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REVIEW ARTICLE

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Trusted Intelligent Sensing for Sport–Medicine Integrated Physical Activity Interventions: A Framework and Research Agenda

Chad Jensen, Anthony Murphy, Liam Morley

Faculty of Nursing, University of Alberta, Edmonton, AB T6G 1C9, Canada.

Abstract

Physical inactivity is among the largest modifiable contributors to the global burden of cardiovascular disease, type 2 diabetes, and several cancers, yet one in three adults worldwide still does not meet minimum activity recommendations (Guthold et al., 2024). Sports promotion and medical care have historically operated as separate systems: the sports sector delivers activity opportunities without clinical follow-up, while the medical sector treats the consequences of inactivity without prescribing exercise as a therapy. "Sport–medicine integration" — the deliberate coupling of physical-activity promotion with clinical and public-health pathways — is now a stated policy goal, but its delivery has been limited by the lack of trustworthy measurement and feedback between the two sectors. This Perspective argues that high-assurance intelligent sensing — wearable inertial and photoplethysmographic sensors, on-device activity recognition, and privacy-preserving data pipelines — is the missing technical layer that can make sport–medicine integration operable. We define six requirements for "high assurance": clinical-grade accuracy across populations, transparent and human-auditable algorithms, privacy-preserving data handling, fairness across demographic groups, regulatory validity, and a closed-loop feedback path back to both the user and the clinician. We propose a four-layer framework — sensing, assurance, prescription, and feedback — and map the current evidence against it. The field's priority is not more activity trackers but prospective, population-validated intervention trials in which sensing data drive tailored exercise prescriptions and are evaluated against health outcomes rather than step counts alone.

Keywords physical activity; wearable sensors; intelligent sensing; sport–medicine integration; closed-loop intervention

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1. Introduction

Physical inactivity is a global pandemic. In 2022, 31.3 percent of adults worldwide — approximately 1.8 billion people — did not meet the World Health Organization's minimum recommendation of 150 minutes of moderate-intensity activity per week, a proportion that has risen rather than fallen since 2010 (Guthold et al., 2024). The health consequences are substantial: an estimated 5.3 million deaths per year are attributable to physical inactivity, which is a principal driver of the cardiovascular, metabolic, and neoplastic burden that health systems spend most of their budgets treating (Lee et al., 2012). Exercise, conversely, is among the most effective preventive and therapeutic interventions available: it reduces blood pressure, improves glycaemic control, supports weight management, and lowers the risk of recurrent cardiac events, and it is explicitly recommended in cardiovascular prevention guidelines (Visseren et al., 2021).

Yet the delivery of physical activity as health care remains fragmented. Sports and exercise promotion typically sit within education, culture, or municipal recreation departments, while medical care sits within health ministries. A patient who receives a statin prescription for cardiovascular prevention rarely receives a matched exercise prescription, and the recreational runner who wants to know whether their activity load is protective or excessive rarely has a clinical channel for that question. The policy response — variously called "sport-for-health," "exercise is medicine," or in the Chinese policy context *ti-wei ronghe* (sport–medicine integration) — is to build pathways that connect activity promotion to clinical assessment, monitoring, and follow-up.

The technical barrier to closing this gap is measurement. Until recently, physical activity could only be quantified through self-report questionnaires, which are unreliable, or through lab-based accelerometers, which are expensive and unsuited to longitudinal use. The proliferation of low-cost wearable sensors — inertial measurement units, photoplethysmographic optical sensors, GPS, and increasingly on-device machine learning — has, for the first time, made continuous, unobtrusive activity measurement feasible at population scale. But the availability of sensors is not the same as trustworthy sensing. Consumer activity trackers are optimized for engagement, not clinical validity; their algorithms are opaque; their data are held on commercial servers; and their accuracy is documented in self-selected user groups rather than in the diverse populations in which health systems must act (Bent et al., 2020).

This Perspective sets out a framework for what a *high-assurance* sensing layer for sport–medicine integration should provide, where the evidence currently stands, and what research is needed to move from activity tracking to clinically valid, privacy-preserving, closed-loop physical-

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Corresponding author: Chad Jensen, chadjensen04@ualberta.ca

activity intervention.

This is a Perspective and conceptual framework, not a systematic review. We drew on the WHO 2020 physical activity guidelines (World Health Organization, 2020), the WHO 2021 ethics and governance guidance for AI in health (World Health Organization, 2021), the published literature on wearable activity sensing and human activity recognition, and randomised and meta-analytic evidence on wearable-supported physical-activity interventions. We did not apply a formal risk-of-bias instrument; the framework and assurance requirements were synthesised from these sources and from the authors' assessment of the specific failure modes of consumer activity trackers in clinical settings.

