Journal of Physical Activity and Health, 2026, 23, 1525-1535
https://doi.org/10.1123/jpah.2026-0466
© 2026 Human Kinetics, Inc.

Human Kinetics
REVIEW

Wearables for Physical Activity Guideline Development and Health Surveillance: Converging Research and Practice Agendas

Emmanuel Stamatakis,[1,2,3,4] Nicholas A. Koemel,[1,2,3,4] Karen Milton,[5] Sarah K. Keadle,[6] Alex A. Florindo,[7] Mark Hamer,[8] Pedro C. Hallal,[9] and Matthew N. Ahmadi[1,2,3,4]

[1]Turner Institute for Brain and Mental Health, Monash University, Melbourne, VIC, Australia; [2]Mackenzie Wearables Research Hub, Charles Perkins Centre, The University of Sydney, Sydney, NSW, Australia; [3]Victorian Heart Institute, Monash University, Melbourne, VIC, Australia; [4]School of Health Sciences, Faculty of Medicine and Health, The University of Sydney, Sydney, NSW, Australia; [5]Norwich Medical School, University of East Anglia, Norwich, United Kingdom; [6]Department of Kinesiology and Public Health, California Polytechnic State University, San Luis Obispo, CA, USA; [7]School of Arts, Sciences and Humanities, University of São Paulo, São Paulo, SP, Brazil; [8]Division of Surgery & Interventional Science, University College London, London, United Kingdom; [9]Department of Health and Kinesiology, University of Illinois Urbana-Champaign, Champaign, IL, USA

Objective: Etiological epidemiology and health surveillance are interdependent foundations of physical activity research, yet wearable devices have been adopted disproportionately across these 2 pillars of policy and practice. As physical activity research transitions from mostly self-reports toward a combination of mostly wearables and some self-reports, alignment between etiological evidence generation and surveillance systems is becoming increasingly important. We examine the goals, methods, and emerging convergence between wearable-based policy, surveillance, and etiological epidemiology. ***Methods:*** This narrative review compares the wearable-based methods and metrics used for physical activity surveillance and for etiological research and draws on 2 contrasting case studies: the World Health Organization's surveillance-oriented standardization work and the harmonized research infrastructure of the Prospective Physical Activity, Sitting, and Sleep consortium. Building on these case studies and emerging evidence, we outline a 10-year roadmap toward a globally harmonized and translation-ready wearable evidence ecosystem. ***Results:*** Wearables capture high-resolution dimensions of physical activity including the intensity, accumulation patterns, and 24-hour composition of movement that questionnaires cannot resolve. Wearable-based studies have identified strong dose–response associations at substantially lower absolute activity volumes than currently recommended in national and global guidelines and enabled the emergence of novel behavioral phenotypes including activity fragmentation, movement timing, and physical activity micropatterns. However, substantial challenges remain, including methodological heterogeneity, incompatibility between questionnaire- and wearable-derived evidence, limited representation of low- and middle-income countries, and uncertainty around translation into surveillance and guideline frameworks. World Health Organization surveillance initiatives prioritize simple, scalable, and internationally comparable metrics, whereas etiological epidemiology can accommodate greater complexity and methodological innovation. ***Conclusions:*** Convergence between surveillance and etiological epidemiology is both feasible and necessary, but requires harmonized wear protocols and reporting standards, capacity building and equitable infrastructure in underrepresented communities, and clear translation pathways between research-grade and policy-grade wearable metrics.

Keywords: wearable devices, accelerometry, epidemiology, public health surveillance

Key Points

- Wearables are transforming physical activity guideline development by revealing strong health benefits at substantially lower activity volumes than questionnaire-based evidence, creating a need to reconcile device- and self-report–based thresholds.
- Convergence between etiological epidemiology and surveillance is both feasible and necessary, built on shared core wearable metrics, harmonized protocols, and open, translation-ready processing pipelines exemplified by WHO initiatives and ProPASS infrastructure.
- A 10-year roadmap is proposed that prioritizes technical standardization, equitable expansion of device-based evidence to underrepresented regions and populations, and governance and communication strategies that ensure wearables-informed guidelines are interpretable and actionable in policy and practice.

Koemel https://orcid.org/0000-0002-5463-6894
Milton https://orcid.org/0000-0002-0506-2214
Keadle https://orcid.org/0000-0002-9569-9306
Florindo https://orcid.org/0000-0002-4429-0826
Hamer https://orcid.org/0000-0002-8726-7992
Hallal https://orcid.org/0000-0003-1470-6461
Ahmadi https://orcid.org/0000-0002-3115-338X
Stamatakis (emmanuel.stamatakis@monash.edu) is corresponding author, https://orcid.org/0000-0001-7323-3225

Etiological epidemiology and health surveillance are 2 cornerstones of population physical activity (PA) science and practice that share many methodologies but pursue different goals. Etiological epidemiology seeks to characterize causal relationships between movement behaviors and health outcomes, generating the dose–response evidence on which guideline thresholds are set. Health surveillance, in turn, monitors PA trends across time and

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

countries, tracks population adherence to those guidelines, and quantifies the burden of physical inactivity. The 2 are tightly interdependent: surveillance metrics ultimately need to reflect the etiological evidence that guidelines are based on, while etiological studies remain free to explore novel exposures and metrics ahead of, and informing, the next round of guidelines. Definitions of key-related terms are provided in Table 1.

Contemporary PA guideline development typically combines an expert scientific committee, systematic reviews of the evidence, and a structured appraisal framework such as GRADE (Grading of Recommendations Assessment, Development and Evaluation) or GRADE-ADOLOPMENT.[2,3] Recent examples include the 2020 World Health Organization (WHO) Guidelines on Physical Activity and Sedentary Behavior,[4] the 2018 US Physical Activity Guidelines,[5,6] and the 2026 Australian 24-Hour Movement Guidelines for Adults and Older Adults.[7] For global surveillance, the WHO STEPwise approach to noncommunicable disease risk factor surveillance (STEPS), which uses the Global Physical Activity Questionnaire,[8] remains the dominant infrastructure for monitoring adult PA and has produced internationally comparable estimates across more than 150 countries; however, those national estimates are exclusively self-report-based.[9]

The transition from self-report to a combination of self-report and wearables in both etiological and surveillance epidemiology has been underway for more than 2 decades but has progressed unevenly. Wearable-based studies contributed only an estimated 5% to 10% of the evidence synthesized in the WHO 2020 guidelines, reflecting methodological heterogeneity and the slow emergence of universal standards, a gap explicitly flagged by WHO's 2020 Guidelines Development Group.[10]

The 2 types of evidence yield considerably different estimates: although device- and questionnaire-derived dose–response curves have broadly similar shapes, wearables yield markedly stronger magnitudes of risk reduction at substantially lower absolute amounts.[11,12] The case for continued investment in wearable-based methods rests on further scientific gains that questionnaire-based epidemiology cannot deliver. For example, wearables are not affected by social desirability bias or recall limitations, provide a continuous and complete account of behavior, and resolve PA intensity at a temporal resolution measured in seconds rather than days. This precision has unlocked entirely new exposure categories, such as PA micropatterns, defined as brief bouts of moderate to vigorous intermittent lifestyle PA lasting up to 3 minutes, and very brief bouts of vigorous intermittent lifestyle PA lasting up to 1 minute. Such novel exposures have shown strong inverse associations with diabetes, cardiovascular events, incident cancer, and mortality,[13–18] and their utility in the intervention context is currently being evaluated.[19–24] Wearables also enable the routine quantification of light-intensity activity,[25] sedentary thresholds[26] and breaks, posture and posture transitions, accumulation profiles of activity bouts, sleep duration, and integrated 24-hour movement profiles, none of which questionnaires

