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WEARABLE HEALTH TECHNOLOGIES AND THE MEDICALIZATION OF EVERYDAY LIFE: A SOCIO-MEDICAL REVIEW

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ABSTRACT

Consumer wearable technologies have evolved from simple activity trackers into multisensor systems that continuously measure physiological and behavioural signals, generating algorithmic assessments of cardiac rhythm, sleep, recovery, stress, and metabolic responses. This trajectory increasingly blurs the boundary between wellness products and medical devices. This narrative socio-medical review examines how wearable health technologies contribute to the medicalization of everyday life by transforming ordinary activities into quantifiable indicators classified as normal, suboptimal, or potentially requiring intervention. Particular attention is given to digital medicalization, the Quantified Self, algorithmic norms, anticipatory risk, responsibilization, patient-generated health data, and the commercial circulation of bodily information. Through a synthesis of clinical and socio-ethical literature, we evaluate the dual nature of wearable tracking. While wearables may support prevention, self-knowledge, chronic-disease management, symptom documentation, and active healthcare participation, continuous monitoring can also intensify health anxiety, encourage compulsive checking, generate false alerts, and reproduce social or algorithmic inequalities. Their ultimate impact depends on device validity, design assumptions, business models, regulatory frameworks, clinical context, and individual user vulnerabilities. The challenge is not to reject digital health monitoring, but to develop technologies and governance practices that support care and autonomy without converting every bodily variation into a medical problem.

KEYWORDS

Wearable Health Technologies; Medicalization; Self-Tracking; Digital Health; Patient-Generated Health Data; Health Equity

CITATION

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Methodology

This article presents a critical narrative review with a socio-medical orientation, an approach suited to integrating heterogeneous clinical, technological, sociological, and ethical literature [10, 11]. The source set was assembled through targeted searches of PubMed/MEDLINE, Scopus, and Web of Science, supplemented by backward citation searching. Search concepts included wearable health technology, self-tracking, the Quantified Self, medicalization, biomedicalization, healthism, health surveillance, digital health, wearable-related anxiety, algorithmic bias, and the patient–physician relationship. The review includes consumer-grade and medical-grade wearables and examines them as socio-technical systems embedded in commercial, institutional, and cultural contexts [12, 13]. It does not claim exhaustive coverage or the methodological equivalence of a systematic review; no pooled effect estimate or formal risk-of-bias assessment was undertaken.

Introduction

Consumer wearable technologies were initially popularized as tools for counting steps, estimating energy expenditure, and supporting physical activity. They have progressively developed into multisensor systems capable of monitoring heart rate and heart rate variability, recording single-lead electrocardiograms, estimating peripheral oxygen saturation, measuring skin temperature, and generating algorithmic assessments of sleep, recovery, and stress [1–3]. Continuous glucose monitoring further extends this trajectory by making interstitial glucose data available not only to people with diabetes but increasingly also to healthy consumers seeking to optimize nutrition, exercise, and metabolic performance [4]. The validity of wearable measurements nevertheless varies by metric, device, population, and measurement context [5].

This expansion represents more than an increase in the number of measurable variables. When wearable algorithms classify a cardiac rhythm as irregular, sleep as insufficient, stress as elevated, or a glucose response as suboptimal, ordinary physiological fluctuations are translated into categories that resemble clinical findings.

Direct-to-consumer devices capable of identifying possible atrial fibrillation illustrate how consumer products are beginning to perform screening functions previously associated with medical equipment, although their accuracy remains dependent on the device, measurement conditions, population, and proprietary algorithms [6]. Consequently, the distinction between wellness technology and medical technology is becoming increasingly porous.

From a socio-medical perspective, this development can be examined through the concept of medicalization: the process through which experiences, behaviours, or conditions previously regarded as ordinary, social, or non-medical become defined and managed in medical terms [7, 8]. Medicalization is not inherently harmful. It may legitimize previously overlooked suffering, reduce moral blame, and facilitate access to diagnosis, treatment, and institutional support. However, it may also extend medical authority into new areas of everyday life, individualize problems with social or environmental causes, and increase dependence on biomedical categories and technological systems. Contemporary medicalization is no longer driven exclusively by physicians; industries, healthcare organisations, consumer demand, commercial markets, algorithms, and digital platforms increasingly participate in defining which conditions and variations are medically relevant [9].

This review examines how consumer wearable technologies reshape the boundaries between health, risk, and disease by transforming ordinary sensations, behaviours, and routines into continuously measurable and medically interpretable data. It addresses how these technologies redefine health and normality; influence behaviour, self-perception, and health-related identities; support prevention and clinical care; and create psychological, ethical, and social risks. The central argument is that wearables should be understood neither solely as empowering tools of prevention and self-care nor simply as instruments of medical control. Rather, they produce an ambivalent socio-technical model in which greater access to health information and opportunities for early detection coexist with expanded medical categories, intensified self-surveillance, and increasing dependence on algorithmic norms and digital platforms.

Conceptual foundations

From classical to digital medicalization

Classical accounts of medicalization emphasized the role of physicians, medical institutions, and professional authority in defining previously non-medical conditions as illnesses or disorders requiring diagnosis and treatment [7]. In this model, medicine expanded its jurisdiction by applying clinical categories, diagnostic criteria, and therapeutic interventions to an increasing range of human behaviours and experiences. However, Conrad's later analysis of the "shifting engines of medicalization" demonstrated that this process is no longer driven primarily by the medical profession. Pharmaceutical and biotechnology industries, healthcare markets, insurers, patient and consumer groups, and the commercial promotion of medical products have become increasingly influential in determining which conditions are recognized as medically significant and potentially treatable [9]. Wearable technologies extend this transformation by introducing new actors into the production of medical meanings, including consumer electronics manufacturers, digital platforms, software developers, application designers, data analysts, and proprietary algorithms.

