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Ergonomics Sensing in Industry 5.0 Human-Robot Collaboration: Current Trends and Future Directions

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Abstract

Human robot collaboration is moving from pilot cells to routine production as manufacturers seek flexible automation that can coexist with skilled work, frequent changeovers, and high product variety. Industry 5.0 further emphasizes human centric system performance, where worker well-being and long-term health outcomes are treated as design requirements. In many production settings, ergonomic risk is dynamic. It changes with layout, pace, product mix, and within shift fatigue. As a result, one-time ergonomic assessments are often insufficient for collaborative workcells where robot timing and handover geometry can influence sustained reaches and repeated trunk flexion. Ergonomics sensing offers a practical pathway by estimating posture, exposure, and related workload indicators in real time and enabling collaboration policies that adapt to changing human state. This paper synthesizes sensing technologies used in collaborative environments, including wearable, vision and depth, robot embedded, and multimodal configurations. It then organizes ergonomic metrics and estimation pipelines that translate raw signals into interpretable outputs such as posture risk indices, exposure measures, fatigue proxies, and workload indicators. The paper also analyzes how sensing can improve collaboration through robot motion adaptation, task allocation, and workcell commissioning decisions, while considering safety constraints and deployment barriers such as occlusion, privacy, and usability. Finally, a practical framework is proposed to connect modular sensing inputs to ergonomic state estimation, decision making, and verification, with the goal of supporting more consistent reporting and more actionable translation from measurement to intervention in Industry 5.0 human-robot collaboration (HRC).

Keywords
Industry 5.0, Human-Robot Collaboration (HRC), Ergonomics sensing, Wearable sensors, Vision-based ergonomic assessment

1. Introduction
Human robot collaboration is moving from pilot cells to routine production because manufacturers want flexible automation that can coexist with skilled work, frequent changeovers, and higher product variety. At the same time, Industry 5.0 shifts the target from automation alone to socio technical performance, where worker well-being is treated as a design outcome, not a side effect. A recent systematic review on human factors and ergonomics in Industry 5.0 emphasizes that human centric work environments are expected to improve health, safety, and well-being while supporting resilience and sustainability (Trstenjak et al., 2025). This framing matters for human robot collaboration (HRC) because the strongest reasons to keep people in the loop are also the reasons that raise ergonomic concerns.

In many real production settings, ergonomic risk is not stable. It changes with product mix, workstation layout, tool wear, part presentation, and pace. It also changes within the same worker across a shift as fatigue builds. Static ergonomic evaluations are often performed during workstation design or after an incident, but that timing misses the dynamic nature of collaborative work. The gap is especially visible in shared workspaces where the robot's position and timing can push a worker into sustained reaches or repeated trunk flexion if handover points and task division are not carefully managed. The practical implication is that ergonomic performance cannot be guaranteed by a one-time assessment alone. It requires continuous monitoring of human state and continuous adjustment of collaboration policies.

Ergonomics sensing provides a great solution to close this gap in literature. The basic promise is straightforward. Sensors estimate posture and exposure in real time, and then the system uses this information to guide collaboration. In the last few years, vision-based posture evaluation using pose estimation has become more feasible and more accurate, and wearable sensing has become more common in industrial ergonomics reviews and deployments (Iyer et al., 2025; Naranjo et al., 2025). At the same time, collaborative robotics research has increasingly shown that ergonomic objectives can be embedded into control and planning. For example, Maurice et al. proposed a framework that monitors joint overloading torque and optimizes robot motion to bring the human into a better working configuration during power tool operations (Kim et al., 2021). In parallel, task planning and operations research communities have begun to incorporate fatigue models into task reallocation for human robot collaborative workshops, such as the work by (Yao et al., 2024).

Even with this progress, the literature also reports repeated barriers that prevent widespread adoption. Researchers use different sensing configurations, different ergonomic indices, and different validation protocols, which makes it hard to compare results across studies. Evidence from real manufacturing environments is growing, but it remains uneven and often short term (Agostinelli et al., 2024). There is also a recurring monitor only pattern where systems estimate ergonomic risk but stop before translating estimates into collaboration decisions. A recent Industry 5.0 focused study on ergonomics and safety in collaborative robot systems points to the absence of standardized guidelines and the overlap between safety and ergonomics as major challenges (Suryoputro et al., 2025). It is important to note that these issues motivate a review that does not only list sensors and indices but also explains how sensing becomes actionable inside collaboration.