Table 1 Definitions of Key Terms Used in This Article

Term	Definition
Etiological epidemiology	The branch of epidemiology that seeks to characterize causal (or causal-like) relationships between exposures—such as physical activity, sedentary behavior, and sleep—and health outcomes. Etiological evidence underpins the dose–response thresholds adopted in physical activity guidelines.
Cohort study	An observational, longitudinal study design in which a defined group of participants is followed over time, with periodic measurement of exposures (eg, physical activity) and ascertainment of health outcomes (eg, cardiovascular disease- or cancer-related mortality).
Compositional 24-h movement profile	A representation of how a person's 24 h are distributed across mutually exclusive behaviors—sleep, sedentary time, light-intensity physical activity, and moderate to vigorous physical activity—analyzed jointly rather than as independent exposures.
Exercise	A subset of physical activity that is planned, structured, repetitive, and undertaken with the specific intent of improving or maintaining one or more components of physical fitness.
Health surveillance	The continuous, systematic collection, analysis, and interpretation of population-level health-related data—including physical activity levels and other chronic disease risk factors—used to monitor trends, evaluate the impact of policies and interventions, and track population adherence to public health guidelines.
Physical activity	Physical activity is any bodily movement[1] produced by skeletal muscles that results in energy expenditure.
Physical activity micropatterns	Brief bouts of moderate or vigorous intermittent lifestyle (incidental) physical activity. The concept is open to other analogous patterns concealed in raw sensor data, and that can only be revealed through high-resolution processing of continuous data from wearable devices.
Physical activity domain	The contextual category in which physical activity is performed. Four domains are conventionally distinguished: occupational (work-related), transport (eg, walking and cycling for travel), domestic (household tasks and caregiving), and leisure time (recreational and structured exercise).
Physical activity prevalence	The proportion of a defined population that meets a specified physical activity criterion (most commonly the WHO threshold of 150–300 min of moderate-intensity or 75–150 min of vigorous-intensity physical activity per week, or equivalent combination of moderate and vigorous activity)
VILPA	The first identified physical activity micropattern phenotype. It corresponds to brief, unplanned bouts (typically up to 1 min) of vigorous-intensity physical activity accrued during daily living, eg, carrying shopping uphill, brisk stair climbing, that are normally captured by current wearable-based methodologies. VILPA has been shown to be consistently associated with lower noncommunicable disease risk.
Wearable device	A body-worn sensor—most commonly a triaxial accelerometer worn on the wrist, thigh, hip, or lower back—that captures movement-related signals at high temporal resolution and from which physical activity, posture (eg, sedentary behavior or standing), and sleep can be derived.

Abbreviations: VILPA, vigorous intermittent lifestyle physical activity; WHO, World Health Organization.

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

capture meaningfully. Step-based metrics, which can only be quantified using devices, are emerging as intuitive surveillance indicators that map directly onto consumer wearables, show consistent dose–response associations across cohorts, and are increasingly proposed for inclusion in future guidelines.[27–29]

Two further developments sharpen the potential of wearables for surveillance and etiological research alike. First, machine-learning approaches, including self-supervised methods,[30,31] now classify activity types, postures, and intensity zones from raw accelerometry with accuracy approaching laboratory reference measures.[30] These methods support harmonization across studies,[32] devices[33] and even wear sites,[34] making population-scale analyses tractable and inclusive. These and other analogous developments[15,18,35–39] have supported the ongoing gradual shift to 24-hour movement guidelines and have encouraged wearables uptake in many recent large cohorts internationally, including HUNT (Norway)[40] and Lifelines (The Netherlands).[41] Second, consumer-grade devices have brought wearable PA monitoring to hundreds of millions of users worldwide, opening opportunities for monitoring at unprecedented scale; however, they do not yield representative samples and introduce proprietary algorithms, version drift, and limited cross-device comparability.[42] Such constraints have limited their use for guideline-grade evidence and surveillance.

Despite these developments, device-based evidence remains heavily concentrated in a handful of high-income countries representing only 10% to 15% of the world's population, while device cost and poor research infrastructure remain major barriers to adoption in low- and middle-income countries (LMICs).[32] These converging pressures have catalyzed coordinated action across the field. The WHO has formally entered the wearables space through a series of expert meetings between 2023 and 2025, including the November 2023 scoping meeting, the June 2025 Montreal meeting, and the November 2025 Utrecht meeting on integrating wearable technology into population health monitoring, and is now developing global guidance on devices, protocols, and analytic methods.[4,43–45] In parallel, consortia such as the Adult Accelerometer Consortium,[46] the Steps for Health Collaborative,[47] and the Prospective Physical Activity, Sitting, and Sleep consortium (ProPASS) have been building the harmonized epidemiological infrastructure needed to generate device- and placement-inclusive, guideline-ready wearables evidence at scale.[32,48] A reasonable longer-term ambition is for wearable-based PA estimates to become as internationally comparable as today's Global Physical Activity Questionnaire-based STEPS data, although doing so will require sustained investment in capacity building, research infrastructure, and equitable access to devices in LMICs.

In this article, we examine the goals, methods, and emerging convergence of these 2 complementary agendas (Figure 1) and outline a realistic roadmap for the next 10 years (Figure 2).

Is Convergence Between Surveillance and Etiological Epidemiology Possible?

Surveillance and etiological epidemiology pursue different but complementary goals when using wearable data, and understanding these differences is essential before considering how their methods should converge. PA surveillance aims to monitor population trends over time, requiring metrics that are simple, applicable across data collection waves and countries, and robust to variation in device hardware, sensors, placement, and field logistics. Its overriding priorities are representativeness, reproducibility, and cost-effectiveness.

Etiological epidemiology, by contrast, seeks to characterize causal relationships between PA exposures and health outcomes to determine the dose–response evidence on which guideline recommendations are set. It can afford considerably greater methodological complexity. For example, complexity in the exposure's characterization that reduces measurement error can improve causal inference[49] and capture biologically relevant relationships in addition to inter- or intraday patterns.

Despite these functional differences, convergence is both possible and desirable provided it is based on the principles of interoperability: shared core constructs, consistent terminology, and transparent translation between layers of methodological complexity. If surveillance metrics drift too far from those used in guideline-relevant etiological research, they may lose policy meaning.[50–52] Conversely, if etiological research moves toward ever more complex or nonstandardized constructs, such as composite scores, fragmentation indices without clear units, or uncalibrated circadian metrics, translation into public health guidance becomes weak and potentially inactionable.[53–55]

A useful way to structure the convergence challenge is to view it in 3 layers (Figure 1). The shared core metrics layer draws on those being prioritized for the next iteration of the WHO's STEPS surveillance through ongoing scientific meetings[56] and encompasses minutes of moderate to vigorous PA,[46,57] daily step count,[29,58,59] and total sedentary time.[15,60,61] These constructs are interpretable across diverse segments of the global population, map to clear guideline-relevant thresholds, and can be measured with acceptable validity. For surveillance purposes, a binary classification of physical inactivity (meeting or not meeting guideline recommendations) may be sufficient and operationally practical in many policy contexts, analogous to how population surveillance treats obesity, hypertension, or smoking as binary exposures. However, the higher resolution data wearables capture can benefit surveillance by providing novel insights into PA behaviors within and across days. In etiological research, the use of more than 2 exposure categories, ideally continuous dose–response analyses, is often essential to provide granularity in characterizing relationships and detailed associations with health outcomes across the exposure continuum. The novel PA and sedentary behavior phenotypes layer comprises richer metrics such as bout length,[62–65] PA micropatterns,[13,14,16,36] fragmentation,[66,67] and timing.[68,69] These add scientific value in prospective cohort studies but, given their novelty, require further replication and translation before they can be scaled to routine surveillance systems. Finally, the noncommunicable diseases layer integrates etiological evidence on PA and sedentary behavior to characterize relationships with health outcomes and to generate hypotheses for further investigation. Outputs in this layer sit at the leading edge of the field and carry potential to change guidelines and interventions in the future. The complexity and novelty of these phenotypes and their associations with health outcomes require carefully defined pathways to inform replication and incorporation into guidelines, interventions, and surveillance frameworks. However, traditional observational evidence cannot definitively establish causality between highly granular phenotypes and disease risk. Experimental studies and causal inference observational designs[70] examining the health effects and mechanistic pathways are also important. Such evidence will further our understanding, including confirmation of whether such phenotypes represent causal behavioral targets for interventions aimed at different population groups.

