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From Hazard Detection to Pre-Symptomatic Prediction: Can Wearable Sensors Identify Trajectories of Work-Related Musculoskeletal Risk Before Symptoms Develop in Healthcare Workers?

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Abstract: Background: Work-related musculoskeletal disorders (WRMSDs) remain common among healthcare workers, especially in roles that involve patient handling, sustained posture, repetitive movement, and prolonged physical workload. Conventional ergonomic tools are useful for identifying hazardous tasks, but they usually describe exposure at a single point in time. Wearable sensors offer a different possibility by allowing posture, movement, muscle activity, and workload to be measured repeatedly during real work. Objective: This integrative review examines whether wearable sensing can move occupational health beyond hazard detection toward earlier identification of workers whose biomechanical profile is changing before pain or functional impairment appears. It also proposes a Pre-Symptomatic Musculoskeletal Risk Trajectory (PMRT) Framework to guide prospective research. Methods: A structured PubMed search was conducted, supported by a Scopus-style cross-database search strategy using equivalent title, abstract, and keyword concepts. Searches combined terms for healthcare workers, WRMSDs, patient handling, wearable sensors, inertial measurement units, electromyography, posture, ergonomics, machine learning, fatigue, recovery, and prediction. Priority was given to systematic reviews, meta-analyses, prospective studies, field studies, and healthcare-specific wearable investigations. Reference lists of key reviews were also screened. The review is integrative rather than systematic and does not report pooled effect estimates. Results: Current evidence shows that wearable systems can quantify non-neutral posture, movement, muscular activation, cumulative physical exposure, and some aspects of fatigue and recovery. Inertial sensors and surface electromyography are the most established technologies in healthcare ergonomics. Machine-learning studies can classify current posture, task, or musculoskeletal status with promising accuracy. However, prospective evidence showing that wearable-derived changes predict future symptom onset in initially asymptomatic healthcare workers remains scarce. Conclusion: Wearables are already useful for exposure measurement, but true pre-symptomatic prediction has not yet been demonstrated. The proposed PMRT Framework treats musculoskeletal risk as a longitudinal process involving exposure, response, recovery, adaptation, and eventual symptoms. Prospective cohorts with worker-level validation and clinically meaningful outcomes are needed before wearable-based prediction can be used in occupational health practice.

Keywords: *wearable sensors; occupational health; healthcare workers; work-related musculoskeletal disorders; ergonomics; inertial measurement units; machine learning; prediction; digital biomarkers*

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1. 0 Introduction

Work-related musculoskeletal disorders remain a persistent occupational health problem in healthcare. WRMSDs represent an important occupational health concern because repeated exposure to biomechanical demands can accumulate over time, potentially contributing to pain, functional limitations, sickness absence, reduced work capacity, and loss of productivity. Nurses, nursing assistants, surgeons, therapists, technicians, and emergency personnel routinely perform tasks that combine force, repetition, awkward posture, sustained standing, and patient handling. These demands are often dynamic and task-dependent, varying across shifts, patient conditions, staffing levels, work intensity, and recovery opportunities, making brief observational assessments potentially insufficient for capturing cumulative individual exposure. Meta-analytic evidence consistently places the lower back, neck, and shoulders among the most affected body regions in nursing and other healthcare professions (Sun et al., 2023; Suganthirababu et al., 2023; Wang et al., 2024). More recent regional reviews also show that the burden remains high across Europe and Asia (Gorce & Jacquier-Bret, 2025; Jacquier-Bret & Gorce, 2025).

Although the occupational hazards associated with WRMSDs are well recognized, identifying hazardous exposure does not necessarily establish how an individual worker's musculoskeletal risk changes over time. Rapid Upper Limb Assessment and Rapid Entire Body Assessment remain widely used because they convert observed posture, force, and task characteristics into practical risk categories (McAtamney & Corlett, 1993; Hignett & McAtamney, 2000). However, these observational approaches are generally dependent on selected tasks or assessment periods and may provide limited information about exposure variability, cumulative workload, movement patterns, and physiological responses across an entire working shift. Hospital-specific observational approaches have also shown that physical demands vary substantially across healthcare occupations (Janowitz et al., 2006).

