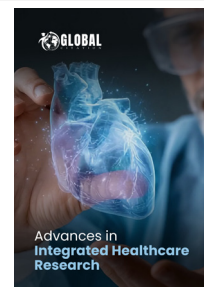




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Integrating Wearable Technologies into Preventive Healthcare: A Narrative Review of Emerging Clinical Applications

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Abstract

Background:

Wearable technologies can continuously capture physiological and behavioral data and are becoming more capable of being applied to preventive health care. They may enable the ability for risk factor modification, early detection, longitudinal risk stratification, and alerts for deterioration when integrated to clinical pathways.

Methods:

The methods used in this narrative review were to conduct a search of the literature to identify relevant clinical applications of wearables in preventive health and to summarize them. The following types of studies were taken into account: reviews and clinical trials, validation studies and cohort studies. Evidence was classified based on its preventive function and clinical effectiveness, validity of measurement, and requirements for implementation. Results: Wearable technologies were associated with increased physical activity and showed potential for scalable atrial fibrillation detection. Cuffless blood pressure, metabolic prevention, sleep monitoring and circadian rhythms, fall-risk, and infection monitoring also showed promising potential. However, the evidence was of limited quality due to the low accuracy, sensitivity and specificity of tests; limited durations of follow-up and limited implementation into clinical workflows. Increased clinical benefit was found when wearable-derived data were validated and fed into professional decision making.

Conclusions:

Wearables can play a positive role in reinforcing preventative care, when used

within a clinically driven care pathway. Outcome-based trials, interoperability, health equity, data minimization and continued clinical engagement should be the focus of future studies.

Keywords:

Wearable Technologies; Preventive Healthcare; Digital Biomarkers; Remote Monitoring; Cardiovascular Prevention; Personalized Medicine

1. Introduction

Preventive health care has always relied on one-off visits, self-reported behaviors, and measures taken in a highly controlled clinical setting. Although these snapshots continue to be useful, they often fail to capture the variation expressed by individuals on a day-to-day basis, nor the asymptomatic deterioration, nor the context of the individual's environment in which risk takes place (Alipour et al., 2025). Because of wearable technologies, the information architecture has changed, picking up longitudinal signals in everyday life. Different types of smartwatches and activity trackers, along with patches that track electrical activity from the heart, rings, smart garments, and biosensors attached to the skin can measure motion, heart rate, heart rhythm, oxygen saturation, temperature, sleep, glucose, and other biochemical and physiological data. Miniaturization, flexible electronics and wireless communication bring the number of measurable signals into a much wider scope, with at the same time reduced burden on the user and cloud analytics (Babu et al., 2024). Preventive benefits of wearables aren't based upon continuous measurement itself. The idea of prevention ideally needs to be linked by a chain of events and concepts a strong signal from the data; a clear interpretation of the risk; prompt documentation and action of the health care provider; and a meaningful outcome for the patient (Bender & Berry, 2023). A step count could be used in primary prevention to increase physical activity and raise awareness when feedback does, an irregular pulse alert could be used in secondary prevention to inform, act upon, and lead to a confirmatory (e.g. electrocardiographic) assessment that results in effective stroke prevention, and gait variability could be used in the prevention of falls in tandem

with formal testing, with an effective intervention triggered if this were raised. Inaccuracies in sensing, suboptimal algorithms, alerts that are not reviewed or data that never becomes "actionable" in clinical use, on the other hand, can lead to anxiety, overdiagnosis, disparities in care access and unnecessary use (Bhaltadak et al., 2024).

The evidence base has come to contain a large number of sources, but these are not consistent. Digital biomarker reviews have all underscored a recurring theme that physical activity and cardiac biomarkers to date appear to be the main area, and many in development are still primarily focused on tech validation and not patient outcomes (Chen et al., 2025). There are repeatable effects on behavior when using a wearable activity tracker with both clinical and non-clinical populations, but the accuracy of consumer devices is highly dependent on device generation, device location and type of activities. Progress in the field of cardiovascular applications is further ahead than in most other areas and towards a pragmatic clinical evaluation. Cuffless blood pressure, sleep-derived biomarkers, infection alerts, and fall prediction are all still up for question when it comes to calibration, burden of false positive results and next steps to effectively prevent that event (Cricco et al., 2025). This narrative review investigated the integration of 'wearable technologies' in preventive healthcare to critically evaluate where development of clinical application went beyond monitoring. Five functions were identified and reviewed Changing risk behavior, Early detection of disease, Longitudinal risk stratification, Personalized preventive feedback, and identifying level of physiological deterioration. It added the criteria of analytical validity, clinical validity, and clinical utility, as a device can measure a signal accurately without having an impact on a decision or an outcome (De la Torre et al., 2025). It also considers implementation in its considerations of effectiveness. Interoperability, physician burden, privacy, equity, compensation or reimbursement and user experience were all viewed as factors of whether a performance measurement was a preventive benefit, as opposed to being a secondary technical concern (Dinc & Ardic, 2025).