The concept of biomedicalization is particularly relevant here because it draws attention to the growing importance of technoscientific innovation, risk surveillance, data management, and the continuous optimization of bodies that are not necessarily considered ill [14]. Through sensors, automated classifications, personalised scores, notifications, and behavioural recommendations, wearable systems can define desirable physiological ranges, identify deviations, and encourage corrective action before any healthcare professional has evaluated the user. At the same time, users themselves participate in this process by voluntarily collecting bodily data, comparing results with standardised targets, and incorporating platform-generated interpretations into their understanding of health, risk, and normality [15, 16]. Digital medicalization may therefore occur without the direct presence of a physician: medical norms and forms of health surveillance can be introduced into everyday life through continuous interaction between users, commercial devices, platforms, and algorithmic systems.

Healthism and the moralization of self-tracking

The normative dimension of wearable self-tracking can be further understood through Robert Crawford's concept of healthism. Crawford described healthism as an ideology that locates the causes of health and illness primarily within individual behaviour and similarly places responsibility for improvement at the level of personal choices, discipline, and lifestyle [17]. In this framework, health becomes not only a desirable condition but also a continuing personal project, a moral obligation, and an indicator of whether an individual is acting responsibly. Such an emphasis may obscure the influence of working conditions, income, education, housing, environmental exposure, and unequal access to healthcare by presenting health outcomes predominantly as consequences of individual conduct. Wearable technologies can intensify this logic by translating health into daily goals, scores, streaks, progress indicators, and personalised recommendations. Prompts such as "close your rings," "reach your goal," or "improve your sleep score" are therefore not entirely neutral reminders. They establish particular standards of desirable behaviour and encourage users to evaluate themselves in relation to continuous activity, sufficient recovery, nutritional control, and measurable physiological optimization.

Digital self-tracking may consequently promote an ideal of the disciplined, productive, and continuously self-improving subject whose health is treated as evidence of effective self-management [15, 18]. Although such mechanisms may motivate beneficial behavioural changes, they may also moralize illness and inactivity, generate guilt when targets are missed, and understate the structural conditions that constrain individuals' capacity to follow algorithmically prescribed lifestyles. Contemporary analyses of mHealth therefore suggest that its promise of autonomy can coexist with an intensified expectation that individuals remain permanently responsible for monitoring and optimizing their own health [19].

The Quantified Self and the datafication of the body

The concept of the Quantified Self refers to practices through which individuals collect, visualize, and interpret numerical information about their bodies, behaviours, and everyday experiences in pursuit of greater self-knowledge and self-improvement. Wearable devices facilitate this process by converting phenomena such as movement, sleep, heart rate, stress, recovery, and glucose variation into standardised metrics that can be compared over time and evaluated against predefined targets [15, 20]. For analytical purposes, it is useful to distinguish between three interconnected dimensions of embodiment. The lived or experienced body is known through sensations such as fatigue, pain, energy, anxiety, or perceived sleep quality. The biological body consists of physiological processes and signals occurring within the organism, only some of which can be captured by sensors. The digital body profile, by contrast, is a selective and computationally produced representation assembled from measured signals, platform-defined categories, statistical comparisons, and algorithmic interpretations.

Ruckenstein describes a related phenomenon as the creation of a "data double": a data-based reconstruction of the person that becomes an object of observation, interpretation, and interaction [21]. This digital profile should not be understood as a transparent or complete reflection of the biological body, because it depends on what a device is designed to measure, how data are sampled, which reference ranges are used, and how results are visualized. Nevertheless, scores and graphs may acquire considerable epistemic authority, leading users to reinterpret bodily sensations through numerical outputs—for example, feeling insufficiently rested because an application reports a low sleep score, despite an initially positive subjective assessment. Critical research therefore emphasizes that self-tracking technologies do not merely record a pre-existing self. By accentuating selected bodily processes, establishing norms, and directing attention towards measurable outcomes, they actively shape bodily awareness, health practices, and understandings of what the body is and what it should become [20, 22].

From everyday life to medical data

Wearable health technologies contribute to the medicalization of everyday life by translating ordinary activities, sensations, and routines into quantifiable indicators that can be interpreted through the language of health, risk, and bodily normality. A walk becomes a step count or an activity target; physical exertion is represented as time spent within algorithmically defined heart-rate zones; rest is converted into a recovery or readiness score; and sleep is divided into duration, efficiency, stages, and an overall measure of quality.

Similarly, physiological signals associated with autonomic arousal may be processed into an estimated stress level, while the consumption of a meal can be represented by the magnitude, timing, and variability of the subsequent glycaemic response recorded by a continuous glucose monitor [4, 15]. These outputs are not

simple reproductions of bodily reality. They are computational products generated through the selection of particular sensor signals, sampling procedures, reference values, and proprietary algorithms; definitions of composite measures such as "sleep quality" or "sleep score" may consequently vary between devices and platforms [25, 26]. The same distinction is especially important for stress and emotion: most wearables do not measure a subjective emotional state directly but infer it from physiological proxies such as heart rate variability, electrodermal activity, respiration, movement, and skin temperature [27, 28].

Through these processes, mundane experiences acquire the characteristics of digital biomarkers—quantifiable physiological or behavioural measures that may be used as indicators of biological processes, health states, or potential pathology. Everyday life is therefore not merely documented but reorganized within a medicalised interpretive framework: movement can appear insufficient, recovery incomplete, sleep suboptimal, stress excessive, or a postprandial glucose increase undesirable. By attaching norms, thresholds, scores, and risk categories to routine activities, wearable systems encourage users to understand daily living as a continuous sequence of measurable health events requiring evaluation and, potentially, corrective intervention.

Producing normality and deviation

Wearable technologies do not merely measure health-related behaviour; they also participate in defining what should count as sufficiently healthy, active, rested, or physiologically normal. Daily step targets, sleep scores, heart-rate zones, readiness indicators, and recovery thresholds divide continuously varying bodily states into categories such as optimal, acceptable, insufficient, or abnormal. However, these classifications raise fundamental questions: Who determines the correct number of daily steps? What constitutes "good" sleep? Are population averages appropriate standards for every individual?

Although commonly used targets may appear universal, evidence indicates that relationships between step counts and health outcomes vary according to age, baseline activity, health outcome, and measurement method; substantial health benefits can also occur below the widely promoted threshold of 10,000 steps per day [29, 30]. Similarly, recommendations concerning sleep duration are population-level guidelines rather than precise descriptions of the optimal sleep needs or experiences of every person [31].

