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To cite this article: Hari Iyer, Eunsik Kim, Chang S. Nam & Heejin Jeong (22 Aug 2025): A scoping review on emerging technologies and automation of musculoskeletal ergonomic assessments, Ergonomics, DOI: [10.1080/00140139.2025.2547286](https://doi.org/10.1080/00140139.2025.2547286)

To link to this article: <https://doi.org/10.1080/00140139.2025.2547286>



Published online: 22 Aug 2025.



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REVIEW ARTICLE



A scoping review on emerging technologies and automation of musculoskeletal ergonomic assessments

Hari Iyer^a , Eunsik Kim^b , Chang S. Nam^{c*}  and Heejin Jeong^a 

^aThe Polytechnic School, Ira A. Schools of Engineering, Arizona State University, Mesa, AZ, USA; ^bMechanical, Automotive, and Materials Engineering, University of Windsor, Windsor, ON, Canada; ^cEdward P. Fitts Department of Industrial and Systems Engineering, North Carolina State University, Raleigh, NC, USA

ABSTRACT

Ergonomic suitability is critical in tasks involving musculoskeletal movement. Many industries have examined best practices and assessed workers' ergonomic conditions during physical tasks. Prolonged awkward postures are a known cause of discomfort and restricted mobility in areas such as the arms, spine, and neck. Technologies like computer vision and human activity recognition can help identify and prioritize ergonomic improvements. This paper presents findings from a two-decade scoping review on the role of automation and study design in ergonomic assessments of physical workplace tasks. Articles were sourced from Scopus, PubMed, IEEE Xplore, Engineering Village, and Google Scholar. Eighty-four studies were analyzed to evaluate the use of technologies in data collection, experimentation, analysis, and validation. We examined how participant variables (e.g. sample size, body part of interest) and validation accuracy impact study outcomes across domains. Integrating advanced technologies into ergonomic evaluations can enhance worker safety and productivity by supporting real-time, evidence-based decision-making.

Practitioner Summary: This scoping review examined 84 studies on ergonomic assessments involving automation technologies like computer vision and wearable sensors. The findings showed automation improves data collection, analysis, and validation accuracy. These advancements support real-time, reliable ergonomic assessments; however, epidemiological studies are needed to confirm their direct impact on musculoskeletal disorder outcomes.

ARTICLE HISTORY

Received 22 May 2025
Accepted 3 August 2025

KEYWORDS

Musculoskeletal disorders; computer vision; neural networks; human activity recognition

1. Introduction

1.1. Background and rationale

Occupational safety and health are significant concerns across sectors of the economy, especially within the industry (Suárez Sánchez 2014). This is particularly true of industries involving lifting of heavy goods, assembly line jobs, prolonged sedentary work at a desk, and repetitive task routines including military tasks (Blanco et al. 2022; Daneshmandi et al. 2017; Fang, Fu, and Zheng 2022; Raei et al. 2024). Bad ergonomic practices often stem from accessibility and workers' line of sight of vital objects or other workers. Parno et al. (2017) reported a high prevalence of work-related musculoskeletal disorders in the lower and upper back among Iranian workers, with rates exceeding 38%. These can lead to continued departure from a commonly assumed body posture in pursuit of a better performance outcome (Roveshti et al. 2024).

A developing knowledge base of human performance examination can help automate systems for human workers (Parasuraman 2000). Computer vision (CV) can analyze posture and movement non-invasively to enable a naturalistic work environment (Iyer et al. 2024b). Depth sensing (Khosrowpour, Niebles, and Golparvar-Fard 2014; Li and Lee 2011; Plantard et al. 2017) can be combined with regular camera imagery to get information about limb and head extension and movement. Simple cameras measure postural and musculoskeletal parameters using pose estimation models like MediaPipe (Iyer and Jeong 2024; Jeong and Kook 2023; Lugaresi et al. 2019), which detect joint angles and postural deviations. However, field of view limitations in stationary cameras can hinder full motion capture and lead to occlusions. These challenges can be resolved with multi-camera setups or depth cameras, along with advancements in image-processing algorithms that compensate for

CONTACT Heejin Jeong  heejin.jeong@asu.edu  Ira A. Fulton Schools of Engineering, Arizona State University, Mesa, AZ, USA

*New affiliation, Center of Excellence in Product Design and Advanced Manufacturing, North Carolina A&T State University, Greensboro, NC, USA

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incomplete data. Prince et al. (2008) highlighted the necessity for precise and dependable measurements of physical activity to assess varying levels of activity, interventions, and the connections between physical activity and health outcomes. However, general measurement techniques must be further specialized for assessing posture and its effects on long-term musculoskeletal health (Khandan et al. 2016). The review presented in this paper focuses on ergonomic assessment to compare how different studies used ergonomic tools for their specific use case.

Procedures used to quantify and rate the posture-based ergonomic risk in physical workers performing specific industry-related tasks include the Ovako Working Posture Analysis System (OWAS), Rapid Entire Body Assessment (REBA), and Rapid Upper Limb Assessment (RULA) (Kee 2022; Kohammadi et al. 2016). In the current review, industries and sectors were focused on studying the ergonomic and musculoskeletal strain imposed on various parts of the worker's body, comprising upper limbs, below the knee, back, and neck.

This review provides several valuable insights for both researchers and practitioners. First, it synthesises two decades of ergonomic research trends, offering a reference point for scholars interested in how automation methods such as computer vision, machine learning, and wearable sensors, are currently applied to posture and motion assessments. Second, it identifies practical limitations and challenges in validation, offering guidance for future studies aiming to implement these tools reliably in industrial settings. Third, by mapping ergonomic tools to specific body parts and industry domains, the review supports the targeted development of task-specific assessment systems. Finally, its comparative evaluation of validation accuracy across varying levels of automation helps set realistic expectations for tool performance, which is essential for translating findings from this study into deployable ergonomic solutions.

The review studies summarized in Table 1 highlight the applications of existing ergonomic assessment methods and their research questions, strengths, and limitations, providing the rationale for the current review. Table 1 includes three different types of reviews: Scoping reviews, systematic reviews, and meta-analyses. For instance, Grooten and Johansson (2018) offered an overview of observational ergonomic methods but lacked in-depth statistical analysis, leaving gaps in quantitative validation techniques. Similarly, Reiman et al. (2021) explored Industry 4.0 applications but did not include real-world empirical testing, limiting the practical applicability of their findings. Veerasammy, Davidson,

and Fischer (2022) focused on multi-task exposure and recovery requirements but did not address how automated tools could be integrated into these assessments. Anacleto Filho et al. (2024) emphasized the role of virtual tools and artificial intelligence in assessing biomechanical risks but did not analyze specific validation challenges or industry-specific applications of these tools. These limitations collectively highlight the need for a comprehensive review that not only examines automated ergonomic assessment tools but also evaluates their validation accuracy, data collection methodologies, and applicability across diverse settings. By comparing automated and observational techniques, this study aims to provide novel insights into improving ergonomic risk assessments through automation, addressing both technological and practical challenges. The current review seeks to identify how these advancements can enhance real-time ergonomic evaluations and decision-making, bridging the gaps identified in prior reviews while contributing to a deeper understanding of automation in ergonomic science.

The rest of the paper is structured as follows: Section 2 describes the methods, including the literature review framework, inclusion and exclusion criteria, and the PRISMA-ScR process used to identify and select relevant studies. Section 3 presents the results, comparing ergonomic assessment techniques across various industry applications. Section 4 discusses the findings, interpreting their implications for the field of ergonomics, identifying technological and methodological challenges, and proposing potential solutions. The current study's limitations are also discussed in this section. Finally, Section 5 concludes the review by summarizing the key contributions and suggesting directions for future research.

1.2. Objectives and research questions

Following are the four research questions (RQs) that were formulated to analyze the techniques and methodologies employed in ergonomic and musculoskeletal studies from this search. The justification for including each RQ is subsequently described.

RQ1: How do study design factors— such as sample size, participant selection criteria, and the body part of interest—influence validation accuracy in ergonomic assessment studies?

Sample size holds significance for studies requiring replication or further development based on existing work, influencing aspects like recruitment, budgeting, and data analysis. Two studies with identical methodology but different sample sizes may lead to various

Table 1. Comparison of different reviews for ergonomic tools and assessment techniques.

Review studies	Review type	Application	Number of papers reviewed	Research questions	Novelty	Strengths	Limitations
Grooten and Johansson 2018	Scoping review	Observational ergonomic risk assessment	19	- Types of observational methods for MSDs - Body parts assessed by methods - Frequency, duration, intensity measurement	Overview of various observational methods	A wide variety of tools reviewed	Lacks in-depth statistical analysis
Reiman et al. 2021		Ergonomics in Industry 4.0	37	- Human factors and ergonomics (HF/E) inclusion in Industry 4.0 - Ergonomic challenges in manufacturing - HF/E maturity in organisations	HF/E role in Industry 4.0	Detailed discussion of HF/E maturity	Lack of empirical data and real-world testing
Veerasammy, Davidson, and Fischer 2022		MSD risk assessment tools	34	- MSD causation theories for multi-task exposure - Tools/models for accumulated exposure	Comprehensive summary of existing tools/models	Provides a broad overview of MSD tools	Limited to multi-task exposures and recovery requirements
		MSD assessment from a sex perspective	31	- Mapping tools to MSD theories - Gender-specific risk factors for MSDs - Gender bias in MSD assessment - Inclusion of gender in existing tools	Gender-focused review in MSD risk tools	Considers sex-based analysis	Limited evidence on gender-specific tools due to exclusion criteria
	Zerguine et al. 2023		Office ergonomics training programs	5	- Effectiveness of e-learning for ergonomics - User satisfaction in online training - Knowledge gained from online programs	Focus on online training tools	Included articles from grey and peer-reviewed literature
Anacleto Filho et al. 2024		Digital/virtual tools for biomechanical risks	34	- Effectiveness of AI in assessing risks - Digital human modelling in risk tools - VR usage in risk evaluation	Integrated analysis of digital/virtual tools with biomechanics	Emphasizes contemporary technology like AI, and VR tools	Potential bias in the selection of samples
Iyer et al. (current work)		Automation of observation-based ergonomic assessment tools	84	- Study design's impact on validation accuracy - Evaluation of body parts for ergonomic assessment - Correlation in data collection method, automation in analysis, and accuracy of validation - The industry domain served for the ergonomic assessment	Comparison of observation vs. automated ergonomic assessment techniques	An exhaustive list of articles reviewed with detailed research questions	Only considered journal articles, potentially excluding conference papers and books in this field
Joshi and Deshpande 2019	Systematic review	Comparison of ergonomic assessment techniques	39	- Most common observational techniques - Correlation between outputs - Applicability of techniques	High focus on inter-method variability	Analyzes comparison outputs across sectors	Inconsistent conclusion categories across methods due to lack of literature availability
Sabino et al. 2024		Ergonomic assessment in healthcare	29	- Ergonomic tools in healthcare settings - Risk factors and ergonomic criteria in healthcare jobs	Emphasis on wearable technologies	Includes analysis for different kinds of medical professionals	Limited to healthcare ergonomics only
Stucky et al. 2018	Meta-analysis	Analysis of surgical ergonomics	40	- Tool applicability for nurses/dentists/surgeons - Symptoms of ergonomic strain - Impact of ergonomics on multiple body parts - Analysis of typical surgery types like open or minimally invasive	Detailed bodily analysis for multiple types of surgical procedures	Over 5,000 survey responses analyzed	Some ambiguity in self-reported data between surgery types
Mondal et al. 2022		Manual lifting ergonomics	11	- Determinants of manual lifting tasks - Physiological responses to lifting - Risk factors in manual lifting	Detailed assessment of lifting tasks	Uses factor analysis to validate determinants	Limited by small sample size

