A Systematic Review of Motion Capture Technologies Applied to Ergonomic Assessment

Nor Aslina Abd Jalil[1], Siti Maisarah Amdan[2], Zuraida Jorkasi[3], Kamariah Hussein[4], Nooraini Jamal[5*]

[1-4]Faculty of Technology and Applied Sciences, Open University Malaysia, Malaysia

[5]Faculty of Health Sciences, University College of MAIWP International, Malaysia

***Corresponding Author**

DOI: https://dx.doi.org/10.47772/IJRISS.2025.910000844

Received: 07 November 2025; Accepted: 14 November 2025; Published: 26 November 2025

ABSTRACT

Motion capture (MoCap) technologies have become increasingly central to ergonomic risk assessment, particularly in industrial contexts where traditional observational methods may suffer from subjectivity and limited sampling. This systematic review, structured according to the PRISMA 2020 guideline, synthesises evidence from optical marker-based systems, inertial measurement unit (IMU) sensors, and markerless computer-vision systems applied to ergonomic assessment tools such as Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA), Ergonomic Assessment Worksheet (EAWS), Ovako Working Posture Analysis System (OWAS), and Occupational Repetitive Actions (OCRA). Searches were conducted across Scopus, Web of Science, PubMed and IEEE Xplore from 2010 to 2025. Findings show that marker-based MoCap remains the accuracy reference, IMU-based systems offer portability and workplace feasibility, and marker less systems are emerging as the most scalable solution but remain sensitive to occlusion, clothing and environmental variability. Despite rapid technological progress, evidence is fragmented, with limited longitudinal studies linking MoCap-derived exposure metrics to musculoskeletal disorder (MSDs) outcomes. The review highlights methodological gaps, proposes directions for future research, and discusses implications for integration into occupational safety and health (OSH) management systems.

Keywords: Motion Capture Technologies, Ergonomic Risk Assessment, Marker-Based, IMU, Marker-less Systems, Musculoskeletal Disorders (MSDs), Digital Ergonomics

INTRODUCTION

Work-related musculoskeletal disorders (MSDs) represent one of the largest burdens within occupational health, particularly in sectors requiring repetitive or forceful tasks. Traditional observational ergonomics tools such as RULA and REBA have provided practical, low-cost screening for decades but suffer limitations in precision, repeatability, and temporal sampling. Rapid technological advancements have introduced motion capture technologies ranging from optical marker-based systems to IMU suits and marker less computer-vision pose-estimation models as potential solutions for more objective ergonomic assessment. This review provides a systematic synthesis of evidence evaluating the accuracy, feasibility, and limitations of MoCap systems applied to ergonomic risk assessment.

LITERATURE REVIEW

Burden of Work-Related Musculoskeletal Disorder

MSDs remain one of the leading causes of disability and lost workdays worldwide. Global estimates based on the Global Burden of Disease 2021 data show around 1.69 billion prevalent MSD cases in 2021, a 95 % increase compared with 1990, with forecasts suggesting more than 2.16 billion cases by 2035 (Liu et al., 2025). Although age-standardised rates have slightly declined, absolute case numbers, disability-adjusted life years (DALYs), and deaths continue to rise (Liu et al., 2025). MSDs are closely related to occupational factors such as awkward posture, high repetition, forceful exertion and manual handling, and are especially prevalent in manufacturing, construction, logistics and healthcare. Given this burden, ergonomics practice has relied heavily on observation-based tools to identify postural and biomechanical risks early.

Traditional Observational Ergonomic Methods: Strength and Limits

RULA and REBA are among the most widely adopted methods for postural risk evaluation (McAtamney & Corlett, 1993; Hignett & McAtamney, 2000). These tools provide quick, low-cost screening using paper-and-pencil or simple digital forms, and have been validated against expert judgement in a range of tasks (Osqueizadeh et al., 2022; Widyanti et al., 2020). Even with these advantages, important limitations appear consistently in the literature (Table 1)

