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Review article

The future of healthy ageing: Wearables in public health, disease prevention and healthcare☆

Marilyne Menassa[a,*], Ilona Wilmont[b,c], Sara Beigrezaei[a], Arno Knobbe[d], Vicente Artola Arita[a], Jose F. Valderrama V[a], Lara Bridge[a], W.M. Monique Verschuren[a,e], Kirsten L. Rennie[f], Oscar H. Franco[a], Frans van der Ouderaa[g]

[a] Department of Global Public Health & Bioethics, Julius Center for Health Science and Primary Care, UMC Utrecht, Utrecht University, the Netherlands
[b] Institute for Computing and Information Sciences, Data Science, Radboud University Nijmegen, Nijmegen, the Netherlands
[c] Stichting Je Leefstijl Als Medicijn, the Netherlands
[d] Leiden Institute of Advanced Computer Science, Universiteit Leiden, Leiden, the Netherlands
[e] National Institute for Public Health and the Environment, Bilthoven, the Netherlands
[f] MRC Epidemiology Unit, University of Cambridge, Cambridge, United Kingdom
[g] Leyden Academy on Vitality and Ageing, Leiden, the Netherlands

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ABSTRACT

Wearables have evolved into accessible tools for sports, research, and interventions. Their use has expanded to real-time monitoring of behavioural parameters related to ageing and health. This paper provides an overview of the literature on wearables in disease prevention and healthcare over the life course (not only in the older population), based on insights from the Future of Diagnostics Workshop (Leiden, January 2024).

Wearable-generated parameters include blood glucose, heart rate, step count, energy expenditure, and oxygen saturation. Integrating wearables in healthcare is protracted and far from mainstream implementation, but promises better diagnosis, biomonitoring, and assessment of medical interventions.

The main lifestyle factors monitored directly with wearables or through smartphone applications for disease prevention include physical activity, energy expenditure, gait, sleep, and sedentary behaviour. Insights on dietary consumption and nutrition have resulted from continuous glucose monitors. These factors are important for healthy ageing due to their effect on underlying disease pathways.

Inclusivity and engagement, data quality and ease of interpretation, privacy and ethics, user autonomy in decision making, and efficacy present challenges to but also opportunities for their use, especially by older people. These need to be addressed before wearables can be integrated into mainstream medical and public health strategies. Furthermore, six key considerations need to be tackled: 1) engagement, health literacy, and compliance with personalised feedback, 2) technical and standardisation requirements for scalability, 3) accountability, data safety/security, and ethical concerns, 4) technological considerations, access, and capacity building, 5) clinical relevance and risk of overdiagnosis/overmedicalisation, and 6) the clinician's perspective in implementation.

1. Introduction

Throughout the life course, people experience gains and losses across biophysiological and psychological dimensions, accompanied by progressive losses in bodily functions and an increased risk of multimorbidity and mortality [1]. Governed by the interactions between individual and environmental capacities, ageing healthily is a lifelong endeavour necessitating a shift from focusing on age-related disease treatment to prevention. This shift is essential when observed from the lens of biological ageing that progresses at different rates among

Abbreviations: AI, Artificial Intelligence; BMI, Body Mass Index; CGM, Continuous Glucose Monitoring; ISPAH, International Society for Physical Activity and Health; IPEN, International Physical Activity and the Environment Network.

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* Corresponding author.
E-mail address: m.menassa@umcutrecht.nl (M. Menassa).

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individuals of the same chronological age, manifesting in varying signs of ageing and disease at similar times in life [2].

Behavioural and environmental factors play a key role in maintaining good health [3]. Low population adherence to behavioural guidelines and the need to identify individuals at risk have given rise to an increasing need for personalised advice in what is termed today as precision health, integral to disease prevention and management [4]. An important tool for precision health is artificial intelligence (AI) with an expanding role of wearables for real time monitoring of biomarkers of ageing, metabolism, behaviours, and health [5]. Advances in technology have made wearables popular and accessible for tracking behaviour for professional and recreative sports, research, and healthcare.

In this paper, we present an overview of wearables in prevention and healthcare, starting with an introduction on biomarkers of ageing. The insights presented are based on discussions at an international workshop on the 'The Future of Diagnostics' organized by the Dutch Society of Research on Ageing, Leiden, 10–12 January 2024. The search terms for the discussed literature based on these insights in PubMed, Scopus, Web of Science, Embase, Medline, and Google Scholar are available in Appendix 1. Accordingly, we generate summary points (*S1–S5*) and recommendations (*R1–R5*), concluding with a vision for future implementation that integrates key considerations (*C1–C6*) for medicine and public health.

