ISSN 1846-6168 (Print), ISSN 1848-5588 (Online)
https://doi.org/10.31803/tg-20250105140152

Subject review
Received: 2025-01-05, Accepted: 2025-01-08

Use of Artificial Intelligence (AI) in the Workplace Ergonomics of Industry 5.0

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Abstract: Industry 5.0 emphasizes human-centricity, sustainability, and resilience as its core characteristics, with a focus on developing socio-technical systems that enhance human health, safety, and well-being while fostering sustainable societal practices. The human-centric perspective places significant importance on human factors and ergonomics, aiming to align technological advancements with the needs and capabilities of individuals. In this context, artificial intelligence (AI) emerges as a transformative tool for advancing human factors and ergonomics by optimizing workplace conditions and supporting human-centered design principles. This paper conducts a literature review to explore the applications and potential of AI in addressing human factors and ergonomics challenges, providing insights into its role in shaping the future of human-centric systems within Industry 5.0.

Keywords: ergonomics; human-centered; human factors; Industry 5.0; management; manufacturing; optimization; organization; workplace

1 INTRODUCTION

Industry 5.0 represents a human-centered, resilient, and sustainable paradigm designed to address the shortcomings of Industry 4.0. While Industry 4.0 focused on automation and digitalization, it often neglected the human role and perspective, leading to challenges in its adoption within the manufacturing sector. In contrast, Industry 5.0 emphasizes the integration of socio-technical systems where humans are placed at the center, fostering effective communication and collaboration with machines. This shift is critical in overcoming challenges posed by global uncertainties and volatile market conditions, which demand resilience and sustainability with a broader societal impact [1, 2].

In Industry 5.0, humans remain the key drivers of production systems, necessitating technological solutions tailored to their needs. The evolution of technology has shifted human roles toward more complex tasks, emphasizing interdisciplinary collaboration and the integration of ergonomics to enhance productivity while mitigating workplace illnesses and injuries [3]. Providing workers with both physical and cognitive support tools is essential for enabling efficient and safe operations. Collaborative machines, for example, can reduce ergonomic and cognitive strain, enhance safety, improve process monitoring, and boost productivity. These advancements result in higher product quality and increased competitiveness for businesses [4].

However, many small and medium-sized enterprises (SMEs) face barriers to adopting collaborative technologies, such as limited in-house expertise, high upfront costs, and employee resistance to change. To overcome these challenges, SMEs can collaborate with technology providers for support and training or invest in employee skills development. This process is further strengthened by applying a human-centered design approach that incorporates human factors into production systems, addressing the physical, psychological, social, and cultural needs of workers. Such strategies ensure not only successful implementation but also sustainable growth and resilience in the Industry 5.0 era [5].

Artificial intelligence (AI) refers to the simulation of human intelligence in machines designed to perform tasks that typically require cognitive abilities such as learning, reasoning, problem-solving, decision-making, and understanding language. AI systems leverage algorithms, data analysis, and computational models to process information, adapt to new inputs, and make autonomous or semi-autonomous decisions, often with capabilities exceeding human efficiency in specific domains [6].

In the context of Industry 5.0, AI plays a pivotal role in enhancing human-machine collaboration by enabling smarter, more adaptive, and human-centric production systems. AI drives innovation by [7]: Supporting Human Decision-Making; Enhancing Ergonomics and Safety; Enabling Personalized and Adaptive Systems; Improving Productivity and Quality; Facilitating Resilience and Sustainability; and Bridging Skill Gap. By fostering collaboration between humans and machines, AI empowers a human-centric approach in Industry 5.0, prioritizing worker health, safety, and well-being while driving technological and societal progress. Artificial intelligence (AI) plays a critical role in autonomous systems, yet its integration introduces complex safety challenges, especially in human-AI interactions. These challenges arise as human roles evolve alongside increasingly autonomous machines era [8].

