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Combining inertial-based ergonomic assessment with biofeedback for posture correction: A narrative review ☆

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ABSTRACT

Work-related musculoskeletal disorders (WRMSDs) are the most reported work-related health problem in the European Union, representing an economic burden equivalent to 2% of its gross domestic product. Awkward postures are one of the main risk factors. Several postural assessment tools try to identify ergonomic exposure factors for evaluating WRMSD risk, yet these are commonly based on observation. Replacing observations with objective measurements can bring more accuracy and reproducibility to this analysis; hence, a direct measurement approach for the assessment is desired. This review looks for two-fold solutions, able to not only monitor workers' posture using inertial sensors but also to return that information to the user, in a biofeedback loop. It presents systems for posture risk assessment, regarding ergonomic methods, sensors' and actuators' characteristics, and validation protocols. In particular, this review advances previous manuscripts by exploring the literature regarding different biofeedback strategies and ways to encode meaningful information in the cues, i.e., able to deliver intuitive ergonomic guidance so that the user becomes aware and changes into a more neutral posture. The combination of inertial sensors and vibrotactile motors stood out, due to its effectiveness in reducing postural risk. Directional feedback to guide users' segments individually was found to be a promising strategy, although its validation is still limited. The results of the reviewed manuscripts pointed out the relevant practices, potentialities, and limitations of the existing solutions, allowing the identification of future challenges.

1. Introduction

Work-related musculoskeletal disorders (WRMSDs) are the most prevalent work-related health problem in the European Union (De Kok et al., 2019). Despite the economy's advances towards automation, many jobs still consist of risky and physically demanding tasks. In many situations, manual handling activities have not lost expression since their higher flexibility and lower investment costs still make them the suitable solution (Lind, Diaz-Olivares, Lindecrantz and Eklund, 2020). Working conditions that include repetitive motions, manual handling tasks, excessive force, sustained or regular awkward postures, prolonged sitting and standing, or vibrations from hand tools are risk factors for developing WRMSDs (Da Costa & Vieira, 2010; De Kok et al., 2019; Lee et al., 2021; Lins, Fudickar, Gerka, & Hein, 2018). Among WRMSDs, the most frequent type reported is backache, followed by muscular pain in the upper limbs (De Kok et al., 2019).

WRMSD consequences are associated with a work-limiting pain that decreases psychological health, job satisfaction, and productivity, and may lead to worker absenteeism or even to early retirement (De Kok et al., 2019; Lee et al., 2021). In 2015, for example, 53% of the workers with WRMSDs reported being absent from work for at least one day. These workers are not only more prone to be absent from work, but they are also usually absent for more days (De Kok et al., 2019). It was estimated that the total costs of WRMSDs represent up to 2% of the gross domestic product of the European Union, or €240 billion (Bevan, 2015).

Ergonomics tries to address the issue of how to lower the risk of WRMSDs by taking proper preventive measures. It ensures that work is designed considering workers' capabilities and constraints, trying to optimise health, safety and productivity (Great Britain. Health and Safety Executive, 2002). Besides interventions such as the redesign of

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the workplace or shift schedules, it is important to obtain an exact overview of the types and frequency of the workers' postures, identify the non-neutral ones, and change them, improving the ergonomics of the job (Lins et al., 2018). Indeed, musculoskeletal disorders have been proven to be less frequent when an ergonomic risk analysis that leads to the adoption of interventions is conducted (Pimparel, Madaleno, Ollay, & Gabriel, 2022).

In the process of assessing the WRMSD risk, there are multiple mechanisms for evaluating exposure to risk factors that underlie these injuries. This evaluation can be done in three main ways, listed next by increasing precision and invasiveness to the worker: self-reports, observational studies and direct measurements. Self-reports collect data regarding exposure to both physical and psychosocial factors, resorting to diaries, interviews and questionnaires, in which workers are asked to estimate the prevalence of postures or the frequency of movements, but it lacks precision since workers' perceptions are subjective and unreliable (David, 2005; Lee et al., 2021; Spielholz, Silverstein, Morgan, Checkoway, & Kaufman, 2001).

