, model quantization and distillation, feature learning and adaptive sampling are introduced to accelerate inference for resource-constrained devices.

Wearable technologies in healthcare provide examples of the promise and pitfalls of AI analytics (Fraser et al., 2025; Kumar et al., 2025).

Recent reviews show AI-enabled wearables hold value in supporting diabetes management, chronic disease surveillance, rehabilitation and personalised interventions. Accuracy and reliability of AI outputs however depend on several needed factors including generalisable data sets, clinical validation, model explainability and robustness to real-world deployment scenarios. A model that is shown to perform well in laboratory settings may not generalise to the real-world due to variations in physical parameters, physiology, operational or environmental conditions.

5.4 Human-Computer Interaction and Multimodal Interfaces

Wearable technology can change the interface between humans and computers, writes Hughes and Karwowski (2025). Unlike laptops and smartphones, wearables are often characterised by the frequency and duration of the communication between humans and computers, which relies on brief glances, vibrations, voice interactions, gestures, gaze and body postures or even ambient feedback. As a result, the topic of human-computer interaction (HCI) is especially important when designing wearables. The right information has to be conveyed at the right time and in the right way without causing distraction or mental load. Smartwatches and bands are characterised by touchscreens and buttons, haptic feedback and voice commands. Smart glasses and head-mounted displays use gaze tracking, spatial gestures, speech recognition, object recognition and augmented reality overlays. Smart rings and textile sensors may offer new ways of inputting information without having screens. Finally, when designing extended reality wearables, designers have to consider a range of extra factors such as field of view, depth perception, fatigue, motion sickness, the privacy of bystanders and social acceptability of wearing camera-enabled devices in public spaces.

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As stated in Hughes and Karwowski (2025), it is needed to assess various natural interaction modalities used in AR, especially regarding their influence on user experience and on setting-sensitive interface design. In wearable HCI, it is not about augmenting the body but optimizing it, i.e., making the wearable's features congruent with the user's state, the task, the environment and the body. A good wearable interface should be glanceable, interrupted, accessible, explicable and considerate towards the user's attentional resources.

5.5 Security, Privacy, and Trust

Wearables can collect data about the individual's health status, movement patterns, work behavior, emotional state, sleep quality, location, social routines and biometric identity (Zhang et al. 2025). This data exposure creates important cybersecurity and privacy risks including unauthorized device access via insecure Bluetooth pairing, data leakage due to cloud misconfiguration, model inversion, inference attacks (e.g., location tracking, re-identification of anonymized data), manipulation (e.g., altering sensor readings) and malicious firmware updates. Considering the sensitivity of wearable data, security should not be an afterthought but should be incorporated into the design process from inception. All security considerations must span the whole lifecycle of device and software development and include basic controls such as secure boot mechanisms, encrypted data storage, secure communication protocols, authenticated device pairing and role-based access control. Also, privacy-preserving data aggregation, vulnerability disclosure processes, software bill of materials, patch management policies and user-accessible consent options are also needed. The need for governance may be particularly pressing for wearables that operate in clinical or workplace environments, where the wearable's data is relevant to more stakeholders.

According to the latest analysis, a serious threat comes from these devices. It happens because wearables provide various types of biological information to mobile devices via internet or cloud services and they might also offer therapy (Zhang et al., 2025). In the case of health monitoring wearables, a security breach can endanger both privacy and safety of the user. Therefore, it is required that the technology is very trustworthy and the usage, management and protection of user data comply with current regulations and do not confuse medical guidance with wellness.

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Table 2 summarizes the wearable computing stack and the main computer science contributions at each layer.

Table 2. Wearable computing as a full-stack computer science system.