2. Review Approach

A structured secondary analysis of clinical and translational literature by means of a narrative synthesis was performed to elaborate on the literature regarding wearable technologies in prevention. This search included a multidisciplinary scholarly index of biomedical, engineering, and health-informatics publications as well as backward citation searching from several high-profile, influential systematic reviews and landmark trials (Ferdous & Rahman, 2025). Search terms included wearable devices, a single search term for each of the following: smartwatch, activity tracking device, biosensor, digital biomarker, prevention, screening, remote monitoring, cardiovascular disease, diabetes, hypertension, sleep, fall, infection, and older adult. Ongoing and large observational cohorts, prospective validation studies, pragmatic trials, and meta-analyses/systematic reviews published between 2018 and 2026, and peer-reviewed, were given priority. Previous research that had an important methodology and/or clinical outcome for the question being addressed was saved. Evidence was acceptable if the device was body-worn or skin-mounted for the measurement of one or more of the following: physiological, behavioral, biochemical; and the application reported was considered to have a reasonable preventive application (Gupta et al., 2025). Consumer wellness studies were eligible for inclusion if they assessed clinically relevant measurement(s), risk factors, pathways to detection or health care outcomes. Only limited studies were used on a prototype engineering basis, and did not involve human validation, to contextualize emerging sensors. Specific interventions limited to a smartphone-only were not included unless it was part of a mobile-enabled pathway or they were implantable. Meta-analytic pooling was not performed in the review as the interventions, populations, sensors and outcomes were very heterogeneous (Haghighy et al., 2024). The data were conceptually extracted in the categories of device modality, signal, target population, prevention function, object of comparison, primary outcome, level of evidence and limitation in implementation. The results of the findings were synthesized at three stages that are related. The first level pertained to measurement performance, accuracy, wear adherence, missingness

and artefact. The second focused on clinical validity, that is, association to disease, risk or physiological change. The third related to clinical utility either in terms of behavior change, confirmed diagnosis, initiation of therapy, reduction in events or optimal use of resources. Prospective and randomized studies were weighted more heavily than the findings of retrospective algorithm studies, which were given credit as findings to test hypotheses (He et al., 2023). Due to the research question being about integration across a range of different clinical applications and not the impact of one standardized intervention, the narrative method was chosen. In this approach, the differences in intended use of the study and implemented program were still maintained, and these differences resulted in the ability to compare between mature use case and emerging use case. It also championed the difference between detection and prevention more identification of abnormalities was not considered to be a positive driver of better health without a credible path joining the detection to a positive action. No patient information was independently collected, and institutional ethics approval was not needed on the basis that this study relied on secondary sources that were published as well as studies which were publicly disclosed.

3. From Wearable Signals to Preventive Action

Wearables take stream of data from sensors and transform them into information that can help prevent problems from arising after that. Raw accelerometry measured along with PLE, ECG, temperature, pressure, EDA and biochemical sensing, must first undergo quality control. The recorded signal can be affected by motion, skin contact, pigmentation, perfusion, placement of device, batteries and changes in firmware, and properties of the proprietary preprocessing. The device then obtains a metric that can be the number of steps, resting heart rate, irregularity of the heart rhythm, the length of the sleep period, the glucose trend, or variability of gait. The algorithms can refer to population thresholds or, increasingly, with the user's own reference (Huang et al., 2025). A particular relevance of personal baselines to prevention is that

many changes early in life are subtle and variable in nature. Normal population (resting) values are not insignificant in terms of an individual. Likewise, when combined with one another, decreased activity, sleep changes and decreased heart-rate variability can be a red flag. Digital biomarkers thus differ to consumers' data alone, since they must have a clearly specified biological meaning, be reliably acquirable and show evidence of a clinically relevant state of change. Multimodal fusion can boost sensitivity but also leads to increased complexity and risk of the model learning device/behavioral artefacts. Moreover, we need to translate the risk. Preventive systems can either provide self-feedback, create a dashboard for the clinician that can trigger confirmatory testing, or progress to urgent review. This pathway is represented in Fig. 1 as a closed loop as opposed to a one-way data pipeline. Whether there is prevention benefit is based on the action being undertaken: is it proportionate to risk? Lower risk does not require as high-level of validation, or explicit confirmation rules, for behavioral feedback as alerts for lower risk of atrial fibrillation, hypoxemia, infection or

hypertension. The “intended use” must therefore impact on the level of evidence that is required (Isreal, 2021). There can also be a problem of a denominator with the continuous data. With millions of measurements processed the patterns which are rare could generate significant alert levels when there are high numbers of measurements with a pattern, even though specificity may look good. This is increased in low prevalence populations. Relying on alert thresholds, refractory periods, signal-quality filters and risk enrichment is fundamental to not medicalizing normal variability. Clinical pathways should be established to identify who has access to the data, the frequency of review, when and how data represents a deviation which requires action and when a device should be recalibrated or replaced. These governance elements will clarify that, in the absence of them, continuous monitoring could result in the devolution of interpretative tasks to patients and clinician, while still not providing a preventive benefit (Kariasa et al., 2025).

An evaluation of measurement quality needs to take place on three levels. Analytical validity is the ability

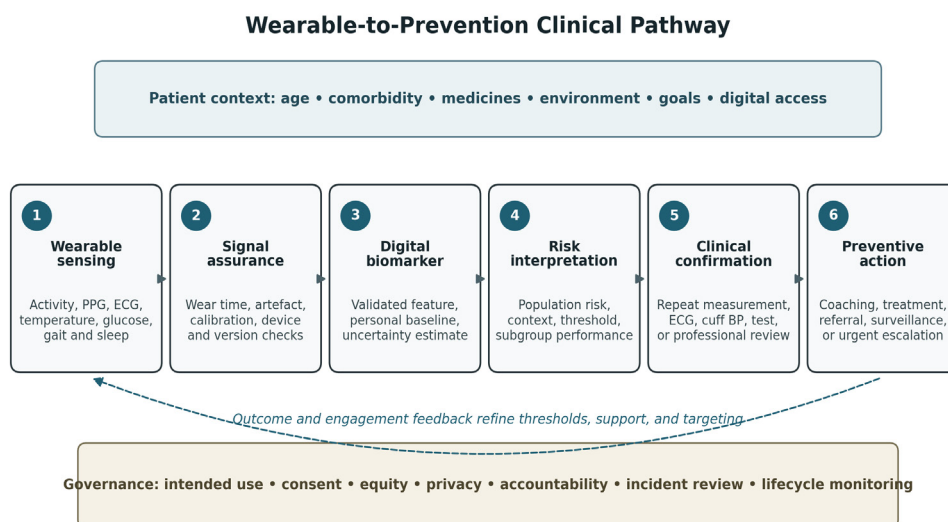


Figure 1. Wearable-to-prevention clinical pathway. Preventive value emerged when validated signals were interpreted within patient context, confirmed proportionately, and connected to accountable action.