2 METHODOLOGY

To gain insight into the most relevant work published in the literature, the Web of Science database was browsed. The objective was to understand the characteristics of the current use of AI tools in ergonomic design of workplace and organization but also it is potential for the future use. This is why the database Web of Science was searched by keyword "AI in Ergonomics". Among the 674 records, found 35 were chosen for the detailed analysis.

3 RESULTS

The results were grouped by the common topic in three different groups among which use of AI in ergonomics of the workplace is found: (1) Posture prediction, (2) Risk analysis and assessment and (3) Organizational challenges.

3.1 Posture Prediction

Traditional motion capture uses specialized sensors and cameras, but the more accessible method is conventional video recording. Evaluation of AI-based computer vision techniques was used to automate human movement annotation from video. Four machine learning algorithms (random forest, K neighbors, neural network, and decision tree) were trained on performance datasets, producing automated annotations across Laban's four dimensions—effort, space, shape, and body. Results showed that these AI-generated annotations were accurate compared to manual Laban annotations, offering a promising tool for systematic movement analysis from video [11].

Traditional ergonomics assessment methods in digital human modeling (DHM) tools primarily focus on observing work characteristics, with direct measurement methods designed for easy integration into DHM. However, these methods have historically lacked action levels, which are thresholds for necessary ergonomic interventions. This is why there is a solution that integrates recent physical load exposure calculations and action level recommendations into a DHM tool, using the IPS IMMA tool and Xsens MVN motion capture. In two use cases—one with simulated human motions and one with real motion capture data—the demonstrator calculated and color-coded exposure data for specific postures and velocities, highlighting extreme action levels. The results suggest that DHM tools can effectively incorporate automated ergonomics assessments, aligning with Industry 4.0 and 5.0 goals for automation and digitalization in ergonomics [9].

Collaborative robots (cobots), which are part of Industry 5.0 concept, offer a way to reduce operator workload and lower the risk of occupational injuries, such as musculoskeletal disorders (MSDs). Innovative ergonomics optimization framework provide human tracking to monitor and assess operator posture, identifying ergonomic risks and suggesting improved poses. A feedback interface notifies users of non-ergonomic postures and recommends adjustments, while a workpiece position controller adjusts the cobot's end-effector to help improve operator posture. A user study conducted on a human-robot polishing task showed promising results, with positive feedback from users and improved REBA (Rapid Entire Body Assessment) scores, indicating reduced ergonomic risk [10]. Another study demonstrates the value of AI in ergonomic posture assessments, especially for methods like the Ovako Working Posture Assessment System (OWAS), by training algorithms on Xsens MVN MOCAP data. The results indicate that AI can accurately predict postures, offering a foundation for AI-assisted ergonomic assessments and establishing a specialized database to enhance future AI training [13]. MOCAP-/AI-based framework demonstrated improved accuracy, consistency, and efficiency compared to manual methods. This advancement supports the design of healthier, safer, and more productive job tasks and work environments [14].

ERG-AI is an innovative AI/ML pipeline developed to address the gap in sustainable, sensor-based, uncertainty-aware posture prediction combined with large language models (LLMs) for communicating occupational health risks and recommendations. Designed to predict extended worker postures using data from multiple wearable sensors, ERG-AI enables personalized health risk assessment based on individual worker performance. Utilizing LLMs such as GPT-4 and LLAMA-2, the model translates posture predictions and uncertainty estimates into clear occupational health insights. ERG-AI demonstrated robust data handling, enhancing posture prediction accuracy in real-world applications. Findings indicated that while basic postures were effectively identified, complex movements like kneeling and stair climbing posed prediction challenges, underscoring the importance of specific sensors, such as those positioned on the thigh, for balancing system cost and accuracy. Feedback from occupational health experts pointed to a need for even more personalized recommendations tailored to individual attributes and job roles, suggesting a pathway for further refinement of LLMs to provide customized ergonomic guidance [12].

3.2 Risk Assessment

Integrating AI and other digital technologies with a focus on human factors will be essential for advancing biomechanical risk assessment and facilitating technology adoption. Additionally, successfully incorporating these technologies into industrial settings may require workforce reskilling, upskilling, and efficient system design to manage information flow and improve user-technology interactions [16].