clinical decisions (Faber and Fonseca 2014). It is important to note that the relationship between sample size and clinical decisions is context-dependent and not always absolute. In ergonomic assessment, human subjects are commonly used as data sources. Thus, this research question was added as part of the review. The participant selection generally depends on the kind of experiment and the study conducted, especially for ergonomic assessment. For example, for virtual reality (VR) based research, the headset-induced motion sickness population must be excluded. When designing a study, it is vital for investigators to not only establish appropriate inclusion-exclusion conditions but also evaluate their influence on the study's validity (Patino and Ferreria, 2018). This research question was included to analyze any data shortcomings and study the logic of choosing the correct subjects for the study. Ergonomic assessment techniques depend on what part of the body is being studied. Tasks like assembly, culinary work, and construction involve greater use of upper limbs. Walking and running-based tasks may involve more usage of lower limbs and trunk. Repetitive use of a specific body part can cause an increased risk of musculoskeletal disorder (MSD) (Azizi et al. 2016). A substantial burden of musculoskeletal disorders has been reported among high-risk occupational groups such as drivers and manufacturing workers, with the lower back, neck, and shoulders being the most frequently affected regions (Omidianidost et al. 2016; Yarmohammadi et al. 2019). Parno et al. (2020) conducted a meta-analysis of 45 studies across Iran, identifying low back and neck pain as the most prevalent work-related MSDs. Thus, the body part of interest also plays a role in deciding the data collection and analysis techniques. The current review recorded the body part of interest to analyze the depth and technique of assessment used in each case.

RQ2: What types of data collection methods, levels of automation in data analysis, and wearable technologies are used for ergonomic assessments in industrial settings?

The data collection could be in different modalities, including surveys, experiments, and self-assessments (Iyer, Reynolds, et al. 2024). It is important to know which of these were used in the study since it could help quantify any biases and incorporate tolerances for experiment designs. Thus, this research question was added to analyze trends and decisions regarding the data collection strategies of the reviewed studies. With an increasing volume of data, analysis becomes more challenging. For example, a recorded video of a

subject performing a task could be split into thousands of image frames. Thus, automation in analysis is crucial. These include deep learning techniques like neural networks, CV, and machine learning algorithms (Breiman, 2001; Iyer and Jeong 2024; Macwan et al. 2024). Deep learning technology originated from artificial neural networks and has become a popular subject in the computing world. Its ability to learn from data has made it widely applicable in various fields such as healthcare, visual recognition, text analytics, cybersecurity, and many more (Sarker 2021). However, constructing a suitable model is challenging due to the dynamic nature and diverse variations in real-world complications and data. This research question was added for automated ergonomic assessment to see how the data type and size impact algorithm selection. Wearable technologies like augmented reality (AR), smartwatches, head-mounted displays, activity trackers, and biomechanical analysis sensors are emerging technologies that automate data measurement (Iyer, Isingizwe, et al. 2024). For ergonomic assessment, it could also provide more accurate readings than self or manual assessment. However, this brings about the challenge of interrupting a naturalistic work environment due to the worker wearing the device. Stefana et al. (2021) reviewed wearable devices for ergonomics. Over half of the relevant articles were published in 2020 and 2024, indicating a growing trend. Due to this technology's relevancy and widespread adoption, this research question was investigated in the current review.

RQ3: How does validation accuracy of ergonomic risk assessments vary across different body parts of interest, such as upper limbs, lower limbs, or the full body?

Once the results of a study are obtained, the validation process is essential to quantify the efficacy and future usability of derived knowledge. Automated ergonomic assessment involves developing software tools and algorithms that perform the analysis. Automation is important for this operation because it can have a heavy volume of data. This research question investigated the validation technique used against the ergonomic assessment techniques presented in the studies. In experiments involving human subjects, mitigating risks as much as possible is critical. For software algorithms and wearable devices that studies propose, quantified validation data for safe and reliable usage for future and real-life applications is needed. The validation accuracy can help instil confidence in potential adopters of the technology. This metric was collected from the reviewed studies and reported to analyze the degree of validation accuracy

based on the automation methods chosen and the trade-off against their manual counterparts.

RQ4: In which industry or domain (e.g. construction, culinary, aviation manual tasks, driving tasks) does the study belong?

Ergonomics are a part of many physical tasks across industries like construction, transportation, food preparation, assembly, and manufacturing. Ramos-García et al. (2022) studied the impact of ergonomic features on job fulfilment and occupational well-being among university workers during the Severe Acute Respiratory Syndrome Coronavirus 2 pandemic. Similarly, better ergonomic assessment and suitable training could impact job satisfaction for industries like construction, which involve comparatively heavier manual labour and repetitive tasks (Farrokhi, Khankeh, and Poursadeqiyan 2019; Hosseinihousheh et al. 2021). This review included the research question to collect information on the sector that studies targeted to help maximize the impact of automation in ergonomic assessment to the largest population pool.

The team developed these research questions based on reported studies from the initial literature search.

2. Methods

The current review followed the Preferred Reporting for Systematic Reviews and Meta-Analysis Extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al. 2018). The corresponding checklist is provided in the Appendix. Scoping reviews across various fields have used PRISMA-ScR for the initial phases of the review process (Balakrishnan et al. 2022; Major, Clabault, and Wild 2021; Morid, Borjali, and Del Fiol 2021; Wu and Ho 2023).

The search criteria were decided based on a selection of phrases and keywords that are of interest in ergonomic assessment technique analysis. They are as follows:

- (Auto* OR Real-time)
- AND (ergonomic* OR Human factors)
- AND (observ* OR ergonomic assess* OR rapid upper limb assessment OR rapid entire body assessment OR Ovako Working Posture Analysis System OR Posture, Activity, Tools and Handling OR Biomechanical human modelling OR digital human modelling OR Body part discomfort scales human modelling OR The Job Content Questionnaire OR Plan for Identifying av Belastnings faktorer (PLIBEL) OR Rodgers muscle fatigue analysis OR National Institute for

Occupational Safety and Health (NIOSH) lifting equation OR Energy prediction model OR Threshold limit value (TLV) for Lifting OR The Washington Industrial Safety and Health Act (WISHA) Lifting Calculator OR Ohio lifting guidelines OR the Manual handling assessment charts (MAC) tool OR Snook tables OR Strain index OR Occupational Repetitive Actions OR TLV for hand activity OR TLV for upper limb muscle fatigue OR Assessment of repetitive tasks OR Muscle fatigue equations OR Novel Ergonomic Postural Assessment Method OR Agricultural Whole-Body Assessment OR American National Standards Institute (ANSI) Z-365 OR Baseline Risk Identification of Ergonomic Factors OR Manual Tasks Risk Assessment tool OR The Lifting Fatigue Failure Tool OR The Distal Upper Extremity Tool OR Ergonomic Job Measurement System)

One option from the three lists mentioned above was selected to form different search queries. The queries were then run through five literature databases employed as part of the search: IEEE Xplore, PubMed, Engineering Village, Scopus, and Google Scholar. All combinations of possible queries were formulated using an automated Python script that resulted in a list of queries to be fed into the search system. The search was done using Python libraries to search through these databases. The libraries include IEEE Xplore Python API, Scholarly library for Google Scholar search, Elsaply module for Elsevier search, and PyMed library for PubMed filtering and search. These libraries helped assemble the above keywords in a programmatic data structure to automate the initial parts of the literature search. In some cases, the corresponding results were also validated using the journal's web search filter and tools. Keywords were searched for in the topic and abstract sections of the search results. The inclusion criteria for this review required studies to (1) focus on ergonomic assessment techniques, with an emphasis on automation and validation methods; (2) be published in peer-reviewed journals between 2000 and 2024 to ensure relevance to contemporary practices; (3) involve human subjects or simulations relevant to ergonomic studies; and (4) provide quantitative or qualitative data on study design factors, data collection, analysis methods, or validation techniques. Studies were excluded if they (1) were unpublished, working papers, conference papers, book chapters, or dissertations; (2) did not focus on ergonomic assessment methods; (3) lacked clear methodologies or validation techniques; or (4) did not include sufficient

details for meaningful analysis, such as missing information about sample size, automation levels, or body parts assessed.

