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บทความปริทัศน์
(Review article)

Systematic review of machine learning strategies for adapting collaborative robots to human body size variations

การทบทวนวรรณกรรมอย่างเป็นระบบของกลยุทธ์การเรียนรู้ของเครื่องจักรสำหรับการปรับการทำงานร่วมของโคบอทให้เหมาะกับขนาดร่างกายมนุษย์

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ABSTRACT: This systematic review examines the adaptation of collaborative robots (cobots) to enhance human–robot collaboration (HRC) by addressing ergonomic challenges arising from human body size variations. Following PRISMA guidelines, we comprehensively searched peer-reviewed studies from 2021 onward in Scopus and Google Scholar. Methods were synthesized and methodological strengths and weaknesses evaluated. Keyword analysis reveals growing interdisciplinary integration of ergonomics, artificial intelligence, and collaborative robotics. The findings indicate that future research should prioritize the development of real-time adaptive systems capable of continuous posture monitoring, comfort improvement, and enhanced worker safety in dynamic industrial environments.

Keywords: Cobot; Machine learning; Posture assessment; Ergonomics; Human robot collaboration

บทคัดย่อ: การทบทวนวรรณกรรมอย่างเป็นระบบนี้ตรวจสอบการปรับตัวของหุ่นยนต์ทำงานร่วมกันเพื่อยกระดับความร่วมมือระหว่างมนุษย์กับหุ่นยนต์ (HRC) โดยมุ่งแก้ปัญหาด้านการยศาสตร์ที่เกิดจากความแตกต่างของขนาดร่างกายมนุษย์ ผู้วิจัยใช้แนวทาง PRISMA ค้นหางานวิจัยที่ผ่านการทบทวนโดยผู้ทรงคุณวุฒิตั้งแต่ปี 2021 เป็นต้นมา จากฐานข้อมูล Scopus และ Google Scholar ดำเนินการสังเคราะห์วิธีการต่าง ๆ และประเมินจุดแข็ง-จุดอ่อนของระเบียบวิธีวิจัย การวิเคราะห์คำสำคัญแสดงให้เห็นการบูรณาการแบบสหวิทยาการที่เพิ่มขึ้นระหว่างศาสตร์การยศาสตร์ ปัญญาประดิษฐ์ และหุ่นยนต์ทำงานร่วมกัน ผลการทบทวนชี้ว่า การวิจัยในอนาคตควรให้ความสำคัญกับการพัฒนาระบบปรับตัวแบบเรียลไทม์ที่มีความสามารถในการติดตามท่าทางอย่างต่อเนื่อง เพิ่มความสะดวกสบาย และยกระดับความปลอดภัยของผู้ปฏิบัติงานในสภาพแวดล้อมอุตสาหกรรมที่มีความเปลี่ยนแปลงสูง

คำสำคัญ: โคบอท; การเรียนรู้ของเครื่องจักร; การประเมินท่าทาง; การยศาสตร์; ความร่วมมือระหว่างมนุษย์และหุ่นยนต์

1. INTRODUCTION

The rapid integration of collaborative robots (cobots) into industrial and manufacturing environments has transformed human–robot collaboration (HRC), enabling shared workspaces where humans and robots perform tasks synergistically. Unlike traditional industrial robots, cobots are designed to work alongside humans, offering flexibility, safety, and efficiency in tasks such as assembly, material handling, and pick-and-place operations.

However, the effectiveness of HRC depends on addressing ergonomic challenges particularly those arising from anthropometric variations among workers, such as differences in height, arm length, and reach capabilities. Poor ergonomic design in HRC can lead to musculoskeletal disorders (MSDs), reduced productivity, and higher rates of workplace injuries, with studies reporting that 30–50% of industrial workers experience MSDs due to repetitive or awkward postures [1].

Adapting cobot behavior to individual body dimensions is therefore essential for optimizing ergonomic outcomes, enhancing worker comfort, and ensuring inclusive workplace design for diverse populations, including both tall and short individuals. Consequently, the design of industrial workstations should be guided by the anthropometric characteristics of the intended user population to achieve proper dimensions and layout [2].