Traditional human-based risk assessments for muscle injuries can lead to inaccuracies and even cause injuries due to expertise requirements. Risk Assessment System for Muscle Injuries (RASMI) using AI technology is used to evaluate electric welders' postures based on Rapid Entire Body Assessment (REBA) standards. RASMI identifies potential causes of muscle injuries and issues warnings when a welder's posture poses a risk, providing precise, cost-effective assessments. Results show that RASMI effectively evaluates injury risks and is positively received by workers, who appreciate its role in promoting long-term health and well-being through posture adjustment and behavior modification alerts [15].

Holistic job improvement framework, which automatically performs root cause analysis and recommends control strategies to mitigate musculoskeletal disorder (MSD) risks was also presented. Using deep learning-based Natural Language Processing (NLP) techniques like Part of Speech (PoS) tagging and dependency parsing, the system analyzes textual descriptions of job actions (e.g., "pushing") and objects (e.g., "cart") to infer root causes of MSD risks (e.g., excessive shoulder forces due to small caster size). These insights guide an expert-based Machine Learning (ML) system to identify specific work-related causes and recommend targeted solutions, such as larger diameter casters, to lower risks. Unlike existing AI-based MSD risk assessment tools, which focus solely on scoring, this framework extends beyond scoring to diagnose root causes and provide actionable controls, combining AI, computer science, and ergonomics. The system's robustness stems from integrating action-object inferences from text with risk scores and exposure types from video analysis. Even without text, the system can utilize motion capture from videos to identify root causes, although this leads to less efficient recommendations. This approach streamlines and enhances the job improvement process, making it more efficient and effective in reducing MSD risks [17].

Understanding human cognitive and behavioral responses, such as vigilance, processing intensity, gaze patterns, and visual scanning efficiency, is essential for designing effective AI-assisted inspection systems. Results of one study show that these cognitive factors impact inspection performance, emphasizing the need for protocols, drones, and AI systems tailored to reduce cognitive overload and prevent errors. Additionally, insights into gaze and scanning patterns associated with missed information provide practical guidance for inspectors to improve their performance [18].

The Level of Preventive Action (Lpac) methodology, adapted for construction sites, establishes preventive action levels by monitoring quantitative data related to physical and behavioral conditions using sensors in both the construction environment and on workers. Integrating Lpac with BIM (Building Information Modeling) technology allows for real-time data collection on environmental conditions, safety systems, worker behavior, and emotional states. This setup enables comprehensive preventive action controls and immediate communication of safety measures to workers through a mix of direct and AI-driven methods. By using body sensors, location sensors, and AI, Lpac supports dynamic safety assessments, adjusting preventive actions based on real-time data rather than estimates. This approach enhances safety coordination, improves the safety climate, and optimizes construction site conditions to prevent accidents. Lpac is applicable in both known and unknown environments, adapting flexibly to varying construction conditions and communicating risk levels efficiently, helping foster a collaborative safety culture with worker participation [19].

Knowledge acquisition through domain experts and historical data remains crucial for effective human reliability and human factor analysis across fields. However, fully utilizing this knowledge requires implementing fuzzy expert systems and AI models to enhance HFA outcomes [20].

A cost-effective, vision-based method for automatically monitoring ergonomic and fatigue risks was developed using a 3D camera system and AI-driven posture analysis to track body movements and repetitive motions. Laboratory trials demonstrated that this method achieves joint motion tracking with 3.5° accuracy, performs similarly to human operators in ergonomic risk assessments, and effectively monitors repetitive tasks. The system supports data visualization, real-time analysis, and report generation, making it a valuable tool for enhancing manufacturing environments [21].

3.3 Organizational Challenges

The integration of Artificial Intelligence (AI) into ergonomics is transforming workplace optimization by enhancing worker well-being and operational efficiency. Bibliometric analyses revealed AI's significant impact on ergonomics and safety, establishing this synergy as a key element in the evolution of Industrial Engineering. The report advocates for strategic funding, interdisciplinary collaboration, and workforce development to support this field, emphasizing AI's potential to create safer, efficient, and ethically focused workplaces [22]. It is crucial for researchers to develop AI teammates that incorporate an understanding of human team members' needs into their adaptive behaviors, ensuring effective and supportive collaboration [23].

