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WEARABLE TECHNOLOGIES IN HEALTH MONITORING: EFFECTIVENESS IN PREVENTING LIFESTYLE DISEASES

Dagmara Gładysz *(Corresponding Author, Email: dagmaragladys226@gmail.com)*
The University of Rzeszów, Rzeszów, Poland
ORCID ID: 0009-0001-4237-1382

Joanna Barwacz
The University of Rzeszów, Rzeszów, Poland
ORCID ID: 0009-0002-8805-4961

Magdalena Adamik
The University of Rzeszów, Rzeszów, Poland
ORCID ID: 0000-0002-9272-3059

Marta Czarnowska
Ludwik Rydygier Collegium Medicum, Nicolaus Copernicus University, Bydgoszcz, Poland
ORCID ID: 0009-0002-4547-2098

Radosław Sciepuro
Ludwik Rydygier Collegium Medicum, Nicolaus Copernicus University, Bydgoszcz, Poland
ORCID ID: 0009-0006-6430-4398

Agnieszka Zaleszczyk
The University of Rzeszów, Rzeszów, Poland
ORCID ID: 0009-0005-7639-2156

ABSTRACT

Research objectives: This comprehensive systematic review and meta-analysis aims to critically evaluate the clinical evidence on the effectiveness, feasibility, and cost-effectiveness of wearable technologies in health monitoring and the prevention of lifestyle diseases between 2020 and 2024.
The study focuses on two main pillars of innovation: devices for monitoring physical activity and health parameters (smartwatches, fitness bands, continuous glucose monitors) and artificial intelligence (AI)-based data analysis systems that enable early risk detection and personalization of health interventions.
In addition, the review analyzes the ethical, legal, social, and implementation (ELSI) barriers that must be overcome to enable the large-scale implementation of wearable technologies in healthcare systems.
Methods: A scoping review of scientific literature was conducted in databases including PubMed, Scopus, and Google Scholar, using inclusion criteria that included randomized controlled trials (RCTs), systematic reviews, and meta-analyses published from January 2020 to July 2024.
Seven key meta-analyses and twenty RCTs were analyzed in detail, focusing on effect sizes (Hedges' g, standardized mean difference - SMD), adherence rates, and impact on clinical endpoints. The risk of systematic error and regulatory frameworks were also assessed.
Main results: Wearable technologies showed moderate to high effectiveness in monitoring health parameters and modifying health-related behaviors. A meta-analysis of interventions using wearable devices to monitor physical activity showed a statistically significant increase in the number of steps per day (weighted mean difference: 1519 steps/day, 95% CI 1096-1942) and moderate to large effect sizes (SMD = 0.449) compared to control groups (Hodkinson et al., 2021; Tang et al., 2020).
Continuous glucose monitoring (CGM) has shown particularly high effectiveness in diabetes control. A meta-analysis of 15 RCTs (2,461 patients) showed a significant reduction in HbA1c (weighted mean difference: -0.17%, 95% CI -0.29 to -0.06) and an increase in time in range (TIR) of 70.74 minutes (95% CI 46.73-94.76) compared to standard care (Maiorino et al., 2020).
The main barriers included: problems with measurement accuracy in real-world settings, user fatigue leading to low long-term adherence, protection of health data privacy, and lack of standardization and interoperability between devices and EHR (electronic health record) systems.
Conclusions: Wearable technologies are becoming an integral part of preventive medicine and chronic disease management. The future lies in blended care models that combine continuous health monitoring with AI predictive algorithms and clinical oversight.
Long-term RCT studies (≥12 months) and a clear regulatory framework regarding the accuracy of medical devices, data collection ethics, and legal liability must be established before widespread implementation in healthcare systems.

KEYWORDS

Wearable Technologies, Wearables, Health Monitoring, Lifestyle Diseases, Diabetes, Cardiovascular Diseases, Preventive Medicine, Digital Therapeutics, Artificial Intelligence in Health

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1. Introduction

1.1. The global burden of lifestyle diseases: Epidemiological and economic context.

Lifestyle diseases—including cardiovascular disease (CVD), type 2 diabetes mellitus (T2DM), obesity, hypertension, and chronic obstructive pulmonary disease (COPD)—are currently the leading cause of morbidity and mortality worldwide, accounting for over 70% of all deaths globally (World Health Organization, 2023).

According to WHO data, approximately 1.28 billion adults worldwide suffer from hypertension, 537 million people live with diabetes, and over 650 million are obese (World Health Organization, 2023). Furthermore, projections indicate that the number of people with diabetes will rise to 783 million by 2045, mainly due to aging populations, urbanization, and unhealthy lifestyles.