The significance of this topic lies in its potential to bridge human factors engineering with advanced robotics, addressing a critical gap in personalized HRC. As industries strive for automation that supports diverse workforces, including those with physical limitations (e.g., elbow contracture [3]), cobots capable of real-time or design-phase adaptations to anthropometric characteristics can reduce ergonomic risks, improve task efficiency, and promote worker well-being. The study found that among 236 injury cases in MMH tasks, ~52.5% were caused by lifting/lowering, ~39% by pushing/pulling, and 8.5% by carrying [4].

Emerging technologies, such as reinforcement learning (RL), vision-based tracking, and anthropometric workstation design, have shown promise in tailoring cobot actions to human needs [5,6]. However, the literature lacks a comprehensive synthesis of these approaches, particularly regarding adaptations for extreme height variations (e.g., <1.5m or >2m) and the integration of subjective comfort metrics with objective ergonomic assessments.

This systematic literature review aims to evaluate and synthesize research on how cobots adapt to variations in human body size, with a focus on ergonomic optimization in industrial settings. The specific objectives are to:

(1) identify the methods and tools used for anthropometric adaptation in HRC, including RL and motion capture;

(2) assess their effectiveness in reducing ergonomic risks (e.g., through RULA/REBA scores) and enhancing productivity; and

(3) highlight current research gaps, such as limited studies addressing extreme anthropometric ranges or subjective comfort.

Table 1 Definition of Key terms

Key Term	Author/Source	Defintion	Meaning/Significance in Context
Collaborative Robots (Cobots)	ISO/TS 15066:2016 (referenced in Colim et al., 2021)	Robotic systems designed to work interactively with humans in shared workspaces, equipped with safety features and adaptive capabilities to ensure safe and efficient collaboration.	Cobots are central to HRC, enabling adaptive behaviors (e.g., adjusting trajectories or handover positions) to accommodate human body size variations, such as height, to reduce ergonomic risks and enhance productivity in industrial tasks.
Ergonomics	International Ergonomics Association, 2020 (referenced in Boschetti et al., 2022)	The science of designing work environments and tasks to fit human physical and cognitive capabilities, minimizing strain and optimizing performance.	Ergonomics guides cobot design to minimize musculoskeletal disorders (MSDs) by adapting to anthropometric differences (e.g., height, reach), ensuring comfortable postures and reduced strain for tall and short workers.
Anthropometry	DIN 33402 [1]	The measurement of human body dimensions (e.g., height, arm length, reach) to inform design and adaptation.	Anthropometric data enables cobots to tailor actions (e.g., end-effector height, workstation layout) to individual body sizes, critical for ergonomic optimization across diverse populations.
Human-Robot Collaboration (HRC)	Villani V [8]	A paradigm where humans and robots share tasks, requiring mutual adaptation to ensure safety, efficiency, and ergonomic alignment in collaborative workspaces.	HRC emphasizes dynamic cobot adaptations (e.g., via RL or vision-based tracking) to human body sizes, ensuring ergonomic safety and efficiency in tasks like assembly or co-manipulation for varied statures.

Table 1 provides a structured overview of the foundational concepts central to this systematic review of cobots adapting to human body size for ergonomic optimization. Each key term is defined with reference to authoritative sources, and its meaning or significance is contextualized within the scope of HRC and ergonomic design. The table serves as a detailed explanation of the terminology, establishing the necessary technical and conceptual boundaries for the research inquiry.

Research Question

Against this established conceptual background, this review seeks to answer: What machine learning techniques, leveraging vision-based input, are currently employed to enable collaborative robots to adapt to diverse human physical scales and ergonomic needs in real time?

2. METHODS

2.1 Searching strategy

To meet the study's objectives, a systematic literature review was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines[9], which since 2009 have established a widely accepted framework for transparent and replicable reviews. Relevant publications were identified through four major bibliographic databases Scopus, Google Scholar, IEEE Xplore, and arXiv. The focus is on empirical and simulation-based research within the domain of HRC.