Traditionally, productivity and worker well-being optimizations are handled separately, often resulting in suboptimal solutions and prioritizing one objective over the other. One study uses data mining methods on real-world multi-objective optimization data to extract actionable insights for optimizing both productivity and worker well-being in workstation design. By analyzing a welding gun workstation, the study identified critical design constraints that, when removed, could improve work efficiency and accommodate diverse anthropometric needs. The findings suggest that using data-driven rules and insights from previous cases can streamline future workstation designs across various tasks, such as assembly lines, improving overall productivity and worker health. Implementing the optimization and knowledge discovery process in a user-friendly digital tool could further support engineers by guiding them through the process based on their expertise [31]. The integration of artificial intelligence (AI) into workplaces offers significant potential for productivity and progress, but also raises critical occupational safety and health (OSH) concerns. AI can increase risks such as stress, discrimination, precarious employment, musculoskeletal disorders, and job intensification, especially when used for heightened monitoring and micro-management. Key risks include unfair treatment in AI-augmented HR decisions, overwork due to insufficient training, privacy issues from intensified surveillance, and the deskilling of jobs, particularly in manufacturing and gig work. To harness AI's benefits without compromising OSH, the report suggests focusing on assistive and collaborative AI, rather than universal AI, to enhance supportive roles. Benefits of AI include improving workplace relationships, aiding decision-making, and allowing workers more time for personal and career development by handling repetitive tasks. For safe AI integration, recommendations include comprehensive training, consistent oversight by OSH authorities, and a worker-centered approach that prioritizes human command over AI. It concludes that OSH risks stem not from AI itself, but from the ways in which it is implemented, underscoring the importance of regulatory oversight and worker involvement [38].

The field of Explainable AI (XAI) seeks to make AI decisions understandable, yet often overlooks the human element. Unlike typical AI-centric XAI approaches, this framework lets users define and rank features according to their preferences, compare these with the AI's weighted features, and explore the rationale behind AI decisions through a chatbot. The study found that agreement between user and AI factors depends on shared knowledge and experience, emphasizing the need for alignment in human-centered XAI to enhance understanding and trust. These insights offer a foundation for future human-centered XAI advancements [24].

Integrating the Worker Fatigue Model into Airbus's industrial system architecture enhanced their ability to predict system performance based on workforce composition, which may include human-robot teams or a mix of experienced and less experienced workers. The model, adapted from existing fatigue models, accounts for worker characteristics, tasks, and robot assistance, simulating scenarios like fully manual and semi-automated work. Variables such as worker skill, age, and motivation were used to measure fatigue and error probabilities. Results indicated that workforce composition—particularly higher ratios of high-skilled workers—significantly reduced fatigue and improved system performance, demonstrating the model's value for workforce planning and technology integration [25].

How people build trust with AI partners compared to human partners is through a two-stage process: initial trust and feedback-based iteration. Using repeated trust games, the study measured investment behaviors, emotional responses, and neuroactivity. Results indicated that initial trust in AI partners had a stronger influence on final trust than with human partners, while feedback from human partners had a greater impact on trust and emotional arousal than feedback from AI. Positive emotions were more pronounced in interactions with humans, and neuroactivity in the prefrontal cortex was higher when participants made investment decisions with human partners, underscoring the stronger influence of human feedback on decision-making and emotional responses [27].

Human Factors and Ergonomics (HFE) should contribute to the sustainable and ethical development of AI: deciding when to automate versus augment human work, ensuring control and accountability in AI outcomes, and addressing power imbalances among AI stakeholders. Suggested actions for the HFE community include converting ethical considerations into design principles, embracing broader, multi-stakeholder perspectives, and fostering interdisciplinary collaboration within a design science framework. These measures aim to enhance HFE's role in creating AI systems that are socially and economically beneficial [29].

