

Risk Management of Work-Related Musculoskeletal Disorders Using an Artificial Intelligence Approach (Narrative Review)

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Abstract

Background: In today's world, it is crucial to apply methods that help predict, assess, and prevent work-related musculoskeletal disorders (WMSDs) within the framework of risk management. The advent of artificial intelligence (AI) has introduced a new perspective on employee occupational health and safety. This study aimed to manage the risk of musculoskeletal disorders based on an AI-driven approach.

Materials and Methods: In the present study, the databases ISI Web of Science, Scopus, Medline (via PubMed), Science Direct, and Google Scholar were used. The keywords for the article searches included 'work-related musculoskeletal disorders (WMSDs)', 'artificial intelligence (AI)', 'WMSDs risk management', 'WMSDs prediction', 'WMSDs risk assessment', and 'WMSDs prevention'.

Results: Studies have indicated that the application of AI for risk management—specifically in the prediction, identification, evaluation, and prevention of musculoskeletal disorders—has proven to be both effective and beneficial. Further, AI helps managers monitor the health status of their workforce and avoid placing excessive pressure on employees. Nevertheless, as with any new tool, AI has its drawbacks in risk management for disruptions.

Conclusions: The application of AI in WMSDs risk management warrants further investigation and testing to ensure that AI algorithms can be developed into a single, standardized solution with high reliability and accuracy for managing WMSDs risks.

Keywords: Musculoskeletal Disorders, Risk Management, Artificial Intelligence

Introduction

In the year 2020, musculoskeletal disorders emerged as the second most prevalent cause of non-fatal disability, affecting a staggering number exceeding 1.63 billion individuals globally [1]. The study of global burden of diseases (GBD), injuries, and risk factors meticulously delineates five distinct musculoskeletal conditions, namely rheumatoid arthritis, osteoarthritis, low back pain, neck pain, and gout, shedding light on the pervasive nature of these ailments. Moreover, a sixth residual classification encompassing various other musculoskeletal disorders covers an extensive array of

acute and chronic afflictions targeting the loco motor system and connective tissues, including bones, joints, ligaments, tendons, and muscles [1, 2]. Work-related musculoskeletal disorders (WMSDs) represent an inevitable occupational health challenge which significantly compromises the quality of life for workers, highlighting the urgent need for proactive intervention strategies. The detrimental repercussions stemming from exposure to hazardous work settings can hinder the employment prospects of workers, thereby exacerbating the socioeconomic consequences associated with WMSDs [3]. Both the international labor organization (ILO) and the world health

organization (WHO) have identified WRMSDs as a burgeoning epidemic demanding heightened scrutiny and prioritization in terms of research and policy formulation [4]. Literature suggests that the etiology of WMSDs is complex and multifactorial, though the exact cause remains unclear [5]. Commonly cited risk factors include individual demographics (such as gender, age, and previous spinal complaints) [6], job physical exposures (such as manual lifting, awkward postures, fast work pace, vibrations) [7], as well as psychosocial factors (including anxiety, job burnout, and job satisfaction) [8]. The risk of musculoskeletal injury is elevated when workers in various industries repetitively perform tasks involving heavy workloads and sustain unnatural postures for extended periods [9, 10]. Owing to the widespread occurrence and prolonged duration of WMSDs, they are a major contributor to long-term disability among workers and have significant implications for individuals, businesses, and society at large [11]. Musculoskeletal injuries and diseases can result in mobility issues, diminished physical strength, lowered quality of life, lower income, as well as other hardships for workers [12]. Various surveys on musculoskeletal injuries highlight the severity of this issue, with data from the United States, Japan, Europe, and Korea revealing a substantial number of lost workdays given cumulative musculoskeletal injuries and illnesses [10].

In recent years, significant efforts have been made by all industrialized countries to eliminate or lower the occurrence of WMSDs and diseases, particularly through promoting risk management strategies (8, 13, 14). This focus on risk management is widely acknowledged as a crucial element of business processes in both the private and public sectors on a global scale. Every organization, irrespective of its nature or size, needs to contend with various risks that can potentially impede the attainment of its objectives [15]. It is imperative for organizations to establish a comprehensive framework of principles and guidelines that are universally accepted at both national and international levels. This would ensure a consistent and effective approach to managing risks associated with repetitive musculoskeletal injuries and diseases. By implementing such standardized risk management practices, organizations can proactively safeguard the health and well-being of their workforce while boosting overall operational efficiency [15, 16]. The traditional approach of addressing musculoskeletal risks involves responding only when health issues manifest themselves, reflecting a reactive approach. This method highlights a certain level of ignorance towards the issue and at times offers solutions that are not comprehensive, primarily focusing on managing the symptoms rather than proactively working towards averting the repercussions and eradicating the root causes (underlying causal factors) which often remain

unidentified [16, 17]. Conversely, the modern approach emphasizes proactive management, intending to pinpoint potential factors that may contribute to the development of such conditions. In this way, the interventions put in place are more likely to be effective on preventing the occurrence of musculoskeletal disorders (MSDs) [15].