This paper reviews ergonomics sensing for Industry 5.0 human robot collaboration with three goals (Figure 1). It synthesizes sensing technologies that estimate physical workload and related constructs in collaborative workcells. It organizes ergonomic metrics and estimation pipelines that translate sensor data into interpretable information. It then proposes a practical framework that connects sensing outputs to collaboration decisions in a way that is well supported by existing studies and that maps the key research gaps. Despite rapid progress in wearable and vision-based ergonomics assessment, there is no widely adopted structure that links sensor choices, ergonomic metrics, and real time collaboration decisions in Industry 5.0 workcells. The result is a fragmented body of work that is difficult to compare and difficult to translate into factory ready systems (Ciccarelli et al., 2025; Naranjo et al., 2025; Suryoputro et al., 2025).

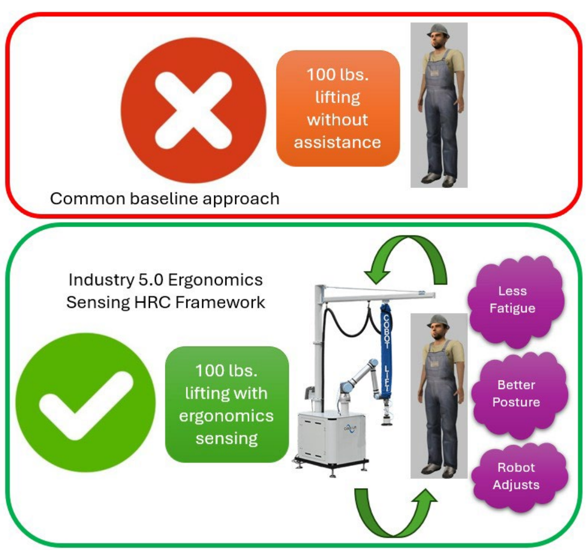

Figure 1. Why ergonomics sensing is needed in Industry 5.0 HRC

1.1 Objectives

The research objectives of this paper are listed below:

1. To synthesize ergonomics sensing technologies used in human robot collaboration and classify them by sensing modality, intrusiveness, and industrial feasibility, grounded in recent review and validation studies.
2. To organize ergonomic metrics and estimation pipelines used in collaborative settings, including posture risk indices, exposure measures, and fatigue estimation, with emphasis on how raw signals become decision ready outputs.
3. To analyze how ergonomics sensing improves collaboration through changes in robot behavior, task allocation, and workcell configuration, and to compare these approaches against the broader HRC task allocation literature.
4. To propose a practical framework for Industry 5.0 ergonomic HRC that addresses gaps reported in recent studies, including standardization, monitor to action translation, and deployment constraints such as privacy and usability.

2. Literature Review

Ergonomics sensing sits at the intersection of three research streams. The first stream is industrial ergonomics, where traditional observation-based methods such as Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA) have been used for decades but are limited in complex workflows. The second stream is sensing and perception, where wearable and vision-based systems aim to estimate posture and work exposure automatically. The third stream is HRC, where collaboration quality depends on both safety requirements and human centered performance. Industry 5.0 helps align these streams around a shared priority. Human centricity is treated as a design requirement alongside productivity and resilience (Trstenjak et al., 2025). In HRC, this means that a well performing system should reduce the likelihood of harmful postures, avoid excessive repetition, and manage fatigue accumulation while still meeting cycle time targets. The ergonomic HRC review by Lorenzini et al. is influential because it links ergonomics assessment tools and human state monitoring technologies to robot behavior adaptation, and it shows the need for clearer frameworks and stronger validation (Lorenzini et al., 2023).

Safety standards remain a nonnegotiable boundary for collaboration in shared workspaces. ISO TS 15066 specifies safety requirements for collaborative industrial robot systems and supplements ISO 10218 guidance on collaborative operation for industrial robots (ISO Committee, 2016). Safety, however, is not the same as ergonomics. Safety focuses on preventing acute harm and hazardous contact, while ergonomics addresses long term risk related to work related musculoskeletal disorders (WMSDs) and fatigue. The Industry 5.0 ergonomics and safety perspective emphasizes that the overlap between these domains is real and can create confusion during implementation, which increases the need for clear methods that integrate both perspectives without collapsing them into a single metric (Suryoputro et al., 2025).

Recent literature shows two clear trends. One trend is the rapid progress of sensing technology for ergonomic assessment, supported by large scale reviews of wearable sensors in industrial ergonomics and by validation studies of vision-based assessment in real manufacturing environments (Agostinelli et al., 2024). Another trend is the increasing use of human state information in collaboration decisions, including task allocation reviews, fatigue driven task reallocation methods, and ergonomic control frameworks that adjust robot motion to support safer human posture (Petzoldt et al., 2023; Yao et al., 2024). Based on these trends, this paper structures the literature review and motivates a practical framework.