Using the research questions, 84 papers were filtered out and distributed amongst three participant organizations (one researcher from each organization) for analysis and review. The papers were distributed randomly, and there was no bias across researchers due to the lack of set expectations for the review. The reviews were compiled and verified by the primary researcher. The initial search yielded a list of papers ($n=567$) containing the search terms and a few papers found through other resources ($n=3$). After removing duplicates, the number of screened articles was reduced ($n=536$). The exclusion criteria excluded some records ($n=73$), and the resulting filtered list ($n=463$) was parsed manually to identify the studies that addressed the research questions indicated above. This reduced the number of papers to be reviewed to a more concise list ($n=84$). Figure 1 shows the summary of the PRISMA-ScR process used in this study. Each article was charted independently by two additional reviewers to minimize bias and ensure relevance. Discrepancies between reviewers were resolved through discussion and, when necessary, consultation with the primary reviewer. For complex cases or missing information, these issues were documented in the results (Table 2), thus improving the reliability of this review. Data were collected on several variables: sample size, body part of interest, data collection

technique, data analysis technique, validation technique, and validation accuracy. The sample size referred to the number of participants in each study. The body part assessed indicated areas like the upper limbs or trunk. Data collection methods included techniques like video recording or sensors, sometimes simplified to a single approach. Analysis methods ranged from statistical models to machine learning. Validation methods, used to confirm accuracy, included expert comparisons and statistical tests, with accuracy reported as a percentage or error rate. Lastly, each study's industry, such as construction or healthcare, provided details about the applicability of findings across related fields. In this review, we used accuracy to refer to the degree of agreement between a system's output and a validated ground-truth measure, often quantified using metrics such as classification performance or root mean squared error (RMSE). Validation referred more broadly to the process of evaluating a system's performance against established benchmarks or reference methods. Reliability, in contrast, described the consistency or repeatability of a system's outputs across different trials, raters, or conditions.

3. Results

Table 2 lists the reviewed studies, detailing each study's sample size, the body part assessed, data collection and analysis methods, validation techniques, and accuracy results. It shows the range of approaches

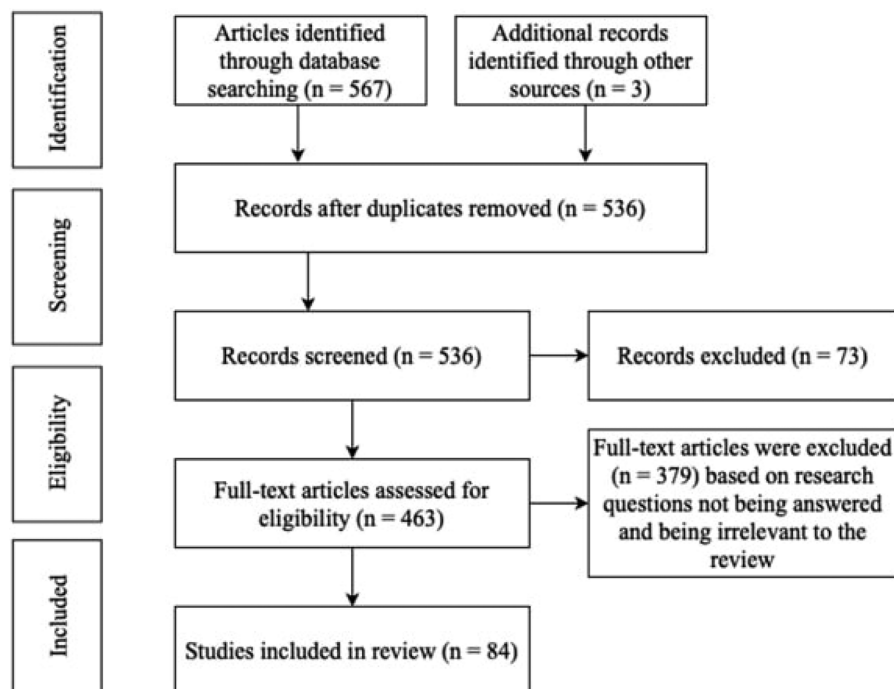


Figure 1. Overview of PRISMA-ScR process and criteria.

Table 2. Summary of reviewed papers (sorted by year).

Study	Sample size	Body part of interest	Data collection technique	Data analysis technique	Validation technique	Validation accuracy
Paquet, Punnett, and Buchholz 2001	5	Multiple joints	Posture, activities, tools, and handling observation	Proportion of agreement	SAS statistical software	High validation agreement for arms and knees, and moderate for trunk
Spielholz et al. 2001	9	Upper limbs	Video recording	Myosoft 2.0	Statistical analysis tools	High accuracy for direct measurement
Fulmer and Buchholz 2002	8	Multiple joints	Still photography and video recording	Audio dosimeter (DuPont MK-3)	Observatory validation	Not specified
Lowe, 2004	28	Upper limbs	Simulated experiments	Categorical scales for posture categories	Static recordings were collected	54.2 and 22.2% Inaccuracy for frequent and peak posture limits
Lowe, 2004	28	Upper limbs	Simulated experiments	Cumulative probabilistic	PEAK Motus system	Misclassification: Over 47, 25.0, and 8% for flexion of the elbow, the elevation of the shoulder, and the elevation plane
Bao and Silverstein 2005	134	Upper limbs	Pinch/grip dynamometer	Paired <i>t</i> -tests for EMG	Pinch force estimation	4.8% overestimation
Karayiannis et al. 2005	1	Upper limbs	Video recording	Motor activity signals from video recordings	Temporal motor activity signals XLH(t) YLH(t) produced by two motion trackers	Movement not accurate
Janowitz et al. 2006	497	Multiple joints	Video recording	REBA calculation	Risk rating software	Reliability for upper limbs: 0.54 and lower limbs: 0.66
Marsot, Claudon, and Jacqmin 2007	10	Upper limbs	Force sensors on knife	Comparing knife blade grade and inclination	Biomechanical stresses comparison and manual assessment	Cutting force ratio compared closely to manual validation
Lämkull, Hanson, and Örtengren 2009	9	Upper limbs	Digital human modelling (DHM) tools and ratings from 6 professional ergonomists	Evaluation using working height, working distance, clearance, and hidden assembly	DHM tool and the ergonomist's visual judgments	Total agreement between 75 cases: 48%
Yang 2009	1	Multiple joints	Digital human model	Denavit Hartenberg method and Jacobian Row Rank method used to calculate workspace	Resulting workspace was demonstrated using two body parts - knee and leg	Not specified
Pärkkä, Cluitmans, and Erms 2010	7	Upper and lower limbs	Wireless motion bands from Nokia are transmitted to the PDA using Bluetooth	Decision tree classifier	Leave-one-subject-out cross-validation	Accuracy 94%
Straker et al. 2010	1	Trunk	Physiometer, 3-Space Fastrak, and Peak Motus 8 systems	Independent equations of regression	Fastrak and Peak data to compare the physio metre with	Maximum error of almost 3.7 when estimating kinematics of shoulder and elbow
Ryan et al. 2011	2	Multiple joints	Handwritten notes and drawings of worksite layouts	Activity-on-arc network and Mixed integer linear programming	Domain experts examined results and provided feedback	Not specified
Kuo and Wang 2012	1	Multiple joints	Modeled using an Anthropometric dataset from the previous study	Coded natural language instruction modelling	Domain expert analysis	Conventional evaluation by experts validated
Udani et al. 2012	10	Trunk	Head-mounted display for ergonomic intervention based on ultrasound data	Ergonomist analysis	After tasks, practitioners subjectively rated the quality of the head-mounted display	Validation led to poor accuracy for definitive inferring
Bao, Silverstein, and Stewart 2013	19	Multiple joints	EMG sensors	ANOVA for EMG	Validation MVC reference	Not specified
Karhula et al. 2013	95	Multiple joints	Likert scale measurement	Mann-Whitney <i>U</i> -test and logistic regression	Questionnaires	Listed as future work
Huang and Pan 2014	580	Multiple joints	Anthropomorphic datasets	Particle swarm optimisation	Against ground truth data	Average estimation error for body parts: 2.48%
Prairie and Corbell 2014	9	Trunk	CUELA sensor system	Exposure variation analysis	Accuracy of the CUELA system measuring the joint angles and strain	Binary, no difference between urgent and non-urgent transport
Ohlendorf et al. 2015	21	Trunk	CUELA sensor system	CUELA software for posture analysis	CUELA analysis compared to VICON	Experts validated the study as acceptable
Shi et al. 2015	89	Trunk	Human safety model dataset	Landmark-driven radial basis function (RBF)	Cadaver testing was used for the validation	Reasonable agreement between the simulation and tests

(Continued)

Table 2. Continued.

Study	Sample size	Body part of interest	Data collection technique	Data analysis technique	Validation technique	Validation accuracy
Large et al. 2016	38	Head	SensoMotoric Instruments (SMI), eye-tracking glasses	One way ANOVA	Compared to pre-existing results in others	Accuracy confirmed through result similarity
Peppoloni et al. 2016	10	Upper limbs	EMG and IMU sensors	Automatic segmentation analysis	RULA automatically compared to traditional human assessment	Accuracy for RULA: 94.79%
Schall et al. 2016	6	Trunk	IMU and optical motion capture	Root means square differences (RMSD)	Linear mixed model regression	RMSD estimates were similar (within 1.5°)
Xu et al. 2016	6	Multiple joints	Azure Kinect	Universal hybrid decision tree (UHDT) and automated GPS context classifying algorithm	Results validated by comparing proposed system to the existing models	Error for Lower Body Motion Tracking: (3.08 ± 1.77) %, and for Upper Body Motion Tracking (Kinect System): Average error 4.53%
Cui et al. 2017	12	Lower limbs	EMG, EEG, and MMG sensors	Multimodal fusion framework	5-Fold cross-validation	EEG: 98.61%, EMG: 97.78%, and MMG: 96.85%
Gallagher et al. 2017	304	Trunk	Manual measurement	LIFFT	Against two epidemiological databases	Accuracy 92%
Park 2017	1	Multiple joints	Azure Kinect and motion capture system	Posture estimation algorithms	The difference in absolute value between Kinect and the motion capture system feature data for each exercise posture	Mean offsets were greater for squat and lunge tasks
Plantard et al. 2017	19	Multiple joints	Azure Kinect	Kolmogorov-Smirnov test and Spearman's rho	Compared with the two expert's assessment	Left body part: 74% and right body part: 73%
Gallagher et al. 2018	772	Upper limbs	Video recording	Distal Upper Extremity Tool (DUET)	Logistic regression	High validity
Li et al., 2019	6	Multiple joints	WiFi signal analysis for HAR	Posterior probability-based combination strategy	Mean prediction accuracies of prediction combination and classification models	An average accuracy of over 96% in line-of-sight and over 90% in not line-of-sight situations
Totry and Wade 2018	10	Upper limbs	EMG and IMU sensors	KNN and one-way ANOVA	KNN classifier used prediction accuracy to validate the prediction	Accuracy of KNN: 89.2%
Abobakr et al. 2019	6	Upper limbs	Image generation pipeline	ConvNet neural network models	Against real datasets of 24k images	Average accuracy 89%
Jun et al. 2019	1	Multiple joints	Experimental case study	Virtual Reality Peripheral Network (VRPN)	Human model generated using depth cameras (Kinect)	Three test scenarios: 100%, 60%, and 100%
Li, He, et al. 2019	1	Multiple joints	Data collected from the risk rating of 4 scenarios	Automated data computation and processing into a GUI	Post-3D visualisation ErgoSystem automatically calculated risk ratings from REBA and RULA	Not specified
Lowe, Dempsey, and Jones 2019	405	Multiple joints	Assessment survey	Chi-square statistic	Observation study	Not specified
Mokarami et al. 2019	8	Multiple joints	REBA evaluation	Analysis of ergonomic intervention	The manual technique of validation	MSD risk was significantly reduced
Wang et al. 2019	6	Multiple joints	2D camera to detect hand and ankle location	Bounding box for humans and moment of loading and unloading	Ghost effect and spatial and temporal factors allow for motion detection	Accuracy: 82.9%
Zhang et al. 2019	1	Multiple joints	Human activity recognition technologies were used. WISDM, UCI HAPT	U-Net, dense prediction, and sliding window prediction algorithms were compared.	Algorithms are verified using Accuracy, Precision, Recall, F1-Score, Fw-score evaluation metrics	UNET showed a 3.3% improvement from the second-highest score in OPP Gesture data, which was mainly short-term actions
Barshan and Yurtman 2020	8	Multiple joints	Xsens MTx, with accelerometer, gyroscope, and magnetometer	Orthogonal Matching Pursuit (OMP)	P-Fold and Leave-One-Subject-Out (L1O) methods	Accuracy 98.2% for the P-Fold method and 87.2% for the L1O method
Dias Barkokebas and Li 2021	13	Multiple joints	VR headset recording	RULA and REBA calculation	VR and actual physical experiment	Accuracy RULA: 80% and REBA: 86%
Hara et al. 2020	6	Multiple joints	IMU sensors	Motion capture analysis	Cross-comparing order-picking data	F-scores of P_high: 95.5%, P_low: 98.2%, P_med: 75.7%, P_unload: 97.4%
Li, Martin, and Xu 2020	11	Upper limbs	Human 3.6M Dataset	Deep learning models that were trained using the Human 3.6M dataset	Using video footage of subjects performing lifting tasks	Accuracy of 93%