The public health crisis caused by lifestyle diseases also has enormous economic consequences. According to OECD and WHO reports, the direct and indirect costs of chronic diseases in developed countries (e.g., the United States, the EU) account for approximately 5-7% of GDP, mainly due to sick leave, reduced productivity (presenteeism – working while sick), long-term drug treatment, and costly medical procedures (OECD, 2023).

The economic context highlights the urgent need for cost-effective solutions that enable early detection, prevention, and management of chronic diseases before serious complications requiring hospitalization or surgical intervention develop.

Furthermore, the COVID-19 pandemic and the associated restrictions on access to routine healthcare have dramatically worsened the control of chronic diseases in millions of patients worldwide. Lockdowns, clinic closures, and fears of infection have led to disruptions in continuity of care and an increase in decompensation of diabetes and cardiovascular disease, while also exposing critical shortcomings in traditional care models based solely on in-person visits.

As a result, the years 2020-2024 have become a turning point for the development and validation of digital solutions—including wearable technologies—designed to overcome these barriers by providing continuous, remote, and scalable health monitoring.

1.2. The evolution of wearable technologies in healthcare (Digital Health Wearables).

The search for scalable and accessible solutions has led to the rapid development of wearable technology—electronic devices worn on the body that collect biometric and health data in real time.

While early wearables were limited to simple pedometers and heart rate monitors, recent years have seen an evolution toward two advanced pillars: medical devices for continuous monitoring and intelligent data analysis systems.

1.2.1. Health monitoring devices.

There has been a transformation from simple pedometers to advanced biosensors capable of measuring:

- Heart rate and heart rate variability (HRV)
- Blood pressure (ambulatory BP monitors)
- Glucose levels (continuous glucose monitors – CGM, including real-time and flash glucose monitoring systems)
- Blood oxygen saturation (SpO_2)

● Sleep quality and physical activity
● ECG (arrhythmia detection, including atrial fibrillation)

These devices have undergone miniaturization, increased measurement accuracy, and improved comfort, allowing them to be worn 24/7 without significant discomfort. The integration of these devices into healthcare (remote patient monitoring, RPM) has demonstrated the ability to detect disease exacerbations, facilitate proactive management, and reduce emergency department visits and length of hospital stays, particularly in patients with CVD and COPD (Kamei et al., 2020; Mattison et al., 2022).

1.2.2. AI systems and predictive analytics.

Artificial intelligence and machine learning (ML) algorithms are revolutionizing the way data from wearable devices is transformed into actionable insights:

● Risk prediction: Algorithms detect early signs of health deterioration (e.g., increased resting heart rate as a marker of impending heart failure exacerbation)

● Personalization of health goals: Systems tailor recommendations for physical activity, diet, and sleep to the individual needs and capabilities of the user (Dynamic Treatment Regimes, DTR)

● Just-in-Time Interventions (JITAI): Notifications and micro-interventions delivered at the optimal moment (e.g., a reminder to be active after a long period of sitting or a hypoglycemia alert)

1.3. Justification of the time frame (2020-2024).

The focus on literature published between January 2020 and July 2024 is not accidental, but reflects the convergence of three key factors that have marked technological and clinical maturity.

1.3.1. Technological maturity of sensors.

Miniaturization, longer battery life, and lower production costs of biosensors have enabled the mass adoption of wearable devices among the general population. Smartwatches and fitness bands have become commonplace, allowing for large-scale clinical trials outside the laboratory setting. According to estimates, the market for wearable devices for medical applications is growing at a rate of 27.9% per year (2020-2027), reflecting their growing role in healthcare (Jafleh et al., 2024).

1.3.2. Integration of AI and predictive algorithms.

The development of advanced ML and deep learning models (e.g., neural networks, ensemble algorithms, Transformers) has enabled the processing of vast amounts of biometric data in real time and the extraction of clinically relevant patterns. The introduction of predictive models based on longitudinal data (e.g., predicting diabetes decompensation based on CGM glucose trends) has increased the clinical value of wearable technology (Uhl et al., 2024).

1.3.3. Post-pandemic momentum.

The COVID-19 crisis forced healthcare systems to rapidly adopt digital tools, accelerating funding, the development of telehealth infrastructure, and the number of RCTs validating these interventions. Patients and clinicians have become more open to remote monitoring as a supplement or alternative to traditional visits. Meta-analyses from 2020-2024 confirm that interventions using wearable technology, especially when combined with consultations with medical staff, show clinically significant benefits in populations with chronic diseases (Longhini et al., 2024).

1.4. Research questions.

This review aims to answer the following key research questions:

1. What is the clinical effectiveness (effect size, Hedges' g, SMD) of wearable technology-based interventions (physical activity monitoring, CGM, cardiovascular parameter monitoring) compared to standard care or a waiting list control group in the prevention and management of lifestyle diseases (diabetes, CVD, obesity), based on RCT studies published between 2020 and 2024?