The applicability of technological norms becomes particularly problematic when devices are used by older adults, people with chronic diseases, individuals with disabilities, or users whose working patterns and daily routines differ from those assumed during product design. For example, commercial wearables developed primarily around walking and running may inadequately represent wheelchair propulsion, upper-body activity, restricted mobility, or the need to prioritize rest rather than increased exertion [32]. More broadly, the quality and fairness of wearable classifications depend on the representativeness of development and validation datasets, the selected reference populations, sensor performance, and often undisclosed computational models [33, 34]. A technological norm may therefore be experienced as objective because it is expressed numerically and produced automatically, even though it remains the outcome of statistical generalization and design decisions regarding what should be measured, which comparison groups should be used, and where the boundary between normality and deviation should be placed. When these decisions remain invisible, users may interpret a failure to reach a standardised target as evidence of personal deficiency or ill health, rather than as a possible mismatch between a generalized technological model and their particular body, condition, or way of life.

From the healthy user to the "at-risk" subject

Wearable health technologies shift attention from the detection of existing disease towards the identification of possible future illness. This transformation reflects what Armstrong described as the rise of surveillance medicine: a model in which medical observation extends beyond symptomatic patients to apparently healthy populations, while risk factors and early abnormalities become legitimate objects of monitoring and intervention [35]. A user may feel well and have no established diagnosis, yet still receive an irregular-rhythm notification, a persistently low sleep or recovery score, or an alert concerning an unusual change in resting heart rate or temperature. Such measurements do not necessarily demonstrate disease, but they can reposition the user within a field of uncertainty in which physiological deviation is interpreted as a possible precursor of illness.

Wearable and mobile technologies have already enabled consumer-led screening for atrial fibrillation among individuals without a previous diagnosis, illustrating how the search for clinically silent abnormalities increasingly occurs outside conventional healthcare encounters [36]. Similarly, longitudinal data concerning

activity, sleep, heart rhythm, and other physiological parameters are increasingly investigated as predictors of future clinical outcomes rather than solely as descriptions of a person's present condition [34, 37]. The possible benefits of this anticipatory model include earlier recognition of otherwise unnoticed conditions and an opportunity for timely clinical assessment. However, screening alerts are not equivalent to confirmed diagnoses, and uncertain or false-positive findings may generate anxiety, repeated checking, self-diagnosis, and additional medical consultations [13]. Risk thus becomes a condition that requires continuing observation and management in its own right. Within this framework, health no longer means simply the absence of symptoms or diagnosed disease; it becomes a provisional and unstable status that must be repeatedly verified through data.

The algorithm as a mediator of bodily knowledge

Wearable devices rarely provide direct access to raw physiological signals. Instead, computational models translate sensor data into categories such as sleep quality, recovery, stress, or abnormal cardiac rhythm. These outputs are model-dependent interpretations shaped by sensor selection, sampling, reference datasets, classification thresholds, and often proprietary algorithms [33, 38]. Simplified scores and warnings may acquire epistemic authority, influencing what users accept as credible knowledge about their bodies.

Crawford, Lingel, and Karppi argue that self-tracking increasingly produces bodily knowledge through interactions among users, sensors, algorithms, platforms, and commercial institutions [39]. This may create tension when subjective experience conflicts with device assessments, with numerical outputs perceived as more trustworthy. Orthosomnia illustrates this problem: users may become concerned about tracker-identified poor sleep despite reassuring subjective or clinical assessment [40]. Algorithms therefore not only describe the body but shape interpretations of health and risk. Their outputs should remain subject to critical evaluation as partial, probabilistic assessments rather than infallible bodily knowledge.

Empowerment and potential health benefits

Wearables can also support self-knowledge, prevention, and more active participation in healthcare. Repeated tracking may reveal links between activity, sleep, heart rate, symptoms, medication, diet, and perceived well-being. A review of 67 empirical studies identified uses including motivation, behaviour change, illness management, data sharing, and patient–professional collaboration [41]. An umbrella review of 39 systematic reviews and meta-analyses found that activity trackers were associated with about 1,800 additional daily steps and 40 more minutes of walking, although effects on other outcomes were smaller or inconsistent [42].

Wearables may be particularly useful for documenting intermittent symptoms, identifying patterns, monitoring treatment responses, and providing data between consultations. Consumer-device data can complement clinical assessment in diabetes, cardiovascular disease, obesity, and other behaviour-related conditions, although routine clinical integration remains limited [43]. They may therefore support a more informed and active patient role. However, empowerment is not automatic: benefits depend on usability, personalised feedback, sustained engagement, digital literacy, and professional interpretation [44].

Validating patients' experiences

Patient-generated health data may strengthen the credibility of patients whose symptoms are intermittent, context-dependent, difficult to recall, or absent during a brief clinical consultation. Longitudinal records of activity, heart rate, sleep, temperature, symptom severity, and daily functioning can give temporal and visual form to experiences that might otherwise be described only through retrospective self-report. This may be particularly valuable for people with multiple chronic conditions or poorly understood illnesses, whose fatigue, pain, cognitive difficulties, post-exertional symptoms, or autonomic disturbances can fluctuate substantially from day to day.

Research involving people with multimorbidity indicates that smartwatch-based symptom tracking can support the collection of frequent information about changing health states outside clinical settings [45]. A systematic review similarly found that patient-generated health data can improve patient–clinician communication, increase health awareness, and provide clinicians with a better understanding of patients' conditions between consultations [46]. Qualitative research on Long COVID/post-COVID condition further suggests that self-tracking can generate knowledge about an uncertain and frequently contested illness, helping some patients challenge stigma, unequal clinical relationships, and the dismissal of symptoms as merely subjective [47]. In this sense, wearable data may function as an evidentiary supplement to the patient's account,

making their experience more communicable without replacing embodied knowledge or personal testimony. However, numerical records do not validate symptoms automatically. Clinicians may treat patient-provided data as signs requiring contextual interpretation rather than as definitive diagnostic evidence, particularly when their provenance, accuracy, or clinical relevance is uncertain [48]. Their value therefore depends on device validity, data completeness, appropriate presentation, and the clinician's willingness, expertise, time, and technical capacity to interpret them.