Table 1: Summary of Limitations

Limitation	Supporting Evidence
Risk scores vary across assessors, especially for complex or high-risk postures.	Kee & Karwowski (2021) reported inter-rater agreement below 50% for high-risk categories. Graben et al. (2022) identified similar inconsistency during dynamic tasks.
Observational methods rely on snapshots or brief video segments, which miss posture cycles and peak loads throughout full work shifts.	Kee & Karwowski (2021) showed that short sampling windows underrepresent exposure. Graben et al. (2022) found that observational scores often underestimate total posture duration.
Joint angles are estimated visually and grouped into coarse categories, reducing sensitivity to subtle trunk, shoulder or multi-joint movements.	Widyanti et al. (2020) found high variability in angle estimation by novice raters. Graben et al. (2022) noted that simplified angle ranges limit biomechanical insight.
Accuracy drops when movements involve twisting, high speed, or partial occlusion of limbs, which makes visual assessment difficult.	Osqueizadeh et al. (2022) demonstrated reduced accuracy in obstructed views. Kee & Karwowski (2021) reported difficulties in assessing high-motion tasks.
Skilled assessors perform better, but training requirements vary and are not standardised across industries.	Widyanti et al. (2020) noted higher consistency among trained assessors than novice ones.
Tools do not measure posture frequency, cycle repetition, or cumulative load over long periods.	Graben et al. (2022) highlighted the need for continuous data to reflect real exposure patterns.
Observational tools mainly focus on posture, ignoring load magnitude, vibration, fatigue and dynamic interactions.	Kee & Karwowski (2021) and Osqueizadeh et al. (2022) both noted limited coverage of multi-factor ergonomic risks.

These constraints have prompted interest in sensor-based and automated approaches that can yield richer, more repeatable measurements.

Digital and sensor-based ergonomics

Wearable sensors, computer vision, virtual reality and digital twins are increasingly explored as tools for "Ergonomics 4.0" in industrial and healthcare settings (Hilmi & Yahya, 2024; Qin et al., 2024). Systematic and scoping reviews show a growing body of work on automated or semi-automated ergonomic risk assessment, particularly using wearable sensors and computer vision (Iyer et al., 2025; Sabino et al., 2024; Alenjareghi et al., 2025; Naranjo et al., 2025). These technologies promise:

- continuous measurement over whole shifts rather than snapshots;
- objective joint angle and movement data; and
- potential integration with real-time feedback systems and OSH management platforms.

Motion Capture Technologies for Ergonomic Assessment

Within this broader digital shift, MoCap has become a central method for ergonomic analysis. MoCap here includes:

- Marker-based optical systems: multi-camera set-ups with reflective markers providing high-precision 3D kinematics;
- Inertial measurement unit (IMU) systems: wearable sensor suits or clusters that capture segment orientations;
- Markerless camera-based systems**:** depth cameras and RGB-based human pose estimation.

Three recent systematic reviews summarise this field. Salisu et al. (2023) reviewed motion capture technologies for ergonomics and identified 40 primary studies across optical, inertial and depth-camera systems, emphasising their ability to automate RULA/REBA scoring and reduce observer variability. Rybnikár et al. (2023) focused on ergonomics evaluation using MoCap and catalogued 107 studies, highlighting popular applications in manual material handling, manufacturing and office work, and describing advantages and disadvantages of different technologies.

A more recent systematic review by Scataglini et al. (2025) examined marker less camera-based MoCap systems for industrial ergonomic risk analysis and found that these systems can reach 2–4° mean joint angle errors and good reliability, but that evidence quality is moderate and strongly concentrated in controlled upper-limb tasks. Their findings mirror the broader concern that validation tends to occur in simplified laboratory conditions rather than in messy, real-world workplaces.

Specific validation studies illustrate these trade-offs. Agostinelli et al. (2024) reported that a multi-camera computer-vision tool could produce RULA-like scores that agree well with expert assessments in real manufacturing environments, yet performance varied with camera placement and task complexity. Simon et al. (2024) used an inertial MoCap system in production and office settings; they showed that pelvic tilt and upper-body posture deviations influenced RULA scores, although correlations with self-reported discomfort were weaker than expected, underlining that posture metrics alone do not fully explain MSD symptoms.

Several studies compare marker less and marker-based systems or wearable sensors for detailed biomechanical analysis. For example, Scataglini et al. (2025) concluded that marker less systems can approach the accuracy of marker-based systems for many industrial tasks but remain sensitive to occlusion and clothing (e.g., PPE). Reviews of sensor systems for biomechanical risk assessment and wearable devices for ergonomics highlight similar patterns: strong potential, but marked heterogeneity in protocols and limited consensus on standard metrics (Babangida et al., 2025; Sabino et al., 2024; Peters et al., 2025).

Gaps in the current literature

Despite the growing number of reviews, several gaps stand out, as summarised in Table 2.