2. Which technological factors (sensor accuracy, AI integration, personalization, user experience, support from healthcare professionals) are most critical for clinical effectiveness and patient adherence?

3. What are the main ethical, legal, and social (ELSI) barriers to the large-scale implementation of wearable technologies, including: device accuracy and medical certification, health data privacy protection, algorithmic bias, the digital divide (inequalities in access to digital technologies), and legal liability?

4. How can new models of integrated healthcare optimally combine continuous monitoring through wearables with clinical supervision and behavioral interventions to provide a cost-effective and consistent path to the prevention of lifestyle diseases?

2. Methodology

2.1. Search strategy and inclusion/exclusion criteria

This review was planned as a systematic literature review with elements of meta-analysis, which means that, in addition to a qualitative discussion of the results of individual studies, where possible, an attempt was also made to quantitatively synthesize data on clinical outcomes. The process was based on current recommendations for reporting review studies (PRISMA 2020), with particular emphasis on a transparent description of the search strategy and criteria for selecting studies for analysis.

The search was conducted in five major databases: PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and Google Scholar. These databases were selected for their complementary nature—PubMed/MEDLINE primarily covers biomedical literature, Scopus and Web of Science provide broad interdisciplinary coverage, while IEEE Xplore allows for the inclusion of studies in the fields of biomedical engineering, algorithms, and technical solutions related to wearable devices. Google Scholar was used as an auxiliary tool, mainly to identify works that may not have been indexed in other databases or appeared as preprints.

The time frame was set for January 2020 – July 2024, which was dictated by two reasons. Firstly, this period saw very dynamic development of wearable technologies (both in terms of hardware – new generations of smartwatches and sensors – and software – development of AI algorithms, cloud integration, telemedicine). Secondly, this period includes, among other things, the COVID-19 pandemic, which has accelerated the implementation of remote health monitoring solutions and may affect the nature and scale of available research. The search was limited to publications in English and Polish, reflecting both the dominant language of scientific communication in medicine and the possibility of including works from Polish centers.

The search strategy was based on a combination of keywords and MeSH terms related to both wearable technologies and lifestyle diseases. Examples of combinations of phrases used include:

- "wearable" AND ("continuous glucose monitoring" OR "CGM" OR "flash glucose monitoring"),
- "activity tracker" OR "fitness tracker" OR "smartwatch" AND ("type 2 diabetes" OR "obesity" OR 'hypertension' OR "cardiovascular disease"),
- "remote patient monitoring" AND ("heart failure" OR "chronic obstructive pulmonary disease"),
- "wearable" AND "machine learning" OR "artificial intelligence" AND "cardiometabolic".

Where possible, additional restrictions (e.g., "randomized controlled trial," "systematic review," "meta-analysis") were applied in the publication type field to narrow the results to studies with a higher level of methodological reliability.

The inclusion criteria were formulated to capture studies that were as representative as possible and, at the same time, methodologically sound, concerning the use of wearable technology in the context of lifestyle diseases. The following were included:

- randomized controlled trials (RCTs),
- systematic reviews and meta-analyses,
- pilot studies and feasibility studies, if they evaluated the practical application or acceptability of wearable devices, provided that:

1. the population consisted of adult patients with lifestyle diseases (cardiovascular disease, type 2 diabetes, obesity, hypertension, COPD),
2. the intervention involved a specific type of wearable device, such as: continuous glucose monitoring (CGM) systems, activity trackers, smartwatches with vital sign monitoring, ambulatory blood pressure monitors, or other body-worn sensors,
3. at least one endpoint related to: a) clinical parameters (e.g., HbA1c, blood pressure, body weight, lipid indices), b) health behaviors (physical activity, sedentary behavior), c) outcomes related to safety or technology acceptance (adherence, drop-out, adverse events).

Exclusion criteria included:

- case reports, letters to the editor, commentaries, narrative reviews without a clearly defined methodology,
- studies in which the intervention was based solely on a mobile application, without a wearable component (no sensor worn by the patient),
- works focused on conditions other than lifestyle diseases (e.g., rare diseases, acute traumatic conditions),
- publications in which wearable technologies served only as a research tool (e.g., for short-term activity measurement for epidemiological purposes), without a therapeutic or preventive intervention component.

All records from the databases were imported into a dedicated bibliography management program (e.g., EndNote/Zotero/Mendeley), where duplicates were removed. Next, two independent researchers selected titles and abstracts, and in case of discrepancies, decisions were made by consensus or with the participation of a third reviewer.

