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Review

Digital and Virtual Technologies for Work-Related Biomechanical Risk Assessment: A Scoping Review

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Abstract: The field of ergonomics has been significantly shaped by the advent of evolving technologies linked to new industrial paradigms, often referred to as Industry 4.0 (I4.0) and, more recently, Industry 5.0 (I5.0). Consequently, several studies have reviewed the integration of advanced technologies for improved ergonomics in different industry sectors. However, studies often evaluate specific technologies, such as extended reality (XR), wearables, artificial intelligence (AI), and collaborative robot (cobot), and their advantages and problems. In this sense, there is a lack of research exploring the state of the art of I4.0 and I5.0 virtual and digital technologies in evaluating work-related biomechanical risks. Addressing this research gap, this study presents a comprehensive review of 24 commercial tools and 10 academic studies focusing on work-related biomechanical risk assessment using digital and virtual technologies. The analysis reveals that AI and digital human modelling (DHM) are the most commonly utilised technologies in commercial tools, followed by motion capture (MoCap) and virtual reality (VR). Discrepancies were found between commercial tools and academic studies. However, the study acknowledges limitations, including potential biases in sample selection and search methodology. Future research directions include enhancing transparency in commercial tool validation processes, examining the broader impact of emerging technologies on ergonomics, and considering human-centred design principles in technology integration. These findings contribute to a deeper understanding of the evolving landscape of biomechanical risk assessment.

Keywords: physical ergonomics; musculoskeletal disorders; technology; digital; virtual

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1. Introduction

Human factors and ergonomics (HFE) concepts have become instrumental since the first rationalisation of work during the late nineteenth and early twentieth centuries, with Frederick Taylor, Henry Ford, and Henry Fayol and their focus on optimising the interaction between people and other elements of the work system. Obviously, at that time (AKA Industry 2.0 [1]), no one mentioned human factors or ergonomics, but topics such as cooperation between workers, company management, training, and motivation were already being discussed [2]. Nowadays, it is even more decisive in the context of human-centred design to help companies understand worker needs, reduce work-related risks, facilitate workstation adaptability, and promote sustainability [3].

Ergonomics can be divided into three main branches: physical, cognitive, and organisational [4]. Physical ergonomics is concerned with the physical demands of work. It incorporates anthropometrics, physiology, and biomechanics elements to mitigate the risk of musculoskeletal disorders. Furthermore, physical ergonomics also considers environmental factors such as temperature, lighting, and noise in the workplace. Addressing these physical characteristics aims to prevent stress and ensure a comfortable working environment. On the other hand, cognitive ergonomics focuses on how humans process information, including perception, memory, reasoning, and motor response, as it aims to optimise human–information interaction. Organisational ergonomics deals with the broader production system, including people, technology, and the environment, seeking to optimise sociotechnical systems for workers' performance and well-being [5].

This research centres on physical ergonomics, focusing on work-related biomechanical risk assessment. The field of ergonomics has been significantly shaped by the advent of evolving new technologies linked to new industrial paradigms, often referred to as Industry 4.0 (I4.0) and, more recently, Industry 5.0 (I5.0) [6]. Within this context, there is a trend in considering evolving new technologies, such as artificial intelligence (AI), digital human modelling (DHM), motion capture systems (MoCap), and other technologies for biomechanical assessment. These technologies can be categorised as virtual, involving elements that are not physically present but can be simulated or emulated (e.g., DHM) and digital, encompassing digital or electronic elements, such as digital images, videos, and other visual inputs (e.g., computing vision [CV]).

Only a limited number of studies have been found within the existing literature reviews that explore the connection between biomechanical risk assessment and evolving new technologies.

For instance, Cárdenas-Robledo [7] conducted a systematic literature review illustrating the application of extended reality (XR) technologies within the context of I4.0 across different industry sectors. Similarly, Fang et al. [8] conducted a systematic review of the use of head-mounted display (HMD) AR in various manufacturing processes. Also, da Silva et al. [9] examined the use of VR and DHM to assess physical ergonomics during the product development process in the industry. Yin and Li [10] conducted a systematic review of research methods and application cases in a DHM assembly process simulation. Donisi et al. [11] conducted a systematic review of the literature focusing on integrating wearable devices and AI algorithms in physical ergonomics applications. Lastly, Mgbemena et al. [12] conducted a comprehensive analysis of existing literature on hardware and software technologies to identify the tools employed for ergonomic evaluation in manufacturing environments.

The aforementioned studies underscored the integration of advanced technologies for improved ergonomics in different industry sectors, highlighting the potential of these technologies in enhancing physical ergonomic evaluations and mitigating biomechanical risks. However, these studies tend to evaluate specific technologies, such as XR [7], HMD [10], wearables, and AI [11], for biomechanical work-related assessment. In this sense, research is lacking in exploring virtual and digital technologies in evaluating work-related biomechanical risks. In this context, this study examines the state of the art regarding the employment of virtual and digital tools for work-related biomechanical risk assessment, considering both literature and commercial tools available on the market. To the best of the authors' knowledge, this is the first paper in the peer-reviewed literature to review digital and virtual technologies' applications to biomechanical risk assessment.

2. Relevant Literature

2.1. Work-Related Biomechanical Risk Assessment

Work-related biomechanical risk assessment evaluates the risk of injury based on the physical interactions and movements within a work environment. It is vital in injury prevention, workplace safety, and medical treatment planning [13]. Work-related biomechanical risk assessment provides valuable insights into how physical forces interact with our bodies and can help design safer workplaces, creating environments that promote well-being [14].

According to Massiris Fernández et al. [15], there are four distinct categories under which biomechanical risk assessment methods can be classified: self-assessment, observational methods, direct measurement, and computer-based assessment. These categories are differentiated by their approach to evaluating and mitigating risks, and their appropriateness depends on the risk assessment's specific context and research objectives. Although computer-based methods are of interest in the current study, given its technological focus, the description of self-assessment, observational, and direct methods is also necessary (Table 1). This requirement is due to the usual combination of methods for biomechanical risk assessment, also present in the reviewed tools (Section 4).