The limitation is that these methods usually answer a present-tense question: is this task or posture hazardous now? They are less suited to a different question that matters for prevention: is this worker showing a measurable change over time that precedes pain, functional limitation, or a clinically meaningful WRMSD? This distinction exposes an important gap between ergonomic hazard identification and prospective risk prediction: current exposure does not necessarily indicate future symptom development, and a worker may experience progressive changes in movement or muscular loading before reporting clinically recognizable symptoms.

Wearable technology makes that second question increasingly plausible. Small inertial sensors, accelerometers, electromyography systems, pressure sensors, and other devices can collect repeated measurements without restricting assessment to a brief observation period. Depending on the sensing modality, these systems can provide information on joint and trunk kinematics, movement frequency, posture duration, muscular activation, asymmetry, physical workload, and fatigue-related changes. Reviews published in 2024 and 2025 show rapid growth in wearable ergonomics, with inertial measurement units (IMUs) and surface electromyography (sEMG) being the dominant technologies (Motta et al., 2024; Sabino et al., 2024; Babangida et al., 2025). Much of the existing literature, however, has focused on validating sensor-derived measurements, classifying postures or activities, estimating ergonomic exposure, or identifying concurrent musculoskeletal conditions rather than establishing whether longitudinal sensor-derived changes precede subsequent symptom onset. Yet technological capability should not be confused with clinical prediction. Detecting trunk flexion accurately is not the same as predicting which worker will develop low-back pain several weeks or months later. A valid pre-symptomatic prediction model would require measurements obtained before symptom onset, followed by prospective observation of subsequent outcomes in workers who were initially asymptomatic.

Similarly, high accuracy in classifying current posture, task type, fatigue state, or existing musculoskeletal status should not be interpreted as evidence that a wearable system can predict future WRMSD development. This review therefore addresses the unresolved prospective evidence gap between wearable-based exposure assessment and true pre-symptomatic prediction of WRMSDs.

Therefore, this integrative review aims to evaluate whether wearable-sensor technologies can identify longitudinal trajectories of musculoskeletal risk among healthcare workers before the development of clinically meaningful symptoms and to determine the methodological and evidentiary requirements necessary for such prediction to be scientifically defensible.

The review further aims to synthesize the available evidence into a Pre-Symptomatic Musculoskeletal Risk Trajectory (PMRT) Framework that integrates exposure, biomechanical response, fatigue, recovery, adaptation, and subsequent symptom development.

The significance of this approach lies in its potential to shift occupational musculoskeletal health from predominantly reactive identification of hazardous tasks toward longitudinal and preventive monitoring of individual risk. If prospectively validated, wearable-derived trajectories could support earlier ergonomic intervention, targeted workload modification, and individualized prevention before symptoms become clinically established. However, such applications require prospective validation, clinically meaningful outcome definitions, appropriate temporal separation between sensor measurements and outcomes, and worker-level validation before wearable-based prediction can be considered suitable for routine occupational health practice.

2.0 Search Strategy and Evidence Selection

A structured literature search was conducted in PubMed, while a Scopus-style cross-database search strategy was developed using equivalent title, abstract, and keyword combinations to facilitate reproducibility across multidisciplinary citation databases. Because authenticated Scopus access was not available during manuscript preparation, no claim is made that a formal Scopus database export or Scopus-specific retrieval was completed. The final search was conducted in **[insert month and year/date]**, with the strategy designed to identify literature published up to the date of the final search.

The search strategy was structured around four conceptual blocks: population, occupational exposure and sensing technology, musculoskeletal outcomes, and prediction or longitudinal analysis. These concepts were combined using Boolean operators (AND/OR) and adapted to the syntax of the relevant database. Population terms included healthcare worker, nurse, nursing assistant, surgeon, therapist, technician, paramedic, and allied health professional. Exposure and technology terms included patient handling, manual handling, wearable sensor, inertial measurement unit, accelerometer, gyroscope, surface electromyography, smart insole, pressure sensor, posture monitoring, ergonomic assessment, and biomechanical load. Outcome and analytic terms included work-related musculoskeletal disorder, WRMSD, low-back pain, neck pain, shoulder pain, upper-limb symptoms, fatigue, recovery, musculoskeletal function, machine learning, prediction, prospective, longitudinal, and risk trajectory. Particular attention was given to studies distinguishing exposure classification or concurrent status detection from prospective prediction of subsequent musculoskeletal symptoms or disorders.