Chronic disease management and clinical monitoring

Wearable technologies may be particularly valuable for people with chronic conditions that require repeated or continuous observation, because they can capture physiological and behavioural patterns that remain invisible during an isolated clinical consultation. In diabetes care, clinically validated continuous glucose monitoring systems provide information on glucose trends, time within and outside target ranges, nocturnal events, and responses to meals, exercise, medication, and daily routines. Such data can support treatment adjustment and self-management, and continuous glucose monitoring has become an established component of care for many people with type 1 diabetes and selected groups with type 2 diabetes [49, 50]. In cardiology, ambulatory ECG patches, event monitors, and some smartwatch functions may record intermittent rhythm abnormalities that are absent during a standard ECG, thereby supporting the assessment of palpitations and the detection of atrial fibrillation. However, diagnostic performance varies across devices and rhythms, and consumer-generated alerts generally require confirmation using clinically interpreted electrocardiographic evidence [6, 51]. Wearable inertial sensors may similarly assist the longitudinal assessment of neurological disorders by measuring gait, tremor, bradykinesia, motor fluctuations, falls, or responses to medication under real-world conditions. In Parkinson's disease, such monitoring can reveal variability between clinical visits, although limitations in validation, standardization, usability, and regulatory acceptance continue to restrict routine adoption [52].

Medicalization and responsibilization

Health as an endless project

Wearable technologies may transform care for health from an occasional response to illness into an open-ended project of bodily optimization and permanent improvement. Because tracking is continuous and its metrics are comparative, achievement is rarely final: reaching today's activity target establishes a new baseline for tomorrow, while sleep, resting heart rate, heart rate variability, recovery, and fitness can always be further improved. Schüll describes wearable devices as instruments of technologically assisted self-regulation that incorporate lifestyle management into everyday decision-making and encourage individuals to remain continuously attentive to how ordinary actions affect their future health [16].

Within this logic, health is not treated as a stable condition that can simply be attained and maintained. Instead, it becomes a provisional achievement that must be repeatedly measured, demonstrated, and renewed. Self-tracking practices consequently operate as "technologies of the self" through which users are encouraged to examine, discipline, and transform their bodies in pursuit of an idealized version of themselves [18, 20]. Goals, trends, streaks, rankings, and readiness scores reinforce feedback loops in which each recorded improvement reveals another possible area of intervention. Such mechanisms may support motivation, routine formation, and beneficial behavioural change, but they may also convert self-care into a persistent obligation and make rest, inactivity, or failure to record data appear as lapses of personal discipline. Empirical research suggests that wearable users can experience empowerment, motivation, and accountability, while also reporting anxiety, frustration, guilt, or self-consciousness, particularly when they are unable to track their activity [53]. The critical issue is therefore not optimization itself, but the absence of a clear endpoint: when every metric can be improved, health risks becoming an achievement that is never complete and a form of work from which the individual is never entirely released.

Between voluntary monitoring and coercion

The use of wearable health technologies exists on a continuum between voluntarily chosen self-monitoring and monitoring that is strongly encouraged, institutionally expected, or effectively imposed. Lupton distinguishes private self-tracking, initiated by individuals for their own purposes, from pushed self-tracking, in which an external actor encourages people to collect and engage with personal data, and from imposed self-tracking, in which participation is required under conditions that leave little meaningful opportunity to refuse [24].

In healthcare, pushed self-tracking may form part of chronic- disease management when patients are asked to record glucose levels, blood pressure, activity, symptoms, or medication use and transmit the resulting data to professionals. Such arrangements can improve continuity of care and reveal clinically relevant patterns, but they may also transfer additional monitoring work and responsibility to patients, particularly when participation is presented as an expected component of being an engaged or compliant patient [54]. A clinician's recommendation does not in itself constitute coercion; however, voluntariness becomes questionable when patients believe that refusing a device may negatively affect the quality of care, access to services, or how their commitment to treatment is judged.

Similar concerns arise when employers link participation in wearable-based wellness programmes to financial rewards, insurance contributions, productivity assessment, or professional opportunities. Because employment relationships involve structural inequalities of power, formal agreement or continued participation may not amount to meaningful consent when workers anticipate disadvantages from opting out [55]. In insurance settings, incentives, premium differences, and restricted access to particular policies may likewise transform an apparently voluntary exchange of wearable data into a coercive offer, especially when the economic consequences of refusal are substantial [56]. Pressure may also operate informally within families, where self-tracking practices can influence the routines and health expectations of other household members even without an explicit institutional requirement [57].

The ethical boundary between support and coercion therefore cannot be determined solely by whether a user has technically agreed to wear a device. It also depends on who initiated the monitoring, who benefits from the data, who can access them, whether refusal carries material or relational consequences, and whether participation can be discontinued without loss of care, employment benefits, insurance access, or social approval.

Psychological and clinical risks

Access to continuous health data does not necessarily reassure users and, in some cases, may intensify attention to possible physiological abnormalities. Minor fluctuations in heart rate, sleep duration, oxygen saturation, temperature, or recovery scores can become objects of repeated interpretation, particularly when devices present them through warnings, colour-coded deviations, or comparisons with standardised targets. This may produce a self-reinforcing cycle in which uncertainty prompts repeated checking, checking reveals further variation, and the resulting data lead to online searches, reassurance seeking, additional measurements, or medical consultations.

A clinical report concerning a patient with atrial fibrillation described how smartwatch notifications contributed to persistent worry, hypervigilance towards cardiac sensations, habitual rhythm monitoring, and repeated attempts to obtain professional reassurance [58]. Observational evidence similarly suggests that patients with atrial fibrillation who use wearables may report greater symptom monitoring and preoccupation, more treatment-related concerns, and greater use of formal and informal healthcare resources, although these associations do not establish that the devices themselves caused the distress [59]. False atrial-fibrillation alerts have also been associated with lower perceived physical well- being and reduced confidence in managing chronic symptoms [60]. Wearable outputs may therefore begin to regulate subjective well-being: a user who initially feels healthy or rested may become anxious, fatigued, or dissatisfied after receiving an unfavourable score.