2. The sport–medicine integration gap

The separation between sports promotion and medical care is structural rather than accidental. Historically, exercise physiology and sports medicine developed as disciplines serving athletes, while public health developed around the prevention of infectious and later chronic disease through population-level risk factors. The two communities share evidence on dose–response relationships but do not share delivery infrastructure.

Three operational gaps follow. First, there is no common measurement standard. A clinic assessing a patient's exercise tolerance uses a symptom-limited exercise test; a municipal activity programme records attendance; a consumer wearable records steps. These metrics are not interchangeable, and there is no validated translation between them. Second, there is no feedback loop. A person whose wearable shows declining activity or rising resting heart rate has no automatic channel to a clinician, and a clinician who recommends exercise has no objective way to verify whether the patient has complied. Third, the populations most in need — older adults, people with chronic disease, and people in lower-resource settings — are precisely those least likely to own, wear, or correctly interpret consumer devices.

The promise of sport–medicine integration is to close these gaps: to measure activity in a clinically valid way, to translate that measurement into a tailored prescription, and to feed progress back to both the user and the health system. The sensing layer is the enabling technology, but only if it meets a higher assurance bar than consumer fitness wearables currently do.

3. The sensing layer: what is measured and how

Continuous physical-activity sensing draws on four complementary technologies. Inertial measurement units — accelerometers and gyroscopes embedded in wrist-worn or chest-worn devices — capture movement patterns and, through machine-learning classifiers, identify activity type (walking, running, cycling, resistance exercise) and estimate intensity. Photoplethysmographic sensors derive heart rate and heart-rate variability from optical blood-volume changes, and single-lead ECG sensors can detect arrhythmia, as demonstrated at scale by the Apple Heart Study, in which a smartwatch notification identified atrial fibrillation with a positive predictive value of 84 percent among 419,297 participants (Perez et al., 2019). GPS and barometric pressure add outdoor context and elevation. Increasingly, ambient and vision-based sensing — cameras in homes or gyms, radar-based presence detection — can monitor movement without requiring the person to wear a device, though this raises particularly acute privacy questions.

The analytical layer has shifted from hand-engineered features to on-device deep learning. Convolutional and recurrent networks, and more recently attention-based and transformer models, can classify activity from raw inertial signals with accuracy above 95 percent in controlled datasets (Cheng et al., 2023), and they can run locally on the wearable rather than streaming raw data to a server — a property that matters for both battery life and privacy. On-device inference means that the sensor can recognise activity and intensity without transmitting granular movement traces, which is a prerequisite for privacy-preserving deployment.

These technical capabilities are real, but their clinical validity is uneven. A systematic review of commercially available wearables found that heart-rate error, measured against a chest-strap or ECG reference, varied by device and by activity intensity, with smaller errors at rest and larger errors during vigorous movement (Evenson et al., 2020). Bent and colleagues, in a head-to-head validation of six consumer and medical-grade devices against ECG, found that device-to-device differences were larger than skin-tone differences at rest, but that accuracy degraded during activity and that the small sample could not rule out skin-tone interaction effects (Bent et al., 2020). Activity classifiers trained on young, healthy adults misclassify the movement patterns of older adults, people with neurological conditions, and people using assistive devices. Step counts from consumer devices differ meaningfully across brands at the same walking speed, with systematic biases that vary by device (Evenson et al., 2020). These are not nuisance errors: in a clinical intervention, they directly affect whether a patient is judged to have met their prescribed activity dose.

4. What "high assurance" requires

We propose six requirements for a sensing layer intended to support clinical sport–medicine integration (Table 1). These are derived from the WHO's ethics and governance guidance for artificial intelligence in health (World Health Organization, 2021), from established medical-device validation practice, and from the specific failure modes observed in consumer activity trackers.

*Regulatory validity is a system-level property rather than a sensing-layer property: it governs the whole pipeline from sensor to clinical output, and it is listed here because it is a prerequisite for clinical use of the other five requirements.

The first requirement, clinical accuracy, is the foundation. An activity prescription is only as good as the measurement that monitors it. Validation must be conducted in the populations in which the device will be used, against criterion-standard references (indirect calorimetry, doubly labelled water, research-grade accelerometry), and must report error stratified by age, sex, body mass index, and skin tone rather than as a single average.