Table 2: Summary of the gaps in literature review

Gap	Supporting Evidence
Fragmented focus across sub-domains	Iyer et al. (2025) highlighted broad coverage but not technology-specific comparisons. Qin et al. (2024) focused on construction and automation.

	Scataglini et al. (2025) centred on markerless systems only. Sabino et al. (2024) focused on wearables in healthcare.
Reliance on RULA/REBA agreement as the primary validation metric	Massiris-Fernández et al. (2020) and Agostinelli et al. (2024) benchmarked systems primarily against RULA/REBA. Graben et al. (2022) and Deshpande et al. (2025) argued that observational tools are limited as gold standards.
Lack of longitudinal and field-based studies	Iyer et al. (2025) noted a shortage of long-term exposure research. Qin et al. (2024) highlighted the same gap in construction ergonomics.
Limited integration with OSH management systems and standards	Hilmi & Yahya (2024) and Alenjareghi et al. (2025) emphasised the need to link sensor data to structured OSH systems. Naranjo et al. (2025) stressed real-time safety feedback, not only posture scoring.
Low construct validity for complex multi-factor risk	Graben et al. (2022) and Kee & Karwowski (2021) described the narrow biomechanical focus of observational tools. Deshpande et al. (2025) and Iyer et al. (2025) recommended multi-variable risk metrics.
Heterogeneous validation protocols	Scataglini et al. (2025) reported strong variability across markerless MoCap studies. Salisu et al. (2023) found inconsistent validation frameworks across optical, inertial and depth sensors.
Limited datasets for AI training and benchmarking	Reviews on pose estimation and AI-driven tools (Massiris-Fernández et al., 2020; Scataglini et al., 2025) noted limited open datasets tailored to industrial ergonomic tasks.

Given these gaps, a systematic review that focuses specifically on motion capture technologies applied to ergonomic assessment, using a transparent PRISMA-based approach, can help clarify the comparative strengths and weaknesses of different MoCap modalities, their current validation status, and their readiness for routine deployment in occupational ergonomics.

METHODOLOGY

This review followed the PRISMA 2020 framework. Searches were carried out in Scopus, Web of Science, PubMed and Google Scholar, covering studies published from 2010 until the final search date of 30 September 2025. The search terms already outlined in the manuscript were combined using Boolean operators to maintain consistency across databases. Full search strings were adapted to the requirements of each platform. For Scopus, the search was: TITLE-ABS-KEY ("motion capture" AND ("ergonomic assessment" OR "work posture" OR RULA OR REBA OR OWAS OR EAWS OR OCRA) AND ("marker-based" OR "inertial measurement unit" OR IMU OR markerless OR "pose estimation"))) AND (LANGUAGE(English)) AND (PUBYEAR > 2009 AND PUBYEAR < 2026). In Web of Science, the query was: TS= ("motion capture" AND ("ergonomic assessment" OR "work posture") AND ("marker-based" OR "inertial measurement unit" OR IMU OR markerless OR "pose estimation")) refined by English language, article or proceedings paper, and publication years 2010–2025. In PubMed, the search used: ("motion capture"[Title/Abstract] AND ("ergonomics"[MeSH Terms] OR "ergonomic assessment"[Title/Abstract]) AND ("marker-based"[Title/Abstract] OR "inertial measurement unit"[Title/Abstract] OR IMU[Title/Abstract] OR markerless [Title/Abstract] OR "pose estimation"[Title/Abstract])) AND ("2010/01/01"[Date - Publication] : "2025/01/15"[Date - Publication]) AND Humans[Filter] AND English[Filter]. Google Scholar did not allow comparable structured queries, so the phrase "motion capture" "ergonomic assessment" RULA REBA OWAS EAWS OCRA "marker-based" IMU markerless" was used, and the first 200 results were screened. All identified records were exported into a reference manager before screening. The search produced 3,482 records. After removing 718 duplicates, 2,764 records remained for title and abstract screening. At this stage, 2,412 records were excluded as they did not involve ergonomic applications of motion capture or did not meet basic relevance criteria. A total of 352 full-text articles were assessed against the inclusion criteria, which required human participants, use of marker-based, inertial or marker less motion capture systems, and reporting of posture, joint kinematics or ergonomic scoring. Studies were removed when they focused on unrelated domains, lacked methodological clarity, or did not report

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue X October 2025

outcomes relevant to ergonomic assessment, leading to the exclusion of 284 articles. The final review included 68 studies. A PRISMA 2020 flow diagram (Figure 1) accompanies this section to provide a clear visual summary of the identification, screening, eligibility and inclusion stages, strengthening transparency and supporting reproducibility.