A sleep-specific manifestation of this dynamic has been described as orthosomnia, a proposed concept referring to an excessive or perfectionistic pursuit of ideal sleep based on data generated by consumer sleep trackers. Users may extend the time spent in bed, repeatedly analyse sleep stages, or become distressed by their inability to improve a device-generated sleep score, potentially reinforcing insomnia- related worry rather than improving sleep [40]. More recent cross-sectional research provides preliminary evidence that orthosomnia-related preoccupation may occur beyond isolated clinical cases, although prevalence estimates vary substantially depending on the criteria applied and the concept is not currently a formally established clinical diagnosis [61].

The available literature therefore supports neither the assumption that tracking is psychologically harmful for all users nor the belief that more data necessarily reduce anxiety. Its effects appear to depend on pre-existing vulnerability, the accuracy and frequency of alerts, the perceived authority of device outputs, and whether users receive sufficient contextual information and professional support [13, 62].

False alerts, overdiagnosis, and diagnostic uncertainty

Wearable-generated alerts can support the early identification of clinically relevant abnormalities, but when presented without sufficient context they may also create diagnostic uncertainty and trigger unnecessary medical activity. A notification indicating an irregular rhythm, low oxygen saturation, abnormal heart rate, or unusual physiological trend is not equivalent to a confirmed disease. Its interpretation depends on signal quality, the prevalence of the condition in the monitored population, the device's sensitivity and specificity, and the threshold selected by the manufacturer. Even tests with apparently high accuracy may produce a substantial number of false-positive results when applied to large, predominantly healthy populations in whom the target disorder is uncommon. Validation studies of direct-to-consumer devices have additionally reported considerable proportions of inconclusive rhythm recordings and cases in which normal rhythms were incorrectly classified as atrial fibrillation [6]. Such notifications may lead users to seek urgent or repeated consultations, request additional ECG monitoring or laboratory testing, search for diagnoses online, and become increasingly attentive to otherwise insignificant bodily fluctuations. Among patients with atrial fibrillation, wearable use has been associated with greater symptom monitoring, treatment-related concern, and condition-specific healthcare utilization, while false alerts have been associated with lower perceived physical well-being and reduced confidence in symptom management [59, 60]. At the population level, these effects may increase professional workloads and divert clinical resources towards the interpretation of low-risk, technically inadequate, or non-actionable findings.

False-positive alerts should also be distinguished from overdiagnosis. A false positive incorrectly indicates that an abnormality is present, whereas overdiagnosis involves the genuine detection of a condition or physiological deviation that would not have caused symptoms, functional impairment, or harm during the person's lifetime. Increasing the frequency and duration of monitoring makes it possible to identify shorter, rarer, or previously clinically invisible abnormalities, but the prognostic significance and appropriate treatment of all such findings are not always established. Ethical analyses of smartwatch-based atrial-fibrillation screening have therefore raised concerns about uncertain findings, downstream testing, and the risk of treating device-detected abnormalities whose clinical relevance remains unclear [63].

The opposite error is also possible: the absence of an alert may create false reassurance. Consumer wearables are not necessarily worn continuously, may sample physiological signals intermittently, and can miss events because of limited sensitivity, motion artefacts, poor sensor contact, device removal, or algorithmic thresholds. A recent comparative monitoring study found that wearable systems missed some atrial-fibrillation episodes, in part because devices were not being worn, demonstrating that "no notification" cannot be interpreted as evidence that no abnormality occurred [64].

These risks make it essential to distinguish among screening, diagnosis, and wellness monitoring. Screening identifies an apparently asymptomatic person who may have an increased probability of a condition and should undergo further evaluation; it does not by itself establish disease. Diagnosis requires confirmation using accepted clinical criteria, appropriate-quality data, and interpretation in relation to symptoms, history, risk factors, and other findings. For example, current European guidelines require clinical atrial fibrillation to be confirmed using an ECG recording before risk assessment and treatment decisions are initiated [65].

Wellness monitoring, by contrast, is primarily intended to support general lifestyle awareness, activity, sleep, or well-being rather than to detect or diagnose a specific disease; regulatory guidance similarly distinguishes low-risk general-wellness products from technologies intended for medical purposes [66]. Wearable outputs should therefore be interpreted as signals of varying clinical significance rather than self-sufficient medical conclusions. Their safe use requires communication that explains uncertainty, clarifies the purpose and limitations of each function, and avoids presenting either an alert as a diagnosis or silence as proof of health.

The erosion of trust in embodied experience

The growing authority of wearable-generated metrics may alter not only how users evaluate their behaviour but also how they perceive and interpret their own bodies. Self-tracking data are frequently presented as objective evidence capable of revealing processes that remain inaccessible to subjective awareness. Consequently, a user who wakes feeling rested may revise this initial judgement after receiving a low sleep score, just as someone who feels physically capable may interpret a poor recovery or readiness result as evidence of fatigue or physiological strain. Pantzar and Ruckenstein describe encounters with self-tracking data as forms of "situated objectivity," emphasizing that numerical measurements acquire meaning through their interaction with everyday experiences, expectations, and circumstances rather than functioning as

context-free representations of bodily truth [67]. The relationship between data and embodied knowledge can therefore be complementary: qualitative research indicates that wearables may reveal previously unnoticed bodily patterns and help users articulate sensations that are difficult to interpret independently [68].

However, this relationship becomes problematic when device outputs are automatically treated as more reliable than subjective experience. Consumer sleep trackers, for example, infer sleep duration, stages, and quality from indirect signals, and their estimates can differ significantly from polysomnographic measurements [69]. Clinical accounts of orthosomnia similarly show that some users become preoccupied with improving wearable-generated sleep data even when their perceived functioning or clinical assessment does not indicate a corresponding problem [40]. Studies of athletes and patients further demonstrate that people may alternate between trusting measurements and relying on somatic knowledge, particularly when numerical results conflict with how exertion, fatigue, or symptoms are actually experienced [70, 71]. In such situations, the body may cease to be regarded as something known primarily through lived sensation and instead become an object whose "true" condition must be disclosed by an external computational system.

Medicalization thus extends beyond the classification of behaviours and physiological parameters: it can reshape the phenomenology of embodiment itself by teaching users which sensations deserve attention, how those sensations should be named, and whether their own experience can be trusted without numerical confirmation.