In recent years, there has been a frequent discussion in both the public media and academic literature considering the advancements in Artificial Intelligence (AI). These AI systems are capable of generating predictions, recommendations, decisions, as well as other outcomes with different degrees of independence [18]. In AI field, there has been a growth in novel forms of data that require examination, such as comprehension of textual content, retrieval and interpretation of images, analysis of graphical and network data, among others. The efficacy of AI methodologies can also be evaluated through experimentation and modeling [19]. AI is a broad field covering various techniques and methods enabling computers and systems to perform intelligent tasks [20].

One of the primary branches of AI is machine learning, which can be further classified into several subcategories: 1) Supervised learning: In this approach, models are trained using labeled data, meaning that for each input, the expected output is known. The aim is for the model to learn how to map inputs to outputs. The examples include linear regression, decision trees, support vector machines (SVM), and neural networks [21]; 2) Unsupervised learning: In this case, the data are unlabeled, and models need to identify patterns and structures within the data. Common techniques include clustering and principal component analysis (PCA) [22]; 3) Semi-supervised learning: This method combines both supervised and unsupervised learning by applying a set of labeled and unlabeled data simultaneously [23]; 4) Reinforcement learning: Here, an agent is placed in an environment and learns to make better decisions by performing various actions based on feedback. Techniques in this area include Q-learning algorithms and deep neural networks applied in reinforcement learning [24].

It is evident that the usage of AI is significantly advancing research in ergonomics, driven by the age of extensive data; the convergence of these two realms is expected to take place more frequently [19, 25]. Further, the incorporation of AI into the field of ergonomics is on the rise, aiming to boost safety and efficiency in work environments [26]. AI's role in ergonomics is diverse, including the use of computer vision, a branch of AI, for real-time analysis of worker movements, postures, and environmental conditions. This analysis enables immediate modifications to mitigate ergonomic hazards, promoting safer and more comfortable workplaces [27]. Another use is AI-driven software for virtual ergonomic evaluations, via digital workplace

models where workers can provide workstation data. AI algorithms then propose adjustments for an ideal ergonomic configuration, eliminating the need for an in-person assessor [28, 29].

This study aims to provide a comprehensive review of current available research on the use of various artificial intelligence methods and techniques for identifying, ascertaining, and preventing the risk of musculoskeletal disorders in the workplace. The goal is to identify both the challenges and opportunities associated with leveraging artificial intelligence to promote risk management for these disorders. Further, this study seeks to offer recommendations for researchers and professionals in the field of occupational health and safety, enabling them to effectively utilize new technologies. Thus, this review was performed to explore how an artificial intelligence approach can be applied to manage the risk of work-related musculoskeletal disorders.

Materials and Methods

An in-depth review of the scientific literature was carried out on the risk management of work-related musculoskeletal disorders, with a particular emphasis on

research conducted on artificial intelligence (AI). Since AI is a relatively new field, no timeframe was taken into account for searching for articles. Data were gathered from various online scientific literature sources, including databases such as ISI Web of Science, Scopus, Medline (via PubMed), Science Direct, and Google Scholar. Specific keywords related to work-related musculoskeletal disorders (WMSDs), artificial intelligence (AI), WMSDs risk management, WMSDs prediction, WMSDs risk assessment, and WMSDs prevention were employed in the search strategy. The study's inclusion criteria involved selecting research that included one or more keywords mentioned in the article titles, as well as the articles published in English-language journals. Only studies employing prediction, risk assessment, and prevention of WMSDs using the AI approach were considered for extraction and evaluation. The research selection process is displayed in Fig. 1. In total, 77 articles were identified for screening. A total of 46 articles fulfilling these criteria were chosen for review.