of the sensor to measure the desired variable relative to the reference standard(s) used. An important question is clinical validity, does this derived feature differentiate a clinically important risk condition in the population on whom it is used? Clinical utility is the issue of whether quality of outcomes will be

improved with using that feature compared to current treatment. There is often confusion of these levels. An estimate of heart rate may be accurate but an illness alert which comes from this has not been shown to have good positive predictive value; similarly, a count of steps may be helpful to support behavior change.

Validation must mirror and not aim at a sought-after perfection of hopefully positive, decision consequences (Kasimovskaya et al., 2024). The context also alters how it is understood, Physiological baselines can change due to ageing, medication, autonomic disease and shift work, heat, altitude and exercise and do not indicate pathology. Preventive algorithms should consider the context and should signal uncertainty. Clinicians should be able to see identification of signal quality, as well as minimum wear-time rules and calibration procedures, and confidence estimates. Provenance of data is at least equally important: the clinical summary should list the device used, the sensor, its firmware version, the used algorithm version, the measurement window and the missingness. Such information provides the ability to make recommendations auditable and helps to trace any issues which might arise in terms of performance rather than general blame on patient behavior (Khan et al., 2024).

Table 1. Principal wearable modalities, preventive signals, and implementation constraints.

Modality	Common signals	Preventive applications	Principal constraints
Smartwatch / activity tracker	Steps, activity intensity, heart rate, PPG rhythm, sleep	Lifestyle modification, AF screening, recovery monitoring	Consumer algorithms, charging, false alerts, variable accuracy
Wearable ECG patch	Continuous single-lead ECG	Paroxysmal arrhythmia detection and risk enrichment	Finite wear period, skin irritation, interpretation workload
Smart ring	PPG, temperature, movement, sleep, autonomic indices	Sleep/circadian assessment, illness deviation, recovery	Fit, proprietary features, limited clinical thresholds
Skin patch / smart textile	ECG, respiration, temperature, sweat, pressure	Multimodal surveillance and early deterioration	Durability, calibration, adhesion, biofouling
Continuous glucose monitor	Interstitial glucose trends	Metabolic risk feedback and personalised lifestyle support	Invasiveness, cost, uncertain meaning in low-risk users
Cuffless BP wearable	Pulse transit or wave-form-derived BP estimates	Masked hypertension and temporal pattern detection	Calibration drift, movement effects, limited standards
Inertial sensor	Acceleration, angular velocity, gait and transitions	Fall detection, mobility and functional-risk assessment	Placement sensitivity, simulated validation, adherence

4. Emerging Clinical Applications

4.1 Physical activity and cardiometabolic risk

The most compelling evidence for widespread behavior changes for physical activity is found for physical activity trackers. An umbrella review of 39 systematic reviews and 163,992 participants revealed that activity trackers boost physical activity

by between 1,800-ish steps or 40 more walking minutes per day and had a small effect on reducing body weight. These effects were found for all age groups and clinical populations, indicating that self-monitoring, visibility on the goal and feedback can have an impact on behavior on a larger scale. Improvements in physiological parameters (e.g., blood pressure, glycated hemoglobin, cholesterol, quality of life, pain) were less or lacked consistent results, however (Lan et al., 2024). Much of this gap

lies in the fact that there are two separate elements involved: monitoring and intervention. Passive step display can raise awareness, but few other barriers other than capability, opportunity, motivation, medication, diet, and/or environment are addressed. Wearables were associated with a higher number of steps per day and small decreases in SBP; there was low certainty regarding the effectiveness of wearables on improving either glycemic or anthropometric outcomes in type 2 diabetes. Programs which provided wearables in addition to coaching, personalized goals, education or feedback from a clinician had more consistent results compared to the wearables alone. Wearables thus served best as behavioral tools if at all, in the context of multicomponent prevention interventions (Nazir et al., 2025). There's more cardiometabolic monitoring than activity. Heart rate, electrocardiography, continuous glucose monitoring, sleep and dietary information could all be collected by wearables, and there may be patterns that could be identified prior to the metabolic declines. Even diabetes-related evidence had some limitations, including brief follow-up, small numbers, appalling absence of privacy reporting and the lack of trials focused on preventing the development of preventable complications. Despite the introduction of continuous glucose monitoring, there are now opportunities for personalized lifestyle information even for the nondiabetic population, although for this low-risk population the implications of transient glucose changes are still unclear, so caution should be used when making claims.