(Continued)

Table 2. Continued.

Study	Sample size	Body part of interest	Data collection technique	Data analysis technique	Validation technique	Validation accuracy
Mahmod, Abdullah, and Othman 2020	12	Multiple joints	Task analysis and interview	REBA and MAC assessments	Comparison of Ergonomics Risk Assessment and Advanced Ergonomics Risk Assessment	Not specified
MassirisFernández et al. 2020	5	Upper limbs	Video recording	OpenPose and other CV techniques	Compared to ergonomic experts' assessment	Reported accurate
Caterino et al. 2021	1	Upper limbs	Simulation using IoT	Automatic simulation using the Internet of Things	100-Cycle evaluation of OWAS and Occupational Repetitive Action (OCRA)	Not specified
Liu et al. 2021	18	Multiple joints	Training data (falls data, activities data) and test data (daycare centre)	The sum of Vector Magnitude	Pattern recognition to detect sensitivity, specificity, and accuracy of activity	Seniors: 99.75% and Youth: 99.29%
Ryu et al. 2021	43	Multiple joints	Motion capture suits with IMU	RULA, REBA, and OWAS assessment	Biomechanical analysis with anthropometric data	Rule-based assessment accurate with ground truth from the biomechanical analysis
Seo and Lee 2021	8	Multiple joints	Vision-based methodology	Algorithms identify awkward or dangerous working positions automatically	Validation was attained by obtaining scores from human observers	Classification accuracy of 89%
Wang et al. 2021	15	Multiple joints	iPhone camera	3 Automated AI algorithms with human pose dataset	Experimental environment	Joint point recognition: 87.0%, posture risk: 96.0%
Battini et al. 2022	1	Multiple joints	Motion capture systems with electrocardiogram (ECG)	RULA, REBA, and OWAS calculation	Experiment to assemble bed-side table	Not specified
Blanco et al. 2022	12	Upper limbs	Active upper-limb exoskeleton	Shapiro-Wilk normality test	Cross-study validation	Subjectively high
Chatzis, Konstantinidis, and Dimitropoulos 2022	20	Multiple joints	Static monocular cameras	Multistream deep network	Datasets cross-validation	Highly accurate validation, mean squared error (MSE) <0.3
Dias Barkokebas, Al-Hussein, and Li 2022	5	Multiple joints	Motion capture systems	Xsens MVN analyze software	Comparing simulated motions during the VR experiment to completing the tasks	Maximum global error for RULA: 8.29% and REBA: 12.81%
Fan et al. 2022	29	Multiple joints	Azure kinect	Logistic regression and a multivariate model	Spearman test	Trunk: 80%, Neck: 92.3%, Legs: 86.7, Hands: 86.7%
Fang, Fu, and Zheng 2022	4	Head	Video recording and IMU	Sensor-driven automatic ergonomic assessment	Comparing experiments to calculated scores	Mean errors (x, y, z): (0.72, 0.67, 0.79)
Hida, Okada, and Matsumoto 2022	10	Multiple joints	Motion capture system (OptiTrack)	Direct linear transformation and k-nearest neighbour (KNN)	Leave-one-person-out cross-validation	Accuracy greater than 80%
Hiruma et al. 2022	1	Multiple joints	Intel RealSense RGBD camera	Multilayer perceptron and LSTM	Compared with an ablation study	Pick: 27/30, drag: 30/30, and consecutive: 26/30
Kataria et al. 2022	81	Multiple joints	Video recording	ANOVA and Mann-Whitney U-test	Biomechanical stress was analyzed using ANOVA	Not specified
Lamooki et al. 2022	37	Upper limbs	Experiment using failure fatigue theory	Greedy Gaussian segmentation and first correction	Segmentation/change point signal by sensors to detect statistically significant inertial changes	98% across tasks
Lee and Lee 2022	2	Multiple joints	Camera photography	CPM-based ergonomic posture acquisition and risk analysis deep learning model	CNN output compared to the scores computed manually by experts	Accuracy greater than 0.854
Senjaya, Yahya, and Lee 2022	12	Upper limbs	By utilising a body tracking sensor along with a hand tracking sensor	After the automated RULA assessment, statistical analysis was performed using ANOVA and t-tests	Automated RULA scores were validated with evaluation by an expert	Similarity score of 0.8-0.9 for the areas of interest with automated vs. manual comparison
Van Crombrugge et al. 2022	1	Multiple joints	Videos recorded using three camera setups	Detectron2 neural network used to determine 2D skeletons	RMS of angle error between estimated and ground truth data	Single and combined triangulation results significantly better: over 15° and 10°, respectively

(Continued)

Table 2. Continued.

Study	Sample size	Body part of interest	Data collection technique	Data analysis technique	Validation technique	Validation accuracy
Vianello et al. 2022	1	Multiple joints	Xsens MVN motion tracking	Digital human models, latent ergonomic maps, and variational auto-encoders	Variational autoencoder's 66 outputs used to validate data	Not specified
Villalobos and Mac Cawley 2022	20	Upper limbs	9-Axis IMU: inclinometer, gyroscope, accelerometer	Tree-based machine learning algorithms	Predictive capabilities of the machine learning algorithms	Accuracy: 98%
Weckenborg, Thies, and Spengler 2022	50	Multiple joints	Assembly line balancing dataset	Multi-objective combinatorial optimisation model	Manual cross-validation	The model shows using Cobots reduce energy expenditure
Aghamohammadi et al. 2024	1	Multiple joints	Depth- and color-mode video using Kinect	Gradient data analyzed in four consecutive frames and some self-observed joints were predicted using the CNN model	Human evaluator observation used to examine movements and analyze the system in real-time	Recall: 0.89, precision: 0.87, and F-score: 0.88
Bortolini et al. 2023	10	Upper limbs	3D anthropometric data using Microsoft Kinect	OCRA method for repetitive actions	Against the study of centrifugal electric pump assembly	Mean error: 2–8%
Hamilton et al. 2023	13	Multiple joints	AI-assisted video capture	RULA and REBA scores comparison pre- and post-intervention	Chi-squared test to assess joint angles before and after intervention	Neck unsafe position reduction: 36–14% ($p < 0.01$), Right shoulder unsafe position reduction: 9–2% ($p = 0.03$)
Hossain et al. 2023	11	Multiple joints	Human3.6M dataset	Deep Neural Network for REBA score prediction	Comparison with REBA ground truth	Mean difference: 1.0 point
Jeong and Kook 2023	1	Multiple joints	iPhone 11 Pro shot video	REBA evaluation system using inverse kinematics	Comparison with expert REBA scores	Mean absolute percentage error (MAPE): 15%, RMSD: 0.11
Kusumawardhani, Djamilus, and Lestari 2023	71	Multiple joints	Observations and questionnaires using SNI 9011-2021	Nordic Body Map analysis for MSDs symptoms	Comparison of ergonomic risk scores with MSDs symptoms	
Kavus, Tas, and Taskin 2023	100	Multiple joints	Observed and recorded body angles using the REBA	Comparative neural networks and neuro-fuzzy-based modelling	MSE and RMSD	MSE: 0.0054 (Triangular membership function), 0.0163 (Generalized regression neural network)
Tao et al. 2023	8	Multiple joints	Observation using REBA	Fuzzy Bayesian Network and D-S evidence theory	Comparison with expert assessments	MAPE: 12.5%, RMSD: 0.087
Yuan and Zhou 2023	7	Multiple joints	Monocular RGB camera for 3D pose estimation	Regression of multiple 3D people algorithm with multi-person tracking	Comparison with Noitom motion capture system	RULA accuracy: 83.8%, OWAS accuracy: 90.7%, MAE: 9.4°
Chen and Yu 2024	Not specified	Multiple joints	Collected videos from construction sites	Self-similarity matrix and transform model	Off-by-one-accuracy and MAE	Off-by-one-accuracy: 91.5%, MAE: 5.97%
Fan, Mei, and Li 2024	7	Multiple joints	Motion capture system	Computer vision-based ergonomic assessment	Comparison with ground truth values using the motion capture system	Improved mean per-joint position error for trained models compared to most others
González-Alonso et al. 2024	1	Upper limbs	IMU sensors integrated with Unity 3D and Python	Movement analysis using OpenSim musculoskeletal model and inverse kinematics for RULA	Comparison of the system with a gold standard IMU system.	Average error in the global RULA score of less than 5% compared to the gold standard IMU system.
Jiao et al. 2024	9	Multiple joints	Camera-based motion capture	Deep learning-based REBA scoring	Comparison with expert REBA scores	Average precision of almost 95% on real-world data, comparable to expert evaluation
Li et al. 2024	3	Multiple joints	RGB video using iPhone 14 Pro Max	Heuristic Gaussian cloud transformation, fuzzy inference	Expert survey and comparison with existing methods	Mean absolute error: 0.152–0.193, RMSD: 0.168–0.249, outperforming other methods.
Mazaheri, Neumann, and Trask 2024	14	Upper limbs	Semi-structured interview	Inductive analysis approach	Objective (e.g. tool type, torque) and subjective (e.g. perception, experience) factors	Objective metrics alone are insufficient, so operators' subjective experience is included in risk assessment. The quantitative accuracy is not specified.
Menanno et al. 2024	1	Upper limbs	Video recording	Temporal convolutional neural network and fuzzy inference engine	Comparison of criticality indices before and after collaborative robot implementation	13% Reduction in overall ergonomic risk, improved production capacity by 33%
Sardar and Lee 2024	10	Multiple joints	Deep learning-based detection of body keypoints and centre of mass displacement	RULA- and REBA-ergonomic assessment with ANOVA	RULA and REBA scores compared to determine risk levels	Greater risks observed in vertical compared to horizontal body movements