Observational methods rely on an observer (an ergonomist) and may be field-based or video-based. The former are mostly used for static or repetitive jobs and rely on checklists, although a more comprehensive report of the worker actions can also be performed (David, 2005; Spielholz et al., 2001). Several tools can be found, e.g., Ovako Working Posture Analysing System (OWAS), Postural Loading Upper Body Assessment (LUBA), Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), NIOSH Lifting Equation, or Quick Exposure Check. Like self-reports, these methods are widely used, but they have the drawback of intra- and inter-observer variability (David, 2005). In turn, video-based approaches are targeted to the assessment of posture in dynamic activities and empower more detailed evaluations, since they presuppose dedicated software to objectively analyse the relevant data that the observer visualises in the video and introduces in that software. Yet, they are not so convenient, are time-consuming, require highly specialised staff, and their cost is higher than that of field-based methods (David, 2005).

Direct measurements are based on sensors that are placed directly on the subject for the quantification of exposure risk, namely, 3D motion capture (MoCap) systems. These record movements and insert them in a 3D model (David, 2005; Nogueira, 2011). Postures, defined by position and angular movement of body segments, can be tracked using marker-based methods, which attach optical, sonic or electromagnetic markers to specific points of the body, whose coordinates can be computed accurately in real time (David, 2005). Regarding optical MoCap technologies, they can use either active (light-emitting LED) or passive markers (which reflect the light back to the cameras), like Vicon (Dutta, 2012; Nogueira, 2011). However, these gold standard techniques are expensive, and require specialised software; moreover, they are more suitable for laboratory simulated scenarios rather than real working conditions in the workers' natural environment, which has non-replicable stress factors and/or demands, and this hampers the identification of the usual postures (Cerqueira, Da Silva, & Santos, 2020; David, 2005; Lee et al., 2021). More recently, markerless technology, such as Microsoft Kinect, which integrates depth cameras and computer vision algorithms, has emerged in kinematic analysis. Additionally, advances in wearable technology turned inertial measurement units (IMUs) as promising devices (Cerqueira et al., 2020; Lee et al., 2021). Research indicates that both vision-based methods and wearable inertial sensors are effective on ergonomic assessment tools, however camera-based methods (either based on reflective markers or not) require constrained environments, highly depend on camera positions and light conditions, and may suffer from occlusion (Cerqueira et al., 2020; Yan, Li, Li, & Zhang, 2017), which is likely to happen in dynamic tasks. Both inertial and marker-based MoCaps' measurements can be affected by noise from artifacts inherent to skin movement. In turn, inertial sensors are lightweight, small-sized and, thus, portable and easily embedded in smart garments; also, they are relatively low-cost and low-power devices (Cerqueira et al., 2020; Vignais et al., 2013); moreover, contrary to camera-based motion trackers, IMUs do not suffer from data privacy issues since these latter do not record image/video (Ponce, Martínez-Villaseñor, & Miralles-Pechuán, 2016). Yet, it should be noted that inertial sensors may be affected by a divergence of the output values, drift, over time (Lorenzini, Lagomarsino, Fortini, Gholami, & Ajoudani, 2023), as a result of the integration of the gyroscope data (Lim & D'Souza, 2020). Notwithstanding, due to the best trade-off between accuracy and portability they provide, IMUs are becoming very attractive for the estimation of body segments' orientation and joint angles (Carbonaro et al., 2021). Hence, this literature review focuses on the use of wearable inertial MoCap systems. These rigorous kinematic evaluations can help to manage and prevent WRMSDs by improving the knowledge of the underlying human motions (Lee et al., 2021).

Humans tend to internalise movement patterns, which are hard to correct (Sword Health, 2020). Biofeedback for posture correction may increase self-awareness (Lee et al., 2021), and the training of the work technique is an important aspect in the prevention of WRMSD (Lins et al., 2018). Learning the principles of ergonomics allows workers to become more aware of what may lead to pain or injury (Occupational Safety and Health Administration, 2022), hence, trained workers are less likely to adopt bad postures (Lins et al., 2018). In this context, the amplification of error perception arising from haptic feedback has proved to be successful in inducing motor learning (Lind et al., 2020). Wearable actuator technology, allied with inertial sensors, can provide real-time biofeedback of the error to the worker, empowering him/her with greater posture self-awareness (Lee et al., 2021). This allows a quicker correction of bad postures, without having to wait for the person's intrinsic feedback to come into operation, when pain starts to act, thus avoiding musculoskeletal injuries.