2.2. Characteristics of the selected literature

The literature selection process is illustrated in a flow chart in accordance with PRISMA guidelines. In the first stage, several hundred records were obtained from databases (the exact number will be provided in the final version of the manuscript). After removing duplicates, the remaining works were preliminarily evaluated based on their titles and abstracts. At this stage, publications clearly unrelated to the topic of wearables in lifestyle diseases, conference reports without full text, and studies concerning only mobile applications were excluded.

In the next stage, the full texts of the preliminarily selected articles were subjected to a detailed assessment in terms of meeting the inclusion criteria and the absence of exclusion criteria. This included checking:

- whether a clearly defined intervention using a wearable device was used,
- whether the included population corresponded to the definition of lifestyle diseases,
- whether the reported endpoints were clinically relevant and quantitative,
- whether the study design met the minimum methodological requirements (e.g., for RCTs: randomization, control group).

Ultimately, several dozen studies were included in the review, covering both RCTs and systematic reviews and meta-analyses, as well as selected pilot studies of particular innovative significance (e.g., the first attempts to use integrated AI and CGM systems). The collected works were then grouped according to the predominant type of intervention:

1. Interventions based on continuous glucose monitoring (CGM) – including studies comparing CGM with classic self-monitoring (SMBG), comparisons of rt-CGM and FGM, as well as studies combining CGM with telemedicine and diabetes education.
2. Interventions based on physical activity monitoring – such as the use of pedometers, activity trackers, or smartwatches to increase the number of steps, moderate-to-vigorous physical activity (MVPA) time, and reduce sedentary behavior.
3. Monitoring of cardiovascular parameters – work on the detection of arrhythmias (in particular atrial fibrillation), blood pressure monitoring, and remote patient monitoring (RPM) of patients with heart failure.
4. Integration of wearable technology with AI algorithms – including risk prediction models, early warning systems, dynamic therapeutic regimens (DTR), and JITAI interventions.

Separate tables with study characteristics (population, type of device, duration of intervention, main endpoints, key results) have been prepared for each intervention group, facilitating comparison of the effectiveness of different solutions and identification of research gaps.

3. Results: CGM in type 2 diabetes

3.1.1. Clinical efficacy of CGM – meta-analysis results

A review of the latest meta-analyses on continuous glucose monitoring in adults with type 2 diabetes shows a relatively consistent picture – CGM is associated with a small but clinically significant improvement in glycemic control, especially in patients with poorer baseline metabolic control and in those using insulin therapy.

Meta-analyses including only RCTs suggest that, compared to classic self-monitoring of blood glucose (SMBG) using a glucometer or standard diabetes care, the use of CGM leads to a decrease in HbA1c of approximately 0.2–0.4 percentage points. Although this may seem like a small change at first glance, from a population perspective, it is a difference that is associated with a significant reduction in the risk of microvascular and macrovascular complications, especially when the improvement is sustained over the long term.

In parallel with changes in HbA1c, CGM allows for the assessment of more advanced indicators of glycemic control quality, such as time in range (TIR), time spent in hypoglycemia and hyperglycemia, as well as various measures of glycemic variability. In most studies, the use of CGM led to an increase in TIR by several to more than ten percentage points, while reducing the time spent in undesirable ranges. In practice, this means that patients spend more hours per day with their blood glucose within the optimal range, which has a direct impact on their well-being, physical performance, and the risk of acute complications.

It is also worth noting the differences between the two types of systems: rt-CGM (real-time) provides the patient with up-to-date information on blood glucose levels, along with alarms when thresholds are exceeded, while FGM (flash, “scanned” CGM) requires the patient to actively read the results. Meta-analyses comparing these two types of systems suggest that although both types lead to comparable reductions in HbA1c, rt-CGM may provide greater protection against hypoglycemia, especially in patients at high risk of such episodes, thanks to its real-time alarm function.

3.1.2. Factors affecting the effectiveness of CGM

However, the effectiveness of CGM is not uniform for all patients and all care models. Subgroup analyses indicate that the greatest benefits are seen in individuals with initially high HbA1c levels, those undergoing intensive insulin therapy (multiple injections, insulin pumps), and those receiving active support from a diabetes team (regular data analysis, treatment modification, education).

In studies where CGM was only an “additional tool” left to the patient's own interpretation, the therapeutic effect was significantly weaker. In contrast, programs integrating CGM with structured education, frequent contact with a professional (in person or remotely), and a clear plan for using data to modify insulin doses led to greater improvements in HbA1c and TIR. It can therefore be said that CGM works best as part of a broader behavioral-therapeutic intervention, rather than as a standalone gadget.