A key concern in all 3 layers is the question of validity and precision: *how good is good enough?*[56] For surveillance, a minimum viable wearables data processing architecture must deliver acceptably low systematic error in PA, sedentary time, sleep, and

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

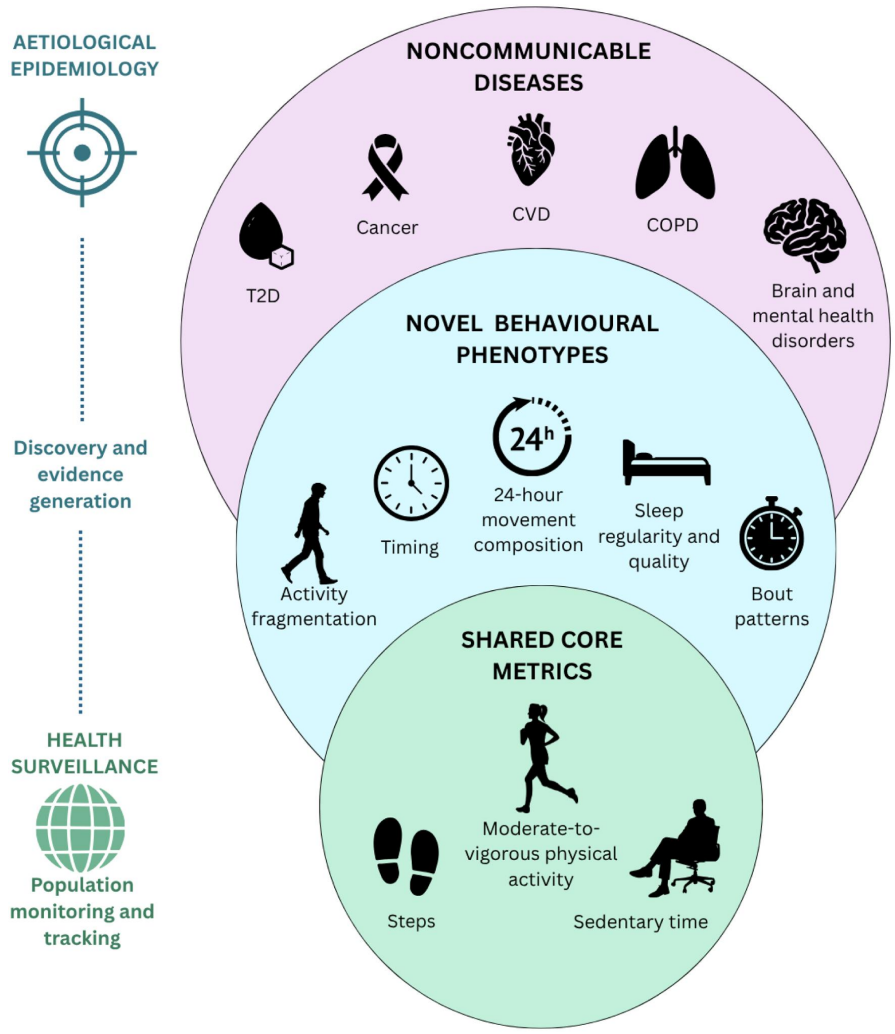


Figure 1 — A model for convergence of wearable-derived metrics for surveillance and etiological epidemiology. CVD indicates cardiovascular disease; T2D, type II diabetes; COPD, Chronic Obstructive Pulmonary Disease.

step estimation across a range of populations and device types. For etiological research, the precision requirements are higher, particularly for novel metrics where even moderate misclassification can obscure or distort dose–response curves. Establishing clear minimum validity and precision thresholds, stratified by intended application, is an unresolved but tractable priority for the field. The convergence challenge is already being addressed from 2 directions: a normative, surveillance-first approach led by the WHO and an evidence-generation, harmonization-first approach by consortia[46,47] such as the ProPASS consortium,[32] both of which are examined as paired case studies[27,71–74] in the sections that follow.

WHO's Global PA Surveillance: A Case Study in Wearable Standards Development and Implementation

The WHO's entry into the wearables space is fundamentally a surveillance initiative, using improved measurement and the growing ubiquity of wearables in research[75–77] and wider populations[78] to identify and, where needed, standardize use to bring global monitoring in line with contemporary practice.[79] While self-report tools can capture behavioral context, they fail to register unplanned or brief activities (typically under 10–15 min) due to cognitive recall limitations.[80–82] In part for this reason, they were designed with leisure-time and transport-related PA in mind; they are poorly suited to capturing light-intensity activity, which is typically incidental (unplanned), and cannot monitor step-based targets. As the wearable-based evidence grows, findings from such studies are likely to feature prominently in forthcoming guidelines, because wearables can measure movement continuously over extended periods. The ability to measure activity and sedentary behavior continuously may provide a more accurate representation of these behaviors. The WHO process is framed around "if and how" wearable-derived measures could be incorporated into national surveillance, rather than a settled decision to move away from questionnaires, because key evidence remains scarce, such as feasibility in low-resource settings and continuity with existing self-report trend data. If a wearable-informed guideline threshold is set, a compatible surveillance system capable of monitoring population adherence would need to be in place. This need for measurement and monitoring infrastructure to co-evolve with

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

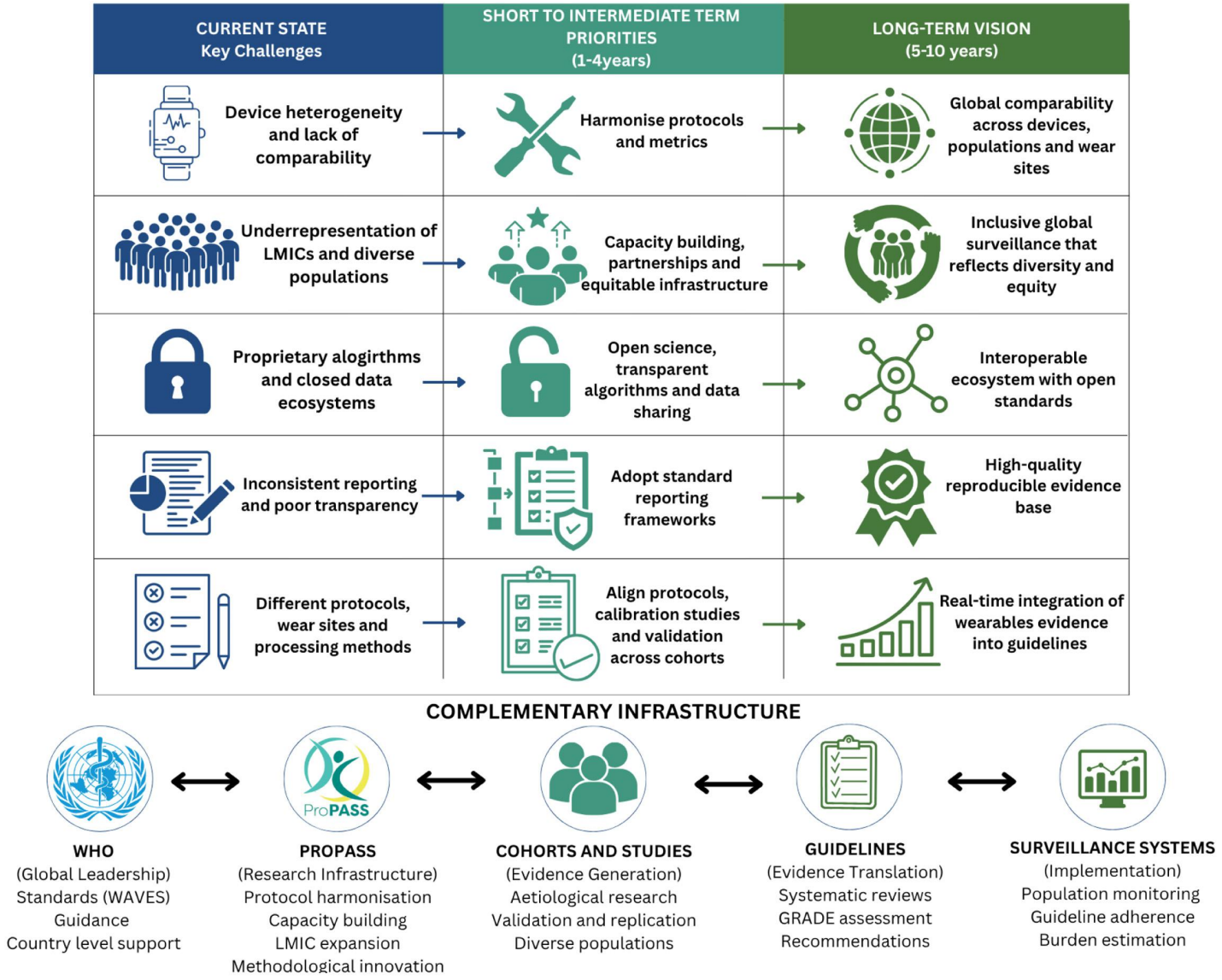


Figure 2 — A roadmap toward a globally harmonized wearable-based evidence ecosystem. GRADE indicates Grading of Recommendations Assessment, Development and Evaluation; LMICs, low- and middle-income countries; WHO, World Health Organization; ProPASS, Prospective Physical Activity, Sitting and Sleep consortium; WAVES, Wrist Algorithms: Verification, Evaluation, and Surveillance.