In this context, the concepts of feedback and biofeedback should be clarified. Feedback consists of providing a measure of the outcome (biological or not) of the system, comparing it with the desired reference, and using this information to let one knows what is happening. On the other hand, biofeedback is based on biological signals and allows the subject to learn to control them, modifying physiological processes people are usually unaware of Beatty and Legewie (1977) and Morone et al. (2021). In the context of this paper, the desired outcome of the system is the ergonomic score, which is computed using inertial signals (the input, considered biological signals). Hence, a biofeedback system is a feedback system, but the reverse may not be true.

Recent reviews provided an overview of the state of the art concerning the application of wearable devices on ergonomics. For instance, Stefana, Marciano, Rossi, Cocca, and Tomasoni (2021) conducted a systematic review exploring the sensors' types and locations, the ergonomic risk factors typically assessed, and the criteria for those assessments. Lim and D'Souza (2020) drew a conceptual framework to review the scientific literature on the use of inertial sensors for biomechanical exposure assessment, regarding modelling, sensing, analysis, assessment and interventions. Although these two reviews demonstrated the potential of using IMUs for ergonomic assessments, they did not concentrate specifically on posture assessment, nor on biofeedback strategies for posture correction. Likewise, Lind, Abtahi and Forsman (2023) dissected the automation of observational risk assessment tools with ambulatory MoCap systems for increasing the accuracy and precision of the measurements, and feedback for work technique training, but the analysis of feedback was limited to the definition of its characteristics and not to the evaluation of its effectiveness. Lee et al. (2021) performed a scoping review regarding the effectiveness of the various types of feedback on the upper body and the devices' wearability during work, revealing improvements in posture but with a low level of evidence, and no improvements in pain; yet, no other haptic feedback modality besides the vibrotactile one was presented. To the best of our knowledge, no review has addressed simultaneously the analysis of inertial-based ergonomic assessment systems and the investigation of distinct biofeedback strategies to provide a more informative alert regarding posture risk.

This narrative review seeks inertial-based systems capable of assessing the ergonomics of workers' postures and providing clear cues for posture correction. This can potentially help to redesign tasks and, thus, prevent musculoskeletal disorders. With this work, we aim to answer the following questions: (i) "What types, number, locations and settings of wearable devices were adopted in the literature studies?"; (ii) "Which ergonomic criteria govern these postural assessments?"; (iii) "When to trigger biofeedback cues and what information can be encoded in them?"; and (iv) "Has biofeedback proved to be effective in posture correction?".

The remainder of this review is organised as follows: Section 2 outlines the search strategy. Section 3 provides an overview of systems for postural ergonomic assessment. Section 4 exposes biofeedback modalities and strategies. In Section 5, state-of-the-art limitations and challenges are discussed. Lastly, Section 6 presents the conclusions drawn from this review.

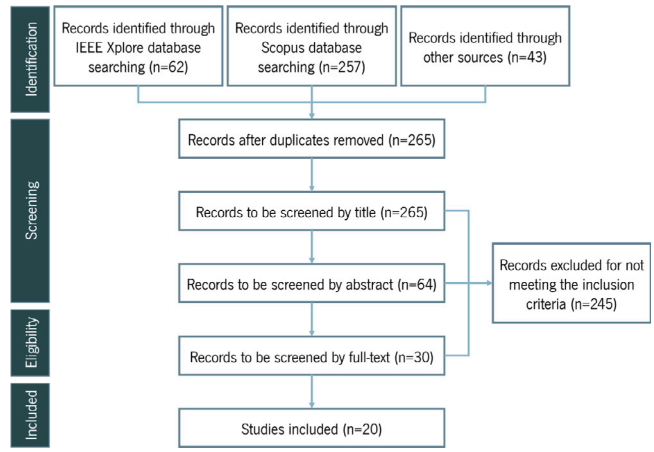

Fig. 1. PRISMA flow diagram for the search strategy.