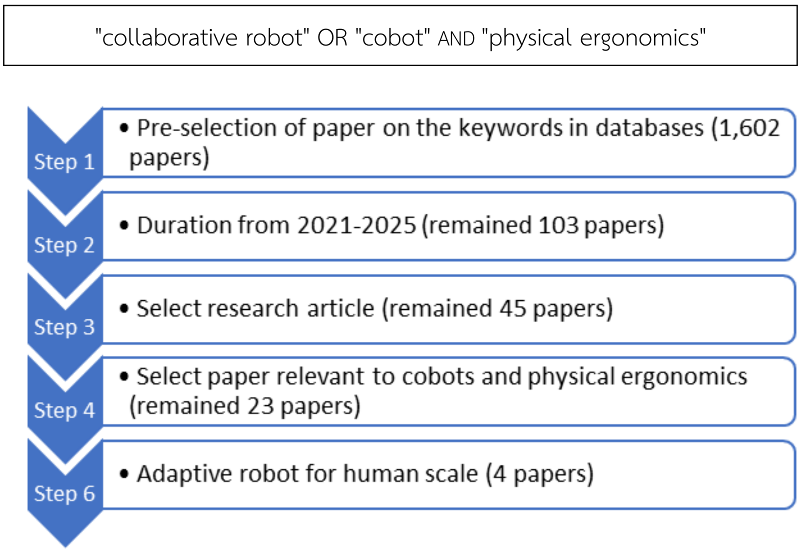

Fig. 1 PRISMA model

The initial search criteria were "collaborative robot" OR "cobot" AND "physical ergonomics." This search yielded 1,602 papers in the database. The first exclusion criterion applied was the publication date, limiting results to the most recent five years. This step reduced the number of papers to 103. We then selected only research articles, excluding review articles, which left 45 papers. An additional exclusion criterion was relevance to both cobots and physical ergonomics. Some papers were excluded because they focused on topics outside our interest, such as safety issues or virtual reality alone. This refinement resulted in 23 relevant papers. The final criterion involved selecting studies on adaptive robots for human scale, which yielded approximately 3-4 papers. This final group addresses both machine learning and other adaptation techniques

2.2 Data Analysis

For the data analysis, the initial bibliographic data exported from Scopus and Google Scholar were quantified for frequency (e.g., publication year, author, and institution) and subsequently subjected to descriptive statistical analysis. Following this step, the collected papers were analyzed based on their keywords to map the relationships and emerging topics across the field. This keyword data was processed to visualize interdisciplinary integration and research trends using network analysis techniques. This approach allowed us to identify dominant themes and the current trajectory of research at the intersection of ergonomics, artificial intelligence, and collaborative robotics.

3. RESULTS

The trajectory of research in this field mirrors emerging interdisciplinary areas like human-robot interaction (HRI), where machine learning facilitates personalized ergonomics, such as fatigue prediction or adaptive task allocation, and this growth surpasses that of general robotics publications, underscoring cobots as a key area of focus. Looking ahead, if the linear trend persists in Scopus and Google Scholar database. Fig. 2 presents publication trends from Scopus, because it provides structured metadata and consistent indexing suitable for bibliometric analysis. Google Scholar was excluded due to duplicate entries and inconsistent metadata.