2.1 Ergonomics sensing technologies in HRC

Ergonomics sensing technologies can be grouped into wearable sensing, external sensing such as vision and depth, robot embedded sensing, and multimodal fusion as seen in Table 1. Each group reflects a different tradeoff between accuracy, intrusiveness, and industrial feasibility.

Wearable sensing has gained visibility because it can follow the worker through occlusions, which is a common challenge in motion capture studies (Avdan et al., 2025), and it does not depend on camera placement. A PRISMA structured scoping review of wearable sensors in industrial ergonomics reports growing use of IMUs, EMG, and pressure sensors, and it notes recurring challenges related to scalability, comfort, and privacy (Alenjareghi et al., 2026; Naranjo et al., 2025; Roy et al., 2025). A related systematic review on smart wearable insoles in industrial environments shows how pressure-based sensing is used to infer activities and workload related patterns, but it also highlights deployment issues such as durability and model generalization (Abdollahi et al., 2024). These findings matter for HRC because collaborative workcells often involve frequent movement and partial occlusion around fixtures, where wearables can provide more reliable tracking than a single camera (Table 1).

Table 1. Ergonomics sensing technologies for HRC

Technology category	Typical inputs	Main ergonomic use	Industrial limitations	Recent evidence
Wearable kinematics	IMUs on trunk, arms, pelvis, or full body	Tracks joint angles, trunk flexion, shoulder elevation, repetition, and posture exposure	Donning time, calibration drift, sensor placement, comfort, battery life, and PPE compatibility	Wearable sensor reviews report increasing use of IMUs for continuous ergonomic monitoring, but also note comfort, scalability, and privacy barriers.
Wearable load proxies	EMG, pressure insoles, grip or contact force sensors	Estimates muscle activity, fatigue indicators, plantar loading, and weight-shift patterns	Sensitive to placement, skin preparation, noise, footwear fit, and durability	Recent wearable and smart-insole studies support their value for workload and WMSD risk monitoring in industrial settings.
RGB vision-based posture	RGB cameras with pose estimation or posture classifiers	Screens whole-body posture, awkward reaches, and RULA/REBA-style risk scores	Occlusion, lighting, camera angle, clothing, background clutter, and privacy concerns	Computer vision tools have been validated in real manufacturing environments for semi-automated ergonomic assessment.
Depth and RGB-D posture	RGB-D cameras, depth cameras, multi-view or 3D pose models	Estimates 3D body landmarks, reach distance, trunk/arm angles, and handover geometry	Setup constraints, occlusion near fixtures, limited field of view, and sensitivity to camera placement	RGB-D and markerless pose studies show promise for 3D posture assessment, but accuracy depends strongly on setup and validation conditions.
Robot-embedded sensing	Joint torque estimates, force-torque sensors, motion state, contact events	Captures interaction load, hand-guiding force, timing, and robot-induced ergonomic effects	Robot signals alone cannot fully explain human posture, fatigue, or muscle demand	Ergonomic HRC studies show robot-side data can support motion adaptation and overload reduction when combined with human-state estimation.
Multimodal fusion	Wearables, vision/RGB-D, robot signals, task context, object weight	Improves ergonomic state estimation, fatigue monitoring, and closed-loop adaptation	Requires synchronization, maintenance, data governance, and more complex deployment	HRC reviews and fatigue-based task reallocation studies show growing movement toward multimodal, human-state-aware collaboration.

Vision and depth sensing systems have advanced rapidly due to improvements in human pose estimation. Several studies report two stage pipelines in which pose is extracted from RGB or RGB D input and then mapped to ergonomic risk indices such as RULA and REBA (Cruciata et al., 2025; Lin et al., 2022). A study integrating RGB D cameras with OpenPose evaluated accuracy against a marker-based reference system, showing that accessible depth and pose estimation can localize body landmarks with errors that may be acceptable for many workplace posture assessments (Liu & Chang, 2022). Evidence from real manufacturing validation is also increasing. Agostinelli et al. evaluated computer vision based ergonomic risk assessment tools in real manufacturing environments, which supports the argument that the field is moving beyond lab only demonstrations (Agostinelli et al., 2024). Even so, occlusion, lighting variation, and privacy considerations remain central barriers in industrial adoption.

Robot embedded sensing includes force torque sensors, joint torque estimates, and motion state signals that can serve as indirect indicators of interaction load and timing. These signals are especially relevant during hand guiding, contact based collaboration, and shared manipulation. They are less intrusive but can be difficult to interpret because robot loads reflect multiple sources, including tool forces and contact events. The value of robot embedded sensing increases when it is fused with either wearables or vision, which reduces ambiguity about whether a measured load corresponds to human exertion or to external disturbances. On the other hand, multimodal fusion combines the strengths of the above approaches. This trend is consistent with broader HRC perception and human modeling work that argues for integrated perception of human state, environment, and task context (Lorenzini et al., 2023; Murugan et al., 2025).