Priority was given to systematic reviews, meta-analyses, prospective cohort studies, field studies, intervention studies, and healthcare-specific wearable investigations because these designs provide stronger evidence for understanding exposure patterns, longitudinal change, and potential predictive relationships. Foundational papers describing RULA and REBA were retained because they provide the conventional assessment context against which wearable methods are compared. Reference lists of major reviews were screened for additional primary studies.

Studies were considered eligible when they addressed healthcare workers or healthcare-related occupational tasks and examined WRMSDs, biomechanical exposure, fatigue, recovery, ergonomic risk, wearable sensing, or predictive analytics relevant to musculoskeletal health. Studies were excluded when they were unrelated to occupational musculoskeletal risk, focused exclusively on non-work-related populations or clinical rehabilitation without an occupational component, or did not provide sufficient information to support interpretation of the relevant exposure, outcome, or sensing approach. Retrieved records were screened for relevance based on title and abstract, followed by full-text assessment of potentially relevant publications.

The final evidence base comprised 40 publications that met the predefined conceptual relevance criteria and were verified as relevant to at least one of four linked domains: (i) the burden and determinants of WRMSDs among healthcare workers; (ii) conventional ergonomic and observational assessment; (iii) wearable-based measurement of biomechanical and physiological exposure; and (iv) predictive analytics, including machine-learning approaches relevant to musculoskeletal risk. Evidence was synthesized narratively and comparatively across these domains, with particular emphasis on the distinction between measurement of current exposure, detection of existing musculoskeletal status, and prospective prediction of future symptom development.

Because this study is an integrative rather than systematic review, the search was designed to achieve broad conceptual coverage and critical synthesis across heterogeneous evidence types rather than exhaustive study capture. Accordingly, no formal meta-analysis or pooled effect estimate was undertaken.

3.0 What Wearables Can Already Measure

Wearable systems have expanded ergonomic assessment from intermittent observational evaluation toward repeated, quantitative, and potentially longitudinal measurement of occupational exposure. Inertial measurement units (IMUs) can estimate trunk and neck inclination, joint orientation, angular velocity, posture duration, movement frequency, and transitions between activities. These measurements can be summarized as time-varying exposure profiles, allowing researchers to characterize not only whether a non-neutral posture occurs but also its frequency, duration, repetition, and distribution across a working shift. Full-shift monitoring of registered nurses has shown that extreme postures may occupy only a portion of the working day, while opportunities for rest and recovery can remain limited, illustrating the importance of cumulative exposure measurement (Schall et al., 2016).

Such temporal information is difficult to obtain reliably from brief observational assessments and may be particularly relevant when musculoskeletal risk results from repeated or cumulative exposure rather than from a single hazardous event.

Healthcare-specific studies provide increasing evidence that wearable sensing is technically feasible during real clinical work, although feasibility does not necessarily establish long-term acceptability, measurement validity, or predictive utility. Wearable sensors have been used to quantify surgeon neck and trunk posture during actual procedures (Meltzer et al., 2020; Carbonaro et al., 2021; Yang et al., 2021; Zulbaran-Rojas et al., 2024; Casu et al., 2025). Collectively, these studies demonstrate that wearable sensors can capture posture-related exposure under complex clinical conditions, including prolonged procedures and constrained working positions, rather than only under controlled laboratory tasks. In pediatric surgery, vibrotactile feedback from a wearable device reduced time spent in suboptimal postures, demonstrating that sensing can support immediate behavioral intervention rather than measurement alone (Soni et al., 2024). Similar feedback approaches have improved posture during simulated nursing tasks and other occupational activities (Lim & Yang, 2023). However, reductions in exposure following real-time feedback should be interpreted as evidence of intervention potential rather than evidence that sensor-derived changes predict subsequent WRMSD onset.

Surface electromyography (sEMG) adds physiological information that posture-based sensing alone cannot provide by characterizing muscle activation patterns and changes associated with fatigue or sustained muscular demand. It can quantify muscle activation and detect changes in electromyographic characteristics that may be associated with muscular fatigue during patient-transfer tasks. Field measurements show that different transfer scenarios produce meaningfully different erector spinae loads (Vinstrup et al., 2024). Assistive devices also influence muscular loading. Ceiling lifts and intelligent beds have been associated with lower erector spinae activity than several manual or low-technology transfer approaches (Vinstrup et al., 2020a). A prospective cohort of 1,285 healthcare workers further linked lower physical exposure during patient transfer with lower low-back pain intensity at one-year follow-up, although associations with back injury were not straightforward (Vinstrup et al., 2020b). These findings are important because they demonstrate that objectively characterized physical exposure can be associated with subsequent musculoskeletal outcomes. Nevertheless, they do not establish that wearable-derived trajectories can identify, at the individual-worker level, who will develop symptoms before symptom onset.