2. Methods

An electronic search was conducted in the IEEE Xplore and Scopus databases. This search was driven according to the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), and analysed studies from 2013 (the year of pioneer paper (Vignais et al., 2013) in this review's topics) to 2023, using the following combination of keywords: (("ergonomic*" AND ("assessment" OR "risk")) OR "posture") AND ("wearable" OR "inertial-based") AND ("feedback" OR "biofeedback"). The search on the IEEE database included all metadata, whereas, on the Scopus database, it was restricted to the article title, abstract and keywords. The selected articles (i) were all written in English and (ii) involved wearable inertial technologies. The exclusion criteria were studies: (i) mentioning optical MoCap systems, (ii) addressing balance/gait training/rehabilitation, (iii) focused on sitting postures, (iv) presenting only a simple/binary assessment or with lack of information (algorithms or experimental protocol), or (v) with a primary focus on human–robot collaboration without further innovation in ergonomics and/or feedback. Review articles were also excluded from the search results. Yet, reviews' references were examined, as well as the references of other selected articles, and the relevant ones were included.

After a preliminary search, completed on 7 June 2023 and revised on 2 January 2024, 62 articles were found in IEEE Xplore, 257 articles in Scopus, and 43 through other sources, as reported in Fig. 1. After removing the duplicates, a screening process by title and by abstract was carried out, until only 30 articles were left to be fully read, in order to find out if they met the inclusion criteria or if they were suitable for this section. Finally, only 20 articles were included.

The included studies were divided into two main topics for greater clarity: the first has a focus on posture monitoring and ergonomic risk assessment (Section 3), and the other on biofeedback strategies (Section 4). Some of the articles were analysed in both, regarding the way the ergonomic assessment is performed and the actuation system, respectively.

3. Postural ergonomic assessment

This section aims to identify the current ergonomic methods employed in posture assessment and to understand how workers' postures are assessed, i.e., whether multiple body parts are assessed individually or as a whole.

A summary of the relevant manuscripts found in the search on ergonomics is presented in Tables 1 and 2. The first divides the manuscripts according to the study goal, the ergonomic method/scale applied, highlighting the sensors used (their type, location and sampling frequency) and the biofeedback system (concurrently, i.e., in real time; or terminal, that is, presented after the trial). Table 2 summarises the algorithms used and the validation methodology of the identified studies, presenting the experimental protocols, ground truths, and metrics used for the validation.

The main targets of these studies are industry (Cerqueira et al., 2020; Huang et al., 2020; Martinez et al., 2022; Merlo et al., 2023; Vignais et al., 2013); the construction sector (Martins et al., 2023; Valero et al., 2017; Yan et al., 2017; Zhao & Obonyo, 2021; Zhao et al., 2021); in one, it was the agricultural sector (Martins et al., 2023); and, in another, health care delivery (Carbonaro et al., 2021).

3.1. Ergonomic methods adopted

Distinct levels of postural ergonomic assessment were found: multiple segments can be assessed separately, assigning a risk level to each of them (local approach), which can help to prevent WRMSDs by identifying the body segments exposed to a higher ergonomic risk; or a global risk can be assigned to the whole body, considering the combination of the different segments (global assessment). In three of the included articles, the risk assessment was performed globally: in two of them, it was based on subjective/qualitative postures (Zhao & Obonyo, 2021; Zhao et al., 2021), whereas, in the other, it was based directly on angular ranges (Valero et al., 2017). Furthermore, these two studies also performed posture classification (in the case of Zhao et al. (2021), that classification was needed to carry out the ergonomic assessment). Most of the studies based their assessment on angular values, and this was the case for the ones that employed a local assessment. In four studies, the assessment was only segment-specific (local) (Cerqueira et al., 2020; Merlo et al., 2023; Valero et al., 2017; Yan et al., 2017); whereas in another five, those local scores allowed obtaining a global score too, for a wider view of the WRMSD risk (Carbonaro et al., 2021; Huang et al., 2020; Martinez et al., 2022; Martins et al., 2023; Vignais et al., 2013). Four studies carried out the assessment in real time (Cerqueira et al., 2020; Merlo et al., 2023; Vignais et al., 2013; Yan et al., 2017).