Table 1. Categories of data collection methods for biomechanical risk assessment.

#	Category	Description	Limited Detailed Characterisation
1	Self-Assessment	This category assesses biomechanical risks through questionnaires, enabling workers to identify potential risk factors present in the work environment.	HFE professionals employ self-assessment questionnaires to estimate biomechanical exposure, considering factors such as postural demands, repetitive movements, precision movements, vibration, manual materials handling, and dynamic tasks of workers. One example is the Mälmo Shoulder Neck Study (MSNS) questionnaire [16].
2	Observational Methods	This category evaluates biomechanical risks by closely observing workers performing their duties at their respective workstations.	HFE professionals use on-site observations and offline video analysis to estimate workers' body-joint angles. On-site observations might include recording data using spreadsheets or templates. Software like Kinovea v2023.1 could be employed to analyse recorded footage and extract biomechanical data for offline video analysis.
3	Direct Measurement	This category involves evaluating biomechanical risks using specialised devices to capture biomechanical data. These devices, attached to the worker's body, measure aspects such as body parts rotation and movements, providing a comprehensive understanding of the physical strain experienced by the worker.	Wearable tools and devices are attached to a worker's body to automatically collect data for biomechanical analysis. One such device used for this purpose is a motion-tracking system composed of inertial measurement units (IMUs).
4	Computer-based Assessment	This category employs computers and software to evaluate biomechanical risks in the workplace.	Human body models, such as DHM, along with computing vision (CV) applications, are employed to automatically derive estimations of human body models.

2.2. Industrial Revolutions and HFE

Technology has been a constant force in human evolution for 2.6 million years [17]. It has driven humanity forward, from the Stone Age to the Bronze and Iron Ages, and it continues to shape our society today.

More recently, with the organisation and systematisation of work in the late eighteenth century, a new era in history began, the Industrial Era, an era influenced mainly by the use of different types of energy, technology, and work practices. This Industrial Era can be divided into the first, second, third, fourth, and, more recently, fifth Industrial Revolutions, each defined by the distinctive advancements in energy, technology, and the role of humans.

In short, the first Industrial Revolution was characterised by using steam power and mechanising production lines. The Second Industrial Revolution introduced electricity and oil from the late nineteenth to early twentieth century, leading to mass production, assembly lines, and streamlined production processes. The third Industrial Revolution, starting in the late twentieth century, was marked by the automation of production lines through the integration of computers and information technology [18]. Beginning in the early twenty-first century, and yet in progress, is the fourth and fifth Industrial Revolution.

Industry 4.0, or I4.0, applies technological advancements from the Fourth Industrial Revolution within the manufacturing industry. It encompasses the digital transformation related to "a real-time, high data volume, multilateral communication and interconnectedness between cyber-physical systems and people" ([19], pp. 11). The fifth Industrial Revolution (i.e., I5.0) emphasises the collaboration between humans and machines, focusing on personalisation and human-centric production [20].

The fourth and fifth Industrial Revolutions are mainly related to digital and virtual technologies. They involve the integration of smart evolving technologies such as AI, DHM, Internet of Things (IoT), cloud computing (CC), robotics, and other technologies into production facilities and operations to create smart factories [20]. Additionally, I4.0—and, more pronouncedly, I5.0—reinforces a sociotechnical perspective over production systems that not only considers the technological sphere (e.g., cyber-physical systems) but also processes, culture, and people [6]. Since evolving technologies can be part of both I4.0 and I5.0 but at varying stages of development, this work will use the term "evolving new technologies" to refer to the latest technologies used in the modern industry context, particularly those that are digital and virtual in nature.

Among evolving new technologies that can have consequences for physical ergonomics, one can cite additive manufacturing, the IoT, AI, cobots, VR, AR, and others [21] (Table 2). The employment of these technologies for work-related biomechanical risk assessment has been discussed in the literature (e.g., [10,22]). Yin and Li [10], for instance, carried out a comprehensive systematic review of DHM application in ergonomics evaluation. Also, Asad et al. [22] conducted state-of-the-art research on human-centred digital twins, their enabling technologies, and implementation frameworks for different industrial applications. Cárdenas-Robledo et al. [7] comprehensively reviewed the applications of XR, which includes VR and AR, across different industries. The authors highlighted the potential of VR and AR technologies to conduct ergonomics assessments. Likewise, Rahman et al. [23] investigated the adoption of wearable sensors, XR, exoskeletons, and robotics in the construction sector, underscoring their potential to improve work conditions and reduce occupational risks.

Adding to the discussion on robotics, Weidemann et al. [24] conducted a literature review to examine the use of cobots in the industrial sector, focusing on their effects on human work, safety, and health within the I4.0 framework. Among the main conclusions, the authors stated that cobots improve productivity and efficiency, enhance safety, augment human capabilities, improve quality, and provide new opportunities by creating collaborative relationships between humans and robots.

Table 2. Technologies, their description, and application to biomechanical risk assessment.

Technology	Definition	Sub-Areas	Sub-Areas Definition	Application to Biomechanical Risk Assessment
AI	AI is a branch of computer science that simulates human intelligence. It involves reasoning, learning, problem-solving, recognising speech, making decisions, and identifying patterns (IBM, 2024). AI can be classified into four main areas: ML, CV, deep learning (DL), and natural language processing (NLP).	Machine learning (ML)	ML enables computers to learn from data without explicit programming. ML analyses large datasets to identify patterns and make predictions.	AI technologies can be used to create human body models by capturing human body movements. These models can provide estimations for biomechanical risk assessment [11]. DL and NLP are not relevant for biomechanical risk assessment.
		Computing vision (CV)	CV extracts information from digital images and videos. It involves methods for acquiring, processing, analysing, and understanding the visual world to produce numerical or symbolic information.	
		Deep learning (DP)	DP employs artificial neural networks with multiple layers to learn complex patterns from data. Inspired by the structure of the human brain, these networks can hierarchically process information, gradually extracting higher-level features from raw data [25,26].	
		Natural language processing (NLP)	NLP investigates the interaction between computers and human language, aiming to equip computers with the ability to understand, interpret, and generate human language through the application of computer science, linguistics, and ML [26,27].	