2. The wearables landscape for healthy ageing

Wearables have evolved into adaptable lightweight devices worn on the head, limbs, or torso as helmets, wristbands, and belts among others [6,7]. Combined sensors such as three-dimensional accelerometers, gyroscopes, photoplethysmography, peripheral skin temperature, and electrodermal activity are used to estimate metrics including gait, energy expenditure, physical and brain activity, oxygen saturation, heart rate and derivative measures, and blood pressure, as well as biomarkers present in biofluids such as saliva, blood, and tears [7]. Wearables are usually coupled with smart applications enabling interpretation of the measures by the user. The derived outputs from algorithms in estimating biometrics and behaviours, provide user feedback to encourage lifestyle adjustments. The role of AI in analysing and interpreting big data generated from wearables is promising for timely and accurate disease diagnosis, management, treatment, and prognosis. Despite systemic biases (such as external validation in other representative populations), wearables and AI can assist humans in monitoring and fast interpreting of data from different sensor inputs while minimising errors in research and clinical outcomes [6,8].

2.1. Biomarkers of ageing and wearables

According to Butler, a good biomarker of ageing is one that predicts age-associated outcomes and longevity better than chronological age and can be safely tested in humans and animals [9]. Over the past decade and with the methodological advancement in training age prediction models, many ageing clocks with different biomarkers have been suggested and wearable sensors have been developed to detect them [10]. The biomarkers estimate the mean absolute difference between the predicted and chronological age in what is termed the "biological age gap." The optimal biomarker would thus better predict age-associated outcomes for function, pathology, and mortality than chronological age. Candidate biomarkers are either cellular (such as telomere length), omics, biophysical, and blood biochemistry, image-based (such as brain, face, and retina), and other cardiac, lung, cognitive, and biopsychological markers (such as subjective age) [11]. However, organs and systems do not age in the same way meaning that ageing biomarkers differ between organs adding another layer of complexity in monitoring changes over the life course [9]. Most of the biomarkers and associated wearables are in the experimental phase and their clinical significance remains challenging for reasons such as standardisation, human diversity, interconnectedness of mechanisms, scalability, cost, and the difficulty in differentiating between benign and harmful age-related changes [10,11] (Table 1. *S1* & *R1*).

Table 1
Wearables and healthy ageing: biomarkers, healthcare, and prevention summary & point-by-point recommendations.

Summary	Recommendations (point-by-point)
Biomarkers of ageing and healthcare	
S1. Coupling a "gold standard" biomarker of ageing with reliable wearables and analytical model for monitoring ageing and improving pathways of prevention and care is a daunting task and is yet to be achieved.	R1. Practical and external validity based on long-standing cohort studies in different populations and contexts is warranted to inform interventions.
S2. Compared to traditional pathways of care, integrating wearables in healthcare promises better outcomes, but with varying degrees of confidence and evidence between diseases.	R2. Rigorous studies that independently tackle diseases where wearables have proved promising are still warranted. Levelling up remote patient monitoring from passive symptom tracking to active participation, potentially even leveraging the power of gamification for compliance, presents a key opportunity for improving healthcare outcomes. Challenges of standardisation of care, skills in use, privacy, data heterogeneity, efficacy, representativeness of different population groups, cost-effectiveness, and data quality and interpretation need to be addressed before wearables become fully integrated into healthcare.
Public health & lifestyle factors	
S3. Precision nutrition: Wearables are essential tools for automating, optimizing, and personalizing general nutrition guidelines. Many challenges remain: traditional time-consuming approaches to keeping food diaries, expensive lab-based nutrition biomarkers, limitations relating to participant adherence and awareness, standardisation of wearable tools, and difficulties to scale up at the population level. Until these challenges are addressed, the use of wearables for precision nutrition will remain experimental.	R3. Challenges need to be addressed with the user in mind before wearables for precision nutrition can be implemented into mainstream public health prevention strategies. Future research needs to focus on the efficacy and cost-effectiveness associated with the use of wearables, setting a gold standard comparator, and using longer follow-up times. Furthermore, tailoring diets to genetic, epi-genetic, food availability and environmental factors of the individual are a significant challenge
S4. Sleep: Wearables can play a significant role in facilitating therapy aimed at resetting circadian rhythms and improving sleep quality, both in diagnosing sleep disturbances and in providing feedback about the efficacy of an intervention. The use of wearables in sleep improvement is promising in early detection of neurodegenerative disorders.	R4. Integrating wearables with traditional health assessments and treatments means that data will be generated from sensors and predictive modelling, circumventing the subjectivity associated with patient-reported symptom assessments. Predictive modelling can facilitate personalised interventions based on both personal and population-level health data. Future research needs to focus on the efficacy and cost-effectiveness associated with the use of wearables, setting a gold standard comparator, and using longer follow-up times.
S5. Physical activity: Wearables are practical and effective in improving physical activity and health outcomes in different age groups.	R5. More intervention and evaluation studies on wearables and physical activity are needed to increase trust in their use for disease prevention and therapeutic purposes. Future research needs to focus on the efficacy and cost-effectiveness associated with the use of wearables, setting a gold standard comparator, and longer follow-up post-intervention.