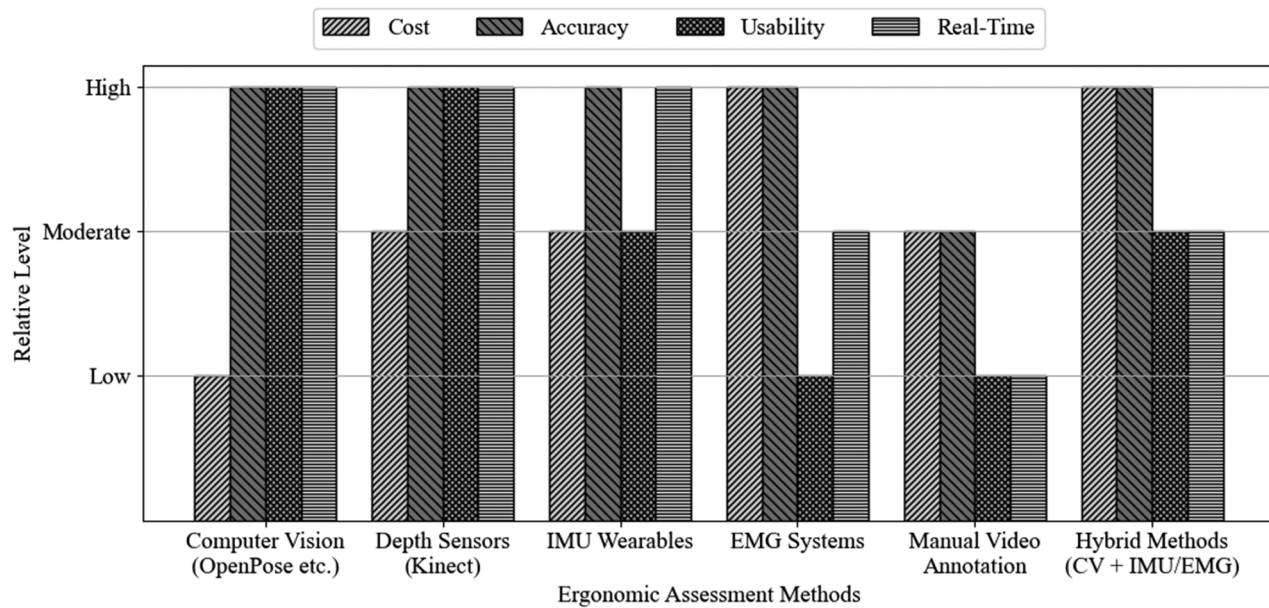


Figure 2. Comparison of ergonomic assessment methods across key dimensions.

used for ergonomic assessments, from video recordings and motion capture to wearable sensors, and how different studies validate their findings. This table helps compare methods and highlights how ergonomic assessments are applied across various settings.

As shown in Figure 2, ergonomic assessment methods differed in important ways across cost, accuracy, usability, and real-time capability. Computer vision and depth sensors offered the most balanced profiles, combining high usability and real-time feedback with moderate to high accuracy at low to moderate cost. IMU wearables and EMG systems provided strong accuracy, but the former required donning sensors, and the latter involved electrode placement, reducing overall usability. Hybrid approaches (e.g. combining vision with IMU or EMG) delivered the highest reported accuracy but demand more resources and setup. Manual video annotation remained low-cost but varied in accuracy depending on coder expertise and lacks real-time support. These comparisons, summarized in Figure 2, highlight key trade-offs to consider when selecting methods for ergonomic assessment in both research and applied contexts.

4. Discussion

The literature review found trends and specific details about the studies conducted, with some outlying cases involving either an esoteric or one-off observation.

The selected papers showed a trend of increasing frequency concerning the recency of publication (Figure 3). The review included reading and extracting

information relevant to the research questions to analyze the studies and discover the automation, data analysis, and validation techniques used.

4.1. Participant data [RQ1]

The participant pool size for the reviewed studies ranged between 1 and 772 ($M=46.61$, Population $SD=126.46$). Wang et al. (2021) involved 15 participants, out of which 9 were male and 6 were female. The participants were tasked to perform a construction activity where gender diversity was crucial. A diverse group of participants of different genders helped provide a more inclusive and job-oriented perspective of the task. Unless specifically required otherwise, the studies generally employed a balanced proportion of male and female participants. The size of the dataset was found to depend on the nature of the task. Huang and Pan (2014) involved 260 participants to simulate real-life work scenarios better. In comparison, Bao, Silverstein, and Stewart (2013) assessed ergonomic intervention for Nicaraguan coffee harvest workers.

Blanco et al. (2022) investigated the impact of an upper limb exoskeleton on simulated workers who performed repetitive industrial tasks. The study's participants were exclusively individuals who were right-hand-dominant. Sometimes, video or quantitative data recording occurs from a certain angle of interest, where the orientation and job-performing position play a key role. Muscle activity using EMG sensors was monitored when usage and fatigue of muscles were relevant to the analysis (González-Izal et al. 2010; Kim

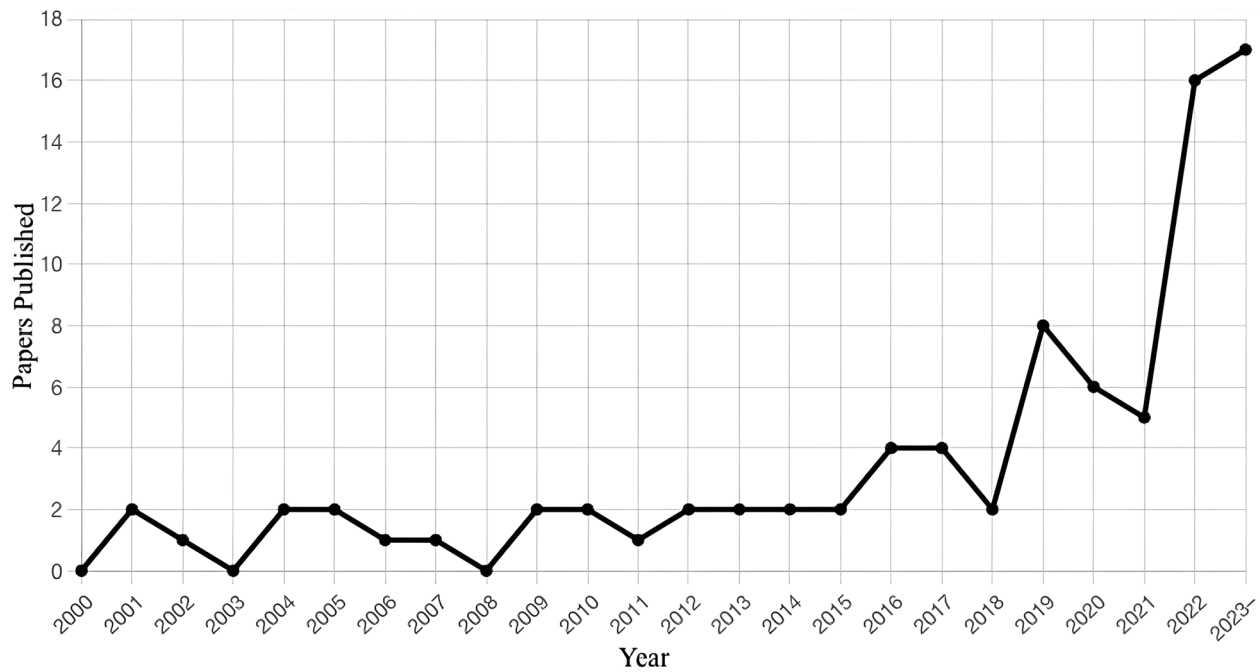


Figure 3. The number of published papers per year.

et al., 2007; Pah and Kumar 2001). The current review recorded the body part of interest to analyze the depth and technique of assessment used in each case. Ergonomic assessment techniques depended on what part of the body is being studied. It was found that ergonomics of multiple joints were most studied (62%), followed by upper limbs (26%), trunk (8%), lower limbs (2%), and head (2%). To understand the relationship between the sample size of ergonomic studies and their validation accuracy, a Pearson correlation analysis (Sedgwick 2012) was performed. Gallagher et al. (2018) used the Distal Upper Extremity Tool (DUET) with 772 participants, validated via logistic regression. Peppoloni et al. (2016) employed EMG and IMU sensors with 10 participants, achieving almost 95% accuracy for RULA scores. Barshan and Yurtman (2020) classified activities with motion sensors, achieving over 98% accuracy. Ryu et al. (2021) and Hida, Okada, and Matsumoto (2022) used motion capture systems for joint assessments, with accuracies exceeding 80%. Villalobos and Mac Cawley (2022) achieved 98% accuracy using 9-axis IMU sensors for upper limb assessments. Dias Barkokebas and Li (2021) validated ergonomic risks in VR with RULA and REBA scores reaching 80 and 86%, respectively. All studies presented in Table 2 involved validation processes to ensure the reliability and accuracy of their findings. These validation efforts varied depending on the methodology employed. For instance, studies utilizing EMG data often validated muscle activity readings against established reference metrics or expert evaluations. Similarly, studies relying on Likert

scales ensured validation through statistical techniques, such as reliability testing and inter-rater agreement analyses. Anthropometric studies frequently compared their measurements against standardized datasets or ground truth values. The analysis included studies from Table 2 that provided both sample size and numeric validation accuracy values. However, the relationship was not statistically significant ($t=-0.186$, $p>0.05$), likely due to the limited number of observations available for the analysis. This analysis was done to assess if there is a potential trend where larger sample sizes could be associated with higher validation accuracies in ergonomic studies. However, the statistical significance of this correlation could not be established, highlighting the necessity for a larger and more diverse dataset to enable robust statistical validation.