The integration of AI into Nuclear Power Plant (NPP) operator support systems has shown significant potential for reducing human error, enhancing safety, and improving operational efficiency. AI-powered systems—ranging from decision support and fault detection to predictive maintenance and automated text analysis—can aid plant operators in rapid situation assessment and response, support continuous monitoring of worker safety, and enable early detection of emerging issues. Despite these advancements, challenges remain in scaling these technologies, ensuring explainability, and bolstering cybersecurity in mission-critical NPP environments. Further research and novel approaches are needed to optimize human-automation interaction, balance task allocation between operators and AI, and design interfaces that support seamless collaboration. While full autonomy in NPPs is a distant goal, AI-enabled intelligent support systems promise to pave the way toward safer, more reliable, and efficient NPP operations in the future [6].

As machine learning (ML) becomes prevalent in industrial systems, Human Factors must innovate to help users understand and interact with autonomous ML capabilities. This includes advancing cooperation between humans and ML algorithms, integrating human sensing into ML, and leveraging ML for assessing human states and capabilities. This study addresses ergonomic injury in semiconductor manufacturing, particularly in the etching process, where repetitive tasks heighten injury risk. Using visual recognition technology and Convolutional Neural Networks (CNNs), the study achieved 95% accuracy in identifying unsafe actions among maintenance personnel, significantly reducing the non-conformity rate from 40% to 15%. These results, communicated via a cloud-based alert system, demonstrate ML's potential to improve ergonomic safety and reduce workplace injuries in semiconductor manufacturing [35].

The new protocol optimizes human-robot positioning and orientation to improve human ergonomics by using an RGB-D camera that monitors joint angles in real-time and assesses ergonomic states. The system identifies six main causes of poor ergonomics and enables six corresponding robot responses to help users achieve an optimal ergonomic posture. This adaptive algorithm allows the robot to adjust the work environment, such as modifying the position of a workpiece, to enhance user comfort continuously. An experimental study validated this approach, demonstrating significant ergonomic improvements through real-time human-robot interaction adjustments [39]. The researchers also developed Contextual Ergonomics Models, using Gaussian Process Latent Variable Models trained on high-dimensional musculoskeletal simulations for specific task contexts. These models enable ergonomic optimization in a low-dimensional latent space, allowing for efficient reconstruction of high-dimensional musculoskeletal models without extensive computational cost. Experiments with eight subjects performing a drilling task demonstrated that optimizing with Contextual Ergonomics Models significantly reduced muscle activation, showcasing the potential of these models in enhancing ergonomic outcomes in robotic systems [41].

4 CONCLUSION

The use of artificial intelligence (AI) in workplace ergonomics holds significant promise, particularly within the context of Industry 5.0. Through this literature review, the topic has been systematically explored and categorized into three primary groups: posture prediction, risk assessment, and organizational challenges. Each of these domains highlights the potential of AI to advance ergonomic practices by leveraging data-driven approaches to address traditional limitations. AI-driven tools in posture prediction enable the identification and correction of potentially harmful movements, contributing to proactive injury prevention. Similarly, AI-based risk assessment methodologies provide insights into workplace hazards, enhancing the ability to mitigate risks effectively. Addressing organizational challenges requires integrating AI to foster adaptive and personalized solutions that not only ensure worker safety and health but also improve overall well-being and job satisfaction. Despite these advancements, this field remains at an early stage, with significant untapped potential. To fully realize the benefits of AI in workplace ergonomics, future research should focus on developing novel frameworks tailored to the unique demands of manufacturing environments. These frameworks should integrate AI's predictive, analytical, and adaptive capabilities to create comprehensive, human-centric solutions that align with the principles of Industry 5.0. In conclusion, the integration of AI in workplace ergonomics is crucial for shaping the future of safe, efficient, and worker-oriented industries. Continued interdisciplinary efforts are essential to advance this field, paving the way for smarter, healthier, and more sustainable workplaces.

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