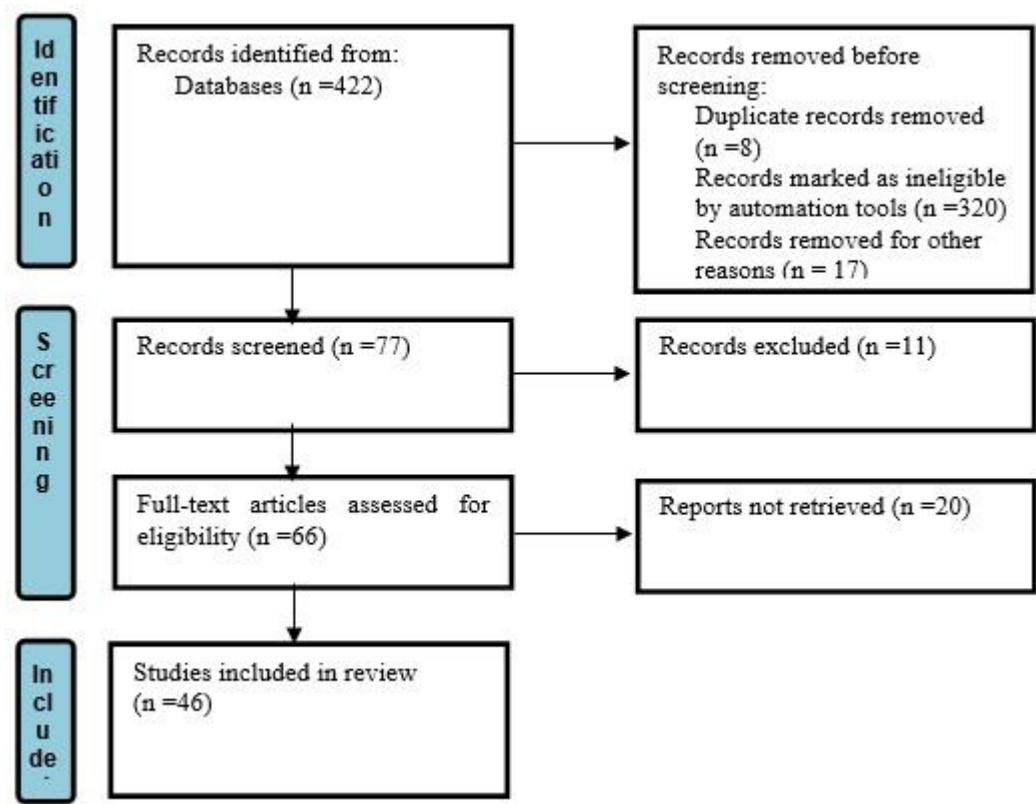


Fig. 1. Study selection flowchart

Results

Risk Prediction and Identification of WMSDs Using Artificial Intelligence: Machine learning (ML) can be employed to predict and classify musculoskeletal disorders [30]. Supervised learning is a type of ML approach that utilizes labeled datasets. These datasets are designed to train algorithms to classify data or make

accurate predictions. By applying labeled inputs and outputs, the model can evaluate its accuracy and improve over time. In contrast, the unsupervised learning approach relies on raw, unlabeled training data. This method is often employed for identifying patterns and trends within datasets or to group similar data points into clusters [31]. A study by Gomez aimed to

predict musculoskeletal disorders among 174 workers in the meat processing industry using ML models. The prevalence of musculoskeletal discomfort was found to be 77%. Functional tree-type models offered the highest accuracy in predicting discomfort in the shoulders and hands/wrists, with values of 83.3% and 83.9%, respectively. The logistic regression (LR) model also demonstrated a high accuracy of 83.3% for predicting back discomfort. Further, the Logistic Model Tree classification model recorded the highest accuracy of 90.2% for predicting neck discomfort. It was noted that the most suitable models for predicting musculoskeletal discomfort are LR and decision trees (DT) [30]. Chandna and Pal ascertained the risk of back disorders among 235 workers in industrial occupations based on a machine support vector algorithm. The data were classified into two categories: low-risk and high-risk disorders, according to five independent variables and one dependent variable, achieving an accuracy of 77% [32]. Nazari et al. undertook an analysis of musculoskeletal disorders in the workplace using the Cornell musculoskeletal disorders questionnaire (CMDQ) along with a multilayer perceptron artificial neural network model. The results of their study indicated that the proposed model exhibits significant precision and accuracy, making it a valuable tool for identifying and predicting musculoskeletal disorders among employees in organizations. This approach has the potential to expedite the identification process and lower costs [33].

The combining of artificial neural network (ANN) techniques with foot plantar pressure analysis represents a major progress in clinical and biomechanical areas, providing a powerful tool for diagnosing, monitoring, and predicting various medical conditions, particularly in the analysis of gait-related disorders such as Parkinson's disease and fall risk detection, where ANNs reveal a high sensitivity in detecting and classifying these conditions [34]. Further, the ability of ANNs to distinguish and categorize foot deformities represents a significant advancement in the fields of diagnosis and treatment [35]. Barkallah et al. reported that ANNs have the capability to efficiently identify improper postures of individuals within a work setting [36].