4.2. Criteria for inclusion and exclusion [RQ1]

Inclusion and exclusion conditions for participants were mentioned in almost all the studies, with the most common exclusion factor being physically unable to perform a task for which the ergonomics were to be estimated (Bao, Silverstein, and Stewart 2013; Gallagher et al. 2018). Age, experience, and physical features like height and weight affected qualification for study participation since these variables directly correlate to style, mannerisms, and ability to perform a given task (Li, Martin, and Xu 2020; Mahmod, Abdullah, and Othman 2020). It was found that the criteria commonly used among the studies to include or exclude

participants were demographics like age, the subjects' industry of work or interest (Chen and Yu 2024), experience (Mazaheri, Neumann, and Trask 2024), and ergonomic capabilities of the recruited participants to ensure they can perform tasks designed as part of the experiment (Fang, Fu, and Zheng 2022;; Udani et al. 2012). Participants who refused to consent were automatically excluded from the respective study.

4.3. Wearable technology for data collection [RQ2]

Depending on the study type and the worker population under investigation, wearable technologies offer data access that would otherwise be inaccessibly challenging to assess solely through visual or observation-based techniques. Examples of such data include EMG, IMU, sensor vests or belts, electroencephalography (EEG), electrocardiogram (ECG), smartwatches, and specific joint angle motion detection. Figure 4 provides a visual overview of wearable systems, illustrating common sensor placements and form factors. This helps contextualize how these devices are utilized to collect postural and physiological data in ergonomic assessment studies. Among these, wearable adaptations include EMG sensors integrated into surface devices (Beniczky, Conradsen, and Wolf 2018) or

clothes (Colyer and McGuigan 2018), IMUs embedded in belts for motion tracking (Stenger et al. 2024), EEG sensors incorporated into headbands (Arsalan et al. 2019), and ECG sensors embedded in chest belts or smartwatches (Weaver, Wooden, and Grazer 2019), enabling real-time physiological, psychological, and motion data collection (Khazai et al. 2019; Lorenzini et al. 2022). The studies included in the current review used diverse wearable technologies for data collection, analysis, and validation. Paquet, Punnett, and Buchholz (2001) conducted a survey of posture that involved the use of electronic inclinometers. These inclinometers were securely fastened to the subject's arms and perpendicular to their legs using Velcro, elastic bands, and tape. This setup allowed researchers to collect data on posture above the shoulders and below the knees while subjects performed construction tasks. Additionally, electrodes were attached to wearable equipment, such as bands and straps, and placed on specific areas of interest, such as arms, elbows, back, and legs (Bao and Silverstein 2005; Spielholz et al. 2001).

Ohlendorf et al. (2015) used computer-based measurement through the musculoskeletal system (CUELA) software and conducted statistical analyses using BiAS 10.8 for automated data collection. To investigate precision, they compared CUELA system measurements to optical motion capture system (VICON, Oxford, UK)

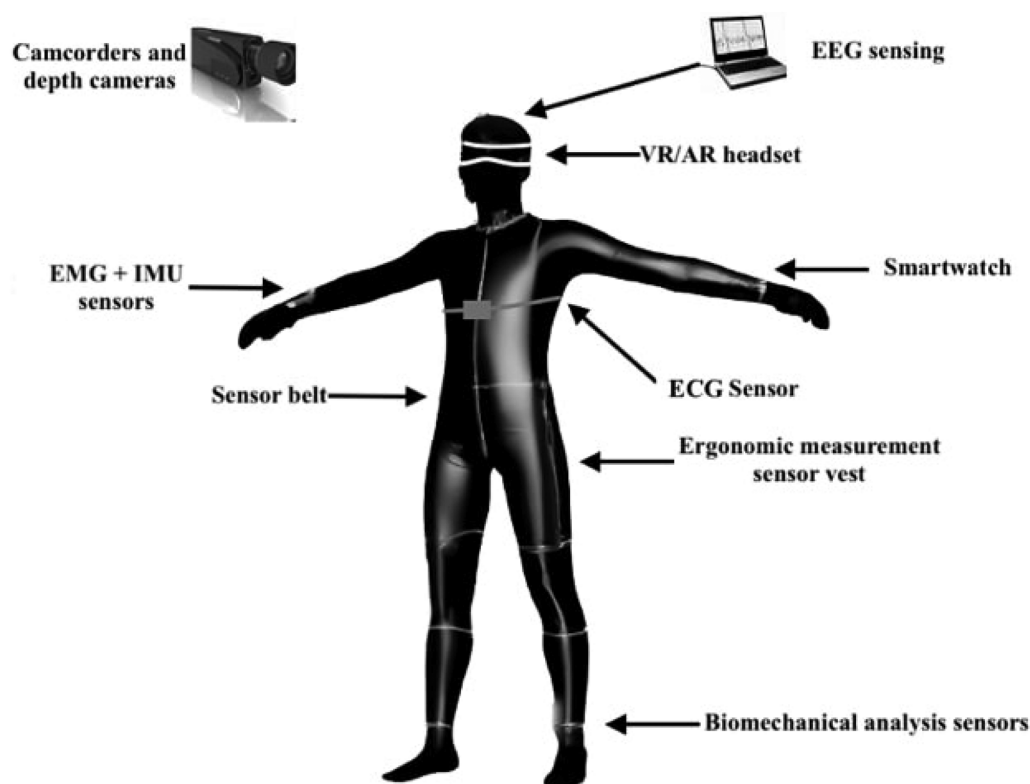


Figure 4. Wearable sensors to capture motion and health data of interest.

measurements. The study focused on culinary workers and involved attaching sensors to their clothes. Prairie and Corbeil (2014) used CUELA sensors to measure the performance of paramedics while performing various tasks, including emergency medical procedures. The participants were required to wear a CUELA system vest while performing the assigned tasks. The validation process involved comparing the CUELA system's measurement of joint angles and strain in high-demand and low-demand situations and differentiating between urgent and non-urgent activities and stretcher and non-stretcher activities. While sensors are commonly used in ergonomic experimentation to collect data, only a subset of these systems can be categorized as wearable technologies. Wearable technologies specifically refer to devices that are designed to be worn as accessories, embedded in clothing, or attached to the body, such as smartwatches, sensor vests, belts, or headbands. Although many ergonomic studies use sensors for data collection, relatively few incorporate wearable configurations, which are characterized by their portability and ability to collect real-time data in naturalistic environments.

4.4. Automation employed in data collection and analysis [RQ2]

Automation was observed in data collection techniques, processing, and validation. This included conducting experiments using wearable devices, extensions, and callipers to mount sensors for data collection. It is important to note that the use of sensors in ergonomic studies is not equivalent to automation but serves as an enabler for automation. Sensors collect data that can be processed using automated systems, such as machine learning algorithms or real-time analysis tools, to reduce manual effort and improve accuracy. While most ergonomic studies rely on sensor-based data collection, only a subset integrates automation for analysis and interpretation.

Fang, Fu, and Zheng (2022) utilized wearable sensors attached to the body to detect manual assembly motion and calculate continual ergonomic risk perception. Some of these studies were multi-staged processes that analyzed joint angles, back-stooping posture analysis, neck rotation, and ergonomics lost due to awkward bending. A quasi-experimental study found that neck, core, and combined stabilization exercises significantly reduced pain and improved range of motion in elderly patients with chronic

non-specific neck pain over 12 weeks (Soroush et al. 2022).

Wang et al. (2019) experimented to evaluate a lifting monitor built using that works using 2D videos. For this experiment, they used a single 2D camera to capture the video data, which was then fed into the algorithm. This highlights the significance and relevance of image processing in analyzing visual data, which would otherwise require manual interpretation by an ergonomist or a human interpreter. The Lifting Fatigue Failure Tool (LiFFT) was developed by Gallagher et al. (2017) to analyze risk in the case of low backloading risk, which can potentially be integrated into automated systems to predict ergonomic risks in real-time using continuous data inputs from wearable sensors or motion-tracking devices. Like lifting, a study conducted in Ilam, Iran, found that the way school students carried their bags significantly influenced the prevalence of musculoskeletal symptoms (Poursadeghiyan et al. 2017).

VR was employed by a few studies, such as in Dias Barkokebas and Li (2021), to assess ergonomic risk in the case of industry-based construction tasks. Similarly, Jun et al. (2019) used depth sensors coupled with a networked link of VR terminals to build a model for human engineering simulation to assess the ergonomic movements of automobile manufacturing workers. Both studies used automated data computation, conversion, and processing through a user-friendly graphical interface to optimise automation. In addition, RULA and REBA score calculations were also integrated into the processing pipeline, which helped provide further insight into subject performance and task technique. In parallel, traditional methods such as the Key Indicator Method have also been applied in occupational settings, like assessing manual load carrying risks among auto mechanics (Yarmohammadi et al. 2016).

Massiris Fernández et al. (2020) aimed to assess ergonomic risks using computer vision and machine learning. The assessment was based on drilling, hammering, wall plastering, and tree cutting. Five publicly available videos of workers performing these tasks were used as the dataset for the study, shot from non-ideal recording angles and in poorly illuminated areas. The videos were chosen to contain at least one challenging condition, such as uneven ground, poor lighting, or moving camera viewpoints. The method detected skeletons of workers using open-sourced neural networks, allowing angles of body joints to be deduced and RULA results to be calculated using machine learning and computer vision. Validation was done by comparing the scores from the automatic system to those assigned by ergonomics experts.