Other important factors include patient acceptance of the technology, ease of use (sensor replacement frequency, comfort), interface readability, and integration with other devices (smartphone, insulin pump). In older patients with lower digital literacy, steep “learning curves” may limit the full potential of the technology. In younger people, who are more familiar with technology, too much focus on data (known as data overload) can lead to anxiety, excessive glucose checking, and a reduced quality of life.

3.1.3. Limitations and challenges associated with CGM

Despite a growing number of studies, the current scientific evidence has important limitations. Most RCTs involving patients with type 2 diabetes are relatively short in duration (usually 3-6 months), making it difficult to assess the extent to which the observed benefits are sustained over the long term and to what extent they are the result of the “novelty” of the technology and increased patient attention to glycemic control.

Another limitation is the way many studies are funded – a significant proportion of them are sponsored by device manufacturers, which may introduce subtle biases (e.g., selection of favorable populations, choice of endpoints). While this does not automatically imply low-quality research, it does require critical interpretation of results and independent verification.

On a practical level, one of the biggest barriers is the cost of sensors and receivers and the issue of their reimbursement. In countries with limited financial resources, the healthcare system may treat CGM as an “additional” technology, intended mainly for selected groups (e.g., patients with T1DM), which reduces the availability of the solution for patients with T2DM, for whom the benefits – although smaller – may be significant at the population level.

Another significant challenge is the accuracy of measurements – although CGM systems are becoming increasingly precise, there are still situations (e.g., rapid changes in blood glucose levels, use of certain medications) in which sensor readings may deviate from reference values. Hence the need to educate patients on how to interpret the results and make them aware that CGM does not fully replace clinical assessment.

3.2. Integration of CGM with AI systems and risk prediction

Recent years have seen rapid development of solutions combining CGM with artificial intelligence algorithms that analyze glycemic data streams in real time. Machine learning models can identify patterns leading to hypoglycemia or hyperglycemia on an ongoing basis and then generate warnings or recommendations (e.g., insulin dose modification, carbohydrate intake, physical activity adjustment).

A particular example of such integration are closed-loop systems (“artificial pancreas”), in which an algorithm controls insulin delivery based on CGM data, minimizing the patient's involvement in daily therapeutic decisions. Although most advanced closed-loop systems are currently being developed mainly for type 1 diabetes, there are also pilot studies in patients with T2DM (e.g., with obesity and insulin resistance) in which automation of insulin delivery can reduce the risk of errors and improve the convenience of treatment.

At the same time, the use of predictive algorithms poses new requirements in terms of safety, transparency, and legal liability. The question arises as to who is responsible for incorrect decisions made by the system (e.g., too high a dose of insulin) – the manufacturer, the software developer, or the clinician who accepted the system as part of the therapy. This requires clear regulations and effective certification of such solutions as medical devices.

4. Results: physical activity monitoring devices

4.1.1. Effectiveness in increasing physical activity

Activity trackers and smartwatches have become one of the most frequently studied types of wearable devices in recent years in the context of preventing lifestyle diseases. Many meta-analyses confirm that the introduction of a device that measures steps, activity time, or heart rate promotes increased physical activity, at least in the short and medium term.

The most consistently observed indicator is the number of steps per day. In randomized studies, the inclusion of an activity tracker, especially in combination with a mobile app and step goals, usually leads to an increase of about 1,000–1,500 steps per day compared to the control group. This is a clinically significant effect – going from, say, 4,000 to 5,500 steps per day can mean a change from very low to moderately low activity, which translates into a reduction in cardiovascular risk.

Another important endpoint is the duration of moderate-to-vigorous physical activity (MVPA). In many studies, wearable-based interventions increased MVPA by several to several dozen minutes per week, which in practice means a few additional short walks or one or two additional exercise sessions. Although these values may seem small, in a population context (hundreds of thousands of users) they represent a potentially significant shift of the entire population towards higher activity levels.

In addition, some studies report a reduction in time spent sitting (reduction in sedentary behavior), especially when devices are programmed to send a signal reminding the user to stand up or take a few steps after a certain period of inactivity. This is particularly important in the context of people who work in a seated position, for whom prolonged sedentary behavior is an independent risk factor for lifestyle diseases.

4.1.2. Factors moderating effectiveness

The effectiveness of activity trackers depends largely on how they are embedded in the overall intervention. Simply giving a patient a device, without a specific program and support, usually produces shorter and weaker effects than multi-component programs.

A powerful “amplifier” is integration with mobile applications that allow users to track their progress, view graphs, compare results with previous weeks, and receive personalized advice. Many programs use gamification elements – points, badges for achieving goals, the ability to compete with friends or support group members. These types of mechanisms increase motivation, especially in younger people.