In a study, ML methods such as decision tree (DT), random forest (RF), and naïve Bayes (NB) were utilized to predict key risk factors linked to WMSDs among bus drivers, with 66.75% reporting WMSDs. Decision tree and random forest models achieved 100% accuracy, while NB offered 93.28% accuracy. The research identified various health and work-related risk factors through a survey and data analysis. It highlighted factors such as physical activities, posture changes, vibration exposure, egress ingress, breaks during duty, and seat adaptability as significant contributors to WMSD pain frequency in bus drivers [37]. Suess et al. performed an experiment on trunk movement under

psychological stress, using XGBoost and TensorFlow ML algorithms for data analysis. Their findings suggest that integrating ML with experimental data offers a valuable approach to studying stress-induced muscle loads as well as forecasting muscle activity during movements influenced by cognitive stress. This combination, along with musculoskeletal modeling, enables the exploration of a wide range of movements and tasks [38]. Villalobos and Mac Cawley noted the application of inertial measurement units (IMUs) for monitoring human activity and utilizing AI for task classification and ergonomic evaluations in the meat-processing sector. They indicated that with affordable IMU sensors on workers' wrists and ML, they could effectively categorize knife sharpness and predict workers' rapid upper limb assessment (RULA) scores [39].

Shahida's study demonstrated that deep learning (DL) algorithm offered the capability to accurately identify a wide range of human postures, resulting in enhanced outputs that are more easily interpretable. The implementation of DL technology contributes to the advancement of various AI applications, facilitating the enhancement of automation, analytical performance, and physical tasks without requiring human intervention. Among the numerous applications of DL, one notable use is in the realm of human pose recognition, a task traditionally undertaken through conventional means. Another term is pose estimation, referring to the process of predicting the positioning of an individual in an image or video by determining the spatial coordinates of key body joints through a machine learning model; this estimation involves the analysis of visual data [40]. Sánchez et al. discovered that the K-nearest neighbor (KNN) technique is effective for identifying workers with WMSDs complaints in the general working population, surpassing traditional statistical learning methods. It also serves as a valuable decision support tool for ergonomic intervention programs by predicting musculoskeletal disorders based on individual and working conditions. It emphasizes factors such as poor lighting, vibrations, uncomfortable seating, and high mental workload as significant contributors to the development of these disorders [41]. Ahn et al. demonstrated that Bayesian network (BN) outperformed ANN, support vector machine (SVM), and DT methods in diagnosing WMSDs as it captured intricate relationships among input and output variables, as well as input variables themselves. All these make it robust in evaluating WMSDs in relation to working characteristics such as working hours and pace [42]. Zhang et al. introduced a DL framework for identifying and forecasting sitting positions utilizing infrared and pressure map data to boost office workers' well-being. The model features specific backbones for each modality, a cross-modal self-attention component, and classification based on multi-task learning. Through

experiments with 20 participants' data, a 93.08% F1-score (F1-score measured the model's performance) was achieved, indicating the potential of the proposed model for applications related to sitting postures [43]. Prisco et al. found superior performance of logistic regression over other ML algorithms in classifying safe/unsafe

postures along load lifting, achieving accuracy and area under the curve values of up to 96% and 99%, respectively. This indicates the potential of their single-sensor AI-based methodology [44]. AI algorithms employed for predicting and identifying the risk of musculoskeletal disorders are summarized in Table 1.

Table 1. AI algorithms used for predicting and identifying the risk of musculoskeletal disorders

Algorithm	Comparison with the standard method	Accuracy (A) (%) or Correlation coefficient (r)	Reference
Logistic Regression (RL)	Direct observation and surveys	A=83.3	[30]
	Inertial measurement unit (IMU)	A=96	[44]
Decision Tree (DT)	Direct observation and surveys	A=90.2	[30]
	Modified Nordic Musculoskeletal Questionnaire (MNMQ)	A=100	[37]
	IMU	A=88	[44]
XGBoost	Electromyography (EMG) sensors	r=0.85-0.95	[38]
TensorFlow neural network (TNN)	Electromyography (EMG) sensors	r=0.75-0.91	[38]
Random Forest (RF)	Modified Nordic Musculoskeletal Questionnaire (MNMQ)	A=100	[37]
	IMU	A=95	[44]
Naïve Bayes (NB)	Modified Nordic Musculoskeletal Questionnaire (MNMQ)	A=93.28	[37]
Support Vector Machine (SVM)	Dataset collected in a field study	71.3-77.01	[32]
	IMU	A=94	[44]
Gradient boosted Tree (GB)	IMU	A=94	[44]
k Nearest Neighbor (kNN)	IMU	A=91	[44]
Multilayer Perceptron (MLP)	IMU	A=92	[44]
Probabilistic Neural Network (PNN)	IMU	A=79	[44]
Deep Learning (DL)	Data collection for sitting posture	A=93.08	[43]
Bayesian Network (BN)	Direct measurements of dentist's movements and a questionnaire	A=Suitable	[45]
Convolutional Neural Network (CNN)	IMU	A=Suitable	[34]
Recurrent Neural Network (RNN)	IMU	A=Suitable	[34]