Additionally, the confidence in skeleton and joint detection was viewed, and angles were compared to those simulated in a lab setting. The CV (OpenPose) detected joint angles with improved ability.

Zhang et al. (2019) studied human activity recognition using motion sensor data and U-Net. The study analysed four datasets, including three pre-existing and one new dataset. The researchers used deep learning to obtain data features fed into the U-Net network. The study compared dense prediction and sliding window prediction algorithms. A human activity recognition framework was developed using U-Net, starting with motion sensor data collected from wearable devices. This data was transformed into an image featuring a single-pixel column and multiple channels. The image was then fed into the U-Net network for activity recognition at a pixel level. The framework encompassed data preprocessing, dense prediction, and subsequent analysis. The study evaluated algorithms based on a sliding window, such as support vector machines and convolutional neural networks, and algorithms based on dense prediction, such as SegNet and U-Net, using accuracy, precision, and recall evaluation metrics. The study also performed activity misalignment analysis on the dense prediction results obtained by the proposed U-Net method on four datasets and compared the results with those of other deep learning methods.

4.5. Study validation techniques and results [RQ3]

Along with the processing and automation of tasks, the current review also looked at the validation techniques and accuracy of the methods and tools employed in the studies. The VR experiment by Dias Barkokebas and Li (2021) was validated by comparing the VR simulation's output to the task's actual performance data. The RULA and REBA calculation error rate was roughly 10% in this case. Lamooki et al. (2022) created an advanced framework that automatically measures ergonomic risk using only a single sensor. The model can accurately quantify risk with an accuracy rate of over 95%. The framework includes automated tools that pre-process the sensor signals and detect statistically significant inertial changes through segmentation and change point signals. Validation in studies such as Ryan et al. (2011) that aimed to integrate human factors into existing tasks, such as road construction, involved subject matter expert advice. This technique might be suitable for initial or small-scale validation as a precursor to automated validation and accuracy testing techniques and algorithms.

Lee and Lee (2022) developed a pre-emptive plan-based and deep learning-powered system to assess ergonomic risk for risky posture recognition. They used automated deep-learning algorithms to validate the system. The algorithms were trained to learn image features and image-dependent spatial models to detect postures automatically and independently. The accuracy of this system was over 0.85 on a scale of 0–1, determined by comparing its outputs with scores computed manually by experts. Barshan and Yurtman (2020) used MATLAB to help automate results for classifying sport-related actions irrespective of the placement of the wearable motion sensor modules. The validation techniques used in the study were the P-Fold and Leave-One-Subject-Out methods.

Xu et al. (2016) studied motion activity reconstruction in the healthcare sector. They used everyday life trend analysis to collect data through body and location sensors that tracked patient activity and position throughout the day. The system was designed for healthcare professionals and users with disabilities, and data was recorded using the proposed system during the research and validation process. The sensors used in the study had a high success rate in detecting user location for context detection.

Various tools, including Kinect sensors, cameras, and motion capture systems, have been evaluated for their ability to accurately capture joint positions, angles, and repetitive actions. For example, Aghamohammadi et al. (2024) and Hamilton et al. (2023) used CNNs and AI-assisted video to estimate joint movements and evaluate posture, demonstrating promising results in reducing the risk of unsafe positions. Many studies focus on upper limbs or multiple joints and explore metrics such as REBA and RULA scores, mean error, and comparisons with ground-truth data. The findings indicate that these technologies, when combined with deep learning models or inverse kinematics, can provide reliable ergonomic assessments that align closely with expert evaluations. Studies such as those by Jeong and Kook (2023) and Yuan and Zhou (2023) show acceptable accuracy in real-world applications, suggesting that automated and video-based assessments could complement traditional observational methods.

We implemented the variable 'Body Parts of Interest' in our statistical assessments to analyze its impact on the validation accuracy of ergonomic assessments. For lower limbs, the accuracies were consistently high, with an overall mean of 97.75%, reflecting strong reliability in the studies. Multiple joints, despite being associated with numerous studies, showed more variability, resulting in an overall mean of 88.24%. Trunk

measurements were highly reliable, with average reported accuracy of 86%. Similarly, upper and lower limbs reported a single study accuracy of 94%, indicating strong reliability in this category. In contrast, upper limbs exhibited a moderate overall mean accuracy of over 86%, suggesting some variability across studies. For the head, there were no specific accuracy measures provided, highlighting a potential gap in the data for this body part. Fang, Fu, and Zheng (2022) reported mean rotational errors of around 0.7°, 0.7°, and 0.8° for the head along the x, y, and z axes, respectively, demonstrating the system's precision in capturing head postural data during manual assembly operations. Based on these findings, we recommend future research to expand the dataset and incorporate more complex models that include interaction effects and more robust regularization methods like Ridge (Hastie 2020) or Elastic Net (Zou and Hastie 2005). These steps will further clarify the observed trends and improve the generalizability of the study's findings, ultimately ensuring that technological advancements in ergonomic assessments are utilized to their fullest potential in improving workplace safety and worker health (Poursadeqiyan et al. 2021; Poursadeqiyan and Arefi 2020).

Across the reviewed studies, validation techniques varied widely, highlighting a persistent lack of standardization in ergonomic assessment research. The most frequently reported methods included ground truth comparisons ($n=11$), motion capture systems ($n=10$), expert validations ($n=9$), and statistical tools or software ($n=9$). For example, Paquet, Punnett, and Buchholz (2001) used SAS statistical software to analyze agreement between coder observations, while Spielholz et al. (2001) employed statistical analysis tools to benchmark video-derived measurements. Motion capture systems such as the PEAK Motus system were used by Lowe (2004) to quantify posture misclassifications, reporting misclassification rates over 47% for elbow flexion. Cross-validation approaches were prominent in wearable sensor studies, such as Pärkkä, Cluitmans, and Ermes (2010) and Cui et al. (2017), both of whom used leave-one-subject-out or k-fold cross-validation to estimate classification accuracy above 94%. The heterogeneous nature and data scarcity of residual musculoskeletal disorders present additional methodological challenges in disease burden estimation, which may lead to underreporting or misclassification (Gill et al. 2023).

Some studies relied on domain experts to evaluate system outputs. Seo and Lee (2021) validated their vision-based classifier against ergonomic risk scores provided by human observers, reporting classification

accuracy of 89%. Others compared their methods to epidemiological databases or gold-standard instruments. Gallagher et al. (2017) validated manual ergonomic risk scores against two large epidemiological datasets, and Schall et al. (2016) compared IMU outputs with optical motion capture using root mean square differences (RMSD), achieving discrepancies within 1.5°. Meanwhile, Peppoloni et al. (2016) used EMG and IMU data to compute RULA scores and compared them to traditional human-based assessments, reporting over 94% agreement.

This wide methodological spread, ranging from statistical regression to domain expert judgement to bio-mechanical simulation, complicates direct comparison across studies and limits the generalizability of findings. The diversity of validation targets (e.g. posture angles, muscle activation, task classification) and data collection conditions (e.g. lab vs. field, single vs. multiple participants) further exacerbate this challenge. These patterns highlight the critical need for more unified validation reporting standards and frameworks to ensure transparency, replicability, and comparability in future ergonomic technology evaluations.

4.6. Applicable industry [RQ4]

The review examined studies from a diverse set of industry use cases. The different tasks the studies deployed portray the scope of ergonomics on the human task force serving industry needs (Figure 5).

For laborious work like construction or assembly tasks, the analysis was geared towards assessing repetitive motions through sensor and computer vision techniques (Iyer et al. 2024a). However, multi-sensor synchronization remains a barrier to measuring coordinated upper and lower body movements in dynamic or multi-planar tasks. Lämkuil, Hanson, and Örtengren (2009) collected and validated data for automotive assembly tasks using digital human modelling tools, with the assistance of professional ergonomists who evaluated the experiment techniques. The tasks involved lifting objects, moving heavy items, and activities that required potentially bad musculoskeletal posture, which could be inconvenient and harmful (Figure 6). Lowe (2004) analyzed the motions of the upper limbs of workers while performing general tasks. Visual Analog Scaling and direct measurement techniques were used to gather data, which was then fed into a probabilistic pipeline to process ergonomic information and develop validation techniques. The study involved domain-independent work like activity recognition, lifting and placing, motion recognition, and overall ergonomic analysis while performing required

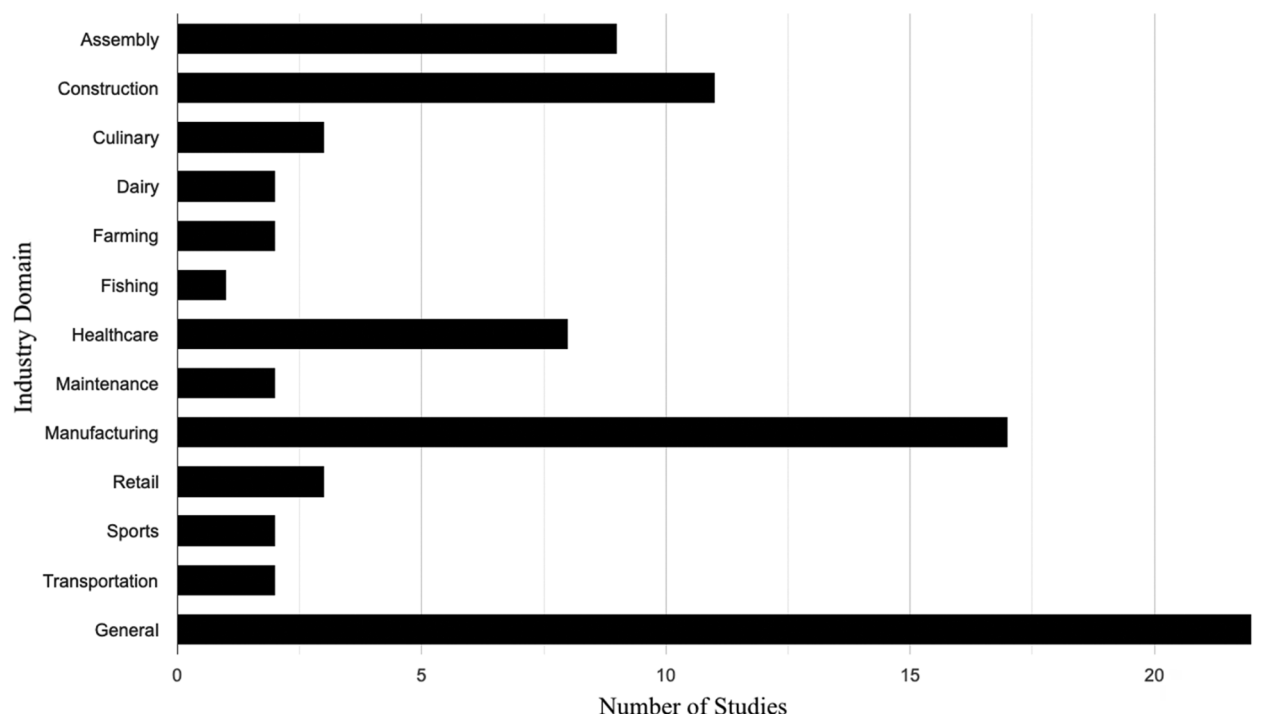


Figure 5. Industry domain catered to by the reviewed studies. Note: 'General' refers to studies involving domain-independent tasks (e.g. lifting, reaching, or sitting) that are not specific to a single industry.