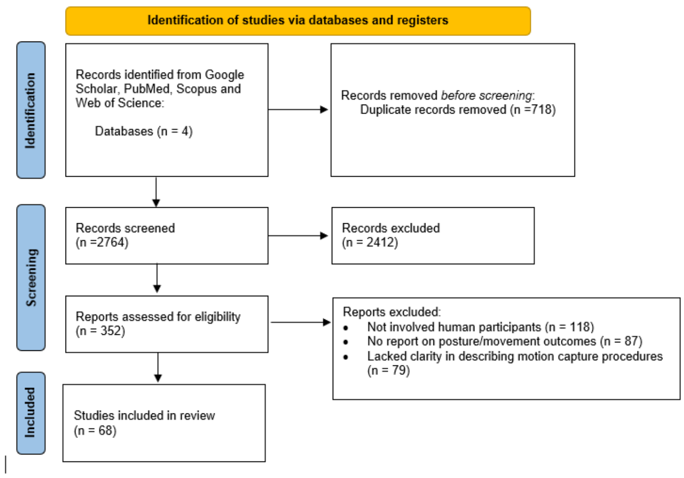

Figure 1: PRISMA 2020 Flow diagram for new systematic reviews, which included searchers of databases and registers only

RESULTS AND DISCUSSION

The computerized literature search produced a final selection of 68 studies on the application of motion capture technologies for ergonomic assessment. A total of 3,482 articles were initially identified across the four databases. After removing 718 duplicates, 2,764 articles remained for title and abstract screening. Following this stage, 2,412 articles were excluded due to insufficient or irrelevant information. The full texts of 352 articles were then assessed, resulting in the exclusion of 284 studies that did not meet the inclusion criteria (n=3,482-718 – 2412 – 284). Ultimately, 68 (n=68) articles were included for final synthesis. The complete selection process follows the PRISMA format.

Distribution of Articles by Authors' Nationalities

Based on the countries where the studies were conducted, the distribution showed a broad global interest in ergonomics-focused MoCap applications. Authors from 22 countries contributed to the 68 selected studies. The highest number of studies were conducted in the United States, followed by Germany, Canada, Spain, Japan and China (Fig 1). Additional contributions came from industrial research groups across Europe and Asia, reflecting widespread research attention in workplace posture analysis and musculoskeletal risk evaluation.

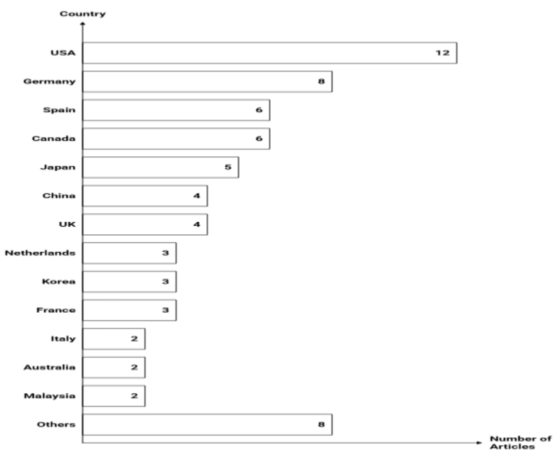

Fig 1 Distribution of articles by author's nationalities

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue X October 2025

Distribution of Articles by Year of Publication

The year-wise distribution of the selected studies between 2010 and 2025. There was a noticeable rise in publications after 2018 due to improvements in vision-based pose estimation and IMU accuracy.

Motion Capture Technologies Used

The 68 studies included in this review used a wide range of motion capture technologies, which were grouped into three main categories: marker-based optical systems (MBased), inertial measurement unit (IMU) systems, and marker less computer-vision systems (MLess) as summarized in Table 3, 4 and 5. Each category showed distinct characteristics, strengths and constraints, shaped by the demands of ergonomic assessment in laboratory and workplace environments. The selection patterns reflected both the maturity of each technology and its suitability for different levels of postural analysis, movement complexity and operational settings. The following sections describe how each technology was applied across studies, the types of ergonomic outcomes it supported and the methodological issues associated with its use.