4.2 Cardiovascular screening and risk detection

The most clinically advanced consumer-wearable application is in detecting atrial-fibrillation (AF). In the Apple Heart Study, the number of participants included in the study was 419,297 and the notifications for irregular pulse was 0.52%, with 34% of the participants with a patch being found to have atrial fibrillation, after all patches were returned for analysis; and the concordance was high between the notifications and the simultaneous atrial fibrillation. The Fitbit Heart Study had 455,699 participants with a reported PPV of 98.2% for the detections of recurrent episodes of IR on the ECG patch monitor

[8]. These studies proved scalable remote screening of the device and that implementing PPG could increase the pool of people being screened to have a confirming test (Obianyo et al., 2024). Randomized patch monitoring built evidence of a difference in diagnosis brought about by wearables. NYHA class, age, or previous history of stroke or TIA were associated with an increase in the number of days of stop patch monitoring, but neither of these nor any other baseline characteristics predicted increased anticoagulant use. This outcome is a good example to show that diagnostic yield does not equate to prevention. Downstream balance hinges on risk of stroke, burden of the arrhythmia, quality of confirmation, eligibility for treatment, bleeding risk and whether the treatment has been demonstrated to reduce events earlier in its treatment journey. Consumer alerts should thus be a starting point on a "Pathway" rather than an independent diagnosis (Pai, 2025). Esthetics are also under investigation as a means of monitoring heart failure, checking adherence with rehabilitation programmers, monitoring PAD and monitoring recovery after a cardiovascular event. Maybe continuous activity and level of heart rate can be considered an indication of decreasing functional reserve, before symptoms are apparent. However, a team of care providers with the capability to read the signals and make changes in treatment are needed to improve outcomes. In the field of prevention, a much better model which has proved most creditable in the field of prevention cardiology is to select a target population, have the sensor superficially validated, have a professional confirm the reading and carry out risk-factor management instead of universal or unsupervised screening.

4.3 Blood pressure, glucose, sleep, and circadian health

Cuffless blood-pressure devices might revolutionize the prevention of hypertension by taking blood-pressure measurements of patients throughout the day and night without patients having to wear a cuff. A systematic review and meta-analysis indicated several devices with a small mean-bias compared to the reference measurements compared to the

reference measurements; however, there was extremely high level of heterogeneity and different validation procedures. Factors such as performance when moving, investigations of change in vascular tone, calibration drift and investigation of nighttime measurement were still concerns. However, small systematic errors might alter the classification of hypertension or the treatment given and use of cuffless measurement should be avoided in preference to find validated cuff measures; those devices should be avoided until evidence has been found for them across skin tones, ages, rhythms, postures and blood pressure ranges are validated (Prieto-Avalos et al., 2022).] The potential for prevention is still great. Masked hypertension, diurnal variability and/or loss of nocturnal dipping can be detected by repeated measurements. But data volumes need to be translated into data summaries that can inform clinicians' actions. Outputs may be percentages of readings above or below a personalized threshold, time-of-day patterns, and confidence intervals and the calibration status, among other forms of output, rather than the continuous raw output estimates. Please make sure the pathway involves confirmatory cuff diagnostics prior to the diagnosis or changes in medicaments. Another growing use is in sleep and circadian (time-of-day) measurements. Wearables quantify the timing, duration, regularity and fragmentation of sleep, as well as temperature patterns and autonomic recovery. Monitoring cardiovascular and metabolic parameters during sleep is relatively movement and food artefact free, hence it offers a stable time window for these measurements. Digital sleep and circadian biomarkers can offer insights into identifying patterns to be linked to HTN, obesity, insulin resistance and impaired recovery. However, consumer-based devices tend to overestimate total sleep time, and discrepancies exist based upon sleep stages and populations. The focus on preventive use should thus be put on strong elements of timing, regularity and sustained deviation and not on proprietary terms for "stages", as clinical diagnoses.

4.4 Healthy ageing, falls, and infection surveillance

Wearable applications for older adults include mobility

monitoring, fall detection, arrhythmia screening, sleep assessment, rehabilitation, and cognitive and mental-health proxies. In controlled studies, accelerometers and gyroscopes can accurately and precisely detect falls when placed on the trunk or lower limb. But, in frail populations, evidence in the real world is less robust, and merely picking up on falls is not enough to stop them from falling. Prevention should include Risk assessment, MEDS, strength and balance intervention, environmental modification and rapid response. Non-effectiveness can result from false alarms, charging requirements, stigma and abandonment (Sharma et al., 2025). Wearable gait features can aid in early detection of "functional decline", with a need for prospective external validity. Clinically interpretable outcome measures like gait speed, gait variability, quality of gait transitions and activity radius seem more pertinent than non-transparent composite outcome measures. The use of the device should be AIDED too, not a substitute for, vision, cognition, home hazards, orthostatic and footwear assessments (Sultana et al., 2025). The tangle of surveillance for infection is a case in point for promise and risk. A wearable electrocardiographic and activity signal were able to distinguish 16/17 people who had an influenza challenge 23 hours before the appearance of symptoms averaged. HW measures from smartwatches showed that smartwatch-RHR, RSS and HRV could provide early warnings of respiratory infections, but PPVs are low (4% to 10%) and a range of factors (stress, poor sleep, exercise, alcohol) were responsible for false positives, in a prospective health-worker study. However, in some countries and communities where prevalence is low, there may be significant over-testing and anxiety when such system is in place but can be of great value in the period before outbreak or for vulnerable populations. Thus, it is important to utilize adaptive thresholds and the context of symptoms for preventive integration and to consider public-health goals that the level of alerts can address.

4.5 Multimodal and biochemical sensing

The scope of prevention extends beyond motion and pulse with emerging skin patches, smart textiles, and minimally invasive sensors in the form of rings. ECGs

can be used in combination with other sensors, such as temperature, respiration and oxygen saturation, electrodermal activity, pressure, hydration, interstitial biochemicals, etc. Multimodal sensing can facilitate discrimination as independent signals can help to differentiate physiological and local artefacts. It also allows enhanced definition of personalized medicine by the characterization of the interaction between behavior, environment, and physiology over time. Translation remains difficult. Sweat or interstitial fluid biochemicals may not necessarily agree with blood levels and sensor drift, biofouling, irritation, and environmental factors may affect sensor readings. The combinations also create a potential

for exponentially higher number of missing data combinations and may mask which of the “signals” triggered an alert. The smallest measurement set (that validates a change in decision) should be preferred by the preventive systems. Other sensors may be warranted when they help with calibration, can help to reduce false alarms, or help to find a leak that can be fixed. Reportability of wearability, failure modes, calibration frequency and the portion that provide analyzable data should be reported in early studies. Along with these outcomes decide whether or not complicated prototypes can operate in lab-free, equitable services (Tyler et al., 2020).