tasks at work. Using a scale that had three categories, the most often occurring posture was wrongly recognized, with likelihoods of over 45%, 20%, and 8% for flexion of the elbow, elevation of the shoulder, and the plane of the shoulder's elevation, respectively. Jun et al. (2019) analysed how human modelling would be done to carry out physical tasks on the automotive assembly line. Four types of movements were selected for this experiment, all focusing on the ergonomics of multiple joints. An experimental case study was conducted to validate the proposed model by employing various depth cameras and a VRPN. A human model was generated through depth cameras (Kinect) and a Microsoft Xbox input device, which automatically collects data to create a digital human model. Three test scenarios were put together that involved modelling in different poses based on the specificity of the tasks as part of the validation. The accuracy of validation was reasonably high for the three test scenarios. Seo and Lee (2021) used automated RULA and REBA calculations with a vision-based analysis and data capture method. The analysis and validation methods were specific to the industry sector being studied to ensure a less biased and more realistic scenario. It is important to note that vision-based systems often struggle to maintain tracking accuracy when tools occlude key joints or when multiple overlapping body parts challenge part-based skeleton extraction.

Real-world applications of these technologies are already emerging across several industries. For example, commercial platforms such as the Microsoft Azure Kinect and wearable IMU systems are increasingly used in logistics and manufacturing to monitor ergonomic risks associated with lifting, bending, and overreaching. Similarly, computer vision-based systems have been deployed in food processing and construction settings where full-body motion tracking is needed without interfering with workflow. While these deployments highlight growing adoption, they also highlight challenges related to environmental variability, occlusion, and system calibration in uncontrolled settings. While this review focuses on comparing technologies across task domains, certain industry-specific factors may influence real-world adoption. For example, the need for contactless systems is particularly important in food processing and healthcare settings, where hygiene and sterility are critical (Poursadeqiyani et al. 2021; Poursadeqiyani and Arefi 2020). In construction and field services, dynamic lighting and occlusion can impair vision-based tracking, requiring robust hardware and calibration protocols. Sectors like logistics or manufacturing may be more amenable to wearable or hybrid systems, given their more structured environments. These practical considerations highlight that ergonomic assessment technologies must be tailored not only to task type but also to industry-specific constraints.



Figure 6. (1) Assembly line task (Lämkull, Hanson, and Örtengren 2009), (2) Dairy farming task (Mokarami et al. 2019), (3) Coffee harvesting task (Bao, Silverstein, and Stewart 2013). The faces from the original images have been blurred to respect privacy of the persons.

4.7. Strengths and limitations of the current scoping review

This scoping review possesses a significant strength in its concentration on literature that encompasses the assessment techniques for various body parts' ergonomics across diverse industries, serving as a foundation for a potential systematic review. Another noteworthy aspect of this study is its summary of automation used in data collection, analysis, and validation concerning different data types (e.g. visual, sensor-based, perceptual). The delineation of automated methods relevant to the industrial domain and its associated body parts of interest might aid future studies in designing ergonomic assessment experiments.

However, several limitations should be acknowledged. First, while the review covered literature on automated ergonomic assessment, it lacked a qualitative analysis to substantiate the findings. While providing a summary of state-of-the-art tools for assessing ergonomics, this scoping review did not explore the

practical application implications of automation techniques. Second, although the literature search followed PRISMA-ScR guidelines, it focused exclusively on journal articles, potentially overlooking valuable articles from other sources like conference papers and reports. Third, the review only included studies published between 2000 and 2024, omitting traditional ergonomic assessment methods published before 2000, which could have provided comparative or validating insights. Furthermore, the exclusion of non-English sources may have introduced selection or publication bias. Some studies in this review also involved very small sample sizes, including single-participant designs. While these were retained due to methodological innovation (e.g. novel sensors or algorithm development), their findings should be interpreted with caution. Broader validation with more diverse participant pools is necessary to assess generalisability.

Although many reviewed studies report quantitative validation metrics, few addressed qualitative aspects of implementation. For instance, wearable systems may

interfere with natural work behaviour or cause discomfort over extended periods, reducing ecological validity. Similarly, video-based systems pose privacy and consent concerns, especially in real-world workplace environments. These concerns highlight the growing need for adherence to emerging ethical frameworks (e.g. ISO/IEC 23894:2023) on AI risk management or the principles outlined by the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems when deploying automated ergonomic systems in workplace settings (Chatila and Havens 2019; Oviedo et al. 2024). These practical and ethical considerations are critical for adoption but are underreported in the literature. Future research should prioritize usability studies and the development of ethical frameworks for deploying automated ergonomic systems in occupational settings. Finally, validation methods varied widely across studies—some relied on expert judgement, others on statistical error metrics, and a few lacked clear validation procedures altogether. This heterogeneity hinders direct comparisons and highlights the need for standardized reporting guidelines.

5. Conclusion

This review highlighted the role of automation in advancing ergonomic assessments. In many studies, manual analysis served as the basis for developing and validating automated systems, demonstrating the potential of automation to improve the measurement of ergonomically quantifiable attributes. The reviewed studies spanned diverse industries and contexts, reflecting the broad applicability of ergonomic assessments in addressing workplace challenges. Beyond automation, study design factors, such as sample size, participant selection, and body part of interest, were also found to significantly influence tool performance and validation accuracy.

In addition to synthesising automation trends, this review offered several implications for advancing of the human factors domain. First, it highlighted the feasibility of implementing automated motion and posture assessment tools using cost-efficient video and wearable systems, for scalable deployment in resource-constrained environments. Second, the findings could inform the design of ergonomic interventions tailored to specific tasks and body parts, supporting practitioner decision-making in diverse sectors such as manufacturing, construction, and healthcare. Third, by comparing validation strategies, the review provided a foundation for standardizing methodological practices, thereby improving the generalizability and reliability of future ergonomic studies. However, successful

real-world deployment still faces practical challenges, including hardware costs (e.g. 360-degree cameras, motion capture systems), the need for specialized training, integration with existing workflows, and concerns regarding worker privacy. Organizational resistance and limitations in infrastructure may also hinder adoption (Jalo and Pirkkalainen 2024; Khandan et al. 2017). These insights can guide the next generation of ergonomic technologies and support the development of real-time monitoring systems for occupational risk management.

Future research should prioritize validating automated ergonomic assessments against long-term musculoskeletal injury outcomes to establish predictive value beyond observational accuracy. There is a need to investigate the usability and acceptance of these technologies in real-world, high-variability occupational settings. Studies should also focus on the integration of multimodal sensing approaches, such as combining computer vision with IMU or EMG inputs, and evaluate how such hybrid systems can be standardized for widespread deployment. Developing benchmark datasets and open protocols to support comparative validation would also accelerate progress in the field. While most studies emphasized validation metrics such as accuracy or error reduction, relatively few addressed user experience, comfort, or deployment barriers. This highlights a critical gap in understanding real world feasibility and user centered acceptance, which should be a priority for future research to ensure practical adoption of automated ergonomic systems. Further research could explore the integration of emerging technologies, such as AR and VR, to enhance ergonomic evaluation techniques, particularly in capturing complex movements and spatial data. Expanding this field with additional surveys and studies could provide details about long-term impacts of ergonomic interventions and support the development of methodologies aimed at preventing and mitigating work-related musculoskeletal disorders. Future development should prioritize creating more diverse and comprehensive datasets to improve the generalizability of ergonomic models across populations and tasks. There is also a pressing need for standardized validation protocols to ensure consistent assessment accuracy across studies. Underrepresented body regions, such as the head, neck, and wrists, warrant greater attention, particularly in occupations involving fine motor tasks or constrained postures. Exploring AI explainability may enhance usability and trust of automated tools in safety-critical applications. Cross-cultural validation is also essential for adapting tools to diverse posture norms, work practices, and ergonomic

standards across global industries. Furthermore, integrating physical and cognitive ergonomic factors, such as combining motion tracking with workload or attention metrics, can strengthen human factors research and system design. Finally, while these tools show promise for ergonomic risk identification, it is important to note that no epidemiological studies to date have confirmed a direct impact on reducing MSD rates. As such, related claims should be interpreted with caution.

Acknowledgments

The authors thank Rebekah Sumrell and Aena Hussain for data collection and charting.

Author contributions

Hari Iyer (H.I.), Eunsik Kim (E.K.), Chang S. Nam (C.N.), and Heejin Jeong (H.J.) contributed to the conception and design of the study. H.I. led the literature search, data extraction, and drafting of the manuscript. E.K. and C.N. assisted with article screening, analysis, and interpretation of the findings. H.J. supervised the study and provided critical revisions for intellectual content. All authors reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This study was in part supported by the National Institute for Occupational Safety and Health (NIOSH), as part of the Pilot Projects Research Programs [#T42OH008672 and #T42OH008673]. Its contents are solely the authors' responsibility and do not necessarily represent the official views of NIOSH.

ORCID

Hari Iyer  <http://orcid.org/0000-0002-8515-2382>
 Eunsik Kim  <http://orcid.org/0000-0002-5925-4668>
 Chang S. Nam  <http://orcid.org/0000-0001-9005-0703>
 Heejin Jeong  <http://orcid.org/0000-0002-0122-532X>

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