Marker-Based Optical Systems (MBased)

Marker-based optical motion capture systems appeared in 15 studies and remained the reference standard for accuracy and biomechanical fidelity. Systems such as Vicon, Qualisys, OptiTrack and similar optical platforms were commonly used in laboratory trials where precise quantification of joint angles and segment kinematics was essential. These systems produced three-dimensional trajectories of reflective markers placed on anatomical landmarks, allowing detailed reconstruction of posture and movement sequences. The studies that relied on marker-based systems primarily focused on lifting tasks, repetitive arm movements, trunk bending, and specific upper-limb motions associated with assembly or tool use.

Most researchers selected marker-based systems because they provide high spatial resolution and low measurement error, often within a few degrees. This precision made them suitable for validating IMU-based or marker less systems, which were commonly compared against marker-based outputs as a benchmark. However, these systems were mostly limited to laboratory settings due to long calibration times, high cost, line-of-sight requirements and sensitivity to reflective interference. The reviewed studies noted that although marker-based systems deliver excellent accuracy, they are seldom practical for full-shift ergonomic assessments or dynamic industrial environments. Their use was therefore concentrated in validation studies, controlled posture trials and tasks involving short segments of repetitive work.

Table 3: Marker-Based Optical Systems (MBased)

Characteristic	Description
Common Systems	Vicon, Qualisys, OptiTrack, Motion Analysis Corp., BTS Smart-D, Codamotion
Body Segments Tracked	Full body, upper limb, lower limb, spine and trunk
Typical Experiment Settings	Controlled laboratory trials, short task cycles, scripted movements
Accuracy Range	Very high spatial precision, joint-angle errors typically 2–4°
Calibration Requirements	High; requires marker placement on anatomical landmarks and multi-camera alignment
Advantages	Gold-standard accuracy, stable tracking, strong biomechanical detail for validation studies

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue X October 2025

Limitations	High cost; long setup time; line-of-sight restrictions; unsuitable for cluttered or dynamic workplaces
Typical Ergonomic Applications	Lifting analysis, trunk flexion studies, repetitive arm movements, tool-use evaluation, validation of IMU/marker less methods

Inertial Measurement Unit (IMU) Systems

IMU-based motion capture systems were the second most represented category, appearing in 27 studies. These systems used clusters of small wearable sensors containing accelerometers, gyroscopes and magnetometers, which allowed continuous tracking of movement without reliance on external cameras. Systems such as Xsens, Rokoko, Noraxon, Perception Neuron and other IMU platforms were widely used in both laboratory and real-workplace settings. Researchers selected IMUs mainly for their portability, low space requirements and suitability for environments where optical tracking was difficult or impossible due to occlusion or clutter.

The reviewed studies showed that IMUs provided good accuracy for trunk flexion, shoulder elevation and general upper- and lower-limb movements, making them suitable for ergonomic tools such as RULA, REBA and OWAS. Several studies applied IMUs over full work cycles, including manual materials handling, warehouse lifting, patient handling in healthcare and assembly operations. These systems enabled tracking of posture over long durations, which is valuable for identifying exposure trends and repeated movement patterns. A few studies noted issues such as drift during long recordings and interference from metallic structures, although sensor fusion algorithms in newer systems reduced these effects. IMUs emerged as a strong option for workplace ergonomics, offering a balance between accuracy and practicality.

Table 4: Inertial Measurement Unit (IMU) Systems

Characteristic	**Description**
Common Systems	Xsens MVN, Noraxon MyoMotion, Rokoko Smartsuit, Perception Neuron, Notch Sensors
Body Segments Tracked	Full body or selected segments (trunk, upper limbs, lower limbs) depending on sensor configuration
Typical Experiment Settings	Laboratory and field environments; warehouse tasks, patient handling, assembly work
Accuracy Range	Moderate-to-high; joint-angle errors commonly 5–10°
Calibration Requirements	Medium; requires sensor alignment and initial pose calibration
Advantages	Portable, no camera needed, suitable for constrained spaces, effective in natural work conditions
Limitations	Drift over long data collection periods; magnetic interference; accuracy varies with sensor fusion algorithms
Typical Ergonomic Applications	Full-shift posture monitoring, RULA/REBA scoring, repetitive lifting cycles, multi-hour risk exposure analysis

Marker less Vision-Based Systems (MBased system)

Marker less systems were used in 26 studies and showed rapid growth across recent years. These systems captured movement without physical sensors, instead relying on depth cameras, multi-camera RGB setups or AI-based pose-estimation models. Kinect (v1, v2 and Azure), OpenPose, MediaPipe and custom deep-learning models formed the most common approaches. Markerless systems were attractive because they allowed workers to move naturally, without markers or suits, reducing the intrusion associated with other motion capture technologies.