Table 2. *Cont.*

Technology	Definition	Sub-Areas	Sub-Areas Definition	Application to Biomechanical Risk Assessment
DHM	DHM is a technique for simulating human interaction with products or workplaces within a virtual environment [28]. It employs three-dimensional manikins in these virtual settings to mimic human interaction with the work environment [29].	For Sub-categories, refer to [10]	Not applied.	DHM provides a virtual platform for analysing human movements and postures in relation to products and work environments [10,28].
Virtuality	Virtuality refers to something simulated or computer-generated, not existing in the physical world.	VR	VR technology creates a three-dimensional virtual environment using computer simulations to simulate human interaction within the virtual working environment [28].	Like DHM, VR simulates human interaction with products or workplaces in a virtual environment [30]. Accordingly, AR can be useful for biomechanical risk assessment in work-related tasks [31].
		AR	AR combines the real world with computer-generated content, creating an integrated and interactive experience [7].	
MoCap	MoCap is a technology-driven method used to digitally record the movement of objects or people [32]. It can be subdivided into optical and wearable systems.	Optical systems: marker-based (MBased)	Within the former, MBased systems use reflective markers placed on specific points of the body. Multiple cameras track these markers to capture the motion. This method is known for its high accuracy but requires a controlled environment with multiple high-resolution cameras (e.g., Vicon [33]).	MoCap technology provides accurate and feasible assessments of various musculoskeletal parameters and can aid in diagnosing and monitoring work-related musculoskeletal disorders. However, challenges related to obtaining accurate data are complex, owing to the nature of the working environment, heavy equipment used by workers, wearing personal protective equipment, and the limitations of MoCap systems [32].
		Optical systems: marker-less (MLess)	MLess systems do not require markers or special suits using advanced CV techniques to track the human body (i.e., Microsoft Kinect V2 [34]).	
		Wearable systems	Within wearable systems, inertial measurement unit (IMU) systems use wearable sensors to measure body motion. The sensors, which include accelerometers, magnetometers, and gyroscopes, can detect changes in speed and direction (e.g., XsensMVN [35]).	

3. Materials and Methods

This scoping review utilised PRISMA Extension for Scoping Reviews recommendations to strengthen its transparency and reproducibility [36]. With the research objective of assessing digital and virtual technologies employed for biomechanical risk assessment methods, a scoping review process including scientific and grey literature was conducted. In March 2024, a search of commercially available biomechanical risk assessment tools was conducted using the Google search engine to identify resources within the grey literature. After trying different search strings with a combination of related terms (e.g., biomechanical risk assessment, ergonomics risk assessment, and musculoskeletal risk assessment), only the most relevant business websites were accessed (i.e., first-page results related to companies offering services through technologies of interest). This search process retrieved 28 commercial tools, of which 24 were included in the review. The following tools were not included: (i) applied technologies of interest to other fields such as quality inspection (e.g., EasyODM, available at https://shorturl.at/RMxBq, accessed on 12 March 2024), back-end operations, machine use, defect detection, etc. (e.g., alwaysAI, available at https://alwaysai.co/, accessed on 12 March 2024), vehicle design (e.g., RAMSIS, available at https://shorturl.at/ZLv46, accessed on 12 March 2024 and SAMMIE, available at https://shorturl.at/FlOc9, accessed on 12 March 2024) and (ii) employed (input-output conventional) computational software to biomechanical risk assessment (e.g., ErgoIBV, available at https://www.ergoibv.com/en/, accessed on 12 March 2024. In other words, the inclusion criteria were based on employing digital or virtual technologies for work-related biomechanical risk assessment (e.g., CV, ML, DHM, VR, and AR).

Reviewed tools were classified according to the following categories: (i) company's name and country, (ii) tool name and cost, (iii) area of application (i.e., which industry the tool was being applied), (iv) technology and required hardware, (v) data collection methods, (vi) biomechanical risk assessment methods and physical risk factors addressed, (vii) and associated scientific evidence. This information was retrieved from the company's website. Item (iv) refers to the type of technology upon which the tool was based, plus the leading hardware required for its functioning. For instance, in the case of VR, the hardware would refer to an HMD. Item (v) refers to the data collection method categories displayed Table 2 (i.e., self-assessment, observational, direct measurement, and computer-based). Item (vi) refers to specific assessment methods (e.g., RULA, REBA, OWAS, etc.) and addresses physical risk factors. The associated scientific evidence (vii) refers to scientific articles validating or applying the tool.

Concerning scientific literature, the Web of Science (WoS) database was surveyed. The search query used was "(ergonom* OR ′musculoskeletal disorders′ OR 'biomechanical risk assessment') AND (′industry 4.0′ OR 'industry 5.0′)" limited to journal articles and conference papers written in English. This search yielded 210 documents in March 2024. Ten documents were selected for inclusion following a PRISMA-guided screening process involving titles, abstracts, and full texts [37]. Only articles directly assessed the employment of evolving new digital and virtual technologies for biomechanical risk assessment were included. Following commercial tools categorisation, reviewed articles were further coded into eight categories: (i) tool name, (ii) area of application (i.e., experimental or industrial), (iii) technology, (iv) hardware, (v) data collection method, (vi) ergonomics methods, (vii) physical risk factors addressed, and (viii) sample size.