guidelines is the central motivation for the WHO's investment in wearable standards.[45,56]

The WHO has formalized this agenda through a series of expert technical meetings between 2023 and 2025.[43,45,56,83] A scoping and planning meeting in November 2023 mapped the evidence landscape and identified the absence of any global guidance on appropriate devices, protocols, or analytic approaches as a critical gap. The first 2025 meeting, held in Montreal in June, advanced practical guidance on minimum device specifications, core metrics, and evaluation frameworks. The second 2025 meeting in Utrecht in November further advanced the integration of wearable technology into population health monitoring systems. Taken together, these meetings represent a structured WHO-led effort to move the field from broad scientific scoping toward normative, implementation-ready guidance.

In terms of practical scope, the WHO process is focused on a tractable near-term agenda: defining a core metric set and device specifications, identifying acceptable protocols, reviewing open-source analysis pipelines—all through an extensive consultation process, which will lead to undertaking planning for country demonstration pathways, particularly in LMICs. The core shared metric set centers on moderate to vigorous PA minutes, daily steps, and sedentary time, a pragmatic approach that prioritizes interpretability and public health promotion over exhaustive exposure characterization.

On the evolving methods agenda, WHO technical discussions have increasingly converged on 4 recurring questions: whether device brand matters, whether wear location matters, whether algorithm choice matters, and what constitutes defensible minimum wear time both within-day and across the monitoring period.[45] Emerging positions suggest that device brand may matter less than previously assumed provided minimum technical specifications such as access to raw signal data are met; that algorithm choice is the most important factor for cross-study and cross-country comparability; that the wrist remains the most practical near-term

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

wear location, while acknowledging unresolved nuances; and that minimum wear-time requirements for surveillance may be more flexible than is sometimes assumed. Recognizing the need for coordinated international research, the WAVES (Wrist Algorithms: Verification, Evaluation, and Surveillance) collaborative was established through WHO-convened meetings to address these methodological gaps and strengthen evaluation of wrist-based algorithms for global surveillance implementation.[45]

The WHO's distinctive contribution to the wearables field is not the generation of new epidemiological findings, but rather global coordination and determination of universal standards for the use of wearables within national surveillance systems. The process is therefore centered on defining what is technically sound, valid, feasible, policy-relevant, and implementable across highly varied international contexts, including LMICs, older adult populations, and settings where ideal scientific protocols must be balanced against cost, device availability, and field logistics.

ProPASS: A Case Study in Epidemiological Infrastructure and Methodological Harmonization

The ProPASS was established in 2017 to address the methodological heterogeneity and weak global representativeness that have constrained the contribution of wearable-based epidemiology to guidelines. From its inception,[48,84] ProPASS' overarching goal has been to spearhead the transition from self-report to wearable-derived evidence for guideline development and translation to intervention design, with concurrent investment in methodological innovation for new metrics and placement-agnostic measurement. As of 2025, ProPASS comprises 41 cohort studies (corresponding to ~277,000 participants) across 5 continents, of which approximately one-third are fully integrated with harmonized data and legal agreements in place.[32]

The consortium's infrastructure logic combines retrospective recruitment of cohorts with existing wearables data and prospective recruitment of cohorts that ProPASS supports to undertake new data collection. Cohorts are deliberately drawn from a widening geography. Prospective studies planned, ongoing, or completed in Chile, Mexico, Saudi Arabia, and South Africa, with further studies planned in other underrepresented settings, are supported through free device loans, fieldwork protocols, training, and capacity building for early-career researchers. Pilot data collection is also being planned within the 26-country PURE study,[85] a deliberate attempt to move device-based epidemiology beyond the high-income settings that currently account for 85% to 90% of the total evidence base.

Methodologically, ProPASS prioritizes harmonization across devices and wear placements.[34] It has developed the first machine learning–based, semisupervised measurement schema for thigh-attached wearables that is also tailored to harmonization with wrist data, with empirical equivalence to video direct observation demonstrated for sitting, standing, walking, running, and cycling. PASS*omni* (formerly known as "ActiPASS"), the consortium's open-source software for processing thigh- and wrist-worn signals, anchors this work and is freely distributed to the global research community.[33,86–89] For data sharing, ProPASS pioneers federated analysis through a bespoke DataSHIELD[90] infrastructure that allows individual-participant analyses to be run remotely without sensitive data leaving host jurisdictions and runs in parallel with a traditional 2-stage meta-analytic pathway for cohorts unable to join the federation. The forthcoming longitudinal data resource and the initial cross-sectional resource[91–94] (currently approx. 15,000 participants, reaching 25,000 participants from 13 cohorts once expansion is complete) will both be accessible to bona fide researchers via a formal data access process. The clinical arm of the consortium, ClinPASS, is under development to extend this infrastructure to secondary and tertiary prevention populations.

Taken together, ProPASS is not simply a consortium that pools data and publishes findings. It is an infrastructure model for how wearable-based etiological epidemiology can become harmonized, globally representative, and reusable. The ProPASS approach is highly relevant to PA surveillance: whereas the WHO is primarily codifying surveillance-oriented norms, ProPASS is building the research architecture that will be used to generate guideline-relevant etiological evidence at scale, and to feed back into WHO surveillance work. The 3 standard surveillance metrics determined by the WHO will also be reported in ProPASS data resource publications. In that sense, ProPASS is both a case study in epidemiological infrastructure and an active agent of convergence between etiological epidemiology and global surveillance.

Remaining Tensions and Unresolved Risks

Despite tangible momentum in both the WHO-led surveillance standardization and ProPASS-driven etiological infrastructure, several tensions remain unresolved and carry risks if left unaddressed as the field moves toward wearable-informed guidelines.

The first concerns the consumer versus research-grade ecosystem divide. Consumer devices reach hundreds of millions of users globally[78,95] and offer unprecedented scale for passive, longitudinal monitoring of PA. Yet undisclosed proprietary algorithms, device- and app-based activity feedback that may modify behavior during measurement, firmware updates across device generations, and very limited or no access to raw sensor data all constrain their utility for generating observational and guideline evidence and for attaining reproducible surveillance estimates. Further, cross-device comparability cannot be assumed even within the same manufacturer's product line because different multisensor algorithms are used. These limitations do not preclude a role for consumer wearables in etiological epidemiology, which can yield new insights into PA and disease risk from devices worn continuously over several years, as exemplified by findings from the All of Us cohort.

A second, often underappreciated risk concerns older adults and people with mobility impairment.[96–98] Both the ongoing WHO processes and earlier systematic reviews have highlighted that algorithms developed and validated predominantly in younger, ambulatory populations perform less reliably in older adults and populations with prevalent disease, particularly for estimating PA intensity and volume.[56] Given that this segment of the population carries a disproportionate burden of chronic disease, physical inactivity, and movement-limiting comorbidities, the current evidence base risks entrenching systematic measurement inequity precisely in the group most likely to benefit from wearable-informed health guidance.

Third, LMIC implementation remains a major structural barrier. High device costs, limited research infrastructure, the absence of robust longitudinal health-record linkage, and scarce fieldwork capacity continue to constrain wearable-based implementation and cohort development in the settings that are home to the vast majority of the global population. Even where devices are available, translational requirements, including local algorithm validation in community- and environment-specific contexts and culturally appropriate protocols, add substantial complexity.

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

Initiatives such as ProPASS and future pilot integration within the PURE study represent important attempts to bridge this gap, but sustained investment and structural equity commitments from funders and global health institutions are essential.