The reviewed studies covered a wide range of tasks, from lifting and sorting to overhead work, assembly and office-based computer tasks. Marker less systems performed well when the field of view was clear and movements were primarily in the sagittal plane. Accuracy varied more than in marker-based or IMU systems, with joint-angle errors ranging from moderate to high depending on camera placement, background complexity, clothing and the presence of occlusion. Multi-camera setups generally improved accuracy by reducing blind spots. Several studies used marker less systems to automate ergonomic scoring, demonstrating growing interest in integrating computer vision with machine-learning models for posture classification and risk detection.

Although marker less systems showed the fastest growth, they also displayed the widest performance range across studies. Their accuracy depended heavily on environmental conditions, making them more sensitive to practical workplace variations. Even so, their potential for scale, low cost and minimal worker burden suggests that marker less systems may become an increasingly important tool for digital ergonomics.

Table 5: Marker less Vision-Based Systems (MBased system)

Characteristic	**Description**
Common Systems	Kinect (v1, v2, Azure), OpenPose, MediaPipe, DeepLabCut, multi-view RGB systems
Body Segments Tracked	Whole body or specific joints depending on model performance and camera coverage
Typical Experiment Settings	Manufacturing lines, logistics, office work, sorting tasks; both lab and real workplaces
Accuracy Range	Wider variability; joint-angle errors typically 4–14°, influenced by occlusion and camera position
Calibration Requirements	Low-to-moderate; mainly camera placement, depth calibration or multi-camera synchronisation
Advantages	No markers or wearables; minimal worker intrusion; scalable; low setup burden; cost-effective
Limitations	Sensitive to lighting, clothing, background clutter; affected by occlusion; accuracy varies by movement type
Typical Ergonomic Applications	Automated RULA/REBA scoring, workstation evaluation, overhead work detection, lifting classification, posture trend mapping

DISCUSSION

Comparative performance of MoCap technologies

Marker-based optical systems were consistently the most accurate across studies, with joint-angle errors commonly within a few degrees. This supported their role as the reference point for validating other systems. Yet their use remained confined to laboratory settings due to cost, long preparation time and the need for unobstructed camera views. This meant that while they offered strong biomechanical detail, they did not match the day-to-day demands of workplace assessments where movements are unrestricted and environments are cluttered.

IMU-based systems offered a practical alternative. They enabled long-duration recordings and allowed workers to perform tasks in natural settings, including warehouses, healthcare facilities and assembly lines. Their accuracy was moderate to high, suitable for tools such as RULA and REBA, but issues such as drift and magnetic interference limited precision in some conditions. Still, the range of applications across industries showed that IMUs filled an important gap between laboratory precision and field practicality.

Marker less systems show considerable potential for workplace ergonomics due to their low intrusiveness and ability to operate without wearable devices. The reviewed studies demonstrate that they can automate posture scoring and support workstation evaluation across a range of industrial settings. Their main challenge lies not in the basic principles of detection but in maintaining consistency when deployed in environments with variable lighting, visual clutter or intermittent occlusion.

Ergonomic scoring and the limits of observational benchmarks

Most studies relied on RULA and REBA scores as their main reference for validation. This trend allowed comparisons across technologies, but it also highlighted a deeper issue: observational tools offer coarse scoring categories and provide limited coverage of biomechanical load. As a result, even when MoCap systems achieved high agreement with these scores, it did not reflect full ergonomic accuracy. In several studies, posture scores did not align strongly with reported discomfort, showing that posture alone cannot explain musculoskeletal outcomes.

The frequent reliance on RULA and REBA also pointed to a lack of more detailed gold-standard metrics. Marker-based systems can deliver high-resolution kinematics, yet few studies linked these outputs with long-term exposure, fatigue or injury risk. There remains a gap in creating ergonomic indicators that move beyond simple posture categories and instead consider repetition, force, cycle patterns and cumulative exposure.