Layer	Typical Components	Computer Science Contribution	Common Failure Points
Sensing layer	IMUs, PPG, ECG, temperature, pressure, chemical, optical, textile sensors	Signal processing, sensor fusion, calibration, noise filtering	Motion artifact, drift, poor placement, missing data
Embedded layer	MCUs, firmware, operating systems, energy management	Embedded software, real-time scheduling, low-power design	Battery drain, overheating, firmware bugs
Connectivity layer	BLE, Wi-Fi, cellular, NFC, device pairing	Protocols, secure communication, synchronization	Latency, dropped packets, insecure pairing
Edge and cloud layer	Phone gateway, edge node, cloud APIs, data lakes	Distributed systems, storage, data pipelines, orchestration	Vendor lock-in, interoperability gaps, privacy leakage
AI and analytics layer	Activity models, risk prediction, anomaly detection, personalization	Machine learning, model compression, federated learning, explainability	Bias, overfitting, model drift, weak validation
Interaction layer	Haptics, displays, voice, AR overlays, dashboards	HCI, accessibility, UX evaluation, adaptive interfaces	Alert fatigue, distraction, poor accessibility
Governance layer	Consent, audit logs, regulatory documentation, risk controls	Secure software engineering, data governance, compliance	Unclear ownership, weak accountability, inadequate post-market monitoring

6. Application Domains

6.1 Healthcare, Rehabilitation, and Digital Biomarkers

The most important applications for wearables are related to healthcare, as described by Kumar et al., (2025) and Tedesco & Komaris (2026). They can continuously track a range of parameters, from blood glucose to arrhythmias to oxygen saturation, sleep quality, gait, recovery progress, drug adherence and stress levels, enabling the remote monitoring of patients. AI-powered wearables then transform these raw data streams from sensors and devices into a set of digital biomarkers (DBs) that generate alerts or personalized suggestions for decision-making support. For conditions such as diabetes, as Fraser et al., (2025) showed, devices like continuous glucose monitors and fitness trackers can combine real-time physiological metrics with behavioral data and AI modeling to better manage glucose variability and insulin therapy, enhancing daily self-management and reducing complications. Recent systematic reviews highlight challenges such as limited demographic representation, inconsistent performance metrics, divergent data sources and quality and insufficient model explainability, factors that impact both computational and clinical aspects. Rehabilitation wearables combine motion sensors, feedback, robotics and artificial intelligence (Xi et al., 2025). Those that use edge computing can watch how well you move, calculate joint angles, identify compensatory motion and customize therapy. In low-resource areas, rehabilitation wearables may reduce the need for multiple clinic visits. They need to be affordable, easily maintained and tested in the clinical setting.

6.2 Sports, Wellness, and Performance Analytics

In sports, wellness and training, wearables monitor everything from training load to sleep patterns, recovery processes, heart-rate variability, running biomechanics, fatigue levels, hydration status and injury risk. However, such systems' value is determined by how interpretable and dependable their metrics are. The actual value of the numbers does not lie in the metrics themselves - heart-rate zone, sleep score, readiness score - but are derived information that involves choices around sensor selections, preprocessing methodologies, model assumptions and variations among individual users. In reality, what has emerged is that sports wearables act more as a testbed for computer science research into themes such as real-time analytics, sensor fusion, personalization and feedback design for behaviour change. That means inaccuracies in data can lead to inaccurate designs that influence user behaviour.

Therefore, developing wearables requires attention to uncertainty, data provenance and evidence-based claims.

6.3 Education, Work, Safety, and Accessibility

Wearables are being developed and deployed in a variety of sectors. In education, wearables such as augmented reality glasses and smartwatches provide learning-enhanced experiences and new interfaces for improving interactive learning experiences through games and simulation-based technical training. In industrial safety, wearables such as hard hats, badges and sensors to measure posture and fatigue and environmental sensors improve worker safety and reduce accidents through better ergonomic safety standards and accident prevention. For accessibility, wearable devices provide navigation support through sensory substitution or communication assistance, fall detection and assistive feedback to users in need. Despite the benefits of these technologies, they also raise vexing considerations related to humans and society. While a safety wearable may improve the overall safety of workers, it may also be used as an instrument of surveillance; while a classroom wearable may lead to enhanced learning experiences, it may also collect sensitive data from minors; while a mental wearable or emotion-recognition wearable may assist users, it may infer their internal states without explicit consent. The development of wearables demands new thinking about computer science design through policy-aware architecture (including privacy by design) and human-centered evaluation for technology development.

7. Emerging Trends Shaping Wearable Technology to 2026

Table 3 highlights the major trends now shaping wearable technology and the corresponding computer science questions that need further investigation.

Table 3. Emerging wearable technology trends and research problems to 2026.