Transformation of medical relationships

Patient-generated data from wearable technologies can transform the patient–physician relationship in two contrasting ways. In a collaborative scenario, longitudinal records of activity, sleep, heart rate, symptoms, or glucose patterns provide a shared informational basis for discussion, enabling patients to describe their everyday health more precisely and participate more actively in decisions concerning care. A systematic review of healthcare professionals' experiences found that their motivations for examining consumer-generated data included benefits for patients, support for clinical work, identification of health patterns, and the strengthening of patient–professional relationships [43]. Qualitative research similarly suggests that smartwatch data may reveal aspects of patients' lives that are unavailable during episodic consultations, facilitate more productive conversations, and create opportunities for clinicians and patients to interpret behavioural patterns together [72]. In this sense, wearables may partially redistribute epistemic authority: the patient is no longer only a recipient of professional assessment but becomes a producer of potentially relevant knowledge about their own health.

The new work performed by the patient

The use of wearable health technologies does not simply involve possessing or wearing a device; it requires patients to perform a growing range of practical, interpretive, and organisational tasks. Devices must be charged, worn correctly, calibrated where necessary, connected to smartphones, updated, and synchronized with digital platforms. Patients may also be expected to check dashboards, interpret graphs and trends, distinguish meaningful changes from technical artefacts, respond to alerts, annotate symptoms, prepare reports for consultations, and decide whether a result requires behavioural modification or professional assessment. Digital monitoring thus creates a form of often invisible patient work that extends clinical observation into everyday life. Lupton argues that the ideal of the "digitally engaged patient" encourages individuals to develop monitoring expertise that was once largely associated with healthcare professionals, while simultaneously making self-care and data production part of their responsibility [74]. Remote monitoring can increase disease-specific knowledge, support earlier intervention, and strengthen self-management and shared decision-making; however, qualitative

Information overload among healthcare professionals

The clinical integration of consumer-generated wearable data may provide valuable insight into patients' health between consultations, but it also creates a substantial informational and organisational burden for healthcare professionals. Continuous monitoring can produce thousands of measurements, fluctuations, alerts, and patient annotations, most of which cannot be individually reviewed during time- limited consultations. Clinicians therefore require summarised trends, clinically meaningful thresholds, and methods for distinguishing actionable changes from ordinary variation, measurement artefacts, or data of uncertain relevance. Research on the use of patient-generated health data indicates that healthcare professionals are concerned about the additional time required to access, review, interpret, discuss, and document these data,

particularly when information is presented through separate applications or unsorted reports rather than incorporated into established clinical workflows [73, 75]. Interoperability remains a central barrier because devices and platforms frequently employ proprietary formats and require separate connections to electronic health-record systems. Without common data and metadata standards, healthcare organisations may need to develop costly, vendor-specific integrations that are difficult to maintain as devices, software, and algorithms change [76]. Even technically integrated data do not automatically become clinically useful: their provenance, quality, measurement context, and intended purpose must remain visible so that consumer-generated information is not treated as equivalent to validated clinical measurements [77].

Data, privacy, and commercial interests

Data generated by wearable devices have not only personal and clinical value but also considerable economic and strategic value. Continuous records of activity, sleep, heart rate, location, stress indicators, and other physiological or behavioural variables can reveal patterns of everyday life that are difficult to obtain through episodic clinical measurements. Their value increases when individual observations are aggregated across large populations and combined with demographic, behavioural, purchasing, or health-related information. Such datasets can be used to refine sensors and algorithms, develop new products, personalize recommendations, classify users, predict engagement, and train analytical or machine-learning models.

Research using large-scale datasets from commercial apps and wearables has already demonstrated their utility for identifying behavioural patterns, constructing predictive models, segmenting users, and improving the design and personalization of digital interventions [78]. More recent studies have also shown that extensive wearable movement datasets can be used to pre-train foundation models for the prediction of mental-health-related outcomes, illustrating how accumulated bodily data may become an infrastructural resource for future analytical systems [79].

Privacy and the limits of informed consent

These limitations indicate that consent should be understood as an ongoing process rather than a single act performed during device registration. Meaningful consent would require accessible explanations of what is collected and inferred, purpose-specific choices, transparent information about recipients and retention periods, effective mechanisms for access and deletion, and opportunities to withdraw permission without losing unrelated core functions. It should also account for changes in data- processing practices and for secondary uses that were not foreseeable when the original agreement was accepted.

Comprehensive reviews of the ethics of self-tracking identify privacy and surveillance, autonomy, ownership and control of data, commodification, social harm, interpretability, and regulatory accountability as central areas of concern [89]. Reviews focused specifically on health-monitoring wearables likewise emphasize personal-data governance, justice, care relationships, uncertain distributions of benefit and harm, and inadequacies in existing regulatory frameworks [81]. The ethical problem is therefore not simply whether data are collected with formal permission, but whether users retain sufficient knowledge, autonomy, and practical control to determine how information generated from their bodies is interpreted, circulated, retained, and used to make decisions about them.

Surveillance capitalism and the secondary use of bodily data

The commercial significance of wearable data becomes particularly visible when examined through the concept of surveillance capitalism. Zuboff uses this term to describe an economic logic in which human experience is transformed into behavioural data that can be analysed to predict, personalize, and potentially influence future conduct [82]. Wearable technologies extend this process to the body by producing continuous streams of information concerning movement, sleep, heart rate, stress, location, and everyday routines. Although these data may initially be collected for a specific health or wellness purpose, their meaning can expand when they are integrated with other information, including purchasing histories, smartphone location records, online activity, demographic profiles, insurance data, or indicators of occupational performance. Lupton's concept of dataveillance emphasizes that self- tracking data may circulate beyond the private relationship between the user and the device, entering wider digital economies in which they are aggregated, interpreted, and repurposed by platforms and institutions [24]. Research on interactive life-insurance programmes illustrates this transition: fitness data generated through users' everyday activity can become part of commercial systems for classifying policyholders, encouraging particular behaviours, and managing risk, while the users themselves perform the unpaid work of producing the data on which these systems depend [83].