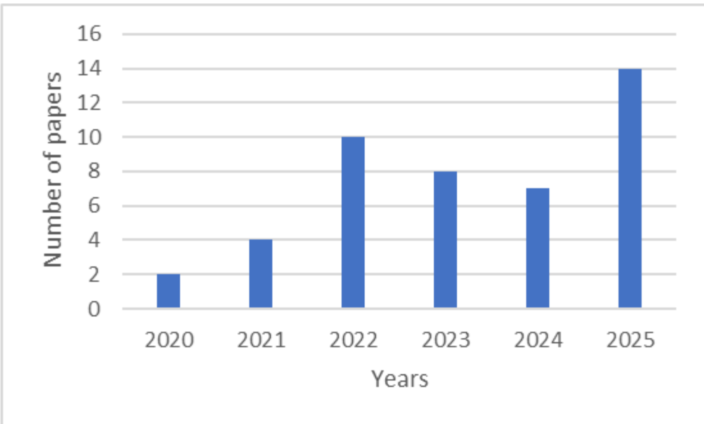

Fig. 2 Number of publications in 6 years in Scopus and Google Scholar database

3.1 Trend analysis

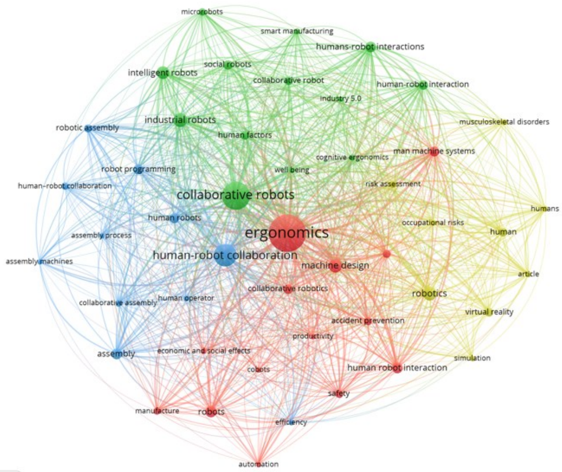

Fig. 3 Keyword co-occurrence network of cobot literature (2020–2025).

A keyword co-occurrence analysis was conducted using VOSviewer to identify thematic clusters in the collaborative robotics (cobot) literature. The resulting network map (Fig. 3) revealed four dominant clusters. The green cluster encompassed terms such as intelligent robots, industrial robots, human factors, and Industry 5.0, representing the technological and industrial integration of cobots. The blue cluster centered on assembly, robotic assembly, collaborative assembly, and human operators, highlighting manufacturing and production applications. The red cluster, which included ergonomics, safety, machine design, and productivity, reflected the emphasis on human-centered design and workplace safety. The yellow cluster groups digital human modelling and risk assessment methods (simulation, virtual reality, digital twins, musculoskeletal disorders, occupational risks), reflecting the increasing use of virtual prototyping for ergonomic evaluation before physical implementation. As expected from the search string, ‘ergonomics’ and ‘collaborative robots/cobots’ were the most central nodes; however, their strong links to emerging terms such as ‘deep learning’, ‘reinforcement learning’, and ‘human pose estimation’ highlight new interdisciplinary directions.

Because the search string included the terms *'cobot'* and *'ergonomics'*, these keywords naturally appear as the most frequent nodes. Therefore, the interpretation emphasizes the relative structure of clusters rather than absolute frequency counts. The yellow cluster indeed represents a smaller theme digital evaluation (VR, simulation) and therefore appears less cohesive than the other clusters.

3.2 Synthesis of adaptive approaches in the four included studies

Table 2. Overview of Key Studies on Adaptive Cobot Frameworks for Ergonomic Human-Robot Collaboration

Paper	Primary Goal	Methodology	Human State Assessment	Key Results & Outcomes
Colim et al.[1]	Improve ergonomics and safety in furniture assembly.	Four-step framework: (i) initial condition, (ii) risk assessment, (iii) requirements, (iv) hybrid workstation design.	Revised Strain Index, Borg CR-10, William Fine (initial); RULA, VAS, Xsens (redesigned).	Hazardous tasks eliminated; RULA shows low risk; optimal dispenser position improved wrist postures.
Martins et al. [3]	Develop RL controller for ergonomics, aiding workers with MSDs.	Two-stage RL: Pre-training (simulation) with Q-Learning/DQN, fine-tuning with human-in-loop.	RULA for ergonomic risk; pain risk via elbow angle constraints; MVN Awinda tracking.	DQN faster (14.1s vs 21.4s, 3 vs 8 steps); ergonomic risk <2.5, zero pain risk across diverse users.
Meregalli Falerni et al. [10]	Optimize cobot pose in HRC for user preferences and ergonomics.	AmPL-RULA: Combines Active multi-Preference Learning (5-Likert scale feedback) with RULA (via Kinect and GPR) to optimize cobot pose (x, y, z, θ_x, θ_y, θ_z).	Cognitive: Pairwise preferences for comfort/motivation; Physical: RULA scores (1-7) for posture risk, tracked via Kinect, predicted via GPR.	20 volunteers; RULA ≤4 (low risk); GPR error 0.9; pose errors < perception thresholds; user satisfaction improved.
Kim et al. [11]	Adapt HRC in real-time to improve ergonomics and productivity.	Unified framework: RGB-D vision for pose tracking, tool recognition, torque estimation, adaptive control.	Overloading joint torques via RGB-D, avoiding wearables.	30.24% torque reduction; adapts to movements, hand switches, tool changes in real-time.