4. Results

This section presents the descriptive results for coding-reviewed commercial tools (Section 4.1.), followed by the critical analysis of the reviewed literature (Section 4.2.).

4.1. Commercial Tools

Table 3 summarises the characteristics of reviewed commercial tools that employ virtual and digital technologies for work-related biomechanical risk assessment. The hardware technology featured in this study pertains to data collection devices, such as smartphones, and the equipment used for modelling and simulation, for instance, those hosting and running virtual analysis (e.g., DHM requires PCs), all within the scope of musculoskeletal risk assessment.

Most tool-owner companies were from the United States (n = 8), followed by France (n = 3), Germany and the United Kingdom (n = 2 each). The remaining tools originate from other European countries. Additionally, only 2 of the 24 tools reviewed were free to use. All of the reviewed tools were applied to industrial contexts. Two tools, AnyBody (#18C) and OpenSim (#21C) could also be used in contexts such as academia, medicine, sports, and other specific health-related areas.

Regarding the technologies employed, AI was the most prevalent, being integrated into 13 tools. These were followed by DHM (n = 12), MoCap (n = 4), and VR (n = 3). Additionally, it was observed that a combination of technologies was used in some tools (n = 5). Among the 24 tools identified, 19 employed a single type of technology. For example, AI was the single technology incorporated in 12 tools and DHM in 7.

Table 3. Characteristics of the reviewed commercial tools that employed virtual and digital technologies for biomechanical risk assessment.

#	Company	Country	Tool Name	Cost	Application	Technology Involved	Hardware	Data Collection Method	Ergonomics Risk Assessment Methods *	Scientific Evidence
#1C	viso.ai [38]	Switzerland	Ergonomic Risk Analysis	Paid	Any industry	AI (CV + ML)	Camera	Computer-based assessment	Not mentioned	No
#2C	ViveLab [39]	Hungary	ViveLab Ergonomic	Paid	Any industry	DHM + MoCap	PC + Wearable (smart clothes)	Computer-based assessment + Direct measurement	OCRA, APSA, EAWS, KIM-MHO, NPW, REBA, and WERA	No
#3C	Soter [40]	Australia	Soter Genius	Paid	Any industry	AI (CV + ML)	Smartphone	Computer-based assessment + Direct measurement	RULA and REBA	No
#4C	Siemens [41]	Germany	Tecnomatix	Paid	Any industry	DHM + MoCap + VR	PC + Wearable (smart clothes + HMD)	Computer-based assessment + Direct measurement	NIOSH, OWAS, LBA, and RULA	[42]
#5C	Dassault Systèmes [43]	France	Delmia	Paid	Any industry	DHM	PC	Computer-based assessment	RULA, MTM, and GARG's energy prediction model	[44,45]
#6C	imk [46]	Germany	EMA	Paid	Any industry	DHM + VR	PC + HMD	Computer-based assessment	NIOSH and EAWS	[47]
#7C	Voxel [48]	USA	Voxel	Paid	Any industry	AI (CV + ML)	Camera	Computer-based assessment	REBA	No
#8C	TuMeke [49]	USA	Tumeke Ergonomics	Paid	Any industry	AI (CV + ML)	Smartphone	Computer-based assessment	RULA, REBA, RSI, and NIOSH	No
#9C	VelocityEHS [50]	USA	VelocityEHS® Industrial Ergonomics	Paid	Any industry	AI (CV + ML)	Smartphone	Computer-based assessment	RULA and REBA	No
#10C	Nawo Solution [51]	France	Nawo	Paid	Any industry	AI (CV + ML) + DHM, VR, and MoCap	Smartphone + PC + Wearable (smart clothes + HMD)	Computer-based assessment + Direct measurement	RULA, REBA, NIOSH, EAWS, and NFX35-109	No
#11C	IBV [52]	Spain	ErgoIA	Paid	Any industry	AI (CV + ML)	Smartphone	Computer-based assessment	REBA, OWAS, and Repetitive Tasks	No
#12C	ErgoSanté [53]	France	LEA	Open	Any industry	AI (CV + ML)	Smartphone	Computer-based assessment	RULA	No
#13C	Intenseye [54]	UK	Intenseye Ergonomics AI	Paid	Any industry	AI (CV + ML)	Camera	Computer-based assessment	RULA and REBA	No
#14C	Protex AI [55]	Ireland and USA	Protex AI	Paid	Any industry	AI (CV + ML)	Camera	Computer-based assessment	Not mentioned	No
#15C	Buddywise [56]	Sweden	The product has no name	Paid	Any industry	AI (CV + ML)	Camera	Computer-based assessment	Not mentioned	No
#16C	FlexSim [57]	USA	FlexSim	Paid	Any industry	DHM	PC	Computer-based assessment	RULA, NIOSH, OWAS, Snook and Ciriello, and MEE	[58]
#17C	Simio [59]	USA	Simio	Paid	Any industry	DHM	PC	Computer-based assessment	Not mentioned	[60]

Table 3. *Cont.*

#	Company	Country	Tool Name	Cost	Application	Technology Involved	Hardware	Data Collection Method	Ergonomics Risk Assessment Methods *	Scientific Evidence
#18C	AnyBody [61]	Denmark	AnyBody	Paid	Academic, Medicine, Sports, and Industry	DHM + MoCap	PC + Wearable (smart clothes)	Computer-based assessment + Direct measurement	RULA and EMG	[62,63]
#19C	PTC [64]	USA	Creo	Paid	Any industry	DHM	PC	Computer-based assessment	RULA, Snook and Ciriello, and NIOSH	[65]
#20C	NexGen Ergonomics [66]	Canada	HumanCad	Paid	Any industry	DHM	PC	Computer-based assessment	NIOSH, Energy Expenditure, OWAS, RULA, Snook and Ciriello, and Mital	[67]
#21C	OpenSim [68]	USA	OpenSim	Open	Academic, Medicine, Sports, and Industry	DHM	PC	Computer-based assessment	RULA, OWAS, NIOSH, LSI, MFI, JRFs, and EMG	[69–72]
#22C	Arvist [73]	USA	Arvist	Paid	Any industry	AI (CV + ML)	Camera	Computer-based assessment	Not mentioned	No
#23C	Everguard [74]	USA	Sentri 360	Paid	Any industry	AI (CV + ML)	Camera	Computer-based assessment	Not mentioned	No
#24C	University of Michigan /Human Tech/ Velocity EHS [75]	USA	3DSSPP	Paid	Any industry	DHM	PC	Computer-based assessment	Not mentioned	[76]

* Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), NIOSH, Ovako Working Analysis System (OWAS), Ergonomic Assessment Worksheet (EAWS), Snook and Ciriello, Key Indicator Method for Manual Handling Operator (KIM-MHO), Occupational Repetitive Action (OCRA), Workplace Ergonomic Risk Assessment (WERA), New Production Worksheet (NPW), Revised Strain Index (RSI), Lower Back Analysis (LBA), Arbeitsplatz-Strukturanalyse (APSA), NFX35-109, Mital, Metabolic Energy Expenditure (MEE), Muscle Electrical Activity (EMG), Method Time Measurement (MTM).

Regarding hardware usage frequency, PCs were the most commonly used, integrated into 12 tools. They were followed by cameras, wearables (n = 7 each), and smartphones (n = 6). Out of the 24 tools identified, 19 utilised a single type of hardware technology. For instance, PCs and cameras were the sole hardware technology used in seven tools, while smartphones were used in five. It was also noted that some tools (n = 5) employed a combination of technologies. For example, PCs were paired with smart clothes and HMDs in tools #2C and #10C, respectively. Additionally, it was observed that most camera hardware-based tools were not limited to ergonomics but extended their evaluation to other areas, such as safety, area control, vehicle safety, housekeeping, behavioural safety, personal protective equipment, and others.

Concerning biomechanical risk assessment methods, out of the 24 tools reviewed, only 5 of them combined different data collection methods (Table 1), namely direct measurement techniques with computer-based assessment (i.e., tools #2C, #3C, #4C, #10C, and #18C). Regarding biomechanical risk assessment methods, the most frequently used was RULA (n = 12), followed by REBA (n = 8), NIOSH (n = 6), OWAS (n = 5), EAWS (n = 3), and Snook and Ciriello (n = 2). Other methods refer to KIM-MHO, OCRA, Workplace Ergonomic Risk Assessment (WERA), New Production Worksheet (NPW), Revised Strain Index (SI), Lower Back Analysis (LBA), Arbeitsplatz-Strukturanalyse (APSA), NFX35–109, and Mital, which were less prevalent with only one instance each. Additionally, some companies employed other types of ergonomics evaluation methods. For example, tools for measuring metabolic energy expenditure (MEE) and muscle electrical activity (EMG) (#21C) are also used. The Method Time Measurement (MTM) method was also noted among the tools employed (#5C).

In terms of the physical risk factors, the most addressed risk factor was "Awkward Postures" (n = 16), followed by "Manual Handling" (n = 9), "Holistic" (n = 8), and "Repetitive Movements" (n = 5). The "Holistic" category incorporates biomechanical, physiological, thermal environment, and psychosocial aspects. Evidence from scientific literature supported 10 of the 24 tools reviewed (tools #4C, #5C, #6C, #16C, #17C, #18C, #19C, #20C, #21C, and #24C).

4.2. Academic Literature

Table 4 presents the key characteristics of the ten reviewed academic studies. MoCap was the most frequently used technology, being employed in 7 out of 10 studies, followed by DHM (n = 5), AI and VR (n = 3 each), and 2D Laser Imaging Detection and Ranging (2D LiDAR), and smartwatch and IoT (n = 1 each). The most employed hardware was wearables (n = 9), followed by PCs (n = 5), Kinect V2 and camera (n = 2 each), laser, scanner, and detector (e.g., 2D LiDAR) (n = 1), and sensors (n = 1). Technologies were often combined. For instance, Pistolesi et al. [77] developed a human-centred posture-tracking system for assembly/disassembly line workers using supervised learning, a smartwatch to monitor upper-body posture, and 2D LiDAR to track leg placement. Caputo et al. [78] proposed a novel approach for validating the design of workplaces on automotive assembly lines in a virtual environment using DHM software and a homemade MoCap system.

Table 4. Characteristics of the reviewed scientific literature tools that employed virtual and digital technologies for biomechanical risk assessment.

#	References	Tool Name	Application	Technology Involved	Hardware	Data Collection Method	Ergonomics Risk Assessment Methods *	Physical Risk Factors Addressed	Sample Size
#1A	Pistolesi et al. [77], 2024	Not applied	Experimental Environment	AI (ML) + LiDAR + microprocessors, sensors, communication, and display (smartwatch)	Wearable (smartwatch) and emitter + receiver + processor (e.g., LiDAR)	Computer-based assessment + Direct measurement	Not mentioned	Not applied	3
#2A	Caputo et al. [78], 2018	Ergo-UAS method	Industrial Environment	DHM + MoCap	PC + Wearable (smart clothes)	Computer-based assessment + Direct measurement	EAWS	Holistic	Not mentioned
#3A	Manghisi et al. [79], 2022	ErgoVR tool	Experimental Environment	MoCap + PL (C#) + VR	Kinect V2 + Wearable (HMD)	Computer-based assessment	RULA	Awkward Postures	Not mentioned
#4A	Sardar et al. [80], 2023	Not applied	Experimental Environment	VR	Wearable (HMD)	Observational assessment	RULA, REBA, and OWAS	Awkward Postures and Holistic	10
#5A	Havard et al. [81], 2019	Not applied	Experimental Environment	DHM + VR + MoCap	PC + Wearable (HMD and smart clothes)	Computer-based assessment + Direct measurement	RULA	Awkward Postures	Not mentioned
#6A	Feldmann et al. [82], 2019	Not applied	Experimental Environment	MoCap	Wearable (smart clothes)	Direct measurement	KIM-MHO	Awkward Postures	3
#7A	Bortolini et al. [83], 2020	Motion Analysis System (MAS)	Experimental Environment	DHM + MoCap	PC + Kinect V2	Computer-based assessment	OWAS, REBA, NIOSH, and EAWS	Holistic, Awkward Postures and Manual Handling	7