Table 2. Narrative synthesis of clinical applications and evidence maturity

Application	Representative evidence	Preventive contribution	Evidence maturity / principal gap
Physical activity	Umbrella and diabetes meta-analyses	Approximately 1,600–1,800 extra steps/day; supports goal-based behaviour change	Moderate–strong; metabolic and long-term outcome effects remain smaller
Atrial-fibrillation screening	Large pragmatic studies and randomized ECG-patch monitoring	Enriches high-risk users for confirmatory ECG and earlier diagnosis	Strong for detection; incomplete evidence for stroke reduction and net benefit
Cuffless blood pressure	Validation meta-analyses	Potential identification of masked hypertension and temporal patterns	Emerging; calibration, nocturnal accuracy, and protocol heterogeneity
Metabolic / glucose monitoring	Systematic reviews and activity-intervention trials	Personalised feedback on activity, glucose patterns, and self-management	Moderate for behaviour; weak for durable glycaemic or complication outcomes
Sleep and circadian health	Validation reviews and conceptual clinical synthesis	Tracks timing, regularity, recovery, and nocturnal cardiometabolic patterns	Emerging; consumer sleep-stage accuracy and actionable thresholds
Falls and functional decline	Umbrella and older-adult evidence maps	Detects falls and quantifies gait or mobility proxies	Moderate for detection; limited evidence that wearables prevent falls
Infection surveillance	Challenge and prospective validation studies	Detects deviation before symptoms and supports testing or outbreak surveillance	Emerging; low positive predictive value and context-related false alerts

5. Evidence Maturity and Clinical Integration

There were three common gaps in evidence in the different applications. One is that analytical validity

was assumed to be similar between different generations of devices. The pace of change is faster for consumer devices than for clinical studies, both in terms of changes in sensors, firmware, algorithms and even policies for accessing data. A limited percentage

of the commercially available measurements are independently validated, and performance estimates vary. Within a prevention program, a device registry, version control, and change assessment process should be kept so that proof which is added to one configuration shouldn't necessarily relate to another. Second, studies often reported intermediate results, instead of results that benefit the patient. The steps, alerts, detected arrhythmias and prediction accuracy can only be put into context when it translates to function, fewer events, and/or more efficient care. The current applications are mapped in Figure 2 according to how well the work was done and if the preventive utility of the measurement was demonstrated. There are relatively good clinical data for promotion of physical activity and for detection of AF – but effects on hard outcomes are incomplete. There are increasingly valid existing cuffless blood pressure and metabolic sensing data with less

evidence of outcomes. There are still significant uncertainties regarding thresholds for action and benefits in the following areas: sleep, fall prediction and infection alerts (Vallée, 2025). Third, there was insufficient specification of implementation. Wearables can create health data that is produced by patients and stretch across consumer, clinical, and commercial boundaries. Consent, minimizing data, retaining data, cybersecurity, secondary use, and patient access – policies are a requirement for health systems. There are also operational guidelines that need to be established such as: who gets who, who or which patients are eligible, how incoming data is accessed and from who, who responds to the alert and within what timeframe. Such decisions will impact on safety and workload. Special caution needs to be taken for Equity. Ownership, digital literacy, language, access to the smartphone device, skin and disability, and ability to charge/synchronize

Relative Evidence Maturity of Preventive Wearable Applications

	Measurement validity	Clinical validity	Pathway readiness	Outcome evidence
Physical activity promotion	Strong	Strong	Strong	Strong
Atrial-fibrillation screening	Strong	Strong	Strong	Moderate
Cuffless blood pressure	Moderate	Moderate	Emerging	Emerging
Metabolic and glucose monitoring	Moderate	Moderate	Moderate	Emerging
Sleep and circadian assessment	Moderate	Moderate	Emerging	Emerging
Falls and functional decline	Moderate	Moderate	Emerging	Emerging
Infection surveillance	Moderate	Moderate	Emerging	Emerging

Qualitative synthesis: maturity reflects the balance of validation, clinical integration, and patient-outcome evidence.

Figure 2. Relative evidence maturity across preventive wearable applications. Ratings were qualitative and reflected the balance of measurement validation, clinical validity, pathway readiness, and evidence for patient-relevant outcomes

a device may impact participation and measurement quality. Inclusion of younger, healthier and less diverse groups of consumers than those most likely to benefit from large consumer studies. Preventive programs should give out devices according to clinical indication, test the use of the devices with those who will use them, report performance of sub-groups and provide non-digital alternatives. Algorithms need to be assessed on differential missingness and rates of false alerts as well as overall discrimination (van den Brink et al., 2021). The one thing that is a hindrance is the need for sustained engagement. Novelty may prompt initial adoption but lose this effect as time goes on, and the lack of data, for example when people take their devices off or out of a pocket when they are unwell, very busy, uncomfortable or discouraged, may be telling. Engagement must not be seen merely as an issue of personal compliance! Support and understanding of the user, a lack of negative feedback, a low burden when using the device and helpful goals can increase persistence by using comfortable hardware, transparent feedback, low use burden, meaningful goals and professional support that respond to students' needs.