2.2. Wearables in healthcare

While medical devices and implants follow strict regulatory processes and are integrated into mainstream medical practice, the use of wearables for diagnosis, biomonitoring, and treatment outcomes remains protracted and far from clinical implementation. Their potential has been explored for diagnostic and remote monitoring of symptoms, disease progression, and clinical outcomes in many diseases, but mainly cardiovascular, surgical, metabolic, musculoskeletal, neurological, infectious diseases, and mental health [12–16].

2.2.1. Cardiovascular diseases and surgical interventions

Atrial fibrillation can be detected with increasing reliability using data from e.g., most smart watches, Oura ring or CART-I ring, combined with external sources of data, such as medical records and self-reported questionnaires [17,18]. Among many other applications is their use in cardiac surgery where patients are given wearables to encourage pre-surgery physical activity and post-surgery rehabilitation, resulting in lower in-hospital stays and treatment costs [19]. Long-term remote continuous monitoring for recovery after other types of surgeries such as spine surgery allows surgeons to identify potential post-operative deterioration based on step count, sleep duration, and heart rate variability [20]. Wearable knee sleeves have been used for post-operative knee surgery involving an engaging system that improved patient compliance to home exercise programmes [21].

2.2.2. Metabolic diseases

For Type-1 diabetes, advanced Continuous Glucose Monitoring (CGM) wearables are used and have resulted in improved glucose control and improved quality of life due to accurate information as to when to dose insulin. Some patients with Type-2 diabetes rely on CGM's and other wearables to improve their diets and physical activity [22]. Normoglycemic individuals are increasingly using CGMs to achieve a flatter glucose response with less extreme spikes following adjustments in meal composition [16]. CGMs and some applications of smartwatches are registered by the Food and Drug Administration for medical use.

2.2.3. Musculoskeletal and neurological diseases

Smartwatches also measure gait which is important for the elderly to aid with falls prevention programmes both in and outside institutions. Emerging studies have explored the potential role of wearables in independent living for the elderly and in early detection of neurodegenerative diseases [23,24]. By monitoring the user's falls, the option to directly call for help can be provided. For e.g., residents in assisted living communities equipped with a system comprising a wristband, location monitoring beacons, and a cloud-based AI-powered platform had significantly lower hospitalisations and fall rates as compared to communities without it [25]. Smartwatches and associated smart applications were reliable in early detection of motor and non-motor symptoms of Parkinson's Disease [26]. The use of Global Positioning System in wearables can allow monitoring of mobility in patients with dementia [23]. However, this is a field ripe for further intervention and standardisation in ageing for improved prevention and care (Table 1. *S2 & R2*).

2.2.4. Infectious diseases

Furthermore, wearables allow time series data of dynamic measurements over time that can estimate oxygen saturation and heart rate recovery. Trends of these parameters over time are highly instructive for early disease detection for e.g., through distinct reductions in oxygen saturation (<90 %) and heart rate recovery. Similarly significant reductions in resting heart rate and heart rate recovery could suggest that the user is losing cardiorespiratory fitness. Other illness-associated physiological and inflammatory responses such as elevations in peripheral temperature, heart rate, heart rate variability, respiratory rate, and energy expenditure can be monitored [27]. Changes in these parameters are indicative of early signs of Lyme Disease, COVID 19, or even insulin resistance, but are not specific to discern between them [28–30].