A fourth risk concerns the relationship between self-report and wearable-derived evidence, specifically measurement incompatibility rather than the well-recognized difference in quality. The 2 approaches measure partially nonoverlapping constructs: self-report captures domain and context (occupational, leisure time, and transport), while wearables capture the context-agnostic intensity, volume, and pattern of movement. Decisions about whether to transition, harmonize, or maintain parallel measurement approaches are not purely technical; they involve conceptual choices about what PA surveillance is intended to measure and for whom. Current international guidelines recommend adults undertake at least 150 to 300 minutes of moderate-intensity PA or 75 to 150 minutes of vigorous-intensity PA per week, or an equivalent combination of both; crucially, this evidence base was derived almost exclusively from questionnaire studies.[4] Questionnaires capture behavioral blocks, which are the continuous periods of time during which a person perceives themselves to have been active, whereas wearable devices capture the actual time spent in movement, and therefore activity, irrespective of the surrounding behavioral context.[76] Relatedly, self-reported intensity reflects a subjective perception of effort and is dependent on the individual's ability to infer their activity intensity, whereas accelerometer-derived intensity is based on the relationship between movement and intensity. Therefore, the same accelerometer-captured movement may be reported differently depending on an individual's subjective exertion; questionnaire- and wearable-based measures are not measuring the same quantity, even when they share the same behavioral label. This distinction has direct implications for how guidelines are framed, where current WHO recommendations are, by construction, recommendations about behavioral blocks (eg, time periods allocated to activity) not about the actual seconds and minutes of movement those blocks contain.

As a consequence, a public health and policy communication challenge is emerging as the evidence base shifts from historical questionnaire data toward increasingly available wearable-based findings. The integration of the 2 evidence bases would require more than the substitution of one measurement instrument for another. It necessitates a re-conceptualization of what the guideline threshold represents. Dose–response estimates from wearable-assessed PA consistently suggest that meaningful health benefits may occur at much lower absolute activity volumes than self-report-based guidelines imply.[35,46,99] When future guidelines incorporate more wearable-based evidence, any potential reductions in recommended amounts risk being misinterpreted by stakeholders and the public as a relaxation of standards, rather than a more accurate measurement of an equivalent health benefit.[77] This carries downstream implications. For etiological research, dose–response curves and intervention targets may need to be recalibrated. For surveillance, monitoring systems built around questionnaire-based thresholds will not be directly comparable to wearable-based equivalents without carefully constructed translation rules. Proactive framing and communication strategies will be as important as the scientific evidence itself, making this as much a governance and translation challenge as a methodological one.

At the same time, wearable-based surveillance introduces an important structural advantage. When device raw signal data are retained, historical data can be re-analyzed to derive newly identified, health-relevant phenotypes as etiological evidence evolves. This creates the possibility of a more dynamic, or "living," surveillance system in which past and ongoing data streams can be harmonized with current scientific understanding, rather than being locked into legacy definitions. Realizing this potential will depend on surveillance systems prioritizing the capture and preservation of raw signal data and transparent processing pipelines.

A Realistic Roadmap for Convergence Over the Next 10 Years

The wearable technology landscape has reached an inflection point.[71] The complementary advances being made by the WHO STEPS surveillance program and ProPASS' harmonized etiological infrastructure now provide the field with a genuine opportunity, and an obligation, to move from parallel development toward active convergence. We outline a roadmap structured across 3 complementary priorities: technical standardization, equitable evidence generation, and translation-ready infrastructure (Figure 2).

The most immediate priority, addressable over the short to intermediate term (1–4 y), is the consolidation of a shared technical foundation. The WAVES collaborative is developing clear direction on algorithm evaluation[100,101] and on acceptable wear protocols for research settings.[102] Both outputs remain under development at the time of writing and should be read as an emerging rather than a settled standard. Widespread adoption of these standards across cohort studies, surveillance systems, and emerging etiological research would substantially reduce the heterogeneity that currently prevents cross-study comparability. Equally important is the adoption of transparent reporting frameworks covering wear placement site, nonwear criteria, software version, and data processing decisions.[56] Without this, the synthesis of findings from different studies can be hindered regardless of the quality of underlying data collection.[103]

Over this same period, the field must invest in expanding its geographic and demographic reach. The LMIC deficit in wearable-based evidence is not simply a global representativeness problem; it is also a scientific adoption problem, as population-level PA patterns, environmental contexts, and disease burdens in high-income countries cannot be assumed to generalize to other settings and populations across the world. Consortium infrastructure such as ProPASS, combined with capacity-building initiatives[104] for early-career researchers in underresourced settings, offers a scalable model for this expansion. Similarly, targeted algorithm development and validation for older adults with mobility limitations, multimorbidity, and frailty should be treated as a scientific priority over this term.[96,98]

Over the longer term (5–10 y), the field needs clearly defined pathways for translating questionnaire-informed evidence that incorporates device-informed evidence for co-existence and surveillance and guideline-relevant applications. Beyond research-grade devices, consumer wearables occupy an important role in population engagement and longitudinal monitoring but require clearly articulated conditions under which their data can and cannot inform evidence synthesis. The ambition of the roadmap for convergence is an integrated ecosystem in which etiological evidence, surveillance infrastructure, and guideline development processes are mutually reinforcing and evolve together.

Ultimately, governments are responsible for making it easy for individuals to choose PA as part of routine living, and equitable access to pleasant, safe, and practical PA must be a societal and policy priority; an agenda that has been[1] central to the policy

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

recommendations in the Global Action Plan on Physical Activity (GAPPA).[105] The wearable-based etiological and surveillance epidemiology discussed in this review provides 2 core evidence-generation platforms to help national and international PA policy and practice achieve these goals.

Acknowledgments

Funding: This study was funded by National Health and Medical Research Council Investigator Grants APP1194510 and APP2040907 (Stamatakis); National Health and Medical Research Clinical Trials and Cohort Studies APP2032328 (Stamatakis, Hamer, Ahmadi); British Heart Foundation grants SP/F/20/150002 and RG/F/25/110168 (Hamer, Stamatakis, Ahmadi); Cancer Research UK grant PRCPJT-Nov23/100005 (Hamer, Stamatakis, Ahmadi); and National Heart Foundation grant APP107158 (Ahmadi). **Authors Contributions:** *Conceptualization:* Stamatakis, Koemel, Milton, Florindo, Hamer, Hallal, Keadle, Ahmadi. *Visualization:* Koemel. *Writing—original draft:* Stamatakis, Koemel, Ahmadi. *Writing—review and editing:* Stamatakis, Koemel, Milton, Florindo, Hamer, Hallal, Keadle, Ahmadi. **Competing Interests:** Several authors are investigators in or members of the ProPASS consortium described in this article.