2.2 Ergonomic metrics and estimation pipelines

Ergonomic sensing is most valuable when raw sensor data is converted into metrics that can guide decisions. Even when the sensors differ, many approaches follow the same general flow. They estimate posture and motion features, summarize these features over meaningful time windows, and convert them into risk scores or workload indicators. How this conversion is defined largely determines how interpretable the results are and how likely the method is to be adopted in practice.

In recent research studies, posture risk indices remain dominant because they are familiar to ergonomists and easier to communicate with stakeholders. Vision based approaches often estimate joint angles from pose data and then map them to RULA or REBA scores as shown in Table 2 (Hossain et al., 2023). Deep learning approaches are also being used to identify unsafe postures in industrial work and to generate automated risk evaluation outputs, which points to more scalable assessment, although model validity remains a concern across tasks and workplaces (Sardar & Lee, 2024). A systematic review comparing measurement based and markerless systems for ergonomic risk analysis reports wide variation in accuracy and reliability across technologies, which reinforces the need for standardized reporting and cautious claims about generalization (Scataglini et al., 2025).

Exposure over time is increasingly discussed because musculoskeletal risk depends not only on posture severity but also on duration and repetition. Many studies still report snapshot risk scores, while fewer report exposure measures such as cumulative time in risk zones. Iyer et al. argue that emerging technologies and automation for musculoskeletal ergonomic assessment still require more specialized methods to capture posture and long-term musculoskeletal health, which supports the need for exposure over time metrics (Iyer et al., 2025).

Table 2. Common ergonomic metrics and estimation pipelines in HRC

Output metric	Typical inputs	Core computation idea	Strength for HRC	Key limitation
RULA/REBA posture risk	Pose or IMU joint angles	Apply scoring rules to posture, force, and repetition	Clear screening for motion or layout changes	Snapshot score without exposure history
Exposure dose	Risk time series, event counts	Sum time in risk zones and repetitions	Captures shift-level cumulative demand	Reporting windows vary across studies
Biomechanical load estimate	Posture, object weight, dynamics	Estimate joint torque or overload	Direct input for robot assistance	Sensitive to model and sensor error
Fatigue state	Video, EMG, force, task history	Update fatigue model over time	Supports reallocation and pacing	Ground truth remains difficult
Cognitive workload	Surveys, timing, errors, interaction features	Combine subjective and behavioral cues	Explains trust, acceptance, and fluency	Continuous sensing can be intrusive

Fatigue estimation is becoming a central component in collaborative planning and scheduling. An important operations-oriented example is task reallocation in a human robot collaborative workshop based on a dynamic human fatigue model, where fatigue is evaluated from multimodal data and used to trigger reallocation (Yao et al., 2024). In robotics, dynamic task allocation to mitigate human physical fatigue has been studied as well, showing that fatigue can be treated as a control objective rather than an external outcome (Baratta et al., 2024). These approaches align with Industry 5.0 goals because they emphasize worker well-being and sustained performance.

It is also important to recognize cognitive workload as part of the Industry 5.0 picture, even when the main sensing focus is physical ergonomics. Prior work in human robot interaction explains common sources of mental workload and outlines practical ways to reduce it, which helps clarify why predictability and transparency matter when ergonomic adaptation changes robot behavior (Carissoli et al., 2024). Another related work in human cobot collaboration also shows that worker well-being and cognitive load are increasingly treated as key factors for adoption and sustained use on the shop floor (Bassi et al., 2025).

2.3 How sensing improves collaboration

Ergonomics sensing affects collaboration through changes in robot motion, task division, and workstation configuration. The literature shows that the impact is strongest when sensing is connected to a concrete decision lever, not only to monitoring dashboards. A direct approach is to modify robot motion to steer humans toward better working configurations. The framework for ergonomic HRC during power tool operations illustrates this idea by estimating human joint overload online and optimizing robot motion to reduce overloading torques (Kim et al., 2021). This style of work is powerful because it connects sensing to an immediate, measurable intervention in the collaboration loop.
Task allocation and reallocation provide another pathway, particularly for shift level ergonomics. Petzoldt et al. synthesize criteria used for assigning tasks in HRC, which provides a foundation for discussing how ergonomic objectives are balanced with productivity and feasibility (Petzoldt et al., 2023). When fatigue models are included, the system can change allocations dynamically. The fatigue-based reallocation approach in a collaborative production workshop shows how fatigue evaluation can trigger reallocation while considering both worker comfort constraints and production efficiency (Yao et al., 2024). The key conceptual shift is that ergonomic state becomes a state variable within the planning problem. Workcell and commissioning stage use of sensing is also common. Vision and wearables are used to identify where risk concentrates, and the findings guide adjustments of fixture heights, part presentation, and robot handover points. Real manufacturing validation studies support the feasibility of using computer vision-based tools to support ergonomic assessment in practice, which strengthens the argument that sensing can be used beyond lab conditions (Agostinelli et al., 2024; MassirisFernández et al., 2020).