Wear time, completeness of data, alert acknowledged and disengagement shall be tracked in programs and the general strategy re-thought in the event of high rates of disengagement. Tiered is the model with the best potential for defense. Wellness feedback when at low risk can continue to be patient directed. Any deviations that are identified as intermediate risk can be referred for repeat measurement, education and/or asynchronous review. Validated confirmation and action need to be taken by the clinician based upon the findings of high risks. Thresholds will be based on prevalence and consequence with more rigorous thresholds for interventions that could lead to the label or to change of treatments. This multi-level approach continues to allow consumers to be free while routing devices around clinical reasoning. There is a clear hierarchy (e.g. on route to the outcome). Feasibility, wear time and data completeness are the first studies to be conducted. The analytical validity, discrimination, calibration, and usability are the focus of subsequent levels. At the higher levels, behavior is examined in relation to how clinicians decide on the patient or service changes, and the treatment

itself. There is good evidence that the adverse events are less likely, the function or quality of life is better, the harms are not unacceptable and the costs are reasonable.

An overall claim of prevention should not be made from lower-level evidence. The amount of evidence should be commensurate with severity of impact of error and extent of deployment. Full pathway needs to be covered to include the economic evaluation. Costs are more than just the price of the device; confirmation testing, data infrastructure, clinical review and support, false-positive investigations and the replacement cycles may be more important. These can include a decreased need for checking in or leaving the hospital early, saving travelling time, and getting focused professional attention and taking care of oneself. Where costs and benefits fall is varied, not only amongst patients, but also among providers, payers and vendors, and a positive business case doesn't necessarily equate to value to society. Budget-impact analyses should include consideration of uptake, disengagement, prevalence of alerts, and capacity of workforce. Clearly, we do need to have decommissioning criteria. Any program should stop, or phase out, wearables if they notice a drift in the program's performance, benefit is not being achieved, inequities are increasing, or a response service cannot be maintained.

6. Implications for Preventive Practice and Policy

Wearables should be treated as a service, instead of a product, at healthcare organisations. Procurement should look at its intended use, that it's independently validated, interoperability, cyber security, accessibility, the stability of the vendor and the resources to respond to data. Even technically correct data can be inappropriate if clinicians are unable to incorporate its data or alerts generating an unmanageable workload. Table 3 suggests what aspects of governance should minimally be put in place and measurable indicators. Clinical pathways should start with a specified focus problem in prevention and on a specific population group. The PV of positive results and overdiagnosis can be lowered

in a broad deployment to low risk users, while a risk-enriched deployment can help with efficiency. A confirmatory criterion, action level, escalation path and stopping rule should be set for each pathway. Patients need to be informed of the abilities and limitations on what the wearables can infer, who gets the data from the wearable, how quickly alerts are read, and when symptoms might need direct care even if there is no alert from the wearable. Moves should be made in research priorities from technical accuracy to comparative effectiveness. Pragmatic trials must assess clinical outcomes and their net benefit in terms of quality of life, level of anxiety, burden on treatment, healthcare utilization and cost within adequate follow up. Report changes in the device types/version or changes in the algorithms. A variety of groups should be studied, measures of performance should be conducted under free living conditions and missing data should be analyzed as a result. Comparative studies are also required to investigate the potential added value of continuous, as opposed to validated intermittent, sensing and to understand if personalized baselines would be better than the use of population thresholds. It is important to have policy for the interoperability and evidence-proportionate regulation. Without data standards there will be summaries of clinically relevant information that would move into records and could overwhelm users. Professional action is often the active ingredient – and it is not a supply of device that should be covered by reimbursement – it's interpretation and response. For the use in public health there are further precautions which should be taken on consent, surveillance

and representativeness. The key policy principle should be the idea of 'accountable prevention,' that is, a transparent, reviewable and equitable pathway should exist between signal and benefit, reflecting the use of wearables. There's a need for staged evaluation to be called on implementation. Preparation should clarify the prevention goal; the target population; what the comparator might be; and the potential benefit and unacceptable harms. A silence prospective phase allows to run the wearable without any output while permitting the evaluation of any completeness, calibration, subgroup performances and alert volume locally. This can then be followed by smaller deployments with trained users, and clearly specified escalation procedures, as well as quick review of incidents. The service will only be expanded if it is safe, feasible and useful as per the predefined safety limits, workload limits and utility limits. A balanced dashboard should be used – in ongoing routine monitoring. Technical considerations include wear time, or transmission success, failure of signal quality, calibration error and algorithm drift. For clinical, confirmation yield, review time, action taken, adverse events and outcome can be indicated clinically. Human indicators are Comprehension, Anxiety, Burden, Trust and Clinician Override. Equity indicators should be developed based on access, 'missingness', false alerts and benefit by demographic and socioeconomic groups. There is a need to review these measures annually by governance committees and/or as a result of major software or hardware developments. It's a model which revolves around using implementation as a learning process but at the same time not letting routine patients be used as guinea pigs in an uncontrolled experiment.

Table 3. Minimum implementation requirements for wearable-enabled preventive services.