Other wearable modalities may provide complementary dimensions of musculoskeletal exposure and physiological response. Pressure-sensing insoles can characterize load distribution and gait, while force and load sensors may help distinguish visually similar movements performed under substantially different external loads. Selected physiological sensors can capture heart rate and other indicators potentially relevant to workload or recovery. Reviews of workplace posture monitoring and broader biomechanical sensing suggest that combining multiple sensor modalities may provide a more comprehensive representation of occupational exposure than a single device (Museck et al., 2024; Babangida et al., 2025). Combining kinematic, muscular, pressure, force, and physiological signals may therefore provide a multidimensional representation of occupational workload that cannot be captured adequately by a single sensing modality. However, additional sensors also increase data-processing complexity, synchronization requirements, participant burden, missing-data risk, and the potential for model overfitting, particularly when the number of measured variables exceeds the number of clinically meaningful outcome events. The practical challenge is therefore not simply whether wearable systems can collect detailed measurements, but whether they can do so accurately, unobtrusively, and consistently during routine clinical work. Nurses and occupational safety professionals have raised concerns about hygiene, comfort, data quality, privacy, and whether monitoring may be repurposed for productivity surveillance (Hechtel et al., 2019; Mueller et al., 2024). These concerns are particularly important for longitudinal monitoring because repeated measurement requires sustained worker acceptance, reliable device adherence, secure data governance, and clear boundaries regarding how individual-level information may be interpreted and used. Technology that performs well under laboratory conditions but compromises comfort, workflow, privacy, or adherence during routine clinical work is unlikely to generate reliable longitudinal data or succeed at scale.

Taken together, current evidence indicates that wearable sensors are already capable of measuring several important dimensions of occupational musculoskeletal exposure, including posture, movement, muscular activation, external loading, and selected indicators of workload and recovery. The evidence is considerably stronger for exposure characterization and real-time feedback than for prospective prediction of future WRMSDs. This distinction is central to the present review: a wearable-derived measure becomes a candidate pre-symptomatic digital biomarker only when its longitudinal change can be shown to precede and reliably predict a clinically meaningful outcome in initially asymptomatic workers. Thus, current wearable technology provides the measurement infrastructure required to investigate musculoskeletal risk trajectories, but further prospective evidence is needed to establish whether these measurements can reliably identify workers approaching symptom onset.

4.0 Hazard Detection Is Not Prediction

The central argument of this review is that occupational ergonomics should distinguish four progressively more demanding levels of evidence: hazard detection, exposure quantification, current risk classification, and prospective prediction. First, hazard detection asks whether a potentially harmful posture, movement, or task is occurring. Second, exposure quantification asks how much of that exposure accumulates over time. Third, current risk classification combines exposure features to place a task or worker into a present risk category. Fourth, prospective prediction asks whether measurements collected before symptom onset can identify workers who are more likely to develop a subsequent musculoskeletal outcome.

Wearable research is currently strongest at the first three levels. Machine-learning models can classify posture, activity, workload, or current musculoskeletal status with promising reported performance. Luo et al. (2024), for example, developed explainable machine-learning models for neck and shoulder WRMSD status among healthcare professionals. That work is useful, but it is cross-sectional. The model identifies patterns associated with an outcome that is already present. Such cross-sectional discrimination may demonstrate association or classification capability, but it does not establish temporal precedence, individual-level risk prediction, or the ability to detect an evolving pre-symptomatic state.

A 2025 systematic review of wearable sensors and machine learning for occupational load-handling tasks reached a similar conclusion. The field shows promise, but studies are generally small and focus on activity classification, posture, or external weight estimation rather than future health events (Peters et al., 2025). This limitation is particularly important for the present research question because activity or posture classification is an intermediate measurement capability, whereas prediction requires a temporally ordered relationship between an exposure-derived signal and a subsequently observed health outcome. The broader wearable literature has the same limitation. Reviews identify rapid technical progress but repeatedly call for standardization, field validation, and stronger longitudinal designs (Motta et al., 2024; Babangida et al., 2025).