Inequality and exclusion

Unequal access and the digital health divide

The potential benefits of wearable health technologies are not distributed equally across populations. Access depends not only on the price of the device itself but also on ownership of a compatible smartphone, reliable internet connectivity, the ability to pay subscription or replacement costs, sufficient digital literacy, and the time required to configure, charge, synchronize, interpret, and troubleshoot the technology. These requirements can disadvantage people with lower incomes, limited education, unstable internet access, disabilities, or limited confidence in using digital systems.

A large United States survey found that wearable ownership was substantially higher among younger, more highly educated, higher-income, privately insured, and urban respondents, whereas people aged 65 years or older, rural residents, uninsured individuals, and Medicaid recipients were less likely to own such devices [84]. A nationwide German study similarly identified lower wearable use among older adults and people with lower educational attainment or below-average household income, while also showing that digital health literacy partly mediated age-related differences in adoption [85].

Bias, limited representativeness, and algorithmic fairness

These limitations are not only technical problems but also matters of health equity and algorithmic fairness. If an algorithm produces more missing data, larger estimation errors, or different false-positive and false-negative rates for certain groups, the resulting recommendations, alerts, and risk classifications may distribute benefits and harms unequally. Canali and colleagues therefore identify data quality, balanced estimation, health equity, and fairness as closely related requirements for the responsible clinical use of wearables, emphasizing the importance of representative datasets and validation within the populations for whom devices are intended [33]. Empirical research on personal- informatics systems further suggests that biases may emerge in raw data and subsequently be reproduced or amplified during model development, with women and users with conditions such as diabetes, hypertension, or joint disorders among the groups most affected in the analysed datasets [86].

Fairness therefore cannot be established by reporting high average accuracy alone. Wearable technologies should be evaluated intersectionally and under realistic conditions, with performance reported separately by age, sex and gender, skin tone, body characteristics, disability, health status, and activity context. Without such testing, a device optimized for the statistically typical user may present its measurements as universally objective while systematically representing some bodies less accurately than others.

Norms designed for the "ideal user"

The goals and classifications embedded in wearable technologies are often designed around an implicit "ideal user": a generally healthy, ambulatory, technologically competent individual who follows a regular daily schedule and has sufficient time, energy, and autonomy to pursue continuous self-improvement. Standardised activity targets, reminders to move, exercise streaks, sleep schedules, and recovery recommendations may appear universally applicable, even though they presuppose particular bodily capacities and ways of organizing everyday life. This mismatch is evident among people with chronic diseases.

In a qualitative study of patients using commercial activity trackers during physiotherapy, the default target of 10,000 steps was frequently perceived as too demanding, and participants preferred goals developed in relation to their individual abilities and treatment plans [87]. For a wheelchair user, step-based measurement may fail to recognize wheelchair propulsion or upper-body activity, while interfaces, fastening systems, touch controls, charging procedures, and feedback mechanisms may present additional accessibility barriers.

Toward responsible wearable health technologies Principles of responsible design

Responsible wearable design should begin with the recognition that physiological measurements and algorithmic interpretations are inherently incomplete and uncertain. Rather than presenting scores, warnings, and recommendations as definitive statements about the user's body, devices should communicate measurement limitations, missing or low-quality data, relevant contextual factors, and the degree of confidence associated with each result. Explainability should extend beyond a general description of the algorithm: users should be able to understand which measurements contributed to a recommendation, why a result changed, what alternative explanations are possible, and what form of action—if any—is justified. Research on explainable wearable-data analytics emphasizes that transparency must be evaluated from the perspective of users and healthcare professionals, rather than treated solely as a technical property of a model [88, 89].

The role of physicians and health education

The responsible use of wearable health technologies requires not only technically reliable devices but also adequate health education and professional support. Users should understand that wearable measurements are influenced by sensor quality, device placement, movement, sampling procedures, missing data, and proprietary algorithms, and that a score, trend, or alert does not necessarily represent a clinically significant abnormality. This is particularly important for complex metrics such as sleep stages, recovery, stress, heart rate variability, and readiness, whose definitions and computational methods may differ substantially between manufacturers [91].

Physicians can help patients evaluate whether a finding is plausible, identify possible artefacts or contextual explanations, and determine whether it requires observation, confirmatory testing, or no further action. The interpretation of wearable data should therefore incorporate symptoms, medical history, medication use, comorbidities, age, functional status, and conventional clinical assessment rather than treating isolated numerical outputs as self-sufficient evidence of health or disease. Systematic evidence indicates that patient-generated data may improve understanding of everyday behaviours and chronic conditions, but healthcare professionals continue to report uncertainty concerning data quality, clinical relevance, interpretation, and appropriate integration into care [43].

Regulation and institutional responsibility

The increasing overlap between consumer wellness products and clinically oriented wearable technologies requires a clearer regulatory distinction among lifestyle monitoring, health screening, and medical diagnosis. This distinction should be based primarily on the device's intended purpose, claims, outputs, and potential consequences rather than on its physical form or commercial label. Under the European Medical Device Regulation, software intended solely for lifestyle and well-being purposes is generally distinguished from software intended for medical purposes, while the current U.S. Food and Drug Administration policy similarly treats low-risk products supporting a healthy lifestyle differently from functions intended to diagnose, prevent, mitigate, or treat disease [66, 83].

A wellness function may provide general information about activity, sleep, or well-being, whereas a screening function identifies a possible abnormality or increased probability of disease and should direct the user towards further assessment rather than present its result as a confirmed diagnosis. A medical device intended to support diagnosis or treatment, by contrast, requires clinical evidence demonstrating that its output is valid and meaningful for the specified purpose, population, and context of use [90]. Manufacturers should therefore not be able to avoid appropriate evaluation by describing clinically suggestive alerts as mere wellness information, while users should be clearly informed about whether a function has been clinically validated, what decision it is intended to support, and what action should follow from its output.

Discussion

The dual nature of wearable health technologies

The socio-medical significance of wearable health technologies lies in their fundamentally dual and context-dependent character. The same device that strengthens users' agency by providing access to personal health information may simultaneously establish a system of continuous self-surveillance in which behaviour and physiology are assessed against externally defined norms. Similarly, monitoring may facilitate prevention and the earlier recognition of clinically relevant changes, while also expanding medical attention towards ordinary fluctuations, asymptomatic risk, and increasingly minor deviations from algorithmic standards. Evidence suggests that activity trackers and self-tracking systems can support physical activity, self-knowledge, behavioural change, and participation in healthcare, although their effects vary substantially across users and settings [41, 42].