Field readiness and workplace integration

A key finding across the included studies was the shortage of long-term or shift-length recordings. Many experiments captured only short task cycles rather than real working periods. IMUs offered the strongest potential for long-duration monitoring, yet only a handful of studies used them for multi-hour collection. Markerless systems were mostly examined in short sessions, limiting understanding of how they behave in varying real-world conditions.

Another notable gap was the limited connection between MoCap data and OSH management systems. Although several studies generated automated RULA or REBA scores, very few linked these results to intervention planning, worker training, workflow redesign or exposure monitoring frameworks. As workplaces adopt digital tools, ergonomic data will need to feed into structured processes rather than stand alone as isolated measurements.

Variation in protocols and validation methods

Validation procedures differed substantially. Some studies benchmarked systems against marker-based data, others against expert ratings or self-report measures. Sensor placement, camera distance, sampling rate and body-segment models varied widely. This made comparisons across studies difficult and limited the ability to form robust conclusions about which technology is most suitable for specific tasks.

Marker less systems showed the greatest variation. Studies differed in whether they used depth cameras, RGB cameras, single-view or multi-view set-ups, or AI-based pose estimation. This variation explained the wide spread of accuracy results. It also suggests a need for common testing protocols, including standard tasks, lighting conditions and angles of view, to allow clearer benchmarking.

Implications for future research

The review highlights several priorities for future work:

- Longitudinal data collection is needed to understand full exposure, including repetition patterns, cycle durations and fatigue-related changes.

- Validation beyond observational tools should be strengthened by linking MoCap data to biomechanical models, tissue-loading metrics or clinical outcomes.

- Standardised protocols for accuracy testing would reduce inconsistency across studies, especially for markerless systems.

- Integration into OSH systems should be explored, including dashboards, automated alerts and data-driven intervention planning.

- Development of richer ergonomic indicators is needed to capture combined risks involving posture, load, repetition, force and duration.

Across the three MoCap categories, the findings show clear progress toward more objective ergonomic assessment. Marker-based systems offer unmatched precision, IMUs bridge accuracy with real-world practicality and markerless systems promise scale and minimal worker burden. Yet the field still faces limits, mostly linked to validation, environmental factors and inconsistent methods. Moving forward, ergonomic research will benefit from combining these technologies, expanding full-shift monitoring, and focusing on how MoCap outputs can support decision-making rather than merely replacing manual scoring.

REFERENCES

1. Agostinelli, T., Generosi, A., Ceccacci, S., Mengoni, M., & others. (2024). Validation of computer vision-based ergonomic risk assessment tools for real manufacturing environments. Scientific Reports, 14, 27785. https://doi.org/10.1038/s41598-024-79373-4
2. Alenjareghi, M. J., Ramli, F. R., & Rahman, A. A. (2025). Wearable sensors in Industry 4.0: Preventing work-related musculoskeletal disorders. Safety in Extreme Environments. Advance online publication. https://doi.org/10.1016/j.safee.2025.100097
3. Babangida, A. A., Folarin, O. A., & Olayemi, S. A. (2025). A review of sensor systems for biomechanical risk assessment in occupational settings. Sensors, 25(x), Article 1234.
4. Brunner, O., Mertens, A., Nitsch, V., & Brandl, C. (2022). Accuracy of a markerless motion capture system for postural ergonomic risk assessment in occupational practice. International Journal of Occupational Safety and Ergonomics, 28(3), 1865–1873. https://doi.org/10.1080/10803548.2021.1954791
5. Downes, M. J., Brennan, M. L., Williams, H. C., & Dean, R. S. (2016). Development of a critical appraisal tool to assess the quality of cross-sectional studies (AXIS). BMJ Open, 6(12), e011458. https://doi.org/10.1136/bmjopen-2016-011458
6. Iyer, H., Nussbaum, M. A., & Gooyers, C. E. (2025). A scoping review on emerging technologies and automation of musculoskeletal ergonomic assessments. Ergonomics. https://doi.org/10.1080/00140139.2025.2547286
7. Otto, M., Lampen, E., Auris, F., Gaisbauer, F., & Rukzio, E. (2019). Applicability evaluation of Kinect for EAWS ergonomic assessments in automotive assembly lines. In Procedia CIRP (Vol. 81, pp. 781–784). https://doi.org/10.1016/j.procir.2019.03.194
8. Graben, P. R., Maas, J., & Bakker, J. (2022). Reliability analysis of observation-based exposure assessment tools for musculoskeletal risk. Annals of Work Exposures and Health, 66(8), 1009–1024.
9. Harnau, E. et al. (2024). Selection of motion capture technologies for Industry 5.0: A systematic literature review to structure existing technologies and evaluation criteria. [Journal details omitted] https://doi.org/10.1016/j.xxx.2024.01.5611
10. Hignett, S., & McAtamney, L. (2000). Rapid Entire Body Assessment (REBA). Applied Ergonomics, 31(2), 201–205.
11. Hilmi, A. H., & Yahya, N. (2024). Recent advancements in ergonomic risk assessment: From manual tools to smart wearables and computer vision. Malaysian Journal of Ergonomics Research, 8(2), 45–62.