The second and third requirements, transparency and privacy by design, are where consumer systems most often fail. On-device inference — the classification happens on the wearable, and only the derived activity summary leaves the device — is the key architectural move. It simultaneously reduces data-egress risk and improves battery life. Where models need to be trained across institutions, federated learning allows model updates to be aggregated without centralising raw participant data; this approach has been demonstrated across multiple institutions in medical imaging and cardiology (Roth et al., 2023) but has not yet been widely adopted in activity sensing.

Fairness requires that the model be trained and validated on diverse populations. A classifier that achieves 95 percent accuracy on a young, healthy cohort but 75 percent accuracy on older adults with gait impairment is not a 95-percent-accurate system; it is a system that fails precisely in the population where activity monitoring has the greatest clinical value. Human oversight means that the sensing output informs, but does not replace, a clinician's judgement — particularly for high-intensity exercise in patients with cardiovascular disease, where excessive activity carries risk.

Table 1. Six assurance requirements for a clinical-grade sport–medicine sensing layer, with proposed minimum benchmarks.

Requirement	What it means for sensing	Proposed minimum benchmark	Current gap
Clinical accuracy	Activity, intensity, and derived energy expenditure match validated references across the target population	Mean absolute heart-rate error ≤5 bpm at rest and ≤10 bpm during activity; activity-type classification ≥80% accuracy in the target population; energy-expenditure error ≤15% against indirect calorimetry	Consumer devices validated in self-selected young users; error rises with age, darker skin tone, and assistive-device use
Transparency	The activity classifier and its confidence are inspectable; the clinician can see why a given activity was classified	Model version, training population, and per-reading confidence disclosed; no opaque black-box output driving clinical decisions	Most consumer algorithms are proprietary
Privacy by design	Raw sensor data stay on the device; only derived, de-identified summaries leave it; federated or on-device training where possible	Raw IMU/PPG traces never leave the device; training uses federated or on-device learning; data-use agreement specifies secondary-use prohibition	Most consumer platforms stream raw data to commercial servers
Fairness	Model error does not systematically differ by age, sex, ancestry, body composition, or health status	Difference in error between any demographic subgroup ≤20% relative to the overall error; subgroup performance reported in validation	Training data skew toward young, affluent, light-skinned users
Human oversight	The sensing output informs but does not replace clinical judgement; a clinician reviews anomalous readings	Arrhythmia detection, activity-decline alerts, and high-exertion readings routed to a clinician within a defined review window	Consumer apps provide direct behavioural prompts without clinical review
Regulatory validity*	The device and algorithm meet medical-device requirements for the intended use	Device classified and authorised as a medical device (e.g., FDA software-as-a-medical-device pathway or EU CE marking) for activity-based exercise prescription	Most activity trackers are sold as general wellness products, not medical devices

Regulatory validity is the formal acknowledgement that a device intended to guide exercise prescriptions in patients is a medical device, not a wellness product, and must meet the corresponding clinical-evidence and post-market-surveillance requirements under frameworks such as the US FDA software-as-a-medical-device programme (U.S. Food and Drug Administration, 2022) or the EU Medical Device Regulation.

5. The intervention system: from sensing to prescription to feedback

A sensing layer alone does not produce a health intervention. The assurance framework sits within a four-layer pipeline, proceeding in sequence from measurement to clinical action: **Sensing → Assurance → Prescription → Feedback**.

The sensing layer captures activity, intensity, heart rate, and context continuously. The assurance layer validates, de-identifies, and audits the sensing output, flagging low-confidence readings and drift. The prescription layer translates the sensing data into an individualised activity dose — type, intensity, duration, and progression — calibrated to the person's age, comorbidities, medications, and goals. This is where sports medicine and clinical medicine must meet: the prescription is informed by exercise physiology (appropriate exercise modalities, progression, contraindications) as codified in guidelines such as the American College of Sports Medicine's exercise-testing and prescription guidance (American College of Sports Medicine, 2021) and the European Society of Cardiology's cardiovascular prevention recommendations (Visseren et al., 2021), and by clinical assessment (cardiac risk, musculoskeletal limitations, drug effects on heart-rate response). The feedback layer returns progress to the user through accessible, non-punitive prompts, and routes anomalous readings — sudden activity decline, unexplained resting heart-rate elevation, arrhythmia detection — to the clinical team for review.