Domain	Required control	Illustrative indicator
Intended use and population	Define preventive problem, eligibility, exclusions, comparator, and stopping rule	Proportion of enrolled users meeting risk criteria
Validation and versioning	Independent device validation, local silent testing, firmware and algorithm registry	Performance by device version and subgroup

Confirmation and escalation	Specify confirmatory standard, reviewer, response time, and emergency advice	Confirmation yield and median time to clinical review
Workflow and workload	Integrate concise summaries into records and resource alert response	Alerts per clinician-week and proportion actioned
Equity and accessibility	Provide devices when indicated, accessible interfaces, language support, alternatives	Access, missingness, and false-alert differences across groups
Privacy and security	Data minimisation, consent, retention limits, encryption, breach response	Data fields collected and security incidents
Engagement and human factors	Monitor wear time, charging burden, anxiety, comprehension, and abandonment	Wear-time completeness and discontinuation rate
Lifecycle monitoring	Review drift, incidents, benefits, costs, vendor changes, and retirement criteria	Quarterly outcome dashboard and documented decisions

7. Strengths and Limitations

This review combined data from all behavioral, cardiovascular, metabolic, sleep, ageing and infectious-disease applications and distinguished between measurement performance and its prevention application. The structured narrative approach allowed for the comparison of the different and contrasting technologies and showed common mechanisms of implementation. But it was not as comprehensive as coming up with database-specific screening, or quantitative pooling. Devices were iterated quickly and some evidence may not apply to the most recent devices or firmware/hardware. Benchmarks may have been skewed towards successful prototypes and/or larger, commercial projects. Evidence was focused in high-income or well-resourced health care systems and was not necessarily relevant to resource-poor health systems. Finally, there were a few emerging applications that relied primarily on validation or observational studies and conclusions regarding outcomes of patients were provisional.

8. Conclusion

Wearable technologies moved the interaction between preventative and clinical care far out of the clinic and into people's day-to-day lives, allowing for behavior and physiology to be sensed (worn) outside the context of clinical visits. They had the best scores regarding ongoing support to keep people physically active and detection of select cardiac

rhythm disorders that is scalable. Less mature, although clinically promising applications included blood pressure, metabolism, monitor sleep, prevent falls, decrease function, and monitor infection. In all domains, word prevention was not well defined as a simple sensing, but rather as a sequence of validation, interpretation, confirmation and action, which was governed. Wearables should thus be used as part of a care pathway based on risk and show clear roles, protect equity points and instill regular performance reviews. To achieve further progress, pragmatic outcomes research, interoperable data systems, transparency of algorithms and models for rewarding meaningful response are necessary. It's not about how much data can be gathered by a device, but whether or not its use can decrease avoidable disease, maintain trust, autonomy, and clinical ability.

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Competing interests:

The authors should declare any financial or non-financial interests relevant to wearable devices, digital health, or preventive healthcare.

Data availability:

No new dataset was generated. The evidence

synthesized in this review is available in the cited publications.

Author Contributions

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Conceptualization, methodology, literature review, analysis, writing, original draft, writing, review and editing, and project administration.

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Conceptualization, methodology, literature review, analysis, writing, original draft, writing, review and editing, and critical revision of the manuscript.

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References

- Alipour, P., El-Aghil, M., Foo, A., & Azizi, Z. (2025). Leveraging mobile health and wearable technologies for the prevention and management of atherosclerotic cardiovascular disease. *Current atherosclerosis reports*, 27(1), 31. [doi: 10.1007/s11883-024-01272-w](https://doi.org/10.1007/s11883-024-01272-w)
- Babu, M., Lautman, Z., Lin, X., Sobota, M. H., & Snyder, M. P. (2024). Wearable devices: implications for precision medicine and the future of health care. *Annual Review of Medicine*, 75(1), 401-415. [doi: 10.1146/annurev-med-052422-020437](https://doi.org/10.1146/annurev-med-052422-020437).
- Bender, B. F., & Berry, J. A. (2023). Trends in passive IoT biomarker monitoring and machine learning for cardiovascular disease management in the US elderly population. *Advances in geriatric medicine and research*, 5(1), e230002.
- Bhaltadak, V., Ghewade, B., & Yelne, S. (2024). A comprehensive review on advancements in wearable technologies: revolutionizing cardiovascular medicine. *Cureus*, 16(5).
- Chen, J., Jastrzebska-Perfect, P., Chai, P., Say, M. G., Tu, J., Gao, W., Halperin, F., Korzenik, J., Huang, H.-W., & Katabi, D. (2025). Barriers to translating continuous monitoring technologies for preventative medicine. *Nature biomedical engineering*, 1-19. [doi: 10.1038/s41551-025-01520-7](https://doi.org/10.1038/s41551-025-01520-7).
- Cricco, R., Segreti, A., Ferro, A., Beato, S., Castaldo, G., Ciancio, M., Sacco, F. M., Pennazza, G., Ussia, G. P., & Grigioni, F. (2025). Advancements in sensor technology for monitoring and management of chronic coronary syndrome. *Sensors*, 25(15), 4585. [doi: 10.3390/s25154585](https://doi.org/10.3390/s25154585).
- De la Torre, K., Min, S., Lee, H., & Kang, D. (2025). The application of preventive medicine in the future digital health era. *Journal of Medical Internet Research*, 27, e59165. [doi: 10.2196/59165](https://doi.org/10.2196/59165).
- Dinc, R., & Ardic, N. (2025). The next frontiers in preventive and personalized healthcare: artificial intelligent-powered solutions. *Journal of Preventive Medicine and Public Health*, 58(5), 441. [doi: 10.3961/jpmph.25.080](https://doi.org/10.3961/jpmph.25.080).
- Ferdous, A. A., & Rahman, S. S. (2025). The Integration of Wearable Devices with mHealth Apps for Remote Patient Monitoring: A Literature Review. *International Journal of Drug Regulatory Affairs*, 13(3), 38-51. <https://doi.org/10.22270/ijdra.v13i3.778>
- Gupta, A., Gupta, V., & Ojha, A. (2025). Transforming Cardiovascular Health: An Emerging Role of Biomarkers, Artificial Intelligence-Driven Imaging, and Digital-Based Technologies. *Diabetes Technology and Obesity Medicine*, 1(1), dtom.2025.0034. <https://doi.org/10.1089/dtom.2025.0034>.
- Haghighayegh, F., Norouziyazad, A., Haghani, E., Feygin, A. A., Rahimi, R. H., Ghavamabadi, H. A., Sadighbayan, D., Madhoun, F., Papagelis, M., & Felfeli, T. (2024). Revolutionary point-of-care wearable diagnostics for early disease detection and biomarker discovery through intelligent technologies. *Advanced Science*, 11(36), 2400595. [doi: 10.1002/advs.202400595](https://doi.org/10.1002/advs.202400595).