The four included studies represent a clear progression from static ergonomic redesign to real-time, learning-enabled adaptation of collaborative robots to individual anthropometric differences (Table 2). Sensing modalities differ markedly: Colim et al.[1] rely on high-precision inertial measurement units (XSens), whereas the three more recent studies[3, 10, 11] adopt non-intrusive vision-based systems (depth cameras, OpenPose, and CaffeNet-based tool recognition). Vision-based approaches enable markerless, continuous monitoring in actual industrial environments and naturally support scalability to diverse body sizes through biophysical constraints and subject-specific scaling.

All studies use validated observational ergonomic tools as their core risk metric: RULA is applied in Colim et al.[1] and Martins et al.[3], REBA in Meregalli Falerni et al.[10], and continuous joint-torque overload (derived from a Statically Equivalent Serial Chain model) in Kim et al.[11]. Notably, in the machine-learning-driven frameworks [3, 11], these traditionally offline scores are transformed into online feedback signals — either embedded directly in the reinforcement learning reward function [3] or used to optimize robot trajectories in real time [11].

The degree of anthropometric personalization increases across the studies. Colim et al.[1] incorporate population-level anthropometric standards (ISO 14738) during workstation design but do not adapt during operation. Meregalli Falerni et al.[10] implicitly handle body size variations through depth-camera tracking but do not explicitly rescale the human model. In contrast, Martins et al. [3] and Kim et al. [11] achieve true individualization: the former scales a kinematic human model and task parameters according to measured height, shoulder width, and limb lengths; the latter performs a one-time offline identification of subject-specific SESC parameters and enforces biophysical bounds on 3D keypoints, ensuring robust pose estimation across a height range of approximately 165–190 cm in their cohort.

Reported ergonomic gains are substantial when real-time adaptation is implemented: DQN-based control reduces task completion steps and ergonomic penalty simultaneously[3], REBA-triggered robot adjustment lowers risk scores immediately[10], and vision-guided torque optimization yields an average 30.2 ± 2.4 % reduction in overloading joint torques across ten participants of varying stature [11].

Collectively, the studies demonstrate that machine learning (deep neural networks for perception and reinforcement learning for decision-making) is the key enabler that shifts collaborative robots from fixed, population-based ergonomic design to genuinely personalized, real-time co-adaptation with workers of different body sizes. This transition markedly reduces musculoskeletal loading and sets the foundation for inclusive human–robot collaboration in Industry 5.0 settings.

3.3 Critical appraisal of methanological approaches

This section analyzes the methods in terms of their strengths and weaknesses. It also includes topics related to how the robot adapts to the diversity of human size and the use of machine learning techniques. This will answer the objective of the study.

Table 3 Method strength and weakness

Reference	Method	Strengths	Weakness	Anthropometrics	ML integration
Physical Ergonomics Improvement and Safe Design of an Assembly Workstation through Collaborative Robotics [1]	Develop a four-step framework for redesigning a manual workstation.	Real industrial case study using motion sensors and subjective measure. Assess the risk with RULA.	Human and Robot work sequential not simultaneously.	Refer to ISO 14738 but lack real time adaptive control.	No
A Human-Sensitive Controller: Adapting to Human Ergonomics and Physical Constraints via Reinforcement Learning [3]	Comparing two machine learning method between Q-learning and Deep Q-Networks	Dynamic personalization; ergonomic adaption	Simplifications in the Human Kinematic Model used in the simulation environment	Comparison of two machine learning for different body height (i.e, 1.62, 1.69, 1.79 and 1.83 meters).	Reinforcement learning, Deep Q-Network
A framework for human–robot collaboration enhanced by preference learning and ergonomics [10]	Preference learning and ergonomics framework	Using REBA method for posture analysis with depth camera.	RULA Classification Errors. 15.1% percentage of wrong classification.	Explicitly designed for human size differences	No machine learning but using analytical and iterative kinematic solver (FABRIK)
A Reconfigurable and Adaptive human-robot collaboration framework for improving worker ergonomics and productivity [11]	Reconfigurable HRC workstation (height/layout adjustable)	Direct anthropometric support.	The research detailed focuses specifically on the computation of the optimal posture when the workpiece pose cannot be changed	Explicitly designed for human size differences	Deep learning model.