The support of medical staff or a health coach is also important. Interventions in which data from the tracker is regularly reviewed by a professional (e.g., every 1–4 weeks) and discussed with the patient usually produce greater and more lasting results than completely self-service programs. This feedback loop allows goals to be adjusted on an ongoing basis, barriers (e.g., joint pain, lack of time) to be analyzed, and the intervention to be tailored to the patient's actual capabilities.

An important element is the personalization of goals. Instead of an arbitrary threshold of 10,000 steps per day, it is increasingly recommended to set a “relative” goal, e.g., to increase the number of steps by 2,000 compared to the baseline. A patient who starts with 3,000 steps is more likely to succeed and stay motivated if the goal is, for example, 5,000 steps, rather than 10,000 right away. This approach is more inclusive and better takes into account the patient's limitations.

4.2. Impact on cardiometabolic endpoints

Many studies have analyzed whether the increase in physical activity induced by wearable devices translates into improved cardiometabolic parameters. The results are more varied than in the case of activity alone, but several trends can be identified.

4.2.1. Body weight and BMI

Interventions using activity trackers are often associated with a small reduction in body weight and BMI, usually in the range of 1–2 kg and 0.3–0.8 kg/m^2 compared to the control group. The most beneficial results are observed in programs that combine activity monitoring with dietary interventions (dietary consultations, calorie tracking apps) and psychological support (e.g., in the area of motivation, working on habits).

Long-term weight loss maintenance is more difficult—in many studies, after the end of an organized intervention, physical activity and body weight gradually return to baseline values. This suggests that wearable devices alone are not a “magic solution,” but rather a tool to support the process of lifestyle change, which must be sustained at various levels (education, social support, environmental changes).

4.2.2. Blood pressure and lipid parameters

The effect of wearable devices on blood pressure and lipid profile is less clear. Some studies have observed a slight reduction in systolic and diastolic blood pressure, usually by 2–5 mmHg, which from a population perspective may be significant for cardiovascular risk. Changes in lipid parameters (LDL, HDL, triglycerides) are more variable—in many studies, there are no significant differences between groups unless the intervention also includes a nutritional component.

4.2.3. Glycemic control in prediabetes and T2DM

In populations with prediabetes and type 2 diabetes, an increase in physical activity monitored using wearables is often associated with a reduction in HbA1c of approximately 0.2–0.5 p.p. and an improvement in other glycemic control indicators (fasting blood glucose, postprandial blood glucose). Some studies have also observed a slower progression from prediabetes to overt diabetes, although this needs to be confirmed in longer and larger studies.

4.3. Adherence and the phenomenon of "user fatigue"

An important topic that recurs in many studies is maintaining long-term user engagement. The interest curve for a new device often follows a "high start – rapid decline" pattern. In the first few weeks, patients regularly check their step count, respond to notifications, and comment on their results. After a few months, however, some of them begin to wear the band less often, turn off notifications, and the device ends up in a drawer.

This phenomenon is referred to as "user fatigue" – fatigue with digital intervention. Its scale varies depending on the population and the nature of the program, but many studies observe a decline in adherence after 3–6 months. High long-term adherence is more likely to be maintained when the intervention has a clear, personally meaningful goal (e.g., preparation for surgery, improvement of athletic performance, reduction of the risk of another cardiovascular event), the data from the device is used during real-life interactions with medical staff, and when the patient receives personalized feedback rather than just raw numbers.

In the context of lifestyle diseases, it is therefore crucial to design wearable programs in such a way as to minimize the risk of "user fatigue" – through meaningful goals, clear benefits, a simple interface, and a realistic information load.

5. Results: Monitoring cardiovascular parameters

5.1. Smartwatches and arrhythmia detection

5.1.1. Atrial fibrillation (AF) detection

Smartwatches based on photoplethysmography (PPG) and single-lead ECG have enabled mass detection of irregular heart rhythms in general populations. The best example is the Apple Heart Study, a prospective, multi-thousand-person population study in which an irregular heartbeat notification algorithm detected episodes of potential AF and referred participants for confirmatory monitoring (patch-ECG). The study showed that irregular heart rate notifications can lead to further diagnosis in people previously unknown to have AF, but the incidence of confirmed AF was lower than the number of notifications (large scale, important limitations regarding the population and lack of random assignment).

Practical implications: smartwatches may increase the detection of unknown AF at the population level, which makes sense in the context of stroke prevention (population-based AF detection → possibility of initiating anticoagulant prophylaxis in appropriate patients). However, clinical benefits (e.g., reduction in strokes) require further RCT studies and cost-effectiveness assessments.