Table 4. *Cont.*

#	References	Tool Name	Application	Technology Involved	Hardware	Data Collection Method	Ergonomics Risk Assessment Methods *	Physical Risk Factors Addressed	Sample Size
#8A	Caterino et al. [84], 2021	Not applied	Industrial Environment	DHM + MoCap + IoT	PC + Wearable (smart clothes) + Embedded systems (sensors)	Computer-based assessment + Direct measurement	OWAS	Holistic	Not mentioned
#9A	Massiris Fernández et al. [15], 2020	Not applied	Industrial Environment	AI (ML + CV)	Camera	Computer-based assessment	RULA	Awkward Postures	Not mentioned
#10A	Ciccarelli, Papetti, Scoccia, et al. [85], 2022	Not applied	Experimental Environment	AI (ML + CV) + DHM + MoCap	Camera + PC + Wearable (smart clothes)	Computer-based assessment + Direct measurement	RULA	Awkward Postures	Not mentioned

* Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), Ovako Working Analysis System (OWAS), NIOSH, Key Indicator Method for Manual Handling Operator (KIM-MHO), Ergonomic Assessment Worksheet (EAWS).

Manghisi et al. [79] developed a software tool that utilises MoCap, specifically the Microsoft Kinect v2 sensors, VR technology, and C# Programming Language (PL) to assess ergonomic postural risk in static postures.

Meanwhile, Sardar et al. [80] sought to comprehend the physical risk levels of manufacturing industry employees during VR interaction for manufacturing tasks. Havard et al. [81] proposed a real-time co-simulation architecture between a digital twin and a VR environment using DHM and VR technology. Feldmann et al. [82] aimed to standardise the ergonomics assessment procedure by digitising the ergonomics analysis tool Key Indicator Method (KIM) through MoCap.

Bortolini et al. [83] introduced the Motion Analysis System (MAS), an hardware/software solution designed to capture and analyse human body movements during manufacturing and assembly tasks through MoCap (Microsoft Kinect v2 sensor) and software (productivity and ergonomic analysis). Caterino et al. [84] proposed a methodology focused on an ergonomic analysis based on MoCap, IoT, and DHM software. Lastly, Ciccarelli, Papetti, Scoccia, et al. [85] introduced a system designed to prevent uncomfortable and potentially hazardous postures using DHM, MoCap, and AI technologies.

Five biomechanical risk assessment methods combined direct measurement with computer-based data collection methods of the ten tools reviewed. The most frequently used risk assessment method was RULA (n = 5), followed by OWAS (n = 3), REBA and EAWS (n = 2 each), and NIOSH and KIM-MHO (n = 1 each). Consequently, the most addressed physical risk factor was "Awkward Postures" (n = 7), followed by "Holistic" (n = 5) and "Manual Handling" (n = 2).

5. Discussion

5.1. Technologies and Hardware Comparison

Various technologies have been used in work-related biomechanical risk assessment. A review of 24 commercial tools for biomechanical risk assessment revealed that AI (n = 13) and DHM (n = 12) were the most frequently used technologies. This was followed by MoCap (n = 4) and VR (n = 3).

In contrast, when examining ten studies from academic literature, MoCap emerged as the dominant method used in biomechanical risk assessments, featuring in seven studies. DHM applications were a close second, appearing in five studies, while AI and VR were utilised in only three studies each (Table 5). Although smartphones, smartwatches, and IoT do not refer to a specific technology but rather to a set of integrated technologies, they are referred to individually in Table 5 for simplicity.

Table 5. Technology use: Comparison between academic and commercial tools that employ virtual and digital technologies for biomechanical risk assessment.

	AI	DHM	MoCap	VR	LiDAR	Smartphones [1]	Smartwatch [2]	IoT [3]	Total
Academic	3	5	7	3	1	-	1	1	21
Commercial	13	12	4	3	-	6	-	-	38
Total	16	17	11	6	1	6	1	1	59

[1] Smartphones—Integration of sensors, microprocessors, communication, positioning, and display technologies. [2] Smartwatch—Integration of sensors, microprocessors, communication, and display technologies. [3] IoT—Integration of sensors, microcontrollers, microprocessors, and communication.

Table 6 compares hardware employed in academic and commercial tools, where differences can also be noted. Among the 24 commercial tools reviewed, PCs (n = 12) emerged as the most prevalent hardware choice, followed by cameras and wearables (n = 7 each) and smartphones (n = 6). In contrast, academic tools exhibited a different pattern, with wearables (n = 9) and PCs (n = 5) being the most commonly employed hardware, followed by Kinect and camera (n = 2 each), IoT, and LiDAR (n = 1 each).

Table 6. Hardware comparison between academic and commercial tools.

	PC	Wearable			Smartphones [2]	Kinect	IoT [3]	LiDAR [4]	Camera	Total
		Smartwatch [1]	Smart Clothes	HMD						
Academic	5	1	5	3	0	2	1	1	2	19
Commercial	12	0	4	3	6	0	0	0	7	32
Total	17	1	9	6	6	2	1	1	9	51

[1] Smartwatch—Integration of hardware (sensors, microprocessor, communication, and display). [2] Smartphones—Integration of hardware (sensors, microprocessor, communication, positioning, and display). [3] IoT—Integration of hardware (sensor, microcontrollers, microprocessors, and communication). [4] LiDAR—Integration of hardware (emitter, receiver, and processor).