References

1. Hallal PC, Lee IM, Sarmiento OL, Powell KE. The future of physical activity: from sick individuals to healthy populations. *Int J Epidemiol*. 2024;53(5):dyae129. doi:10.1093/ije/dyae129
2. Guyatt GH, Oxman AD, Vist GE, et al. GRADE: an emerging consensus on rating quality of evidence and strength of recommendations. *BMJ*. 2008;336(7650):924–926. doi:10.1136/bmj.39489.470347.AD
3. Klugar M, Lotfi T, Darzi AJ, et al. GRADE guidance 39: using GRADE-ADOLOPMENT to adopt, adapt or create contextualized recommendations from source guidelines and evidence syntheses. *J Clin Epidemiol*. 2024;174:111494. doi:10.1016/j.jclinepi.2024.111494
4. Bull FC, Al-Ansari SS, Biddle S, et al. World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *Br J Sports Med*. 2020;54(24):1451. doi:10.1136/bjsports-2020-102955
5. Department of Health and Human Services. *2018 Physical Activity Guidelines Advisory Committee*. 2018.
6. Piercy KL, Troiano RP, Ballard RM, et al. The physical activity guidelines for Americans. *JAMA*. 2018;320(19):2020–2028. doi:10.1001/jama.2018.14854
7. Department of Health Disability and Ageing. Australian 24-hour movement guidelines for adults (18 to 64 years) and older adults (65 +years). https://www.health.gov.au/topics/physical-activity/24-hour-movement-guidelines-for-all-australians/recommendations-for-adults-18-to-64-years
8. World Health Organisation. *Global Physical Activity Questionnaire (GPAQ) Analysis Guide*. 2021.
9. World Health Organisation. *STEPwise Approach to NCD Risk Factor Surveillance (STEPS)*. 2026.
10. DiPietro L, Al-Ansari SS, Biddle SJH, et al. Advancing the global physical activity agenda: recommendations for future research by the 2020 WHO physical activity and sedentary behavior guidelines development group. *Int J Behav Nutr Phys Act*. 2020;17(1):143. doi:10.1186/s12966-020-01042-2
11. Ekelund U, Sanchez-Lastra MA, Dalene KE, Tarp J. Dose–response associations, physical activity intensity and mortality risk: a narrative review. *J Sport Health Sci*. 2024;13(1):24–29. doi:10.1016/j.jshs.2023.09.006
12. Sanchez-Lastra MA, Del Pozo Cruz B, Tarp J, et al. Dose–response associations of self-reported and device-measured physical activity with major adverse cardiovascular events in people with prevalent diseases. *J Sport Health Sci*. 2025;15:101116. doi:10.1016/j.jshs.2025.101116
13. Chong KH, Ahmadi MN, Biswas RK, et al. Dose–response associations of intermittent lifestyle physical activity micropatterns and incident type 2 diabetes. *Diabetes Care*. 2026;49(6):1086–1094. doi:10.2337/dc25-3018
14. Ahmadi MN, Hamer M, Gill JMR, et al. Brief bouts of device-measured intermittent lifestyle physical activity and its association with major adverse cardiovascular events and mortality in people who do not exercise: a prospective cohort study. *Lancet Public Health*. 2023;8(10):e800–e810. doi:10.1016/S2468-2667(23)00183-4
15. Koemel NA, Ahmadi MN, Biswas RK, et al. Can incidental physical activity offset the deleterious associations of sedentary behaviour with major adverse cardiovascular events? *Eur J Prev Cardiol*. 2025;32(1):77–85. doi:10.1093/eurjpc/zwae316
16. Koemel NA, Ahmadi MN, Biswas RK, et al. Vigorous intermittent lifestyle physical activity (VILPA) and mortality risk among US adults: a wearables-based national cohort study. *Int J Behav Nutr Phys Act*. 2026;23(1):17. doi:10.1186/s12966-026-01876-2
17. Stamatakis E, Ahmadi M, Biswas RK, et al. Device-measured vigorous intermittent lifestyle physical activity (VILPA) and major adverse cardiovascular events: evidence of sex differences. *Br J Sports Med*. 2025;59(5):316. doi:10.1136/bjsports-2024-108484
18. Stamatakis E, Ahmadi MN, Gill JMR, et al. Association of wearable device-measured vigorous intermittent lifestyle physical activity with mortality. *Nat Med*. 2022;28(12):2521–2529. doi:10.1038/s41591-022-02100-x
19. Thøgersen-Ntoumani C, Kritz M, Grunseit A, et al. Barriers and enablers of vigorous intermittent lifestyle physical activity (VILPA) in physically inactive adults: a focus group study. *Int J Behav Nutr Phys Act*. 2023;20(1):78. doi:10.1186/s12966-023-01480-8
20. Thøgersen-Ntoumani C, Grunseit A, Holtermann A, et al. Promoting vigorous intermittent lifestyle physical activity (vilpa) in middle-aged adults: an evaluation of the movsnax mobile app. *BMC Public Health*. 2024;24(1):2182. doi:10.1186/s12889-024-19549-9
21. Pang B, McVeigh JA, Thompson C, Thøgersen-Ntoumani C, Stamatakis E, Moullin JC. An Exploration of Adults Transitioning Into Retirements' Perspectives on Vigorous Intermittent Lifestyle Physical Activity. *Health Promot J Austr*. 2025;36(1):e957. doi:10.1002/hpja.957
22. Gray C, Lim K, Palladino J, et al. Enablers and barriers to maintaining physical activity after a vigorous intermittent lifestyle physical activity intervention in adults transitioning to retirement. *J Health Psychol*. Published online April 3, 2026. doi:10.1177/13591053261434374
23. Koemel NA, Bissett M, Ryde GC, et al. Multi-centre randomised controlled feasibility testing of a physical activity micropattern intervention among socioeconomically diverse women. *medRxiv*. 2025:2025.10.28.25339013. doi:10.1101/2025.10.28.25339013
24. Bissett M, Koemel NA, Ahmadi M, et al. Co-designing a digital micropatterns intervention with socioeconomically diverse UK and Australian communities. *J Phys Act Health*. 2026. doi:10.1123/JPAH.2026-0300
25. Prince SA, Chaput J-P, Colley RC, et al. Unlocking the potential of light-intensity physical activity for public health: a call to action for research. *Br J Sports Med*. 2026;60(16):1193–1196. doi:10.1136/bjsports-2025-111179