Trend	Technical meaning	Opportunity	Open research problem
Edge AI and TinyML	Inference and preprocessing move closer to the sensor	Real-time response, lower latency, better privacy	Model compression without loss of safety or fairness

Federated and privacy-preserving learning	Models learn across distributed devices without centralizing raw data	Improved personalization and reduced data exposure	Handling device heterogeneity, adversarial clients, and auditability
Smart textiles and self-powered systems	Sensors and energy harvesting are integrated into fabrics	Comfortable long-term monitoring and sustainable power	Durability, washing, calibration, and scalable production
AI-enabled digital biomarkers	Physiological and behavioral streams become computable indicators of health states	Earlier detection and individualized monitoring	Clinical validity, explainability, and bias control
AR and spatial wearables	Wearables become part of spatial computing and ambient interfaces	Hands-free work, training, telepresence, and assistive overlays	Attention management, privacy of bystanders, and safe interaction
Regulated AI wearables	Medical and high-risk systems face stronger evidence and governance requirements	Safer clinical deployment and public trust	Lifecycle monitoring, post-market updates, and transparent claims
Sustainable and inclusive design	Devices are evaluated for repairability, lifespan, accessibility, and demographic fairness	Broader adoption and reduced environmental harm	Testing across diverse users, contexts, and climates

The most prominent trend from the articles is moving from passive tracking to active inference. The first wearable devices only recorded the user's steps and allowed notification alerts. In contrast, modern wearables recognize patterns and states, then provide recommendations. This trend raises expectations for evaluation, as incorrect suggestions can cause important problems in areas like health and safety. A second trend is the development of unobtrusive wearables without screens. The use of rings, bands, patches, earbuds and sensors embedded in clothing could reduce screen time and increase user comfort and compliance. However, the design of feedback becomes more complex due to the limited nature of the interface and the potential need for a separate screen. A third trend is the emergence of sustainable and self-powered smart textiles. The collection of energy from motion, heat and biochemical signals could reduce the need for frequent charging. These wearables could be particularly useful for long-term health monitoring and occupational safety. However, their reliability would depend on advances in materials science, embedded systems and adaptive signal processing models.

The fourth is the growth of interest in regulated software designing. AI-enabled medical devices and health wearables are now scrutinized for performance metrics, risk management, data quality, human oversight, transparency and lifecycle monitoring. The US FDA keeps a list of AI-enabled medical devices. Many medical AI systems are classified as high-risk in the EU AI Act, which requires risk mitigation, data quality, information transparency and human oversight (FDA, 2026; European Commission, 2025; Gilbert et al., 2024). These changes mean compliance, documentation and lifecycle monitoring have become needed aspects of wearable software designing.

8. Challenges and Research Gaps

8.1 Data Quality, Validation, and Benchmarking

The accuracy of wearable data depends on user behavior and the environment. For example, the accuracy can be influenced by the wear location, the fit, user activity, sweat, ambient temperature, skin color, lighting and sensor drift. Some studies have small datasets, test under controlled conditions or use subjects of similar demographics. To further promote validity, we need to create public benchmarks, standard evaluation techniques, cross-validation experiments across devices and uncertainty-estimating models. We should also distinguish between medical and wellness applications. A wellness score may be useful in triggering personal reflections but a medical application needs stronger evidence. Systems claiming medical benefit should be evaluated for sensitivity, specificity, false positives, false negatives, clinical utility and safety.

8.2 Bias, Equity, and Inclusive Design

Algorithmic bias in wearable computing should be viewed as a quantifiable feature of a system, rather than merely as a broad ethical issue. Models for wearable technology should provide full

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performance reports detailing both overall performance and performance across a variety of subgroups including but not limited to, age, sex, gender, skin tone, body size, disability status, disease status, device placement, occupation, climate and geographic setting. Full reports should detail subgroup sensitivity, specificity, precision, recall, F1 score, AUROC, AUPRC, calibration error, demographic parity difference, equal opportunity difference, equalized odds difference, false-positive-rate gaps, false-negative-rate gaps, predictive parity and worst-group error (Hardt et al., 2016; Bellamy et al., 2019; Bird et al., 2020), as long as these have been gathered ethically and lawfully.