This observation suggests a disparity in the adoption of technologies and hardware devices between academic and commercial spheres. Such differences are related to varying objectives and constraints inherent in each context. For instance, academic studies often aim to develop innovative measurement techniques (e.g., Havard et al. [81]) or refine existing ones (e.g., Feldmann et al. [82]). Conversely, commercial tools primarily target quantifying biomechanical risks within workplace environments.

Moreover, the choice of hardware is influenced by the constraints imposed by the respective contexts. Academic studies typically operate within controlled environments without external factors, such as extreme temperatures, noise, or vibrations, allowing for more extensive hardware adoption. In contrast, the physical characteristics of tasks, such as workers′ movements and industry settings, may impose limitations. Hence, commercial tools often resort to non-intrusive or inconspicuous technologies/hardware, such as AI and DHM.

While “non-intrusive” and “inconspicuous” are frequently used interchangeably, they differ. Non-intrusiveness emphasises the absence of discomfort or disruption, ensuring that individuals are not subjected to unwanted inquiries or discomfort [86]. On the other hand, inconspicuousness pertains to the lack of noticeability, focusing on blending seamlessly into the background to avoid detection. Thus, while both terms imply discretion, non-intrusiveness prioritises comfort and avoidance of disruption, whereas inconspicuousness emphasises avoiding detection. For instance, a security camera positioned discreetly in a company setting may be considered both non-intrusive (if it respects privacy expectations) and inconspicuous (if it blends with the surroundings). Conversely, a safety technician questioning individuals in the same space may be non-intrusive (if the interaction is respectful) but not inconspicuous, as their presence is noticeable.

5.2. Risk Factors and Biomechanical Risk Assessment Methods

Commercial tools were observed to employ more physical workload assessment methods than academic studies, with fifteen methods used in commercial tools versus six in academic studies. Consistent with the findings of Joshi and Deshpande [87], when systematically reviewing ergonomic assessment techniques in various industrial sectors, the most commonly utilised methods were RULA, REBA, and OWAS. These methods were applied in 12, 8, and 5 out of the 24 commercial tools and in 5, 2, and 3 out of the ten academic studies, respectively. Furthermore, commercial tools also addressed "Repetitive" risk factors and incorporated other types of methods, such as physiological (e.g., EMG and MEE) and industrial engineering methods (e.g., MTM). Nonetheless, this difference may be due to the smaller sample of reviewed academic studies.

Regarding assessing risk factors, commercial and academic tools predominantly focused on addressing "Awkward Postures," accounting for 46.7% of commercial and 50.0% of academic tools. The second-most addressed category was "Holistic," accounting for 24.4% of commercial and 35.8% of academic tools. This is followed by "Manual Handling," which was addressed by 20.0% commercial and 14.3% academic tools. The categories "Repetitive Tasks" and "Others" were exclusively addressed by commercial tools. Table 7 provides an overview of physical workload assessment methods employed in the reviewed tools and their respective risk factors.

Table 7. Physical workload assessment methods by risk factors.

Risk Factors	Assessment Methods	Frequency		Sum by Method	Total
		Academic	Commercial		
Awkward Postures	RULA	5	12	17	29
	REBA	2	8	10	
	LBA	-	1	1	
Manual Handling	NIOSH	1	6	7	11
	KIM-MHO	1	1	2	
	Snook and Ciriello	-	2	2	
Holistic	OWAS	3	5	8	16
	EAWS	2	3	5	
	WERA	-	1	1	
	NPW	-	1	1	
	APSA	-	1	1	
Repetitive	OCRA	-	1	1	4
	SI	-	1	1	
	NFX35-109	-	1	1	
	Not mentioned	-	1	1	
Others	Physiology	-	5	1	6
	Cycle Time	-	1	1	

5.3. *Preventive and Corrective Action*

Preventive and corrective measures are two key strategies for managing risks and ensuring safety [88]. Preventive measures are proactive steps to prevent an incident or harm. They aim to identify potential hazards and take action to eliminate or reduce them. On the other hand, corrective measures are reactive strategies implemented to minimise work-related risk factors.

From this background, it was observed that the technologies mentioned above were employed in distinct ways. For instance, DHM and VR can be employed both during the design phase of workstations and the monitoring of existing workplace conditions, as evidenced by reviewed tools (e.g., #4C, #5C, and #6C). Conversely, AI and MoCap systems are more commonly associated with monitoring existing workplace conditions (e.g., #1C, #3C, and #7C).

In other words, technologies employed in workstation design are primarily focused on preventive action, whereas technologies that can only be used for monitoring mainly address corrective action. In this context, DHM and VR technologies could be employed within preventive strategies, and they were employed in both academic and commercial-reviewed tools. Specifically, these technologies were employed in 38.1% of academic and 39.5% of commercial tools. Although their application was not the most prevalent one, it suggests a broad application of DHM and VR across different sectors. In this context, Gualtieri et al. [89], who conducted a systematic literature review to examine the current state of safety and ergonomics in collaborative robotics, concluded that prevention strategies have gained greater attention than protection strategies. Nonetheless, present findings may imply that digital and virtual technologies still target corrective over preventive actions when applied to biomechanical risk assessment.

5.4. Ergonomics Implications

This section concludes the discussion by evaluating this study's results and implications for ergonomics. Recent AI developments are expected to significantly alter how specific processes and tasks are done. In an evolving new technology context, human-centred considerations are paramount to ensure that AI technology is designed and used ethically. Petrat [90] emphasises the need for more research on human-centred aspects of AI, particularly those impacting employees′ well-being and acceptance. Additionally, the author encourages collaboration with other disciplines, such as sociology and economics, to delve into AI′s broader societal and organisational impacts. Given the large number of reviewed commercial tools employing AI, the present study resonates with Petrat's [90] recommendations. As the field of AI for biomechanical risk assessment is in its early stages of development, further research is required to identify the broader implications of employing this tool for workers' well-being and organisations' management within the domains of physical, cognitive, and organisational ergonomics.