Risk Assessment of WMSDs Using Artificial Intelligence: Advanced technology-based methods such as video motion, thermography, and AI are able to ascertain risk factors with greater precision and accuracy, enabling real-time evaluation. These methods streamline the evaluation process compared to traditional methods, which often disrupt worker productivity. This would allow ergonomics practitioners to efficiently assess workers along their actual work activities and process more data within a shorter period of time [46]. The utilization of angle estimation within an AI framework effectively computes measurements instantaneously. This is advantageous as it enables the programming and determination of angles for each specific body part being ascertained [47]. The representative decision tree (RDT), one of the types of ML algorithms, has proven to be effective for minimizing the subjective bias associated with observational techniques in ergonomic evaluations. It also helps in the recognition of risk patterns for WMSDs in sewing machine operators [48]. Olsen et al. examined the discriminatory capacity of ML and DL

algorithms in distinguishing between accurate and inaccurate postures of dental professionals based on features obtained from inclinometer data. The most effective algorithm identified was the k-Nearest neighbor (kNN) model, which offered an accuracy rate of 99.94% [49]. Li et al. conducted an investigation into a novel end-to-end implementation of a DL-based algorithm designed using the RULA technique. The algorithm was designed to process standard RGB images as input and generate the RULA action level, representing a more detailed breakdown of the RULA overall score. The algorithm indicated an impressive performance with 93% accuracy and an operational efficiency of 29 frames per second in identifying the RULA action level. The researchers concluded that incorporation of data augmentation techniques, aimed at enhancing the diversity of the training dataset, can notably boost the model's resilience. This proposed approach well indicates considerable promise for conducting real-time on-site risk assessments of WMSDs to prevent such disorders effectively [50]. Kumar et al. undertook a study on AI's

role in evaluating postural ergonomics during laparoscopic surgery, analyzing surgeons' postures and movements using AI software. The software ascertained parameters such as craniohorizontal angle, craniovertebral angle, demonstrating AI's potential to ameliorate ergonomics assessment. The researchers emphasized the need for further advancements in the software to enable real-time evaluation of postural ergonomics [51]. Kavus et al. introduced a comparative approach involving neural networks and neuro-fuzzy techniques within the rapid entire body assessment (REBA) framework. It covered a wide range of neural network models such as CNN, RNN, MLP, generalized regression neural networks, radial basis function neural networks, and membership functions. Their findings revealed the superior accuracy of the neuro-fuzzy method compared to REBA, offering enhanced flexibility in determining membership within different risk level clusters. This methodology exhibits significant potential in streamlining the evaluation process as well as mitigating the occurrence of musculoskeletal disorders in service and manufacturing sectors. This would facilitate a prompt and pragmatic risk assessment. Ultimately, the amalgamation of proposed ANNs and neuro-fuzzy within the REBA methodology represents an effective decision support system for specifying ergonomic risks in work environments and promptly informing decision-makers of non-ergonomic scenarios [52].

Varas et al. found that AI software using MediaPipe outperformed RULA and REBA in assessing musculoskeletal disorder risks among farmers. AI classified 80% of cases as medium risk in the "split" task, while RULA identified 85% as high risk. AI's accuracy and balanced risk assessment are crucial for effective interventions. AI integration shortened assessment time by 60%, speeding up hazard analysis. This advancement would enable frequent analysis, aiding in early detection and prevention of musculoskeletal disorders [53]. In a study, the researchers reported that by employing PNN as a classification algorithm, the task risk predictor could anticipate classification based on data features, thus introducing a way to predict and ascertain the risk level of the dynamic work process based on its changing risk characteristics, addressing the issue of dynamic work posture evaluation. In the task risk evaluator training, overfitting initially occurred owing to insufficient data, which was resolved by expanding the experimental data, leading to improved prediction and assessment outcomes. PNN can accurately predict the risk level of the entire work process by tracking the changes in limb angles of workers frame by frame [54].