Fairness testing must be tailored to each specific sensing modality: for photoplethysmography, subgroup analysis should cover differences in skin tone and perfusion as well as differing patterns in movement artifacts and ambient light conditions, as well as factors related to sensor contact quality. For gait and rehabilitation wearables, assessments should include users with assistive devices and/or specific neurological conditions, as well as diverse body sizes, on different walking surfaces. For occupational and educational wearables, fairness evaluations should distinguish between model errors and other contextual factors, such as network quality, climate conditions, access to charging and phone compatibility. In reporting, simply providing an overall average accuracy is insufficient because it does not reveal errors that may be clinically or socially important.

Mitigation must be carried out across each stage of the machine-learning lifecycle, from pre-processing - with techniques like enhanced sampling, demographic rebalancing, field-specific data augmentation, signal-quality filtering, missing-data characterization and more complete dataset documentation via datasheets - to in-processing methods such as fairness-constrained optimisation, adversarial debiasing and group-aware regularisation to robustify representations learned. Post-processing mitigation might involve threshold adjustment, group-wise calibration, reject-option classification and uncertainty-aware alerts to help human review of high-risk outputs. A broad range of bias mitigation techniques is supported by tools like AI Fairness 360 and Fairlearn, which provide metric calculation and the ability to run bias mitigation experiments in various stages of a machine-learning model. This can be documented in 'model cards', summarising intended use cases, limitations including expected subgroup performance differences and assumptions about the deployment environment (Bellamy et al., 2019; Bird et al., 2020; Gebru et al., 2021; Mitchell et al., 2019).

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Inclusive design will be necessary, including participatory evaluation of new digital technologies with diverse users from populations different from those used to train and validate models. In addition, regional variability, particularly in low- and middle-income environments, in factors such as affordability, climate, mobile network reliability, smartphone ownership, language, repair access and health-system integration will likely influence the practicality of some digital health tools compared to high-income settings. Before using any wearable model developed in one environment in clinical, occupational, insurance, educational or safety decision-making processes in a different setting, external validation will be needed.

8.3 Security, Privacy, and Consent

Wearables and biosensors collecting user data for prolonged periods contradict conventional understandings of consent because they continuously acquire data for a long time from users who have only granted initial consent during setup, potentially deriving further sensitive details from heart rate patterns (e.g., stress levels) or gait analysis (e.g., neurological conditions). Consent must be adaptable, transparent and easily withdrawn. Privacy-enhancing innovations from the International Medical Device Regulators Forum (2024), Xi et al. (2025) and others demonstrate federated learning, differential privacy, secure environments, homomorphic encryption, on-device decisions, minimal data usage and in-device anonymization. Nonetheless, these strategies must be precisely designed to avoid diminishing system effectiveness. Finding a balance - where protection does not compromise results and insights do not disclose excessive private details - constitutes the central research question.

8.4 Interoperability and Long-Term Use

So, many wearables store their data in proprietary formats that cannot be easily exported. This makes long-term data collection for research, integrating with healthcare systems and providing user data portability a challenge. Interoperability should also include technical standards, data semantics, consent, device provenance and documentation of algorithm changes. Long-term wearables also require addressing questions related to maintenance such as firmware updates, model drift, battery wear, sensor replacement and user support. The longevity of wearables also raises questions around sustainability, including electronic waste, short replacement cycles and the challenge of recycling the trash that is produced, including hybrid materials of electronic components and textiles. Sustainable wearables will need to consider modularity, repairability, battery replacement, recyclability and supply chain responsibility.

8.5 Maturity Differences Across Wearable Domains

Wearable domains vary considerably in technical maturity, validation evidence, and regulatory exposure. To explicitly delineate this distinction, this review employs an indicative five-point maturity rubric: 1 = concept or early prototype; 2 = laboratory validation; 3 = field pilot or limited deployment; 4 = validated domain-specific deployment; and 5 = regulated, standards-aligned, or clinically integrated deployment with lifecycle controls. The scores presented in Table 4 are qualitative synthesis scores rather than meta-analytic estimates. Nonetheless, they clearly demonstrate that consumer adoption does not equate to clinical-grade maturity.

Table 4. Indicative maturity levels across wearable technology domains.