This distinction matters because high classification accuracy can be misleading when it is interpreted as evidence of future injury or symptom prediction. A device may identify excessive trunk flexion with high accuracy and still have limited ability to determine which worker will subsequently develop low-back pain. Prospective predictive validity requires temporal ordering: the predictor must be measured before the outcome occurs, and its performance should be evaluated in participants who were not used to develop or tune the predictive model. Ideally, prediction should also be assessed using clinically meaningful outcomes, appropriate follow-up periods, worker-level validation, and performance measures that reflect calibration as well as discrimination.

The most informative future signal may therefore be longitudinal change rather than a single cross-sectional threshold. For example, two nurses could perform a similar number of patient transfers and receive comparable conventional ergonomic scores, yet one may remain biomechanically stable while the other develops progressively greater muscular activation, asymmetry, reduced movement variability, or slower recovery across repeated observations. Wearables make it possible to observe such divergence. The analytical challenge is to determine which longitudinal changes represent reproducible signals of increasing risk rather than normal within-worker variability, measurement noise, changes in workload, or temporary responses to specific tasks.

This distinction provides the rationale for the PMRT Framework proposed in the next section. Rather than treating any single wearable-derived measure as a predictor, the framework conceptualizes risk as a longitudinal sequence in which occupational exposure may be followed by measurable biomechanical or physiological changes and, in some workers, eventual symptom development.

5.0 Proposed Pre-Symptomatic Musculoskeletal Risk Trajectory Framework

The Pre-Symptomatic Musculoskeletal Risk Trajectory (PMRT) Framework proposed here conceptualizes musculoskeletal risk as a dynamic, longitudinal process rather than as a single exposure score or cross-sectional risk category. The framework is intended to organize hypotheses for prospective research and is not presented as a validated clinical prediction model, diagnostic instrument, or employment decision tool.

The framework begins with occupational exposure. In healthcare, this includes patient lifting, repositioning, bending, twisting, pushing, pulling, sustained neck or trunk posture, repetitive upper-limb work, and prolonged standing. These exposures may vary substantially within and between workers according to task type, patient characteristics, shift demands, staffing conditions, work organization, experience, and opportunities for recovery. Wearable sensing then captures selected components of this exposure. IMUs provide kinematic information, sEMG provides muscular activation information, pressure sensors provide load-distribution information, and other sensors may contribute estimates of external load or physiological recovery. Importantly, the sensors do not measure musculoskeletal risk directly; they measure observable biomechanical, muscular, mechanical, or physiological signals from which candidate exposure and response markers can be derived.

The next step is therefore not simply to generate more data but to transform raw signals into interpretable and reproducible digital biomechanical or physiological markers. Candidate markers include cumulative non-neutral posture, high repetition, increasing muscular activation for the same task, fatigue-related EMG changes, movement asymmetry, altered gait or load distribution, reduced movement variability, and slower return toward an individual baseline. These remain candidate markers, not established preclinical biomarkers. A marker should only be considered a credible pre-symptomatic predictor after demonstrating temporal precedence, reproducibility, association with subsequent clinically meaningful outcomes, and predictive performance in appropriately designed prospective cohorts.

The defining feature of the framework is longitudinal analysis, in which repeated measurements are used to characterize within-worker change over time rather than relying solely on population-level thresholds. A single abnormal movement is therefore not, by itself, a trajectory. Repeated measurements should show whether a worker remains stable, improves after intervention, develops an emerging adverse pattern, or maintains a persistently adverse pattern. Individual baseline data may be especially useful because workers differ in anthropometry, experience, technique, previous injury, and physical capacity. Accordingly, trajectory-based models may need to distinguish meaningful deviation from an individual's usual pattern from normal between-worker differences.

Only after prospective validation should these patterns be translated into a pre-symptomatic risk estimate. In a prospective research design, this stage would represent a decision point at which a validated risk signal could be evaluated for its potential to trigger preventive action while symptoms remain absent or minimal. Any validated risk alert should trigger a supportive workplace assessment rather than be interpreted as evidence of worker deficiency or individual fault. Appropriate responses may include safer patient-handling equipment, task redesign, changes in staffing, recovery time, job rotation, workstation adjustment, or focused ergonomic coaching. Evidence from patient-handling interventions supports the value of engineering controls and assistive devices in reducing physical load and injury burden (Garg & Kapellusch, 2012; Richarz et al., 2023; Callihan et al., 2023). The preferred response should therefore target modifiable work-system factors before attributing risk solely to individual worker characteristics.