In another study, a tool was created for assessing full-

body posture based on fuzzy logic using a fuzzy inference engine (IE). Utilizing an ergonomic map as a starting point, the IE could assess postures using a knowledge base which integrated evaluation criteria derived from established comprehensive body assessment tools such as the REBA, the European assembly worksheet (EAWS), the RULA, and the analysis of occupational repetitive methods [55]. Zhao and Obonyo introduced a DL algorithm known as convolutional long short-term memory (CLSTM) for identifying workers' postures based on the criteria of the Ovako working posture assessment system (OWAS). This algorithm utilized inertial data collected through IMUs positioned on the forehead, chest, arm, thigh, and calf [56]. In an investigation, a spatiotemporal graph convolutional network known as attention-based adaptive (AAST-GCN) was employed to evaluate appropriate ergonomics following the REBA guidelines in an extensive video. This approach could offer a promising strategy to alert individuals with elevated ergonomic risk, enabling them to promptly correct improper body positions or seek medical assistance in a timely fashion [57].

Elsewhere, a study utilized a new quick capture system, based on convolutional pose machines, to ascertain body posture and determine risk levels for musculoskeletal disorders. The study aimed to validate the reliability and feasibility of this system through a simulation experiment. It revealed its consistency with traditional motion capture data, reflecting its potential for rapid on-site assessments. The quick capture system has the potential to compensate for errors that may have been committed by experts [58]. Researchers developed a recurrent neural network (RNN) with the purpose of representing prolonged temporal relationships among body part characteristics. Their efforts resulted in the attainment of an accuracy level approaching 70% [59]. Antwi-Afari and colleagues utilized four supervised machine learning classifiers (ANN, DT, KNN, and SVM) utilizing features derived from foot plantar pressure and linear acceleration to identify and categorize awkward working postures. The most effective classifier among them was the SVM, presenting an accuracy rate of 99.70% [60].

Mudiyansele et al. evaluated the efficacy of surface electromyogram (EMG)-based systems in conjunction with machine learning algorithms for identifying potentially harmful body movements along material handling. Various ML models were created, including DT, SVM, KNN, and RF, to classify risk assessments derived from the NIOSH lifting equation. According to the findings, DT models exhibited a high accuracy of approximately 99.35% in predicting risk levels. This confirms the presence of distinct patterns in sEMG

signal data linked to lifting weights, which can aid in recognizing ergonomically unsafe body postures [61]. The findings of the research undertaken by Donisi et al. indicated that the SVM algorithm offered superior performance in categorizing biomechanical risk categories. These categories were established based on the Revised NIOSH lifting equation, with accuracy levels and area under the receiving characteristic curve values reaching as high as 0.985. This approach would facilitate automated, cost-effective, time-efficient, and operator-independent biomechanical risk evaluation, thus offering significant practical implications for the field of occupational ergonomics [62].

Conforti et al. introduced a methodology for ascertaining safe and unsafe postures in manual material handling (MMH) tasks using wearable sensors and ML algorithms. The ML algorithms were trained with kinematic features derived from linear acceleration and angular velocity signals. Their approach involved utilizing a SVM algorithm, offering a classification accuracy of 99.4% for distinguishing between safe and unsafe postures [63]. Wang et al. introduced a machine

vision-based approach for assessing postural risk in workers using job videos and pressure sensor data, without disrupting their usual tasks. They suggested its applicability in various industries to proactively boost workers' health and productivity through timely interventions based on WMSDs risk assessment [64]. Usage of AI algorithms in the context of observational ergonomic assessment methods may prove beneficial in facilitating the computation of ergonomic evaluations. The development of AI-driven solutions entails development of models through the training process. This process involves incorporating expert judgments with data derived from bodily movements. Although the outcomes exhibit promise, certain models such as the CNN display signs of overfitting, leading to excessively high accuracy rates for the existing dataset. This phenomenon of overfitting presents challenges in anticipating the performance of these models when applied to new datasets. Subsequent examinations are imperative to evaluate the efficacy of various models [65]. AI algorithms employed for assessing the risk of musculoskeletal disorders are reported in Table 2.