Table 3 summarizes the principal methodological strengths and limitations of the four included studies. The earliest work (Colim et al. [1]) stands out for its rigorous real-world industrial validation and multi-phase methodology (initial characterization, motion-capture assessment, digital human modelling, and final workstation redesign). However, it represents a fundamentally static approach: ergonomic improvements are achieved through one-time workstation redesign rather than online adaptation, and human–robot interaction remains sequential rather than truly collaborative. In contrast, the three more recent studies introduce genuine real-time adaptation, with increasing reliance on machine learning. Martins et al. [3] provide the clearest demonstration of reinforcement learning (DQN outperforming classical Q-learning) applied directly to ergonomic objectives, successfully personalizing robot behaviour to individual anthropometry. The main limitation lies in the simplified human kinematic model and the simulated nature of the evaluation, which reduces immediate transferability to physical cobots.

Meregalli Falerni et al.[10] achieve real-time robot adaptation using only lightweight computational tools (REBA scoring + FABRIK inverse kinematics), making the system attractive for industrial deployment. However, dependence on discrete REBA classification and depth-camera data leads to posture misclassification errors (~15%), and anthropometric personalization remains implicit rather than explicit. Kim et al. [11] present the most mature and comprehensive framework, combining markerless deep-learning perception (OpenPose + CaffeNet), subject-specific biomechanical modelling (SESC), and continuous joint-torque minimization. This yields impressive, quantifiable ergonomic gains ($30.2 \pm 2.4\%$ reduction in overloading torques) across participants of varying body size. The primary remaining constraints are the offline calibration step for SESC parameters and the assumption of a fixed workpiece position in some experiments.

Overall, the four studies trace a clear evolutionary path: from offline, population-based ergonomic design ⟶ vision-enabled reactive adaptation ⟶ learning-based proactive personalization. The major outstanding methodological gaps are (1) the lack of long-term, online learning from real human feedback in physical settings and (2) limited validation across extreme anthropometric ranges (<5th or >95th percentile).

These complementary strengths point to a logical future direction: a two-layer hybrid architecture that unites the fast, biomechanically accurate reactive control of Kim et al. [11] with the slow, preference-aware reinforcement learning layer of Martins et al. [3]. Such a hierarchical system would deliver immediate ergonomic safety through model-based optimization while progressively refining trajectories and task parameters to each worker’s unique anthropometry, fatigue profile, and subjective comfort—bridging the current gap between short-term risk reduction and long-term personalization.

4. DISCUSSION

The findings from the trend and data analyses indicate that research on cobots has experienced rapid growth over the past decade, reflecting a clear shift toward interdisciplinary integration between ergonomics, Human Robot Interaction, and AI. The steady increase in publications suggests that ergonomics has become a central theme in HRC research, moving beyond traditional productivity or automation goals toward human-centered design. The keyword network analysis further supports this evolution, with ergonomics and cobots emerging as core terms co-occurring across industrial, safety, and simulation contexts. This highlights a paradigm shift: modern cobots are not only designed to share workspaces with humans but also to dynamically adapt to human variability, posture, and fatigue.

A critical component across the reviewed studies is the use of standardized ergonomic assessment tools such as the Rapid Upper Limb Assessment (RULA) and the Rapid Entire Body Assessment (REBA), which serve as quantitative measures for evaluating musculoskeletal disorder (MSD) risks during human–robot interaction. In traditional ergonomic analysis, RULA is widely applied for assessing static or repetitive upper-limb postures, particularly in tasks involving the arms, neck, and trunk. For instance, Colim et al.[1] employed RULA within both motion capture and simulation environments to identify high-risk postures and guide workstation redesign. Similarly, Martins et al.[3] integrated RULA scores directly into the reinforcement learning reward function, allowing the robot to autonomously minimize high-risk postures based on human feedback, transforming RULA from a diagnostic tool into a real-time control parameter.