5.1.2. Sensitivity and specificity of ECG algorithms

Validations of watch-ECG technology vs. 12-lead ECG have shown very high sensitivity and specificity in distinguishing AF vs. sinus rhythm under controlled conditions (e.g., validation of an ECG app on a watch showing high AF detection rates). However, these parameters vary depending on: sensor type (PPG vs. single-lead ECG), signal quality (motion, artifacts), recording length, and study population (e.g., frequency of AF paroxysms). Device evaluation recommendations indicate that validation results should be reported separately for tests under resting conditions and "in use" (real-world).

RCT studies using Apple Watch, Samsung, Fitbit

To date, most of the evidence comes from large observational series and validations; RCTs on mass screening using smartwatches are limited — there are registries and several smaller trials comparing the intervention (monitoring via smartwatch + diagnostic pathway) with standard care, as well as "Pulsewatch" trials analyzing the impact of alerts on behavior and false alarm burden. The results indicate that the devices improve the detection of irregular heart rhythms, but the effect on hard events (stroke, hospitalizations) has not yet been clearly documented in population RCTs. Further well-designed randomized trials are needed to measure not only diagnosis but also the treatment outcomes resulting from that diagnosis.

5.2. Continuous blood pressure monitoring

5.2.1. Ambulatory BP monitors (ABPM) vs. wearable (cuffless)

Traditional ambulatory blood pressure monitors (ABPM) remain the gold standard for 24-hour measurements, while cuffless devices (based on photoplethysmography, pulse transit time, or other signals) offer continuous measurement and the potential for real-time monitoring. Systematic reviews show that current cuffless devices vary greatly in accuracy—some meet validation criteria, but many do not. The ESH and other organizations emphasize the need for rigorous validation and calibration protocols.

5.2.2. Effectiveness in controlling hypertension

Evidence that continuous/multiparametric BP monitoring by wearables improves hypertension control is promising, but mostly comes from short-term studies with small sample sizes. There is a lack of robust, multicenter RCTs clearly showing a sustained reduction in cardiovascular risk with cuffless wearables alone. Scientific organizations recommend the use of verified, validated devices for clinical decisions and further research on the integration of such measurements with therapeutic interventions (e.g., patient-physician feedback, self-regulation of medications).

5.3. Remote Patient Monitoring (RPM) in heart failure

5.3.1. Early detection of decompensation

RPM, combining data from devices (weight, HR, saturation, heart rate, blood pressure, activity, and in newer systems also multi-channel biosignals from wearable sensors), can detect prodromal signs of HF decompensation days to weeks before clinical deterioration. Examples of analyses using ML models on signals from wearable sensors indicate the possibility of detecting deterioration with sensitivity and specificity reaching clinically useful values in pilot studies.

5.3.2. Reduction in rehospitalization

Clinical evidence is mixed, but there are RCTs and meta-analyses showing that well-designed telemonitoring/RPM programs (with clearly defined intervention pathways and staff responding to alerts) can reduce the number of unplanned hospitalizations and days lost due to hospitalization and, in some studies, mortality. An example is the TIM-HF2 (telemedical interventional management in heart failure) trial, a controlled study that showed a reduction in days lost due to unplanned cardiac hospitalizations or death in a specific HF population using integrated RPM. However, effectiveness depends on: (i) population selection (selected high-risk patients), (ii) signal/algorithm quality, (iii) clinical workflow (what is done after receiving an alert).

5.3.3. Integration with telemedicine

The integration of wearable technologies with telemedicine systems (platforms, automated triage algorithms, 24/7 care teams) is crucial for the data received to be translatable into clinical action. Research shows that technical measurement capabilities alone are not enough—clearly defined clinical response protocols, escalation pathways, and data quality assurance systems are essential. In practice, programs with engaged multidisciplinary care and rapid response mechanisms achieve the best results.

6. Results: AI integration and predictive algorithms in wearable technologies

6.1. Health risk prediction models

Machine learning in the prediction of cardiovascular events

Machine learning (ML) models are trained on signals from wearables (PPG, RR intervals, activity, HR variability) and clinical data to predict cardiovascular events (e.g., AF episodes, HF exacerbations, ischemic events). Systematic reviews show that ML can improve detection and risk stratification compared to simple indicators, but most models remain in the external validation or pilot phase; issues of generalization and overfitting are common.

6.1.1. Algorithms for detecting health deterioration / Early warning systems

ML-based early warning systems combine continuous signals (e.g., increase in resting heart rate, decrease in activity, sudden increase in HR variability) and can detect patterns leading to patient deterioration several days in advance. In pilot studies, the models showed good sensitivity and enabled intervention before exacerbation; however, they still require prospective RCT studies with hard outcomes (hospitalizations, mortality) and an assessment of the impact of "false alarms" on healthcare system resources.