This prevention focus is essential because the purpose of pre-symptomatic prediction should not be to create another surveillance score or productivity-monitoring system. Rather, its intended value is to identify a potentially modifiable period in which occupational exposure, work organization, or recovery conditions can be changed before a worker develops persistent pain or functional impairment. The framework therefore places prevention, worker autonomy, data privacy, and organizational intervention alongside predictive performance as essential considerations for future implementation.

Fig. 1 illustrates the proposed transition from occupational exposure measurement to longitudinal musculoskeletal risk assessment and, subject to prospective validation, pre-symptomatic risk estimation and preventive occupational-health intervention.

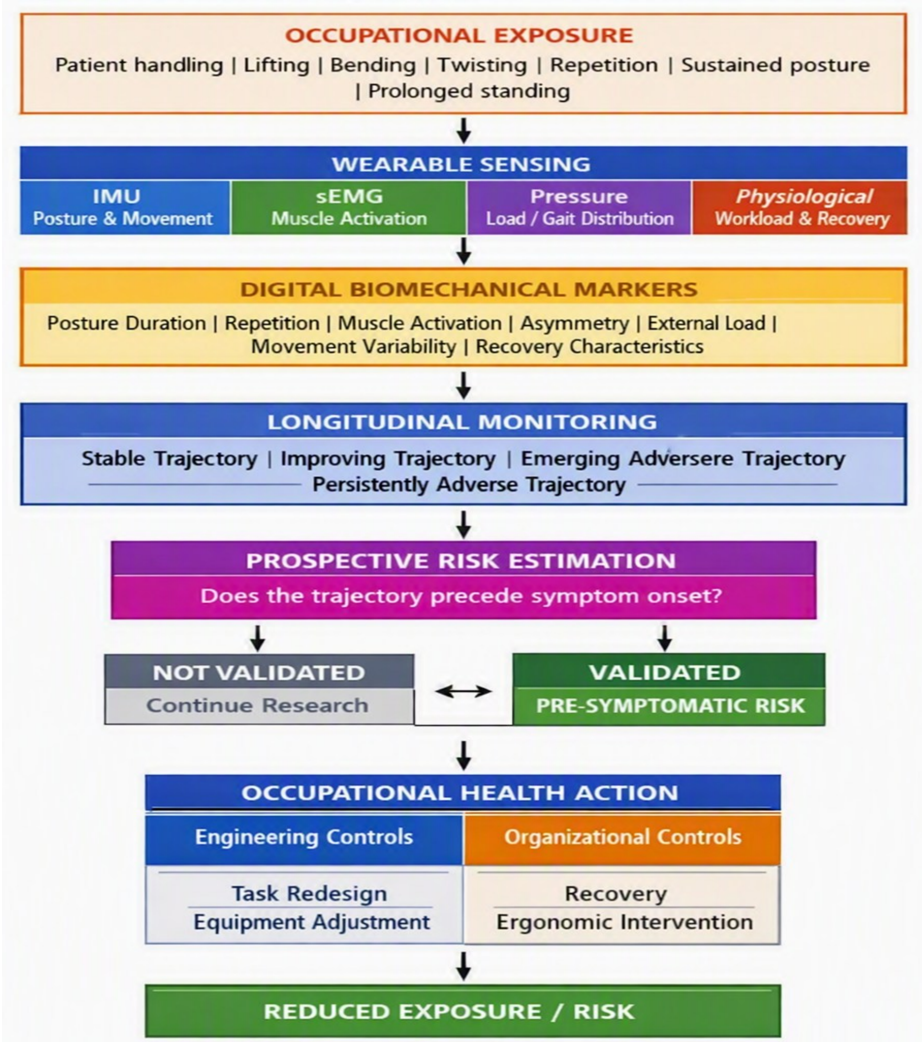

Fig. 1. Conceptual Pre-Symptomatic Musculoskeletal Risk Trajectory (PMRT) Framework showing the proposed progression from occupational exposure and wearable sensing through digital biomechanical marker extraction, longitudinal trajectory analysis, prospective risk estimation, and preventive occupational-health intervention.