On the other hand, REBA, used in Meregalli Falerni et al.[10], extends this analysis to the whole body and incorporates dynamic balance, leg posture, and force exertion making it particularly relevant for collaborative tasks that involve full-body movement or load handling. The REBA-based approach enhances sensitivity to a wider range of ergonomic risks but can introduce classification errors (around 15% as noted in the study) when applied through depth sensors due to occlusion or motion blur. Other tools such as the Revised Strain Index (RSI) and Borg CR-10 scale are also employed to assess hand strain and perceived exertion, respectively, complementing the biomechanical analysis with subjective human input.

Collectively, these tools form the foundation of ergonomic evaluation in human–robot collaboration research. However, their traditional offline nature poses a limitation for real-time adaptive systems. To overcome this, emerging frameworks such as those by Kim et al.[11] integrate sensor-based posture detection and deep learning perception models (e.g., OpenPose) to automatically estimate ergonomic scores in real time. The fusion of classical ergonomic indices (RULA, REBA) with AI-based motion analysis thus represents a key advancement, enabling cobots to monitor, predict, and mitigate ergonomic risks continuously during operation rather than after task completion. This evolution transforms ergonomic assessment from a static evaluation process into an active feedback mechanism for intelligent human–robot collaboration.

Across the reviewed studies, several methodological trends are evident. Early ergonomic frameworks, such as the one proposed by Colim et al.[1], focus on redesigning manual workstations using sensor-based and simulation tools for risk reduction. These studies are grounded in standards like ISO 14738 and use metrics such as RULA and RSI to quantify musculoskeletal strain. However, such systems remain static and sequential, offering limited adaptability during real-time operations. Later works, such as Martins et al.[3], introduce reinforcement learning (RL) to model ergonomic adaptation dynamically. By incorporating Q-learning and Deep Q-Networks, the robot learns to minimize awkward postures through feedback-based control, demonstrating significant improvement in personalization and safety, particularly for users with musculoskeletal vulnerabilities. Nevertheless, the simplified human kinematic model constrains transferability to complex, real-world environments.

The emergence of hybrid frameworks, such as Meregalli Falerni et al.[10] and Kim et al.[11], further reflects the maturation of ergonomic HRC research. Both integrate multi-sensor systems, posture recognition, and adaptive control, enabling robots to modify their configuration in response to human movements. Kim's study, in particular, incorporates deep learning-based vision and dynamic joint torque estimation to achieve real-time adaptation, achieving a 30% reduction in overloading joint torques across diverse participants. These findings mark a transition from static ergonomics to adaptive, data-driven ergonomics where cobots proactively assist rather than passively coexist.

In summary, the discussion highlights a clear trajectory in cobot ergonomics research from static design-based ergonomics toward intelligent, learning-enabled systems capable of real-time human adaptation. Future studies should aim to validate these hybrid frameworks in industrial environments, emphasizing scalability, transparency of AI-driven decisions, and inclusivity across diverse anthropometric populations to ensure that next-generation cobots truly enhance both human well-being and system performance.

5. CONCLUSION

This systematic literature review highlights the growing emphasis on ergonomics within human–robot collaboration (HRC) research, reflecting a shift toward human-centered and adaptive robotic systems. Publication trends and keyword analyses reveal increasing interdisciplinary integration between ergonomics, artificial intelligence, and collaborative robotics. Across the reviewed studies, tools such as RULA, REBA, and RSI remain essential for assessing musculoskeletal risk, though the field is advancing from static evaluations toward real-time, sensor-based, and learning-driven approaches.

The comparison of methodologies shows that traditional ergonomic frameworks (e.g., Colim et al.[1]) provide valuable design insights but lack adaptive control, while newer models such as Martins et al.[3] and Kim et al.[11] incorporate machine learning and deep learning to enable personalization and real-time ergonomic optimization. These findings suggest that future research should focus on developing hybrid frameworks that integrate model-based control with reinforcement learning, supporting continuous posture monitoring, comfort enhancement, and worker safety in dynamic industrial environments.

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