2.2.5. Mental health

For mental health, their relevance, though promising, is suboptimal for predicting depression and patient-response to treatment [31]. When describing behavioural patterns, the picture changes. Studies that mainly used the Oura ring or the Whoop wrist band yielded positive results in describing behaviours associated with neurological stress, depression, anxiety, and affective states [32–35]. Apart from sleep quality, assessment of body temperature has been used to evaluate the severity of depression symptoms [36]. The most accurate parameters for detecting stress and anxiety appear to be heart rate variability, electrodermal activity, and respiratory rate [37]. Detecting mental disorders via machine learning and deep learning models has shown promising results [38,39].

2.3. Wearables in public health: lifestyle factors

At the population level, wearables have been rising in popularity to record in 'real time' a diverse range of physiological functions, providing users with intra-person dynamic personalised feedback, and helping them set goals to improve their lifestyle. Some of the monitored health indicators include heart rate, heart rate variability, heart rate recovery, step count, pulse, and body temperature as well as behaviours such as diet, sleep, and physical activity [13]. Importantly, while some of these indicators such as body temperature is measured directly, others such as heart rate, pulse, step count, and sleep are deduced from photoplethysmography or tri-axial accelerometery [40]. In this section, we shed light on three main lifestyle factors where wearables are mostly used: physical activity, sleep, and nutrition. These are of particular importance for healthy ageing due to their effect on underlying pathways in the pathogenesis of diseases such as cardiometabolic diseases, mental health, cognition, physical functioning, and cancer [41].

2.3.1. Physical activity and wearables

It is almost common knowledge today that adhering to moderate physical activity levels, even below the recommended 150 min/week for adults, reduces mortality risk and brings physical, metabolic, and mental health benefits over the life course [42,43]. Underlying mechanisms involve regulation of cardiorespiratory, immune, neurological, musculoskeletal, and metabolic functions that promote good health [44]. According to the WHO, 80 % of adolescents and 55 % of adults do not meet the recommendations for physical activity [45]. The introduction of tri-axial accelerometers for e.g., as wristbands, smartwatches, belts, and rings resulted in considerable improvement in objectively monitoring physical activity. Being non-intrusive and affordable, these wearables became popular lifestyle monitors among the young and old. Based on estimated daily activity and facilitated by AI, wearable-generated data can distinguish clusters of behavioural patterns and provide a key tool for personalised behaviour for healthy ageing in the population [46]. A recent review of 39 systematic reviews of interventional studies showed that wearables are practical and effective tools in improving physical activity levels as well as physiological and psychosocial health outcomes in different age and clinical groups [47] (Table 1. *S5 & R5*).

2.3.2. Sleep, disease risk, and the role of wearables

Circadian rhythm disruptions due to poor sleep impact body functions and have been associated with an increased disease risk including cardiometabolic and neurodegenerative diseases of old age [48]. For cardiometabolic diseases, underlying mechanisms include lower glucose tolerance, insulinemia, increased evening cortisol levels, higher sympathetic nervous system activity, increased inflammation, disrupted energy balance, and hormonal and lipid dysregulation [49]. Recovery from lack of sleep and resetting the circadian rhythm have been shown to normalise metabolic parameters in older healthy participants [50]. In neurodegenerative conditions like Alzheimer's, Parkinson's, and Huntington's diseases, disruptions in circadian and sleep rhythms are visible well before clinical diagnoses [51]. For instance, excessive daytime sleepiness, obstructive sleep apnoea, restless leg syndrome, and other sleep-related movement disorders are strong predictors of neurodegenerative conditions [52]. Mental illnesses like depression, schizophrenia, and bipolar disorder are often co-morbidities of neurodegenerative conditions. Independently, they are also strongly correlated with disruptions in sleep-wake cycles [53].

The complex interplay between circadian disruptions and the diseases makes sleep an attractive target for personalised therapy and prevention for healthy ageing. Many sleep wearables in the form of smartwatches and rings have been used to estimate sleep. Interestingly, the literature shows that wearables such as the Oura ring among others are well suited for monitoring sleep based on actigraphy, show reduced error in sleep measurement, and are accurate in measuring heart rate [54,55]. It also triangulates its measurements with other parameters like body temperature and circadian rhythm, rather than relying on movement and heart rate variability only like some smartwatches. This means that lying still but being awake could erroneously be interpreted as sleep. The use of such wearables paired with long-term guided feedback on how to improve sleep and exercise behaviours has shown significant improvements in sleep onset latency, daily step count, and heart rate variability. The circadian rhythm however, changes over the life course and shifts to an earlier chronotype with old age [56]. Wearables are not able to discern these changes and tend to produce erroneous estimates of sleep in the elderly, necessitating further validation studies in this age group [57] (Table 1. *S4* & *R4*).