Likewise, integrating wearable sensors and AI opens new avenues for innovation in various fields. This combination allows for real-time data collection and analysis, providing more accurate and timely insights. For ergonomics, combining wearable sensors and AI to prevent WMSD can provide valuable insights for improving workplace safety and workers' comfort. Monitoring work environments and equipment can prevent fatigue accumulation or overload [11]. Also, this combination is particularly beneficial for analysing complex or hard-to-observe work situations [11].

As another relevant technology, the more extensive utilisation of DHM in commercial and academic tools can be explained by its cost-effectiveness, as different workstation designs and manufacturing processes can be simulated in a virtual environment before actual implementation. This is in accordance with Yin and Li (2023), who underscored that DHM assembly process simulation was a cost-effective solution for ergonomics and enhanced efficiency in digital human posture planning. Likewise, Asad et al. [22] highlighted the potential and the features concerning digital twins. The authors stated that the current digital twin (DT) technology focuses primarily on physical assets, neglecting human operators. Accordingly, human-centred DTs are expected to address this gap by incorporating human factors through technologies, such as human-focused sensors and AI. In this sense, human-centred DTs also show immense potential for improving human-machine collaboration in various industrial applications.

Concerning the integration of technologies, da Silva et al. [9] highlight that despite the acknowledged benefits of a combination of VR and DHM, they are not frequently integrated into ergonomics analysis. The author also stated that most studies focus on pre-designed processes, not incorporating VR′s potential for early-stage evaluation. Overall, the research points to a need to bridge the gap between the promising potential of VR and DHM and their actual utilisation in improving ergonomics. The present study also identified this lack of integration, with only three studies combining DHM and VR (#4C, #6C, and #10C). This indicates that companies, although increasingly interested in VR and DHM, might lack a complete understanding of their complementary advantages and limitations, including associated costs.

Regarding remaining technologies, Adriana Cárdenas-Robledo et al. [7] highlighted that XR technologies significantly benefit I4.0/I5.0 by improving training, design, and various industrial processes. In the reviewed tools, VR and AR, resulting from the combination of CV and ML, seem promising for ergonomic assessment. This potential can be realised through a focus on affordability and safety. The same is true for MoCap systems, particularly IMU systems, as they can improve medical diagnosis, assessment, and treatment in various areas, including ergonomics, by assessing and preventing WMSD [32].

Consequently, integrating evolving new virtual and digital technologies with a focus on human factors will be crucial not only for advancing biomechanical risk assessment but also for the technologies' development and widespread adoption. Nonetheless, it is worth noting that integrating new technologies into existing industrial settings may require not only reskilling and upskilling of the workforce, but also an appropriate and efficient system design to cope with changes in the flow of information and user-technology interfaces.

6. Conclusions

6.1. Main Findings and Limitations

The main findings of the present study can be summarised as follows:

- A review of 24 commercial tools for biomechanical risk assessment revealed that AI and DHM were the most frequently used technologies. MoCap and VR followed this. In 10 reviewed academic studies, the most employed technologies were MoCap and DHM.
- Commercial tools often resort to non-intrusive or inconspicuous technologies/hardware, such as AI and DHM.
- Commercial tools were observed to employ more physical workload assessment methods than academic studies. Nonetheless, the most employed methods were RULA and REBA, both in academic and commercial tools.
- In assessing risk factors, "Awkward Postures" were the most prevalent assessed risk factors for both instances. This was followed by "Holistic" assessments and "Manual Handling." Commercial tools exclusively addressed repetitive tasks and other risk factors.
- Regarding technology use, it was observed that technologies are employed in distinct ways. For instance, DHM and VR can be employed both during the workstation design phase and the monitoring of existing workplace conditions (i.e., preventive and corrective measures). Conversely, AI and MoCap systems are more commonly associated with monitoring existing workplace conditions (i.e., corrective measures).

However, this study is not free of limitations. They include the intrinsic limitations of the search strings employed in retrieving relevant academic studies and commercial tools and the use of a single research database (e.g., Web of Science). Likewise, first-page Google results may be subject to the author′s location when searching. It is also worth noting that the concept of "Ergonomics" is often associated with European-based research, and "Human Factors" are the most common term in North America. These limitations may have created a bias in the final sample. However, an equivalent number of European and United States commercial tools may indicate the contrary. Additionally, not finding scientific evidence for specific commercial tools can be related to an anonymous validation process that took place within academia without direct reference to the final commercial tool name.

6.2. Future Research and Recommendations

Based on the findings and limitations of this study, some potential directions for future research and recommendations:

- This study observed that digital and virtual technologies are used in different ways, with some used for design and others for monitoring existing work conditions. Future research could explore the benefits and drawbacks of different technologies and combinations of technologies for biomechanical risk assessment considering different risk factors.
- The study suggested a lack of scientific evidence for commercial tools. Even though this might be due to anonymous validation processes of commercial tools within

academia, it is recommended that commercial tools that target biomechanical risk assessment be more transparent about their validation process.
- This study focused on biomechanical risk assessment. However, it is interesting to evaluate how evolving new technologies may impact ergonomics as a whole. In other words, how does using specific technologies impact physical, cognitive, and organisational ergonomics? Additionally, future research could aim to include a more globally representative sample of academic studies and commercial tools.
- Echoing the findings of other studies, the present study calls attention to the need for human-centred aspects when developing and incorporating evolving new technologies into different industry contexts. Particularly, it is interesting to evaluate how the sociotechnical and management systems can cope with these new technologies. For instance, in relation to decision-making and organisational ergonomics, how can evolving technologies contribute to the horizontal availability of information concerning workers' well-being? And what are the implications?

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