Table 2. AI algorithms employed for assessing the risk of musculoskeletal disorders

Algorithm	Comparison with the standard method	Accuracy (A) (%) or Correlation coefficient (r)	Reference
Representative Decision Tree (RDT)	REBA	95<A	[48]
Deep Learning (DP)	RULA	A=93	[50]
	REBA	r=0.817	[64]
Convolutional Long Short-Term Memory (CLSTM)	OWAS	81.2	[56]
Convolutional Neural Network (CNN)	RULA and REBA	A=Acceptable	[53]
	OWAS	A= exceedingly high	[65]
Artificial Neural Network (ANN)	REBA	A=Suitable	[52]
Multilayer Perceptron (MLP)	REBA	A=Suitable	[52]
	NIOSH lifting equation	A=95	[66]
Convolutional Pose Machines (CPM)	REBA	r=915	[58]
Decision Tree (DT)	NIOSH lifting equation	A=99.98	[60]
	NIOSH lifting equation	A=99.35	[61]
	NIOSH lifting equation	A=97	[66]
	OWAS	A= exceedingly high	[65]
Support Vector Machine (SVM)	NIOSH lifting equation	A=97.17	[61]
	NIOSH lifting equation	A=83	[66]
K-Nearest Neighbor (KNN)	NIOSH lifting equation	A=98.58	[61]
	NIOSH lifting equation	A=90	[66]
	OWAS	A= exceedingly high	[65]
Random Forest (RF)	NIOSH lifting equation	A=97.07	[61]
	NIOSH lifting equation	A=98	[66]
Artificial Neural Network (ANN)	-	98.2	[60]
Logistic Regression (LR)	NIOSH lifting equation	A=79	[66]
Gradient Boost (GB)	NIOSH lifting equation	A=97	[66]
Ada Boost (AB)	NIOSH lifting equation	A=98	[66]
Naive Bayes (NB)	NIOSH lifting equation	A=96	[66]
Graph Convolutional Network (GCN)	REBA	A=Acceptable	[57]

Prevention of WMSDs Using Artificial Intelligence: In recent years, the most commonly used AI algorithms for preventing and lowering the risk of musculoskeletal disorders have been ML and DL [67]. It has been

reported that the RF algorithm is the most preferred algorithm, achieving over 90% accuracy in preventing disorders [49]. Further, the KNN algorithm has achieved over 99% accuracy in body posture

classification and injury prevention [68]. Chan et al. found that although ML techniques are new, they are effective for preventing WMSDs, enhancing prevention efforts at different stages. Various ML algorithms are employed given lack of a superior algorithm. The best model for each problem would be selected based on performance evaluation or background knowledge and data nature [69]. Thanathornwong et al. introduced a BN prediction model aimed at predicting WMSDs in dentists. This model offered a structured depiction of the risk factors linked to WMSDs by capturing the interrelationships among variables relevant to different aspects and the likelihood of WMSDs. Their findings suggested that the BN model designed for forecasting musculoskeletal disorders in dentists can help correct issues related to neck and upper back extensions, resulting in diminished likelihood of WMSDs. This reduction in risk potentially contributes to preventing injuries caused by improper posture and excessive movement ranges along dental procedures [45]. In a randomized clinical trial, personalized self-management support through an AI-based smartphone app did not demonstrate superior effectiveness in enhancing musculoskeletal health compared to usual care or non-tailored web-based support for patients with neck and/or low back pain referring to specialist care [70]. Yan et al. introduced a real-time motion warning system based on wearable inertial measurement units, for facilitating construction workers' self-awareness and self-management of risk factors associated with WMSDs in

the lower back and neck regions, without interrupting their tasks. The system involved a smartphone application linked to IMUs sensors securely fixed to the back of the worker's safety helmet and the upper part of the back. With this system in place, the worker could continue working as usual while being informed about postures and durations of holding positions that are linked to WMSDs in the lower back and neck [71]. Chandna and Pal asserted that in spite of the promising efficacy exhibited by SVM in forecasting and averting musculoskeletal disorders utilizing specific datasets, a significant disadvantage associated with AI-driven modeling methodologies lies in their reliance on data. The outcomes generated by these models can potentially vary based on the dataset employed, the experimental scale, or the volume of data utilized for training [32]. Xie et al. introduced an approach for ameliorating the posture of workers in the context of human-robot collaboration (HRC). Employing a computer vision technique, they identified human postures and computed a continuous awkward posture (CAP) score. They then devised a model-free gradient descent optimization technique to minimize the CAP score of a worker. Their findings indicate the efficacy of the Gradient-based Online Learning Algorithm in HRC (GOLA-HRC) in lowering workers' CAP during HRC tasks, thereby mitigating the risk of musculoskeletal disorders [72]. AI algorithms employed to prevent the risk of musculoskeletal disorders are outlined in Table 3.