6.2. Personalization of interventions: Dynamic Treatment Regimes (DTR)

6.2.1. Reinforcement Learning in Health Goal Optimization

DTR is a framework in which therapeutic decisions are dynamically adjusted to the patient's current condition; reinforcement learning (RL) offers optimization methods for selecting treatment “policies” (e.g., dose adaptation, behavioral reminders). In the context of wearables, RL can adapt the intensity of interventions (e.g., training reminders, medication modifications) based on continuous data. However, most work remains experimental—there is a lack of large RCTs evaluating RL-guided therapies in cardiology.

6.2.2. Just-in-Time Adaptive Interventions (JITAI)

JITAI uses real-time sensory data to deliver “just-in-time” interventions (e.g., coaching to reduce sedentary time, oral reminders), which improves treatment adherence and behavioral outcomes. Pilot studies show that JITAI improves adherence and short-term behavioral goals, but the impact on long-term clinical outcomes requires further testing.

6.3. Explainable AI (XAI) and clinical trust

6.3.1. SHAP, LIME, and other interpretation techniques

Local (LIME) and global (SHAP) interpretability techniques are commonly used to explain ML models in medicine—they allow identification of which features (e.g., decreased activity, increased HR) contributed to a specific alert. XAI facilitates acceptance of models by clinicians and compliance with regulatory requirements for transparency. At the same time, studies point to limitations (e.g., overinterpretation of explanations, sensitivity to feature collinearity), which requires caution in implementation.

6.3.2. Transparency of algorithms for clinicians

For wearable algorithms to be clinically useful, explanations must be understandable, clinically meaningful, and embedded in the workflow (e.g., what to do when the model reports high risk). Integrating XAI with electronic documentation systems and clinician-tailored interfaces improves trust and usability.

6.4. Algorithmic bias and fairness

6.4.1. Representativeness of training data

ML models are highly sensitive to the quality and representativeness of training sets. Much training data comes from populations with limited diversity (e.g., predominantly light-skinned, younger individuals, owners of specific devices), which can lead to reduced accuracy in underrepresented groups (e.g., different skin phototypes affecting PPG, anthropometric differences). Fairness audits and demographically diverse studies are necessary prior to clinical implementation.

6.4.2. Differences in effectiveness between demographic groups

Studies have shown differences in signal quality (e.g., PPG) and algorithm performance between racial/ethnic and age groups—this directly affects the sensitivity/specificity of AF and other signal detection. It is necessary to report model performance stratigraphically (by age, gender, race, comorbidities).

6.4.3 Cross-cultural validation

To ensure fairness, models and devices must undergo cross-cultural and cross-site validation, covering different environmental conditions, lifestyles, and demographics — only then can they be safely used in global healthcare. Furthermore, regulations and guidelines should require such validations prior to clinical use.

Brief summary and practical recommendations

1. AF detection: Smartwatches (PPG + single-lead ECG) have a documented ability to detect potential AF at the population level (e.g., Apple Heart Study), but the impact on hard clinical endpoints requires further RCTs.

2. Continuous BP monitoring: Cuffless technology is promising, but heterogeneity in accuracy requires rigorous validation and adherence to ESH/ISO recommendations before use for therapeutic decisions.

3. RPM in HF: Well-designed RPM programs with clear intervention protocols (e.g., TIM-HF2) can reduce hospitalizations in selected patients. Clinical workflow and alert response are key.

4. AI & XAI: ML improves the predictive capabilities of wearables, but implementation requires transparency (XAI), fairness audits, and external validation.

7. Summary

Wearable technologies, such as smart watches, activity trackers, and biometric sensors, are becoming an integral part of modern preventive healthcare. Numerous studies indicate that these devices enable continuous, non-invasive, and objective measurement of physiological parameters such as heart rate, heart rate variability (HRV), sleep quality, physical activity level, oxygen saturation, and early detection of heart rhythm disorders. Their role in the prevention of lifestyle diseases – especially cardiovascular disease, type 2 diabetes, obesity, and mood disorders – is increasingly well documented.

According to available meta-analyses and randomized controlled trials (RCTs), the use of wearables can lead to statistically significant improvements in health markers, including increased physical activity, weight loss, lower blood pressure, and improved glycemic control. These technologies also support healthy behaviors through feedback, personalization, and behavior modification (mHealth) mechanisms. Machine learning algorithms are becoming increasingly important, as they increase the accuracy of anomaly detection and allow for early identification of clinical events such as atrial fibrillation.

At the same time, scientific literature highlights limitations: variability in measurement accuracy between commercial devices, risk of misinterpretation, population limitations (most studies have involved young and healthy individuals), as well as ethical and data privacy issues. Long-term prospective studies evaluating hard endpoints, such as cardiovascular disease incidence or mortality, are also needed.

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