- He, T., Wen, F., Yang, Y., Le, X., Liu, W., & Lee, C. (2023). Emerging wearable chemical sensors enabling advanced integrated systems toward personalized and preventive medicine. *Analytical Chemistry*, 95(1), 490-514. doi: 10.1021/acs.analchem.2c04527. PMID: 36625107. doi: [10.1021/acs.analchem.2c04527](https://doi.org/10.1021/acs.analchem.2c04527).
- Huang, G., Chen, X., & Liao, C. (2025). AI-driven wearable bioelectronics in digital healthcare. *Biosensors*, 15(7), 410. doi: [10.3390/bios15070410](https://doi.org/10.3390/bios15070410).
- Isreal, O. (2021). Role of IoT Wearables in Personalized Healthcare and Precision Medicine.
- Kariasa, I., Koester, R. A., & Juanamasta, I. G. (2025). Advances in Health Monitoring Technologies: A Systematic Review of Diagnostic Precision, Patient Empowerment, and Integration Challenges. *The Open Biomarkers Journal*, 15(1).
- Kasimovskaya, N., Fomina, E., Krivetskaya, M., Diatlova, E., Egorova, E., & Pavlov, D. (2024). Determination of digital biomarkers of disease progression for digital phenotyping of patients with arterial hypertension. *Vasa*. doi: [10.1024/0301-1526/a001155](https://doi.org/10.1024/0301-1526/a001155).
- Khan, A., Islam, S., Sarkar, A., Islam, T., Paul, R., & Bari, M. S. (2024). Real-time predictive health monitoring using AI-driven wearable sensors: Enhancing early detection and personalized interventions in chronic disease management. *International Journal for Multidisciplinary Research*, 6(5), 1-21. <https://doi.org/10.36948/ijfmr.2024.v06i05.28497>
- Lan, L. Y.-L., Kumar, W. M., Liu, L. S., Roberts, A. K., Chen, S., & Snyder, M. (2024). Biomarkers in precision medicine. In *Biosensors in Precision Medicine* (pp. 35-57). Elsevier.
- Nazir, A., Nazir, A., Shah Wali Jamal, M., Sadiq, S. u. R., Aman, S., Mustapha, M. J., Lawal, S. O., Abdulkareem, M. O., & Bamigbola, M. F. (2025). Wearable Technology and Its Potential Role in Cardiovascular Health Monitoring and Disease Management. *Health Science Reports*, 8(11), e71486. doi: [10.1002/hsr2.71486](https://doi.org/10.1002/hsr2.71486)
- Obianyo, C., Ezeamii, V. C., Idoko, B., Adeyinka, T., Ejembi, E. V., Idoko, J. E., Obioma, L. O., & Ugwu, O. J. (2024). The future of wearable health technology: from monitoring to preventive healthcare. *World J Biol Pharm Heal Sci*, 20(1), 36-55.
- Pai, R. R. (2025). IoT-Enabled Continuous Monitoring Systems for Inflammatory Biomarkers in Preventative Healthcare for Sustainable Development. *International Conference on Sustainable Development through Machine Learning, AI and IoT*,
- Prieto-Avalos, G., Cruz-Ramos, N. A., Alor-Hernandez, G., Sánchez-Cervantes, J. L., Rodríguez-Mazahua, L., & Guarneros-Nolasco, L. R. (2022). Wearable devices for physical monitoring of heart: a review. *Biosensors*, 12(5), 292. doi: [10.3390/bios12050292](https://doi.org/10.3390/bios12050292).
- Sharma, R., Ghosh, G., Abbas, A., & Mahato, K. (2025). Biochemical, biophysical, and digital biomarkers in precision healthcare. In *Nano-bioelectronics for Precision Health Monitoring* (pp. 111-135). Springer.
- Sultana, S., Hriday, M. S. H., Haque, R., & Das, M. (2025). Health monitoring through wearables: A systematic review of innovations in cardiovascular disease detection and prevention. *Strategic Data Management and Innovation*, 2(01), 96-115. <https://doi.org/10.71292/sdmi.v2i01.13>
- Tyler, J., Choi, S. W., & Tewari, M. (2020). Real-time, personalized medicine through wearable sensors and dynamic predictive modeling: a new paradigm for clinical medicine. *Current opinion in systems biology*, 20, 17-25. doi: [10.1016/j.coisb.2020.07.001](https://doi.org/10.1016/j.coisb.2020.07.001).
- Vallée, A. (2025). Digital twins for cardiovascular diseases: towards personalised and sustainable care. *Acta Cardiologica*, 80(9), 1055-1062. doi: [10.1080/00015385.2025.2569027](https://doi.org/10.1080/00015385.2025.2569027).
- van den Brink, W., Bloem, R., Ananth, A.,

Kanagasabapathi, T., Amelink, A., Bouwman, J., Gelinck, G., van Veen, S., Boorsma, A., & Wopereis, S. (2021). Digital resilience biomarkers for personalized health maintenance and disease prevention. *Frontiers in Digital Health*, 2, 614670. doi: [10.3389/fdgth.2020.614670](https://doi.org/10.3389/fdgth.2020.614670).