At the same time, self-tracking data can become instruments of dataveillance, behavioural persuasion, responsibilization, and commercial or institutional evaluation [24]. Personalization therefore coexists with normalization: although recommendations are presented as individually tailored, they are produced through standardised categories, reference populations, design assumptions, and computational thresholds that may represent some bodies and lifestyles more accurately than others. Concerns regarding data quality, balanced estimation, health equity, and algorithmic fairness demonstrate that individualized feedback does not necessarily produce equitable outcomes [33].

Autonomy is similarly accompanied by responsibilization, as greater access to data may allow users to make informed decisions while also transferring additional monitoring work, interpretive responsibility, and

moral expectations of self- management onto them. Knowledge may reduce uncertainty and support communication with healthcare professionals, but unexplained scores and alerts may also increase anxiety, undermine embodied self-trust, or generate disagreement about the meaning and clinical usefulness of consumer- generated data [13, 43].

Finally, the accessibility promised by remote and consumer-based monitoring may coexist with new inequalities related to cost, digital literacy, disability, connectivity, data representation, and access to professional interpretation. These tensions should not be treated as mutually exclusive outcomes. Rather, the same wearable function may be simultaneously useful and medicalising, empowering and disciplinary, depending on the user's needs and vulnerabilities, the purpose of monitoring, the design and validity of the technology, the institutions involved, and the ways in which the resulting data are interpreted, shared, and acted upon. Wearables should therefore be evaluated not as inherently emancipatory or oppressive tools, but as socio-technical systems whose benefits and harms emerge from their specific conditions of use.

How wearables medicalize everyday life

Wearable health technologies medicalize everyday life by extending health observation beyond clinical institutions and embedding it within ordinary routines, including sleep, work, exercise, eating, rest, and emotional experience. This reflects the logic of surveillance medicine, in which medical attention is directed not only towards symptomatic patients but also towards apparently healthy populations whose future risks and minor physiological deviations become objects of continuous observation [35].

Wearables further contribute to medicalization by translating behaviours and bodily experiences into health-relevant indicators or quasi-biomarkers: walking becomes a step count, sleep becomes a quality score, exertion becomes a heart-rate zone, and physiological arousal becomes an estimated level of stress. These transformations do not simply record reality but selectively reconstruct the body through measurable variables, visualizations, classifications, and algorithmically generated "data doubles" [15, 21].

By comparing these outputs with standardised targets and thresholds, wearable systems also establish technological norms that distinguish sufficient from insufficient activity, good from poor sleep, and normal variation from potentially concerning deviation. At the same time, they shift attention from present illness towards future risk: an asymptomatic person may be encouraged to monitor an irregular rhythm, altered temperature, low recovery score, or other indicator whose clinical meaning remains uncertain. Wearables additionally intensify individual responsibility by positioning users as active managers of their own risk, expected to collect data, respond to notifications, modify behaviour, and demonstrate continuing engagement with health. Lupton characterizes the digitally monitored subject as both an object of surveillance and persuasion and as a responsible individual expected to act upon technologically generated health imperatives [23].

Finally, because users usually receive processed scores, alerts, and recommendations rather than raw physiological signals, part of the authority to interpret the body is transferred from embodied experience and clinical judgement to proprietary algorithms and digital platforms. This process is consistent with Conrad's observation that contemporary medicalization is increasingly driven by actors beyond the medical profession, including commercial industries, technologies, and consumers themselves [9]. Wearables therefore medicalize everyday life not merely by detecting disease, but by reorganizing daily experience around continuous measurement, technological norms, anticipatory risk, individual responsibility, and algorithmically mediated knowledge of the body.

Limitations of the review

This review has several limitations. As a critical narrative synthesis, it integrates conceptually and methodologically heterogeneous literature and does not provide an exhaustive or reproducible estimate of the entire evidence base. The field is developing rapidly, while device hardware, software, proprietary algorithms, regulatory status, and commercial data practices may change faster than peer-reviewed evidence can be produced.

The interpretation of psychosocial and ethical effects is also limited by differences in user populations, study designs, device types, and contexts of use. Accordingly, the review identifies recurring mechanisms, tensions, and implications rather than estimating the prevalence or magnitude of every benefit and harm. Future work should combine transparent systematic searches with longitudinal, comparative, and subgroup-specific studies and should report device versions, algorithm changes, validation populations, and relevant commercial or institutional arrangements.

Conclusions

Wearable health technologies are neither neutral instruments that simply reveal pre-existing facts about the body nor inherently harmful systems of surveillance and medical control. Their socio-medical significance emerges from the relationships in which they are embedded: the clinical purposes for which they are used, the assumptions incorporated into their design, the business models supporting digital platforms, the institutions that gain access to the data, and the capacities and vulnerabilities of individual users. Self-tracking may improve bodily awareness, support preventive action, facilitate chronic-disease management, and enable patients to participate more actively in healthcare. At the same time, it may normalize continuous surveillance, transfer responsibility for health management to individuals, reinforce standardized ideals of healthy behaviour, and expose users to anxiety, commercial data extraction, or unequal algorithmic performance.

Critical reviews of self-tracking consequently identify empowerment and improved care alongside concerns involving autonomy, privacy, commodification, discrimination, and social responsibility [80, 81]. These effects are not determined by measurement alone: they depend on whether data are accurate and representative, whether uncertainty is communicated clearly, whether users retain meaningful control, and whether technological outputs are interpreted within an appropriate personal and clinical context.

Requirements concerning data quality, interoperability, access, representativeness, health equity, and fairness should therefore be treated as central conditions of responsible implementation rather than secondary technical considerations [33]. Similarly, the promotion of individual self-management must not replace institutional responsibility for public health or obscure the social conditions that shape people's ability to follow technological recommendations [89].

The central challenge is therefore not to halt the digital monitoring of health, but to develop technologies and governance arrangements that support care, knowledge, and autonomy without transforming every bodily variation, behaviour, and element of everyday life into a potential medical problem.

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