2.3.3. Diet and the gut microbiome: a potential role for precision nutrition

Adherence to a well-balanced diet has long been recommended for a healthy lifespan by preventing or postponing the development of age-related diseases [58]. Diet, among other body functions, directly impacts the gut microbiota meaning that personalised dietary modifications play a key role in improving it [59]. Furthermore, the composition, diversity, and function of the gut microbiota shift over the life course, with the most significant alterations occurring during the transition from adulthood into old age [60]. Though the mechanisms of these changes with ageing are not fully understood, compared to younger adults, microbial diversity and beneficial bacteria are lower in older adults, which is affected by dietary intake, social, physical, and biological environments [61–63]. These alterations are positively associated with several health conditions, including chronic inflammation, cognitive decline, cardiometabolic disorders, and type 2 diabetes [64]. Adhering to a healthy dietary pattern can improve both the composition and function of the gut microbiota, thereby reducing the risk of age-related inflammation and promoting healthy ageing [62,63].

However, nutrient requirements and biological responses to food intake vary between individuals, societies and within age groups, requiring in certain cases further personalization of general dietary recommendations [65]. In the recent decade, precision nutrition has emerged as a potential improved model for recommendations by accounting for interindividual variability in preventing and managing diseases [66]. Despite the challenges associated with recording dietary intake, wearables are evolving towards automation of recording food intake and measuring metabolic state through markers such as glucose, ketones, and respiratory exchange rates based on sweat, saliva, interstitial fluids, and blood [67]. Wearables can be coupled with smartphone applications with large databases of available foods that enable barcode scanning and food photo uploading to compute energy intake [68]. Studies combining several approaches including dietary records, glucose monitoring, and gut microbiome analysis reveal dynamic intra-individual fluctuations in blood glucose responses that could be indicative of impaired glucose tolerance, providing new horizons for personalised nutrition and prevention of metabolic diseases [65,69]. However, these approaches remain challenging and are not as straightforward as accelerometer recording of physical activity for example (Table 1. *S3* & *R3*).

3. Towards an integrated vision for the future of healthy ageing and living opportunities and challenges

Earlier in 2024, Canali et al. published a review on how wearables are used in healthy ageing focusing on 65+ years and the WHO domains of intrinsic capacity i.e. locomotion, sensory functions, psychological aspects, cognition, and vitality [70]. They outlined several opportunities and challenges associated with the use of wearables in this age group. From a clinical and public health perspective, issues relating to population group inclusivity and access to wearables, data quality and representativeness of different user groups, privacy and ethics, user autonomy in decision making, and wearables efficacy, present challenges as well as opportunities for healthy ageing, also when approached from a life course perspective [70]. Given what we have presented so far (*S1–S5* & *R1–R5*), we focus on the following additional six key considerations (*C1–C6*) that are essential for scalability and implementation (Table 2).

3.1. Engagement and compliance to personalised wearable feedback

Despite the potential of wearable technology for monitoring health, detecting illness, or facilitating independent living, the effect is only as powerful as an individual's understanding, motivation and adherence. Whereas a small part of the population uses the data from wearables for active goal setting, many are passive observers, confused by or even mistrust wearable-generated data. Motivation, adherence, and a mind shift from passive observation to taking data-based action need to be increased by health literacy programmes for those who choose it. This can be achieved by co-creating eHealth systems with users in mind and leveraging technology such as AI chatbots to provide personalised feedback and interaction. If data validity is perceived positively and is adequately interpreted, wearables could help enhance awareness, intrinsic motivation, and self-actualisation to improve lifestyle habits and care (*C1*).