Domain	Indicative maturity score	Evidence and Deployment Position	Main Gap
Continuous glucose monitoring and wearable ECG	5	Strongest maturity among wearable domains; regulated use and clinical workflows exist for defined claims.	Subgroup validation, cybersecurity, interoperability, and transparent algorithm updates.
Rehabilitation wearables, gait systems, and exoskeletons	3-4	Promising lab and field evidence, with growing edge-AI rehabilitation research and selected clinical deployments.	Longitudinal trials, therapist integration, affordability, usability, and local maintenance.
Consumer fitness, sleep, and readiness devices	3	Very high adoption, but metric validity and algorithms are often proprietary and device-specific.	Transparent validation, uncertainty disclosure, benchmark comparability, and user data portability.

Sports and performance analytics wearables	3	Strong practical use in training environments; evidence varies by sport, sensor placement, and outcome measure.	Individual calibration, injury-risk validity, fatigue modeling, and responsible feedback design.
Smart textiles and self-powered e-textiles	2-3	Rapid materials and prototype growth, but less mature evidence for long-term field durability.	Washability, sensor drift, manufacturability, repairability, and scalable energy harvesting.
AR, spatial, industrial, and safety wearables	3	Maturing devices and operational pilots, but deployment value is highly context dependent.	Attention management, bystander privacy, workplace consent, environmental robustness, and standards alignment.

This distinction in maturity is significant for research design. A domain may be commercially widespread while still possessing limited evidence for clinical decision-making, and a sensor may be technically mature while its artificial intelligence model remains immature with respect to fairness, calibration, explainability, or post-deployment monitoring.

9. Proposed Research Agenda for Computer Science

The final priority agenda needs to be systematically planned rather than merely a list of the priorities from the survey, to make the manuscript a strategically valuable contribution. This paper presents and discusses six priorities (edge intelligence, privacy-preserving analytics, human-centred interaction, diverse benchmarks, lifecycle security and sustainability) and, as per the analysis presented in this paper and summarised in Table 5, these can be categorised into short-term, mid-term and long-term research horizons.

Table 5. Time-phased research agenda for wearable technology in computer science.

Horizon	**Mapped Priorities**	**Concrete Technical Outputs**	**Success Indicators**
Short term (2026-2027)	Edge intelligence; diverse benchmarks; baseline lifecycle security.	Lightweight and uncertainty-aware inference models; public benchmark descriptors; dataset datasheets; model cards; subgroup reports; secure boot, encrypted updates, SBOMs, and vulnerability disclosure plans.	Reported latency, energy use, calibration, and subgroup metrics; reproducible train-test splits; documented device placement and signal-quality criteria; security controls included before deployment.
Mid term (2028-2030)	Privacy-preserving analytics; human-centered interaction; externally validated domain deployment.	Federated learning pipelines; differential privacy budgets; secure aggregation; adaptive multimodal interfaces; clinical, rehabilitation, occupational, and field-validation protocols.	External validation across devices, regions, and demographic groups; lower false-alarm burden; interpretable alerts; measurable privacy-utility trade-offs; evidence of user trust and accessibility.
Long term (2031 and beyond)	Sustainable smart textiles; governance-aware full	Self-powered and washable textiles; modular and repairable hardware; recyclable electronics; continuous model-drift	Longer device lifespan; reduced charging and e-waste burden; auditable post-market performance; sustained

	lifecycle systems.	monitoring; fairness-drift audits; compliant update trails for regulated wearables.	accuracy after updates; governance evidence that survives clinical, workplace, and regulatory scrutiny.

In the short term, there is a pressing need to focus on methodological hygiene: working with transparent datasets, using disaggregated metrics and reporting uncertainties and reproducibility to support validation. This work can mitigate many issues identified within existing applications (for example, addressing poor reproducibility, hidden biases and exaggerated product claims). There are already tools available to do this. At a midpoint, researchers should seek to integrate privacy-preserving learning technologies with work on HCI evaluation, moving away from isolated single-study prototypes towards resilient systems that have been externally validated across diverse devices and diverse populations. In the longer term, we identify sustainability and governance as critical technical requirements in their own right, rather than auxiliary concerns to technical system development. Sustainable and governable AI-powered wearable technologies may use designs such as modular hardware, reparable smart textiles, auditable AI updates, lifecycle cybersecurity and other concepts of durability, including effective post-deployment monitoring for performance drift, fairness drift and setting-specific safety failures.