Table 3. Collaboration levers supported by ergonomics sensing

Collaboration lever	What sensing provides	Typical intervention	Evidence direction
Robot motion and handover design	Real-time posture, reach, and overload estimates	Adjust handover height, location, path, or approach angle	Ergonomic control studies show reduced overload through robot motion adaptation
Dynamic task allocation	Fatigue, workload, and exposure estimates	Reassign tasks, rotate workers, or adjust pace	Fatigue-aware HRC studies support state-based reallocation
Safety and ergonomics tuning	Human-robot distance, posture, and workspace context	Modify speed, separation, and allowable robot motion	ISO TS 15066 sets safety limits, while ergonomics guides safer options
Workcell improvement and commissioning	Risk hotspots across repeated task cycles	Change fixture height, part location, or task sequence	Real manufacturing studies support CV-based assessment for practical redesign

2.4 Current trends

Several trends are shaping ergonomics sensing in Industry 5.0 HRC. One trend is the shift from qualitative observation toward automated and semi-automated assessment, driven by the need for faster, more consistent evaluation of WMSD risk and the limitations of purely observational scoring in complex, high variability work. Recent sensor-based approaches highlight the value of reducing subjectivity and making assessments easier to repeat at scale (Ciccarelli et al., 2025; Pan et al., 2025). Another trend is the growing amount of validation work in real manufacturing environments. Testing computer vision-based tools outside controlled labs is important because practical barriers often come from occlusion, layout changes, lighting variation, and day to day workflow differences (Umar et al., 2024).

A third trend is the increasing use of fatigue models in planning and scheduling. Fatigue based reallocation in collaborative workshops indicates that the literature is moving toward dynamic human state modeling, which aligns with Industry 5.0 human centric goals (Trstenjak et al., 2025). A fourth trend is the integration of broader human factors such as cognitive workload and well-being into the evaluation of collaborative systems. This is visible in the literature on mental workload in cobot interaction and in reviews of worker well-being and cognitive load in human cobot collaboration (Paliga, 2023).

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Table 4. Current trends in Industry 5.0 HRC

Trend	What is changing	Why it matters in Industry 5.0 HRC	Representative support
Sensor-assisted ergonomic assessment	Moving from observer-only scoring to automated posture and risk estimation	Enables faster feedback and continuous monitoring	Recent Industry 5.0 sensor-based assessment studies
Real-world validation	Moving from lab demonstrations to manufacturing workcell testing	Improves confidence in practical deployment	CV-based ergonomic validation in real manufacturing
Fatigue-aware planning	Treating fatigue as an input for allocation and pacing	Supports shift-level well-being and resilience	Dynamic fatigue models for HRC task reallocation
Human-centered evaluation	Including cognitive load, trust, and well-being	Supports acceptance and sustained use	Mental workload and human-cobot well-being reviews
Reporting standardization	Calling for clearer metrics, protocols, and guidelines	Reduces fragmentation and safety-ergonomics confusion	Industry 5.0 ergonomics and safety review literature

3. Proposed framework for Industry 5.0 ergonomic HRC

Literature provides many components of ergonomic HRC, yet it rarely offers an end-to-end structure that is both implementable and consistent across sensing choices and intervention points. Some studies discuss early framework attempts but also reports limitations and challenges that remain unresolved. The Industry 5.0 ergonomics and safety perspective points to missing standardized guidelines and the overlap between safety and ergonomics. At the same time, several studies show that closing the loop from sensing to action is feasible, either through ergonomic robot motion optimization or through fatigue driven task reallocation.