3.2. Technical and standardisation requirement to enable scalability

Wearable eHealth systems hold intrinsic technical challenges such as usability, interoperability, and hardware reliability that need to be optimised to enable scalability. Typical challenges are inadequate use, inaccuracy of sensors, issues with batteries or power, restricting users' actions within the space being monitored and poor interoperability such as linkage to applications operating on specific platforms (e.g. iOS) and difficulties in pairing devices [71]. A further issue is the lack of understanding of the information provided to the user. Overcoming these challenges will require collaboration between scientists, digital learning experts, and commercial parties. Protocol standardisation and data harmonisation (e.g., derived step counts vary by wearable) are also paramount to improve the validity of findings. For example, different wearables use different sensors, combinations, and algorithms to derive physical activity, meaning that the cut-off points for e.g., between moderate and vigorous physical activity levels are not interchangeable. This requires some standardisation to reduce heterogeneity and enable comparison. While no single governing body exists to enforce a wide set of standards for data collection and processing, the field has matured, so that the analysis of accelerometer data has become standardised. Several organisations such as the International Society for Physical Activity and Health (ISPAH) and International Physical Activity and the Environment Network (IPEN) have set guidelines. However, standards have mostly grown organically from large projects such as the UK Biobank and other projects have started to follow. Additionally, the use of a small number of software packages, notably GGIR R package, has harmonised datasets

Table 2
Key considerations for scalability and implementation.

C1. Engagement and compliance to wearable feedback: Wearables present a viable and acceptable option that can accompany and optimise conventional prevention and therapeutic approaches to more personalised ones. Addressing the mistrust of users and improve health literacy with eTools, in particular by the elderly, is necessary for engagement and can be done through valid feedback based on collected raw data and not only device algorithms. Complexities in human identities, behaviours, and contexts need to be acknowledged which means that personalised recommendations, although highly desired, might be challenging.
C2. More advanced use of data comes with additional procedural choices, and proper standards around machine learning models for ageing research are yet lacking. The same applies to more novel biomarkers and measurement devices, such as CGM. Where acceleration measurement and gait in research was mostly a collaborative, open-source development, CGMs appear to be the domain of large corporations. It remains unclear whether this difference will encourage or inhibit shared practices.
C3. Tightly safeguarding ethical concerns creates vast opportunities for continuous improvement of wearables that can generate data safely and allow personalizing prevention and care. Intrinsic human errors, ethical breaches, bias fallacies, systemic inequalities, and power dynamics should not be transferred to wearables and AI.
C4. Commitment to continuous training and learning is needed to facilitate the streamlined use of these wearable technologies in research and practice. Health psychologists and digital health experts should engage to build trust in wearables through calibration, reproducibility, and benchmarking studies to find the “gold standard” tools and communication routes, thus improving validity, quality, and accuracy for large-scale implementation. Strategic investments need to be streamlined with interdisciplinary research, interventions, and technological developments.
C5. The decision-making will need to always involve the smart system and the healthcare team, together with the patient and their support circle. AI can be a tool to optimise information, but not the final decision maker. In this context, the need for a systematic integration of epistemic, ethical, legal, and social considerations becomes necessary. Total algorithmic automation needs to be avoided and human oversight of the accuracy and efficiency of these tools should be maintained to ensure quality checks and avoid algorithmic injustices. Advancements in AI technology, such as explainable AI (XAI), aim to make AI decision-making more transparent and understandable. Integrating AI with other emerging technologies, such as telemedicine and wearable health devices, can enhance healthcare delivery.
C6. The wearables industry needs to work closely with healthcare providers to optimise the wearables design for efficient and safe use. Guidelines for wearable-generated data needs to be readily available for clinicians.

and analyses for accelerometer-generated data [72]. The procedures around acceleration-based quantification of levels of activity has stabilised [73]. As we move towards more advanced use of accelerometer data and the inclusion of other types of sensors, proper protocols and standards will introduce more challenges. With the advent of recent machine learning methods, specifically convolutional neural networks and recurrent neural networks, a more detailed picture of people's habits and routines emerges [74]. This enables an analysis of more fine-grained determinants of health and their impact on ageing biomarkers for personalised behavioural advice. Nevertheless, comparing data obtained over time within ‘self’ may already be highly instructive to the individual (*C2*).

3.3. Accountability, data safety and security, and ethical concerns

Data privacy, accountability, and procedural transparency are of great concern in the use of wearable-generated data [75]. Data safeguarding and flexibility to (de)activate certain features need to be considered before implementation [76,77]. Breach of confidentiality and data privacy need to be avoided by tight regulation through official channels such as the EU General Data Protection Regulations and the AI Act. Technological entrepreneurs play a key role in ensuring privacy by design i.e., developing wearable technologies without compromising privacy and giving back control of data to users (*C3*).