Table 3. AI algorithms utilized to prevent the risk of musculoskeletal disorders

Algorithm	Reference	Frequency* (%)
ML	[67, 69, 73]	30
DL	[67, 73]	20
k-Nearest Neighbors (KNN)	[68]	10
Random Forest (RaF)	[49]	10
Support Vector Machines (SVMs)	[32]	10
Reinforcement learning	[72]	10
Bayesian network	[45]	10

* Percentage of articles used in this study focusing on AI algorithms for preventing the risk of musculoskeletal disorders

Discussion

AI can effectively develop risk prediction models for WMSDs that healthcare practitioners can use, enabling a quantitative assessment of the impact of occupational variables. This innovation is beneficial for future evaluations of WMSDs in healthcare settings, providing a cost-effective and efficient solution [74]. AI and machine learning algorithms facilitate instantaneous data analysis, thereby offering enhanced accuracy and proactive evaluations of ergonomic conditions. Wearable technologies, including inertial measurement units and pressure sensors, provide ongoing surveillance of employee movements and postural alignments, thereby contributing to mitigation of injuries within industries, healthcare, construction, and manufacturing.

Further, these instruments enable tailored ergonomic interventions by ascertaining individual risk factors in real-time [75]. The advancement of AI-based ergonomic assessments is anticipated to evolve positively over time, leveraging insights from ergonomic professionals and integrating new datasets for enhanced training. In addition, a thorough investigation into the influence of AI-related parameters is warranted on predictions when employing motion capture systems [76]. AI demonstrates versatility in processing both instantaneous dataset snapshots, such as identifying work postures, as well as cumulative data, through mechanisms such as RNN [65]. These types of AI models would facilitate the identification of a wide range of motion-related parameters, including present

occupational duties and previous body positions [77]. The usage of wearable technologies in conjunction with AI algorithms, encompassing both ML and DL, facilitates not merely the examination of force, repetitiveness, and posture but also the analysis of the kinematic characteristics of an individual's actions. Particular kinematic attributes may serve as valuable indicators for managing and anticipating the emergence of any changes that could jeopardize the worker's well-being, while also overseeing the crucial stages along the reintegration process for individuals with impairments, disabilities, or prior medical conditions. Beyond the scope of monitoring, assessment, and development, this methodology introduces novel prospects for ergonomic interventions with an emphasis on educational and participatory preventive measures [73].

While AI has effective and valuable applications in the management of musculoskeletal disorders, it has also its limitations. The limitations of using AI in managing the risk of musculoskeletal disorders include the following: Training AI models require data that are both high-quality and abundant. A lack of access to comprehensive and reliable data can lower the accuracy of predictions. Musculoskeletal disorders can stem from various factors, including individual characteristics, occupational conditions, hereditary influences, lifestyle choices, and physical activity, each with its own unique attributes. Hence, AI models may not be able to correctly identify and analyze all of these variations. Moreover, the complexity of workplace environments and their impact on the development of musculoskeletal disorders may not be fully accounted for by AI models. The use of personal data to train these models also raises ethical and privacy concerns. Ultimately, developing and implementing AI solutions in this field necessitates collaboration among experts from diverse disciplines, such as medicine, engineering, and data science, which can present its own challenges.

Conclusion

WMSDs pose a significant challenge in industrial societies, highlighting the need for effective management. AI has proven effective in risk prediction, identification, evaluation, and prevention of musculoskeletal disorders. It aids ergonomics and occupational health experts by analyzing work environment factors, workstation design, work methods, body posture, and individual worker characteristics. The key advantages of AI include predicting at-risk workers, ascertaining physical conditions, identifying vulnerable body areas, detecting unsafe actions via wearable sensors, recognizing unsuitable environmental conditions and workstation setups, and providing corrective recommendations. AI also offers safer task execution methods, control measures, preventive strategies, and training programs. Further, AI assists

managers in monitoring worker health and avoiding excessive pressure. Nevertheless, challenges exist, such as model complexity, the need for technical expertise, high costs, potential inaccuracies owing to limited data, and over fitting risks. Further research is essential to develop reliable, standardized AI solutions for WMSDs risk management.

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Conflict of interest

None declared.

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Ethical Considerations

As this study is a literature review, no new research was conducted on human or animal subjects. All cited research has been duly acknowledged, and the authors declare that they have no conflict of interest.

Code of Ethics

This review study is a preliminary investigation aimed at developing a proposal and conducting a research project; therefore, it does not have an ethics code.

Authors' Contributions

Mahnaz Shakerian: Study conceptualization, methodology, data curation; Samira Barakat: Study conceptualization, data curation, writing original draft preparation; Elham Saber: Methodology, reviewing, and editing; all authors have read and agreed to the published version of the manuscript.

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