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

26. Rezende LFM, Ahmadi M, Ferrari G, et al. Device-measured sedentary time and intensity-specific physical activity in relation to all-cause and cardiovascular disease mortality: the UK Biobank cohort study. *Int J Behav Nutr Phys Act*. 2024;21(1):68. doi:10.1186/s12966-024-01615-5
27. Mair JL, Aguiar EJ, Stamatakis E, Edney SM. Moving toward the inclusion of step-based metrics in physical activity guidelines and surveillance. *J Phys Act Health*. 2023;20(7):575–577. doi:10.1123/jpah.2023-0180
28. Stamatakis E, Ahmadi M, Murphy MH, et al. Journey of a thousand miles: from 'Manpo-Kei' to the first steps-based physical activity recommendations. *Br J Sports Med*. 2023;57(19):1227–1228. doi:10.1136/bjsports-2023-106869
29. Ding D, Nguyen B, Nau T, et al. Daily steps and health outcomes in adults: a systematic review and dose-response meta-analysis. *Lancet Public Health*. 2025;10(8):e668–e681. doi:10.1016/S2468-2667(25)00164-1
30. Yuan H, Chan S, Creagh AP, et al. Self-supervised learning for human activity recognition using 700,000 person-days of wearable data. *NPJ Digit Med*. 2024;7(1):91. doi:10.1038/s41746-024-01062-3
31. Logacjov A, Bach K. Self-supervised learning with randomized cross-sensor masked reconstruction for human activity recognition. *Eng Appl Artif Intell*. 2024;128:107478. doi:10.1016/j.engappai.2023.107478
32. Stamatakis E, Koemel NA, Atkins A, et al. The Prospective Physical Activity, Sitting, and Sleep consortium (ProPASS): addressing methodological and geographical barriers to inform global public health guidelines, interventions, and precision medicine. *Br J Sports Med*. 2026; 60(16):1198–1204. doi:10.1136/bjsports-2025-111283
33. Crowley P, Skotte J, Stamatakis E, et al. Comparison of physical behavior estimates from three different thigh-worn accelerometers brands: a proof-of-concept for the Prospective Physical Activity, Sitting, and Sleep consortium (ProPASS). *Int J Behav Nutr Phys Act*. 2019;16(1):65. doi:10.1186/s12966-019-0835-0
34. Ahmadi MN, Koemel N, Biswas R, et al. Development and evaluation of wrist- and thigh-worn accelerometer algorithms using self-training machine learning models for classification of activity type and posture: towards device placement-agnostic methods in the ProPASS consortium. *Int J Behav Nutr Phys Act*. 2026;23(1):68. doi:10.1186/s12966-026-01930-z
35. Ahmadi M, Sabag A, Biswas RK, et al. Impact of physical activity patterns on major adverse cardiovascular events in adults with hypertension. *Br J Sports Med*. 2026;60(10):696. doi:10.1136/bjsports-2025-109894
36. Stamatakis E, Biswas RK, Koemel NA, et al. Dose Response of Incidental Physical Activity Against Cardiovascular Events and Mortality. *Circulation*. 2025;151(15):1063–1075. doi:10.1161/CIRCULATIONAHA.124.072253
37. Ahmadi MN, Coenen P, Straker L, Stamatakis E. Device-measured stationary behaviour and cardiovascular and orthostatic circulatory disease incidence. *Int J Epidemiol*. 2024;53(6):dyae136. doi:10.1093/ije/dyae136
38. Windred DP, Burns AC, Lane JM, et al. Sleep regularity is a stronger predictor of mortality risk than sleep duration: a prospective cohort study. *Sleep*. 2024;47(1):zsad253. doi:10.1093/sleep/zsad253
39. Greenwood-Hickman MA, Nakandala S, Jankowska MM, et al. The CNN Hip Accelerometer Posture (CHAP) method for classifying sitting patterns from hip accelerometers: a validation study. *Med Sci Sports Exerc*. 2021;53(11):2445–2454. doi:10.1249/MSS.0000000000002705
40. Åsvold BO, Langhammer A, Rehn TA, et al. Cohort profile update: the HUNT study, Norway. *Int J Epidemiol*. 2023;52(1):e80–e91. doi:10.1093/ije/dyac095
41. Eijsvogels T. *ActiveLIFE*. 2026. https://www.radboudumc.nl/en/participate-in-medical-scientific-studies/list/activelife
42. Strain T, Wijndaele K, Pearce M, Brage S. Considerations for the use of consumer-grade wearables and smartphones in population surveillance of physical activity. *J Meas Phys Behav*. 2022;5(1):8–14. doi:10.1123/jmpb.2021-0046
43. World Health Organisation. *Physical Activity Measurement and Surveillance in Adults: Report of a Scoping and Planning Meeting, 27-28 November 2023*. 2023.
44. World Health Organisation. *Measuring Physical Activity in Adults Using Wearable Technologies*. 2025.
45. World Health Organisation. *Integrating Wearable Technology into Population Health Monitoring Systems for Physical Activity Measurement: Meeting Report, Utrecht, Kingdom of The Netherlands, 25-27 November 2025*. 2025.
46. Ekelund U, Tarp J, Ding D, et al. Deaths potentially averted by small changes in physical activity and sedentary time: an individual participant data meta-analysis of prospective cohort studies. *Lancet*. 2026;407(10526):339–349. doi:10.1016/S0140-6736(25)02219-6
47. Paluch AE, Bajpai S, Bassett DR, et al. Daily steps and all-cause mortality: a meta-analysis of 15 international cohorts. *Lancet Public Health*. 2022;7(3):e219–e228. doi:10.1016/S2468-2667(21)00302-9
48. Stamatakis E, Koster A, Hamer M, et al. Emerging collaborative research platforms for the next generation of physical activity, sleep and exercise medicine guidelines: the Prospective Physical Activity, Sitting, and Sleep consortium (ProPASS). *Br J Sports Med*. 2020; 54(8):435–437. doi:10.1136/bjsports-2019-100786
49. Ahmadi M, del Pozo Cruz B, Biswas R, et al. Target trial emulation of physical activity and cardiovascular disease risk: what is impact of the exposure assessment method? *medRxiv*. 2026:2025.11.02.25339322. doi:10.1101/2025.11.02.25339322
50. Giles-Corti B, Sallis JF, Sugiyama T, Frank LD, Lowe M, Owen N. Translating active living research into policy and practice: one important pathway to chronic disease prevention. *J Public Health Policy*. 2015;36(2):231–243. doi:10.1057/jphp.2014.53
51. Bauman A, Bellew B, Allen J. Physical activity policy and research (the "challenge of research translation"). *J Sci Med Sport*. 2010;12: e7–e8. doi:10.1016/j.jsams.2009.10.016
52. Bull F. Translating science to inform global policy on physical activity. *J Sport Health Sci*. 2018;7(1):3–4. doi:10.1016/j.jshs.2017.10.005
53. Mclaughlin M, McCue P, Swelam B, Murphy J, Edney S. Physical activity—the past, present and potential future: a state-of-the-art review. *Health Promot Int*. 2025;40(1):daae175. doi:10.1093/heapro/daae175
54. Brownson RC, Shelton RC, Geng EH, Glasgow RE. Revisiting concepts of evidence in implementation science. *Implement Sci*. 2022;17(1):26. doi:10.1186/s13012-022-01201-y
55. Estabrooks PA. Physical activity promotion and translational research. *Transl Behav Med*. 2017;7(1):1–2. doi:10.1007/s13142-016-0456-y
56. World Health Organisation. Measuring physical Activity in Adults Using Wearable Technologies: Report Of A Scientific Meeting, 10–12 June 2025, Montreal, Canada. 2026. https://www.who.int/publications/i/item/9789240116696
57. Saint-Maurice PF, Troiano RP, Matthews CE, Kraus WE. Moderate-to-vigorous physical activity and all-cause mortality: do bouts matter? *J Am Heart Assoc*. 2018;7(6):e007678. doi:10.1161/JAHA.117.007678
58. Lee I-M, Shiroma EJ, Kamada M, Bassett DR, Matthews CE, Buring JE. Association of step volume and intensity with all-cause mortality in older women. *JAMA Intern Med*. 2019;179(8):1105–1112. doi:10.1001/jamainternmed.2019.0899