10. Conclusion

Wearable technology is now a mature and rapidly growing area in computer science. Its value lies not only in the device itself but in its intersections with sensing, computation, wireless communication, artificial intelligence, edge processing, security, human-computer interaction and governance. The potential of wearables, which place computing at the body and in the everyday, spans health, safety, productivity, accessibility and experience. This includes emerging directions like wearable intelligence, with opportunities for personalization, immediate analysis, assistive interfaces, smart textiles and digital biomarkers. However, these directions are also associated with risks, including privacy, bias, accuracy, interoperability, surveillance and regulatory compliance. A wearable system that fails technically can mislead. A wearable system that fails ethically can undermine trust. And, a wearable system that fails clinically can harm.

The prospects for wearables in computer science are in this view a systemic issue. Progress will require the collaboration of researchers in embedded systems, data science, software designing, human-computer interaction, cybersecurity, medicine, materials science and ethics. By 2026, the most valuable wearable systems will be those that sense reliably, compute efficiently, communicate securely, explain their outputs clearly, protect personal data and remain useful in unpredictable everyday conditions. Better research culture will require greater transparency about review methods, clearer comparisons of maturity across fields, measured fairness evaluations and clearer agendas to separate immediate designing challenges from longer-term scientific and governance challenges.

References

Ahmed, A., ul Hasan, E., & Hasseni, S.-E.-I. (2025). Smart and sustainable: A global review of smart textiles, IoT integration, and human-centric design. Sensors, 25(23), 7267. https://doi.org/10.3390/s25237267

Baethge, C., Goldbeck-Wood, S., & Mertens, S. (2019). SANRA - a scale for the quality assessment of narrative review articles. Research Integrity and Peer Review, 4, 5. https://doi.org/10.1186/s41073-019-0064-8

Baskan, A., & Goncu-Berk, G. (2022). User experience of wearable technologies: A comparative analysis of textile-based and accessory-based wearable products. Applied Sciences, 12(21), 11154. https://doi.org/10.3390/app122111154

Baumann, S., et al. (2025). Smart healthcare at home: A review of AI-enabled wearables and diagnostics through the lens of the Pi-CON methodology. Sensors, 25(19), 6067. https://doi.org/10.3390/s25196067

Bellamy, R. K. E., Dey, K., Hind, M., Hoffman, S. C., Houde, S., Kannan, K., Lohia, P., Martino, J., Mehta, S., Mojsilovic, A., Nagar, S., Ramamurthy, K. N., Richards, J., Saha, D., Sattigeri, P., Singh, M., Varshney, K. R., & Zhang, Y. (2019). AI Fairness 360: An extensible toolkit for detecting and mitigating algorithmic bias. IBM Journal of Research and Development, 63(4/5), 4:1-4:15. https://doi.org/10.1147/JRD.2019.2942287

Bird, S., Dudik, M., Edgar, R., Horn, B., Lutz, R., Milan, V., Sameki, M., Wallach, H., & Walker, K. (2020). Fairlearn: A toolkit for assessing and improving fairness in AI. Microsoft Research Technical Report MSR-TR-2020-32.

Choi, J., Lee, K. J., & Kim, Y. S. (2016). Wearable devices for health monitoring: BioMEMS and their applications. Journal of Sensors, 2016, 1-15.

Dejene, B. K. (2025). The future of fabric: A comprehensive review of self-powered smart textiles and their emerging applications. Energy Reports, 14, 898-943. https://doi.org/10.1016/j.egyr.2025.07.002

European Commission. (2025). Artificial intelligence in healthcare. https://health.ec.europa.eu/ehealth-digital-health-and-care/artificial-intelligence-healthcare_en

Food and Drug Administration. (2025). Artificial intelligence in software as a medical device. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-software-medical-device

Food and Drug Administration. (2026). Artificial intelligence-enabled medical devices. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-enabled-medical-devices