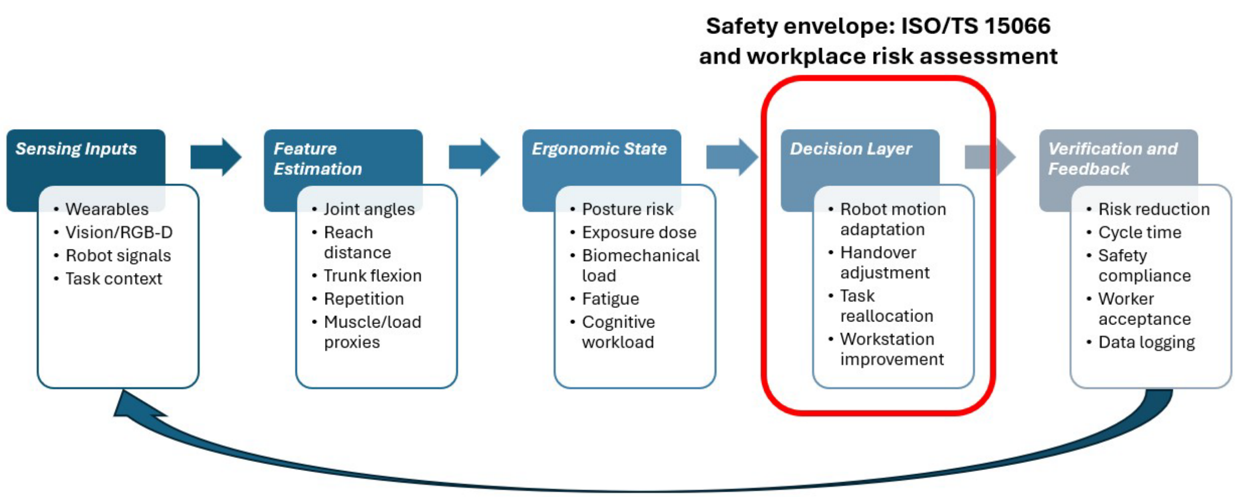

Figure 2. Proposed closed-loop framework for ergonomics sensing in Industry 5.0 HRC. The framework links sensing inputs, ergonomic state estimation, collaboration decisions, and verification under safety constraints.

Based on this evidence, a practical framework should satisfy five requirements, as shown in Figure 2. It must allow multiple sensing configurations, since factories differ in what they will accept. This is consistent with wearable ergonomics reviews that highlight adoption constraints such as comfort and privacy. It must produce interpretable ergonomic outputs that connect to familiar concepts such as posture risk and exposure. This is aligned with the widespread mapping of poses to indices such as RULA and REBA in vision-based pipelines. It must connect outputs to specific collaboration levers such as handover geometry and task allocation, since evidence shows that action focused systems are more valuable than monitor only systems. It must respect collaborative safety boundaries, since collaborative operation is governed by standards and risk assessment. It must include verification and logging so that the system can be evaluated, compared, and improved over time, addressing the comparability gap raised in validation and review studies.

3.1 Proposed Framework

Input layer: The system accepts one or more of these inputs. Wearable kinematics, vision or depth-based posture, robot embedded signals, and task context signals such as tool state or part identity. This modularity is necessary because the literature shows viable solutions across modalities and also reports that no single modality solves all deployment challenges.

Estimation layer: The system estimates posture variables and exposure variables. Posture variables include trunk inclination, shoulder elevation, joint angle patterns, and reach distance. Exposure variables include time in risk zones and repetition counts. Where possible, the system also estimates load proxies, either from object weight and posture or from interaction signals. The biomechanical load direction is supported by research that estimates human joint overload and uses it to guide robot motion.

Ergonomic state layer: The system converts estimated variables to an ergonomic state that has two parts. An interpretable risk score based on posture indices or equivalent rule-based scoring. An exposure and fatigue component that aggregates across time. This combination addresses a known limitation of snapshot scores and aligns with the push in ergonomic technology reviews toward better connection with long term musculoskeletal health. Fatigue estimation and aggregation are justified by fatigue-based reallocation studies that treat fatigue as a dynamic input to planning.

Decision layer: The system selects a collaboration intervention using a policy that prioritizes the least disruptive change that yields meaningful ergonomic benefit while maintaining productivity targets and respecting safety constraints. The decision layer contains three families of interventions drawn directly from literature. One family targets robot motion and handover geometry, supported by ergonomic motion optimization frameworks. Another family targets task allocation and pacing, supported by task allocation reviews and fatigue-based reallocation methods. The third family targets workstation adjustments during commissioning based on identified risk hotspots, supported by real manufacturing validation of assessment tools.

Verification layer: The system verifies whether risk and exposure decrease after intervention without creating unacceptable collaboration costs such as increased cycle time or higher cognitive workload. This verification step is motivated by the fact that cognitive workload and well-being influence acceptance in human cobot collaboration. It also supports standardization and comparison across deployments, an issue highlighted in Industry 5.0 ergonomics discussions.