The evidence for each layer is at different stages of maturity. Sensing and on-device activity classification are technically demonstrated, though not yet clinically validated across populations. The assurance layer is a governance and architecture requirement rather than a technology gap. The prescription layer is where the sport–medicine integration concept is most concrete: exercise prescriptions are already recommended in cardiovascular, diabetic, and oncological guidelines, but their delivery relies on wearable monitoring that has not met clinical-validation standards. The feedback layer is the least developed: most consumer apps provide user-facing prompts but do not route data to clinicians, and the few closed-loop systems that do exist have been tested only in narrow conditions.

The empirical evidence that wearable-supported activity interventions work is reasonably strong, though it rests on short follow-up and surrogate endpoints. Meta-analyses of wearable activity-tracker interventions in older adults report pooled increases of roughly 1,400 additional steps per day relative to control (Lyu et al., 2023), and digital interventions for hypertension produce reductions of approximately 3 to 4 mmHg in systolic blood pressure (Siopis et al., 2023). Effects attenuate after six to twelve months as engagement declines. These effects are clinically meaningful at population scale — a sustained increase in daily activity across a population implies a measurable reduction in cardiovascular mortality — but they are not yet evidence that a sensing-driven, clinically prescribed system improves hard health outcomes.

6. Challenges

Validation across populations. The dominant failure mode is not average accuracy but differential accuracy. Activity classifiers must be re-validated — not assumed to transport — across age, ancestry, body type, and health status. This requires diverse, population-representative validation cohorts, which are more expensive and slower to assemble than the convenience samples on which consumer models are trained.

Privacy and data governance. Continuous activity and heart-rate data are highly sensitive: they can reveal work schedules, religious observance, pregnancy, and medical episodes. Privacy-by-design architecture — on-device processing, federated training, granular consent — is technically available but is not the default in commercial platforms. Health systems deploying such tools must require these properties contractually rather than assuming them.

Engagement and equity. Wearable interventions show the largest effects in the people who are already most engaged with health tracking, and the smallest in the people who need them most. Older adults, people with low digital literacy, people in lower-resource settings, and people without reliable smartphone connectivity are systematically under-served. A sensing system that requires a modern smartphone and continuous data connectivity will widen rather than narrow health disparities unless it is designed with offline delivery, simplified interfaces, and community-based support.

Regulatory and liability. When a wearable-derived activity recommendation contributes to an exercise prescription and an adverse event follows, the lines of responsibility among device manufacturer, algorithm developer, prescribing clinician, and health system are unclear. Medical-device regulation, post-market surveillance, and clear liability frameworks must precede, not follow, large-scale clinical deployment.

Evidence maturity. Most intervention trials are short (three to twelve months), measure step counts rather than clinical events, and are conducted in higher-income health systems. Whether sensing-guided exercise prescriptions reduce cardiovascular events, hospitalisations, or mortality is not yet established. The next generation of trials should randomise at the system level, follow participants for years, and use clinical endpoints rather than step counts.

7. Research agenda

We propose four priorities. First, **population-representative validation** of activity-sensing algorithms, with error reported by demographic subgroup against criterion-standard references. Second, **on-device and federated architecture** as the default for clinical-grade sensing, with independent privacy audits. Third, **closed-loop intervention trials** in which sensing data drive individualised exercise prescriptions in patients at elevated cardiovascular risk, with clinical-event endpoints and long follow-up. Fourth, **equity-focused implementation research** testing whether simplified, low-bandwidth, community-supported delivery can reach older adults and lower-resource populations rather than reinforcing the digital divide.

8. Conclusion

Sport–medicine integration is a policy goal whose technical time has come. Low-cost sensors and on-device machine learning can now measure activity continuously, transparently, and with privacy preserved on the device itself. But a consumer fitness tracker is not a clinical instrument. For sensing to support the integration of physical activity into health care, it must meet six assurance requirements — clinical accuracy across populations, transparency, privacy by design, fairness, human oversight, and regulatory validity — and it must be embedded in a four-layer system that translates measurement into a tailored prescription and feeds progress back to both the user and the clinician. The evidence that wearable-supported interventions increase activity is reasonably strong; the evidence that they improve clinical outcomes when deployed as part of a validated, equitable, closed-loop system is the research field's most important open question.

CRediT authorship contribution statement

C.J. conceived the framework and drafted the manuscript. A.M. contributed to the assurance requirements and evidence synthesis. L.M. contributed to the sports-medicine integration and clinical validation discussion. All authors revised and approved the final manuscript.

Declaration of competing interest

The authors declare no competing interests.

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