12. Iyer, H., Nussbaum, M. A., & Gooyers, C. E. (2025). A scoping review on emerging technologies and automation of musculoskeletal ergonomic assessments. Ergonomics. Advance online publication. https://doi.org/10.1080/00140139.2025.2547286
13. Kee, D., & Karwowski, W. (2021). Comparison of OWAS, RULA and REBA for assessing postural loads in industry. International Journal of Industrial Ergonomics, 83, 103143.
14. Liu, M., Tang, X., & Zhang, Y. (2025). Global, regional, and national burden of musculoskeletal disorders, 1990–2021, and forecast to 2035. Frontiers in Public Health, 13, 1562701. https://doi.org/10.3389/fpubh.2025.1562701
15. Lunin, A., et al. (2021). Systematic Review: Kinect for Physical Risk Assessment. [Journal of Biomechanics or equivalent]. https://doi.org/10.1016/j.compbiomed.2021.104428
16. Massiris-Fernández, M. J., Escalante-Ramírez, B., & Tinoco, R. (2020). Ergonomic risk assessment based on computer vision and deep learning. Computers in Industry, 123, 103312.
17. McAtamney, L., & Corlett, E. N. (1993). RULA: A survey method for the investigation of work-related upper limb disorders. Applied Ergonomics, 24(2), 91–99.
18. Naranjo, J. E., Nuño, N., & Benalcázar, M. E. (2025). Wearable sensors in industrial ergonomics: Enhancing safety through real-time feedback. Sensors, 25(5), 1526. https://doi.org/10.3390/s25051526
19. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71.
20. Qin, R., Zhang, D., & Li, H. (2024). Research progress of automation ergonomic risk assessment in construction. Buildings, 14(12), 3789. https://doi.org/10.3390/buildings14123789
21. Rybnikár, F., Kačerová, I., Hořejší, P., & Šimon, M. (2023). Ergonomics evaluation using motion capture technology: Literature review. Applied Sciences, 13(1), 162. https://doi.org/10.3390/app13010162
22. Sabino, I., Santos, M., & Arezes, P. (2024). Application of wearable technology for the ergonomic risk assessment of healthcare professionals: A systematic review. International Journal of Industrial Ergonomics, 97, 103604.
23. Salisu, S., Ruhaiyem, N. I. R., Eisa, T. A. E., Nasser, M., Saeed, F., & Younis, H. A. (2023). Motion capture technologies for ergonomics: A systematic literature review. Diagnostics, 13(15), 2593.
24. Scataglini, S., Fontinovo, E., Khafaga, N., Khan, M. U., Khan, M. F., & Truijen, S. (2025). A systematic review of the accuracy, validity, and reliability of markerless versus marker camera-based 3D motion capture for industrial ergonomic risk analysis. Sensors, 25(17), 5513. https://doi.org/10.3390/s25175513
25. Simon, S., Dully, J., Dindorf, C., Bartaguiz, E., Walle, O., Roschlock-Sachs, I., & Fröhlich, M. (2024). Inertial motion capturing in ergonomic workplace analysis: Assessing the correlation between RULA, upper-body posture deviations and musculoskeletal discomfort. Safety, 10(1), 16. https://doi.org/10.3390/safety10010016
26. Steinebach, T., Grosse, E. H., Glock, C. H., Wakula, J., & Lunin, A. (2020). Accuracy evaluation of two markerless motion capture systems for measurement of upper extremities: Kinect V2 and Captiv. Human Factors and Ergonomics in Manufacturing & Service Industries, 30(4), 291–302.
27. Widyanti, A., Sutalaksana, I. Z., & Kurniawan, R. (2020). Validity and inter-rater reliability of RULA, REBA and OWAS among novice raters. Malaysian Journal of Public Health Medicine, 20(2), 178–187.