The framework (Fig. 1) distinguishes established capabilities in hazard detection, exposure quantification, and current risk classification from the comparatively unvalidated stage of pre-symptomatic prediction.

6.0 How the Framework Should Be Tested

The PMRT Framework requires prospective evaluation in healthcare workers who are free from clinically meaningful symptoms in the target anatomical region at baseline, so that wearable-derived measurements can be evaluated as predictors of subsequent symptom onset rather than correlates of an already established condition. A practical prospective study could recruit nurses or other patient-care staff, obtain baseline information on age, anthropometry, work role, previous musculoskeletal history, sleep, psychosocial workload, physical activity, and relevant work organization factors, and then collect wearable data during repeated shifts over several months. Baseline assessment should also use a standardized instrument to confirm symptom status and establish individual reference values for the target anatomical regions. Measurement frequency should be sufficient to characterize within-worker variability while minimizing participant burden, with repeated assessments aligned as far as possible with comparable tasks, shifts, and workload conditions.

The outcome must be clinically meaningful, prospectively defined, and temporally separated from the predictor so that wearable-derived measurements clearly precede the observed health event. Examples include first onset of low-back pain lasting a specified number of days, persistent neck or shoulder symptoms, functional limitation, restricted duty, healthcare utilization, or a clinically diagnosed WRMSD. Outcome definitions should be established before analysis and should distinguish transient discomfort from persistent symptoms, functional limitation, restricted duty, healthcare utilization, or clinically diagnosed WRMSD. Prediction horizons should be prespecified and justified according to the expected temporal development of the target outcome, for example 30 days, three months, or six months.

Analysis should explicitly address data leakage, dependence among repeated observations, and temporal correlation, all of which are common challenges in wearable machine learning. Thousands of sensor windows obtained from one worker do not represent thousands of independent participants. Training, validation, and test sets should therefore be separated at the worker level, ensuring that observations from the same individual do not appear across development and evaluation sets. Where temporal prediction is intended, validation should also preserve the temporal ordering of measurements and outcomes. Performance reporting should include sensitivity, specificity, positive and negative predictive values where appropriate, discrimination, calibration, and clinically relevant decision thresholds rather than accuracy alone. External validation in another hospital, healthcare setting, or occupational group would provide stronger evidence of generalizability before wider application.

Because incident WRMSDs may occur less frequently than non-events within a given follow-up period, class imbalance should also be anticipated and handled without introducing information leakage. Missing sensor observations, device non-adherence, and variation in shift exposure should be documented and incorporated into the analysis rather than treated automatically as random loss of information.

A parsimonious sensor configuration may ultimately be more useful than a complex laboratory-based system. The best system will not necessarily be the one that measures the most variables but the one that adds reliable predictive information while remaining comfortable, hygienic, interpretable, affordable, and acceptable during clinical work. Sensor selection should therefore be guided not only by statistical contribution but also by measurement validity, interpretability, cost, maintenance requirements, worker burden, and feasibility of deployment across routine clinical shifts. Worker participation in system design, testing, and interpretation should therefore be treated as a methodological and implementation requirement rather than an optional step (Mueller et al., 2024).

Ethical and data-governance safeguards are equally important, particularly when wearable monitoring generates continuous or worker-identifiable information. Governance arrangements should specify who can access the data, how long data are retained, how individual-level risk estimates are communicated, and whether data may be used for purposes beyond occupational health protection. Wearable data collected for health protection should not automatically be used for productivity scoring, disciplinary action, or employment selection. False positives could lead to unnecessary restrictions, while false negatives could provide false reassurance. Accordingly, the consequences of prediction errors should be evaluated alongside statistical performance, particularly where risk estimates could influence work assignment, access to duties, or perceptions of worker capability. Until prospective validity, clinical relevance, and implementation safety have been demonstrated, wearable-derived risk estimates should support professional occupational health assessment rather than replace clinical judgment, ergonomic evaluation, or worker participation in decision-making.

7.0 Implications for Occupational Health Practice

If prospective studies establish that wearable-derived trajectories can reliably predict clinically meaningful WRMSD outcomes, their greatest occupational-health value would be to support earlier intervention rather than replace existing ergonomic assessment. Current practice often relies on reported discomfort, injury records, workers' compensation data, or observation of high-risk tasks. These sources remain important, but they may identify risk after substantial exposure has already occurred. They may also be influenced by reporting behaviour, access to healthcare, organizational practices, and differences in how workers perceive or communicate symptoms. Repeated wearable measurements could potentially add a forward-looking layer by identifying changes in biomechanical or physiological exposure across comparable work periods, provided that such changes are shown through prospective validation to have meaningful relationships with subsequent health outcomes.