4. Discussion

The proposed framework differs from many existing approaches in the literature because it treats ergonomics as both a real time state and a cumulative exposure outcome, and it explicitly links this state to a set of decision levers that are already supported by peer reviewed evidence. Ergonomic robot motion optimization demonstrates that human physical state can be measured online and used in an optimization loop to move the robot in ways that reduce overload (Kim et al., 2021). Fatigue based task reallocation studies demonstrate that human state can guide planning and scheduling decisions in collaborative production settings (Yao et al., 2024). These studies prove feasibility, but they are often presented as separate categories of contribution. The proposed framework integrates them into a common structure so that researchers and practitioners can decide where to start and how to extend. This integration also addresses an important research gap in the current literature. Many studies demonstrate a specific sensing method, ergonomic score, or robot adaptation strategy, but fewer studies explain how these elements should be connected as a complete decision-making process in Industry 5.0 HRC. As a result, the field still lacks a clear bridge between sensor-level measurement, ergonomic interpretation, and practical intervention.

A recurring limitation in literature is fragmentation of metrics and validation, which reduces comparability. Vision based systems may report pose error or classification accuracy, while ergonomic outcomes are reported as RULA or REBA score changes without consistent exposure measures (Cruciata et al., 2025; Scataglini et al., 2025). Wearable systems may report sensor accuracy and model performance while leaving ergonomic outcomes at a high level, and reviews note that deployment constraints like comfort and privacy affect adoption (Alenjareghi et al., 2026). The proposed framework addresses this by placing ergonomic state in a dedicated layer and by requiring both interpretable risk scores and exposure measures. This does not solve the standardization problem by itself, but it gives a concrete place to define reporting requirements and to align different modalities. The gap is not simply that different sensors are used, but that studies often define success differently. Some emphasize technical sensing accuracy, while others focus on posture score prediction, fatigue estimation, or worker acceptance. Without shared reporting of task conditions, sensor placement, calibration procedures, ground truth methods, exposure duration, and intervention outcomes, it remains difficult to compare findings or determine which approach is most suitable for real manufacturing deployment.

Another important gap is the limited connection between short-term ergonomic scoring and long-term musculoskeletal risk. Many automated assessment methods still reproduce snapshot-based ergonomic tools, which are useful for screening but may not fully capture cumulative exposure, recovery time, repetition, and fatigue across a shift. This is especially important in collaborative workcells because the robot may reduce one type of physical demand while unintentionally increasing another, such as repeated reaching, static holding, or awkward handover posture. Therefore, future ergonomic HRC research should move beyond single-time risk scores and evaluate whether sensing-based interventions reduce exposure over meaningful work periods.

The proposed framework also helps clarify the relationship between safety and ergonomics. Collaborative safety standards define permissible operation modes and require risk assessment (ISO Committee, 2016). Many papers treat safety constraints as separate from ergonomic objectives, which is appropriate, yet in practice these considerations interact. For example, speed and separation monitoring may reduce collision risk but can increase reach distance if handovers are forced into less convenient positions. The Industry 5.0 ergonomics and safety paper explicitly notes overlap and the absence of standardized guidelines, which explains why integrated approaches are needed. In the framework, safety constraints act as an envelope that limits decisions, while ergonomics guides the choice among safe options.

Another discussion point concerns the monitor to action gap. Real manufacturing validation studies show that automated or semi-automated ergonomic assessment can work in practice. Industry 5.0 oriented sensor-based assessment frameworks argue that automation reduces subjectivity and time cost (Martinelli et al., n.d.). Yet these contributions do not automatically translate into improvements unless interventions are defined and tested. By aligning sensing with decision levers that already have evidence in robotics and production planning, the proposed framework supports a more direct translation (Kim et al., 2021).

Finally, acceptance and human centered outcomes are essential for Industry 5.0. Ergonomic adaptation that changes robot motion or task allocation can affect cognitive workload, perceived control, and trust. Prior work in human robot interaction discusses common sources of mental workload and outlines practical ways to reduce it, which helps explain why predictability and transparency matter when robot behavior changes (Carissoli et al., 2024). Related work in human cobot collaboration also shows that worker well-being and cognitive load influence sustained adoption. For this reason, the verification layer includes not only physical ergonomic outcomes but also collaboration costs that can affect acceptance. This point also reveals a gap in how human-centered outcomes are evaluated. Many studies focus on technical performance or ergonomic prediction, but fewer examine whether workers understand, trust, and accept the adaptive behavior. If the robot changes its motion unexpectedly based on sensed fatigue or posture, the intervention may reduce physical risk while increasing mental workload or reducing perceived control. Thus, ergonomic HRC research should include worker feedback, transparency, usability, and cognitive workload as part of validation, not as secondary considerations.

5. Future Directions

Future research should move toward exposure based outcomes that reflect cumulative musculoskeletal risk, rather than relying mainly on snapshot posture scores. Prior work on emerging technologies and automation for musculoskeletal ergonomic assessment argues that posture measurement needs stronger connection to long term musculoskeletal health, which supports the use of exposure over time metrics and fatigue accumulation modeling as standard outcomes. A practical expectation is that studies report both the distribution of posture risk over time and the cumulative time spent in high risk zones, together with repetition or recovery indicators when the task involves cyclic work. This can be implemented with wearable and vision based systems, and it would make comparisons more meaningful across studies that use different sensors and different workplaces (Agostinelli et al., 2024; Naranjo et al., 2025; Scataglini et al., 2025).