3.4. Technological literacy, access, and capacity building

The use of wearables must remain a matter of choice even if incorporated into mainstream prevention and care. However, wearables are quickly evolving with accompanying AI tools that will necessitate commitment to continuous capacity building for users, providers, healthcare professionals, and researchers. Accessibility and ease of use are necessary for professionals and users who should have access to training sessions and should be kept informed on the developments, standardisation, and interpretation of collected parameters. This includes capacity building for clinicians in interpreting the estimated parameters as well as that of the patients in distinguishing what is or is not clinically meaningful, thus preventing unnecessary worrying. For certain population groups such as the elderly and individuals from low socioeconomic status, accessibility and acceptability of wearables will depend on the individual's means, adaptability, technological savviness, perceived importance and physical capability, social influence, and the quality of information delivered [78]. Without careful consideration, the use of wearables is likely to worsen existing health disparities, leaving those with low health and digital literacy at a disadvantage. Factors such as age, race, socioeconomic status, health conditions, eHealth literacy, and geographic location are significant contributors to health inequities resulting from digital health technologies [79]. To ensure that the most vulnerable populations do not fall between the cracks in the transition to eHealth, it is essential to incorporate wearables and related education into health insurance plans to mitigate economic and literacy-related barriers. In addition, wearables should be designed to function in areas with low network coverage, such as rural regions and urban areas with inadequate network infrastructure and should be available in multiple languages to accommodate diverse populations. Moreover, cultural attitudes towards technology and healthcare must be considered, as they can significantly affect the acceptance and trust of wearable devices. Addressing these aspects is imperative to reduce health disparities and promote equitable access to digital health advancements as it becomes more central to prevention and care in health systems [79] (*C4*).

3.5. Clinical relevance and risk of overdiagnosis and overmedicalisation

AI models are fed by the information provided. If the information is incomplete or not representative it may lead to over- or under-diagnosis [80]. If thresholds to diagnose a disease or to create an episode alarm (e.g., arrhythmia, hypo-/hyper-glycemia) are set low or inconclusive to overcome false negatives, an increase of false positives may result [81,82]. However, this type of input will encourage the user to interact with their healthcare provider who can follow up and take proper actions. This may alleviate unnecessary stress and anxiety in patients to avoid overuse of medical resources [83]. On the other hand, underdiagnosing may occur in underserved populations that are not represented in the information fed to algorithms [84] (*C5*).

3.6. Keeping treatment and clinical implementation in mind: the clinician's perspective

Clinicians would benefit and consequently should play a vital role in the successful integration and optimal use of wearables in practice. There is a slow acceptance of wearables from the health professional for patient empowerment, medical history access, behaviour change facilitation, and efficient communication from use of wearables. In the area of diabetology, the use of CGMs is probably most settled and advanced. However, some concerns persist. In the first place is the degree with which general practitioners and health care providers are themselves familiar with wearable outputs and their health implications. In the second place is education, specifically post graduate education of health professionals that should include wearable technology teaching. In the third place is fear of patient self-diagnosis and self-medication that can negatively affect well-being, an increase in clinician workload, and fear of breach of confidentiality [85]. Guidelines for "smartwatch interrogation" in clinical practice is a promising approach for informed decision making based on readily available wearable-generated data [86] (*C6*).

4. Conclusions

Across the many domains of prevention and care, wearables have, to a considerable extent, demonstrated their potential for personalised interventions to promote healthy ageing and living, notably for the elderly. Their use however remains protracted and varies across diseases and pathways of care in terms of benefits, challenges, and added value in mainstream public health and clinical practice. The way forward to reaping the benefits of these technologies in prevention and healthcare necessitates consolidated efforts and a social pact that is not solely based on profit but holds people's health in high regard. Stakeholders including clinicians and medical professionals, tech companies, educators, patients, healthcare systems, academic institutions, funders, and governments should work together and with the entire population to ensure it. Active collaboration between scientists from diverse disciplines such as medicine, biology, computer science, applied mathematics health psychology, digital learning and engineering is needed to advance the safe use of wearables, communication of generated insights, standardisation, efficiency, and reliability within personalised prevention and healthcare.

Ethics approval

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Declaration of competing interest

The authors declare that they have no competing interest.

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Appendix A. Supplementary data

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