If validated, the most appropriate application would be a stepped, prevention-oriented response rather than an automatic individual alert or work restriction. A change in a wearable-derived trajectory should first prompt review of the task and work environment. Occupational health or ergonomics staff could examine patient-handling technique, availability and actual use of lift equipment, staffing, workload, bed height, duration of sustained posture, and opportunities for recovery. Evidence from safe patient-handling programs shows that engineering and organizational controls can reduce injury burden more effectively than relying on individual lifting technique alone (Garg & Kapellusch, 2012; Richarz et al., 2023; Callihan et al., 2023). This approach is consistent with the hierarchy of controls, in which elimination, substitution, engineering controls, and organizational measures are generally preferred over interventions that place primary responsibility on individual worker behaviour. Wearables could therefore help identify where such controls are most needed and whether exposure improves after intervention.

The technology should also be evaluated and, where appropriate, deployed at the group or work-system level rather than being framed primarily as an individual surveillance tool. Aggregated patterns across a unit may reveal that a particular task, shift, procedure, workstation, or staffing arrangement consistently produces elevated exposure. This use is less likely to stigmatize individual workers and is more consistent with prevention through the hierarchy of controls. Individual feedback may still be useful, particularly when workers voluntarily seek real-time coaching or feedback on movement technique, but it should be transparent, proportionate, and explicitly separated from performance evaluation or disciplinary processes.

For healthcare organizations, the practical standard should therefore be prevention-oriented: wearable data should lead to safer work design and measurable improvements in working conditions. If a system only generates individual alerts without changing equipment, workflow, staffing, task organization, or recovery opportunities, it risks becoming another monitoring burden rather than an effective occupational-health intervention. Successful implementation should therefore be judged not only by predictive performance but also by whether the technology produces meaningful improvements in exposure, worker experience, and organizational safety.

8. 0 Strengths, limitations, and research priorities

The main strength of this review is its focus on a specific transition that is often blurred in the literature: moving from measuring hazardous exposure to predicting future health outcomes. It integrates healthcare ergonomics, wearable sensing, biomechanics, and predictive analytics within one testable framework.

The evidence base also has clear limitations. Many wearable studies involve small samples, controlled tasks, or short observation periods. Sensor placement and processing methods vary considerably. External load is often measured less well than posture, even though patient handling may involve unpredictable force. Studies frequently report current ergonomic risk or current symptom status rather than incident disease. These limitations mean that the PMRT Framework is hypothesis-generating.

Future work should proceed in stages. First, researchers should identify wearable-derived variables that are reliable during real healthcare work. Second, longitudinal studies should determine whether these variables change before symptoms. Third, prediction models should be developed with adequate sample sizes and worker-level validation. Fourth, models should be externally validated. Finally, intervention trials should test whether acting on an early risk signal actually reduces WRMSD incidence. A model that predicts an outcome but does not improve prevention has limited occupational health value.

9.0 Conclusion

Wearable technology has already improved the ability to measure posture, movement, muscle activity, and physical workload in healthcare. What it has not yet established is reliable prediction of who will develop a WRMSD before symptoms appear.

That distinction should shape the next phase of research. Rather than treating each hazardous posture as an isolated event, occupational health could examine how exposure, physical response, recovery, and movement patterns change within a worker over time. The proposed PMRT Framework provides a structure for testing that idea.

If longitudinal studies can identify reproducible pre-symptomatic trajectories and show that early workplace intervention changes outcomes, wearable ergonomics could move from describing risk to preventing injury earlier. Until then, wearable systems should be viewed as powerful exposure-assessment tools with promising predictive potential, not as validated disease-prediction devices.

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Author Contributions

Adedayo Toluwanimi Adekola conceptualized the study, developed the methodology, conducted the literature search and analysis, and drafted the manuscript. Oluwatosin Oluwafunmilola Oluwafemi contributed to literature synthesis and critical revision. Ekta Kumar contributed to occupational health interpretation and manuscript review. Funmilayo Omolayo Ruf contributed to conceptual development, critical editing, and final review. All authors approved the final manuscript for submission.