Fraser, R. A., Walker, R. J., Campbell, J. A., Ekwunife, O., & Egede, L. E. (2025). Integration of artificial intelligence and wearable technology in the management of diabetes and prediabetes. npj Digital Medicine, 8, 687. https://doi.org/10.1038/s41746-025-02036-9

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daume III, H., & Crawford, K. (2021). Datasheets for datasets. Communications of the ACM, 64(12), 86-92. https://doi.org/10.1145/3458723

Gilbert, S., Harvey, H., Melvin, T., Vollebregt, E., & Wicks, P. (2024). The EU passes the AI Act and its implications for digital health technologies. npj Digital Medicine, 7, 176. https://doi.org/10.1038/s41746-024-01116-6

Hardt, M., Price, E., & Srebro, N. (2016). Equality of opportunity in supervised learning. Advances in Neural Information Processing Systems, 29, 3315-3323.

Hughes, C. L., & Karwowski, W. (2025). Evaluating interaction design and user experience in augmented reality: A systematic review. Frontiers in Virtual Reality, 6, 1710161. https://doi.org/10.3389/frvir.2025.1710161

International Medical Device Regulators Forum. (2024). Good machine learning practice for medical device development: Guiding principles. https://www.imdrf.org/working-groups/artificial-intelligencemachine-learning-enabled

Kumar, A., Goel, S., Chaudhary, A., Dutt, S., Mishra, V. K., & Kumar, R. (2025). Artificial intelligence-based wearable sensing technologies for the management of cancer, diabetes, and COVID-19. Biosensors, 15(11), 756. https://doi.org/10.3390/bios15110756

Lane, N. D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., & Campbell, A. T. (2010). A survey of mobile phone sensing. IEEE Communications Magazine, 48(9), 140-150.

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Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., & Gebru, T. (2019). Model cards for model reporting. Proceedings of the Conference on Fairness, Accountability, and Transparency, 220-229. https://doi.org/10.1145/3287560.3287596

Mu, G., et al. (2025). Recent advancements in wearable sensors: Integration with machine learning for human-machine interaction. RSC Advances. https://doi.org/10.1039/D5RA00167F

Nasiri, N. (Ed.). (2019). Wearable devices: The big wave of innovation. IntechOpen. https://doi.org/10.5772/intechopen.77458

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hrobjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Perez, A. J., & Zeadally, S. (2021). Recent advances in wearable sensing technologies. Sensors, 21(20), 6828. https://doi.org/10.3390/s21206828

Sfairopoulou, A., Georgoulas, S., & Moessner, K. (2016). IoT wearable devices: Time for a computer science reality check. IEEE Communications Magazine, 54(5), 34-41.

Shi, X., Mishra, D. K., Ozcan, O. O., Karahan, M., Panpan, T., Zhongshan, X., & Kumar, P. V. (2025). Wearable smart sensors integration with AI and machine learning for tracking human health. Biosensors and Bioelectronics: X, 27, 100711. https://doi.org/10.1016/j.biosx.2025.100711

Shin, D. H. (2018). Wearable devices and personalized analytics: Possibilities and challenges. Healthcare Informatics Research, 24(4), 253-254.

Sun, Y., Song, H., Jara, A. J., & Bie, R. (2016). Internet of Things and big data analytics for smart and connected communities. IEEE Access, 4, 766-773.

Tedesco, S., & Komaris, D.-S. (2026). Wearable technology and sensors for healthcare and wellbeing. Sensors, 26(8), 2385. https://doi.org/10.3390/s26082385

Watkins, S. M., & Dunne, L. (2015). Functional clothing design: From sportswear to spacesuits. Bloomsbury Publishing.

World Health Organization. (2021). Global strategy on digital health 2020-2025. World Health Organization. https://www.who.int/publications/i/item/9789240020924

Xi, L., Li, C., Anari, M. S., & Rezaee, K. (2025). Integrating wearable health devices with AI and edge computing for personalized rehabilitation. Journal of Cloud Computing, 14, 64. https://doi.org/10.1186/s13677-025-00795-0

Zhang, B., Chen, C., Lee, I., Lee, K., & Ong, K.-L. (2025). A survey on security and privacy issues in wearable health monitoring devices. Computers & Security, 155, 104453.