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

59. Ahmadi MN, Rezende LFM, Ferrari G, Del Pozo Cruz B, Lee IM, Stamatakis E. Do the associations of daily steps with mortality and incident cardiovascular disease differ by sedentary time levels? A device-based cohort study. *Br J Sports Med*. 2024;58(5):261. doi:10.1136/bjsports-2023-107221
60. Ajufo E, Kany S, Rämö JT, et al. Accelerometer-measured sedentary behavior and risk of future cardiovascular disease. *J Am Coll Cardiol*. 2025;85(5):473–486. doi:10.1016/j.jacc.2024.10.065
61. Raichlen DA, Aslan DH, Sayre MK, et al. Sedentary behavior and incident dementia among older adults. *JAMA*. 2023;330(10):934–940. doi:10.1001/jama.2023.15231
62. del Pozo Cruz B, Ahmadi M, Sabag A, Saint Maurice PF, Lee IM, Stamatakis E. Step accumulation patterns and risk for cardiovascular events and mortality among suboptimally active adults. *Ann Intern Med*. 2025;178(12):1718–1727. doi:10.7326/ANNALS-25-01547
63. Rowlands AV, Schwendinger F, Razieh C, et al. Intensity modifies the association between continuous bouts of physical activity and risk of mortality: a prospective UK Biobank cohort analysis. *J Sport Health Sci*. 2026;15:101078. doi:10.1016/j.jshs.2025.101078
64. Saunders TJ, McIsaac T, Douillette K, et al. Sedentary behaviour and health in adults: an overview of systematic reviews. *Appl Physiol Nutr Metab*. 2020;45(10)(suppl 2):S197–S217. doi:10.1139/apnm-2020-0272
65. Farrahi V, Kangas M, Kiviniemi A, Puukka K, Korpelainen R, Jämsä T. Accumulation patterns of sedentary time and breaks and their association with cardiometabolic health markers in adults. *Scand J Med Sci Sports*. 2021;31(7):1489–1507. doi:10.1111/sms.13958
66. Chen S, Su Q, Shen R, et al. Association of accelerometer-measured rest-activity rhythm patterns and parameters with cardiovascular and all-cause mortality in older adults: population-based cohort study. *Exp Gerontol*. 2026;215:113043. doi:10.1016/j.exger.2026.113043
67. Wanigatunga AA, Di J, Zipunnikov V, et al. Association of total daily physical activity and fragmented physical activity with mortality in older adults. *JAMA Network Open*. 2019;2(10):e1912352. doi:10.1001/jamanetworkopen.2019.12352
68. Ajufo E, Kany S, Churchill TW, Guseh JS, Ellinor PT, Khurshid S. Timing of physical activity and risk of future cardiovascular disease. *Eur J Prev Cardiol*. Published online February 25, 2026. doi:10.1093/eurjpc/zwag127
69. Sabag A, Ahmadi MN, Francois ME, et al. Timing of moderate to vigorous physical activity, mortality, cardiovascular disease, and microvascular disease in adults with obesity. *Diabetes Care*. 2024;47(5):890–897. doi:10.2337/dc23-2448
70. Hernán MA, Dahabreh IJ, Dickerman BA, Swanson SA. The target trial framework for causal inference from observational data: why and when is it helpful? *Ann Intern Med*. 2025;178(3):402–407. doi:10.7326/ANNALS-24-01871
71. Gupta N, Crowley P, Holtermann A, Straker L, Stamatakis E, Ding D. Are we ready for wearable-based global physical activity surveillance? *Br J Sports Med*. 2024;58(7):356. doi:10.1136/bjsports-2023-106780
72. Biswas RK, Ahmadi MN, Bauman A, Milton K, Koemel NA, Stamatakis E. Wearable device-based health equivalence of different physical activity intensities against mortality, cardiometabolic disease, and cancer. *Nat Commun*. 2025;16(1):8315. doi:10.1038/s41467-025-63475-2
73. Christiansen LB, Koch S, Bauman A, Toftager M, Bjørk Petersen C, Schipperijn J. Device-based physical activity measures for population surveillance—issues of selection bias and reactivity. Brief Research Report. *Front Sports Act Living*. 2023;5:1236870. doi:10.3389/fspor.2023.1236870
74. Canali S, Schiaffonati V, Aliverti A. Challenges and recommendations for wearable devices in digital health: data quality, interoperability, health equity, fairness. *PLOS Digit Health*. 2022;1(10):e0000104. doi:10.1371/journal.pdig.0000104
75. Ferguson T, Olds T, Curtis R, et al. Effectiveness of wearable activity trackers to increase physical activity and improve health: a systematic review of systematic reviews and meta-analyses. *Lancet Digit Health*. 2022;4(8):e615–e626. doi:10.1016/S2589-7500(22)00111-X
76. Lee IM, Keadle SK, Matthews CE. Fitness trackers to guide advice on activity prescription. *JAMA*. 2023;330(18):1733–1734. doi:10.1001/jama.2023.19332
77. Gill JMR, Chico TJ, Doherty A, et al. Potential impact of wearables on physical activity guidelines and interventions: opportunities and challenges. *Br J Sports Med*. 2023;57(19):1223. doi:10.1136/bjsports-2023-106822
78. Statista. Forecast Wearables Unit Shipments Worldwide From 2014 to 2024. 2025. https://www.statista.com/statistics/437871/wearables-worldwide-shipments/
79. Troiano RP, Stamatakis E, Bull FC. How can global physical activity surveillance adapt to evolving physical activity guidelines? Needs, challenges and future directions. *Br J Sports Med*. 2020;54(24):1468–1473. doi:10.1136/bjsports-2020-102621
80. Schwarz N. Self-reports: How the questions shape the answers. *Am Psychol*. 1999;54(2):93. doi:10.1037/0003-066X.54.2.93
81. Johnson-Kozlow M, Matt GE. What respondents recall about walking and what self-report items elicit about walking. *Prev Med*. 2004;38(2):227–236. doi:10.1016/j.ypmed.2003.09.043
82. Quinlan C, Rattray B, Pryor D, et al. The accuracy of self-reported physical activity questionnaires varies with sex and body mass index. *PLoS One*. 2021;16(8):e0256008. doi:10.1371/journal.pone.0256008
83. World Health Organisation. Physical Activity Measurement and Surveillance in Youth: Report of a Scoping and Planning Meeting, 8–10 May 2024. 2024. https://iris.who.int/items/3059c28b-0ed8-44cb-bf6c-880d8356c9ca
84. Stevens ML, Gupta N, Inan Eroglu E, et al. Thigh-worn accelerometry for measuring movement and posture across the 24-hour cycle: a scoping review and expert statement. *BMJ Open Sport Exerc Med*. 2020;6(1):e000874. doi:10.1136/bmjsem-2020-000874
85. Population Health Research Institute. *PURE Study Highlights Global Disparities in Activity Limitations and Assistive Device Use*. 2024.
86. Actipass. Actipass Github. https://github.com/Ergo-Tools/ActiPASS
87. Hettiarachchi P, Aili K, Holtermann A, Stamatakis E, Svartengren M, Palm P. Validity of a non-proprietary algorithm for identifying lying down using raw data from thigh-worn triaxial accelerometers. *Sensors*. 2021;21(3):904. doi:10.3390/s21030904
88. Johansson PJ, Crowley P, Axelsson J, et al. Development and performance of a sleep estimation algorithm using a single accelerometer placed on the thigh: an evaluation against polysomnography. *J Sleep Res*. 2023;32(2):e13725. doi:10.1111/jsr.13725
89. Skotte J, Korshøj M, Kristiansen J, Hanisch C, Holtermann A. Detection of physical activity types using triaxial accelerometers. *J Phys Act Health*. 2014;11(1):76–84. doi:10.1123/jpah.2011-0347
90. DataSHIELD Secure Bioscience Collaboration. https://datashield.org/
91. Blodgett JM, Ahmadi MN, Atkin AJ, et al. Device-measured 24-hour movement behaviors and blood pressure: a 6-part compositional individual participant data analysis in the ProPASS consortium. *Circulation*. 2025;151(2):159–170. doi:10.1161/CIRCULATIONAHA.124.069820

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC

92. Blodgett JM, Ahmadi MN, Atkin AJ, et al. Device-measured physical activity and cardiometabolic health: the Prospective Physical Activity, Sitting, and Sleep (ProPASS) consortium. *Eur Heart J*. 2024;45(6):458–471. doi:10.1093/eurheartj/ehad717
93. Ahmadi MN, Blodgett JM, Atkin AJ, et al. Relationship of device measured physical activity type and posture with cardiometabolic health markers: pooled dose–response associations from the Prospective Physical Activity, Sitting and Sleep Consortium. *Diabetologia*. 2024;67(6):1051–1065. doi:10.1007/s00125-024-06090-y
94. Bian W, Ahmadi MN, Biswas RK, et al. Device-measured sleep characteristics, daily step count, and cardiometabolic health markers: findings from the Prospective Physical Activity, Sitting, and Sleep (ProPASS) Consortium. *Circ Cardiovasc Qual Outcomes*. 2025;18(8):e011873. doi:10.1161/CIRCOUTCOMES.124.011873
95. Statista. Fitness Tracker Device Sales Revenue Worldwide From 2016 to 2022. 2017. https://www.statista.com/statistics/610433/wearable-healthcare-device-revenue-worldwide/
96. Beauchamp MK, D'Amore C, Raina P, et al. Establishing global standards on wearable technology for measuring mobility in ageing populations: an international consensus exercise. *Age Ageing*. 2026;55(1):afaf376. doi:10.1093/ageing/afaf376
97. Acquah A, Creagh A, Hamy V, et al. Daily steps are a predictor of, but perhaps not a risk factor for Parkinson's disease: findings from the UK Biobank. *NPJ Parkinsons Dis*. 2025;11(1):355. doi:10.1038/s41531-025-01214-6
98. Baumgart JK, Coyle Asbil HJ, Kebede M, et al. Research for equitable health outcomes: a call for diverse participant samples in wearable device harmonization and standardization approaches. *J Meas Phys Behav*. 2026;9(1):jmpb.2026-0021. doi:10.1123/jmpb.2026-0021
99. Saint-Maurice PF, Graubard BI, Troiano RP, et al. Estimated number of deaths prevented through increased physical activity among US adults. *JAMA Intern Med*. 2022;182(3):349–352. doi:10.1001/jamainternmed.2021.7755
100. Keadle SK, Strath SJ, Giurgiu M, et al. The PhasED framework: a measurement theory-based approach to algorithm development and evaluation. *J Meas Phys Behav*. 2026;9(1):jmpb.2025-0074. doi:10.1123/jmpb.2025-0074
101. World Health Organisation. *5th Expert Meeting on Physical Activity Measurement Using Wearable Devices in Adolescents and Children Through National School-Based or Community-Based Health Monitoring Systems*. 2026.
102. Matthews CE, Hayes HA, Keadle SK, et al. Evaluation of the seven-day administration protocol in the context of population surveillance using wrist-worn accelerometers. In progress.
103. Dibben GO, Santillan C, Brage S, et al. Reporting of accelerometry in health research: a scoping review of current guidance. *Scand J Med Sci Sports*. 2025;35(10):e70143. doi:10.1111/sms.70143
104. Canadian Institutes of Health Research. Digital Health Pathway for Wearables. 2024. Accessed June, 2026. https://cihr-irsc.gc.ca/e/54076.html
105. World Health Organisation. The Global Action Plan on Physical Activity 2018—2030. 2018. https://www.who.int/initiatives/gappa/action-plan

Unauthenticated | Downloaded 11/07/26 04:14 PM UTC