Progress also depends on standardized reporting and benchmarking for Industry 5.0 ergonomic HRC. Work on ergonomics and safety in Industry 5.0 collaborative systems points to the absence of standardized guidelines and to implementation confusion that comes from overlap between safety and ergonomics (Suryoputro et al., 2025). Standardization does not need to begin with a universal dataset. It can begin with a reporting template that includes task description, worker variability, sensor configuration, calibration approach, ground truth method, ergonomic metrics, and the validation setting. Prior comparative work on measurement based and markerless systems shows that accuracy and reliability vary widely across technologies, which increases the importance of transparent reporting and cautious generalization claims (Scataglini et al., 2025). A shared template would also help clarify what "factory ready" means for ergonomics sensing and would reduce the current fragmentation of metrics.

Another important direction is closed loop ergonomic adaptation in real workcells with clear causal evaluation. Sensor based assessment frameworks emphasize objectivity and efficiency, but the next step is to show how assessment drives interventions that remain effective across variability in products, workers, and layouts. Control oriented ergonomic HRC and fatigue driven task reallocation already provide examples of action loops, yet many studies remain limited to short trials or controlled conditions. Future work should report before and after changes in exposure metrics, not only posture scores, and it should include stability checks such as performance under layout changes, different operators, and realistic cycle time pressures. This shift would help close the monitor to action gap and would strengthen the argument that Industry 5.0 HRC can deliver sustained reductions in ergonomic risk.

Finally, future systems should integrate physical ergonomics and cognitive outcomes into an adoption-oriented evaluation. Industry 5.0 emphasizes well-being, and cognitive workload and perceived control are increasingly treated as key factors for sustained cobot adoption. When the robot adapts based on sensed human state, transparency becomes a design requirement, not a cosmetic feature. Unexpected robot behavior can increase stress and may trigger unsafe operator actions, especially in time pressured tasks. Related insights can also be drawn from human centric Healthcare 5.0 work (Avdan & Onal, 2024b). Research on smart healthcare systems that promotes human centric and sustainable practices supports the broader Industry 5.0 view that technology should be evaluated with well-being and sustainability outcomes in mind, not only technical performance. Similarly, work that connects lean thinking to Healthcare 5.0 supports the idea that human centered improvement requires systematic measurement, waste reduction, and continuous feedback loops, which directly aligns with the need for verification and continuous improvement in ergonomic HRC deployments (Avdan & Onal, 2024a). These perspectives reinforce the value of closing the loop from sensing to action while keeping acceptance and usability as measurable requirements.

6. Conclusions

This paper reviewed ergonomics sensing in Industry 5.0 human robot collaboration and organized the literature around sensing technologies, ergonomic metrics, and collaboration levers. Wearables and vision-based systems are increasingly validated and capable of producing posture and risk estimates, and fatigue modeling is becoming part of task planning in collaborative workshops. At the same time, literature shows important gaps in standardization and in translating monitoring into robust interventions that hold up in real manufacturing variability. The main contribution of this paper is that it connects these separate research directions into a practical closed-loop framework for ergonomic HRC. Rather than treating sensing, risk estimation, and robot adaptation as separate topics, the proposed framework shows how modular sensing inputs can be translated into ergonomic state estimation, collaboration decisions, and verification. The proposed framework addresses these gaps by connecting modular sensing inputs to a defined ergonomic state, linking that state to actionable collaboration decisions, and requiring verification that includes both physical and acceptance-related outcomes. This framework contributes to the literature by clarifying how ergonomic sensing can move beyond monitoring and support practical decisions such as robot motion adaptation, handover adjustment, task reallocation, and workstation improvement. The framework is grounded in prior work that demonstrates ergonomic control loops and fatigue-based task reallocation, and it is shaped by the challenges reported in Industry 5.0 ergonomics discussions. The practical implication is that Industry 5.0 HRC systems should be evaluated not only by productivity or safety compliance, but also by their ability to reduce ergonomic exposure, manage fatigue, preserve worker acceptance, and support continuous improvement. For researchers, the findings highlight the need for more standardized reporting, exposure-based validation, and real-world testing of closed-loop interventions. For practitioners, the framework provides a guide for selecting sensing technologies and linking ergonomic information to actionable changes in collaborative workcells. Overall, this paper brings together sensing technologies and metrics, explains how sensing can improve collaboration, and outlines practical directions for future research and deployment.

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Biography

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