Several ergonomic criteria were found to be the basis of the posture assessments: Standard ISO 11226 (Valero et al., 2017; Yan et al., 2017), RULA (Carbonaro et al., 2021; Cerqueira et al., 2020; Huang et al., 2020; Merlo et al., 2023; Vignais et al., 2013), LUBA (Cerqueira et al., 2020; Martins et al., 2023), REBA (Huang et al., 2020; Martinez et al., 2022), OWAS (Zhao & Obonyo, 2021; Zhao et al., 2021), Maximum Holding Time (MHT) (Zhao & Obonyo, 2021; Zhao et al., 2021), and a novel K-score proposed by Martinez et al. (2022). With respect to the ergonomic methods that assess individual segments, the majority focus

Table 1
Summary of the included studies on postural ergonomics monitoring, regarding their goals, ergonomic methods, sensing systems, and biofeedback systems.

Reference	Study goal	Ergonomic method	Sensors			Biofeedback system
			Number and type	Location	Sampling frequency	
Yan et al. (2017)	Real-time local ergonomic risk assessment	Standard ISO 11226	2 Bluetooth YEI 3-Space IMUs (3-axis acc, 3-axis gyr and 3-axis mag)	Back of head and thoracic level	10 Hz	Visual and auditory (both concurrent)
Cerqueira et al. (2020)	Real-time local ergonomic risk assessment	RULA complemented with LUBA	4 MPU-9250 IMUs (3-axis acc and 3-axis gyr)	Back of head, T4 and upper arms	100 Hz	Haptic (concurrent) and visual (terminal)
Merlo et al. (2023)	Real-time local ergonomic risk assessment	RULA	17 wireless Xsens MVN Awinda IMUs (3-axis acc, 3-axis gyr and 3-axis mag)	Head, sternum, pelvis, shoulders, upper arms, forearms, hands, upper legs, lower legs and feet	20 Hz	N/A
Martins, Cerqueira, Vieira, Pombeiro, and Santos (2023)	Local and global ergonomic risk assessment	RULA	17 wireless Xsens MVN Awinda IMUs (3-axis acc, 3-axis gyr and 3-axis mag)	Head, sternum, pelvis, shoulders, upper arms, forearms, hands, upper legs, lower legs and feet	60 Hz	N/A
Vignais et al. (2013)	Real-time local and global ergonomic risk assessment	RULA	7 wireless Colibri IMUs (3-axis acc, 3-axis gyr and 3-axis mag) and 2 bi-axial SG65 goniometers	- IMUs: head, chest, sacrum, upper arms and forearms; - Goniometers: hands	100 Hz	Visual and auditory (both concurrent)
Carbonaro et al. (2021)	Local and global ergonomic risk assessment	RULA	3 wireless Xsens MTw IMUs (3-axis acc, 3-axis gyr and 3-axis mag)	Back of head, thoracic level and sacral level	75 Hz	N/A
Huang, Kim, Zhang, and Xiong (2020)	Local and global ergonomic risk assessment	RULA and REBA	17 Xsens MVN Link IMUs (3-axis acc, 3-axis gyr and 3-axis mag)	Head, sternum, pelvis, shoulders, upper arms, forearms, hands, upper legs, lower legs and feet	N/M	Visual (terminal)
Martinez, Nazarahari, and Rouhani (2022)	Local and global ergonomic risk assessment	REBA and K-score	9 wireless Xsens MTw IMUs (3-axis acc, 3-axis gyr and 3-axis mag)	Head, sternum, sacrum, right upper arm, right forearm, right hand, right thigh, right shank and right foot	100 Hz	N/A
Valero, Sivanathan, Bosché, and Abdel-Wahab (2017)	Local and global ergonomic risk assessment + qualitative postures classification	Standard ISO 11226	8 wireless proprietary IMUs (3-axis acc, 3-axis gyr and 3-axis mag)	Upper back, lower back, upper arms, upper legs and lower legs	50 Hz	Visual (terminal)
Zhao, Obonyo, and Bilén (2021)	Qualitative postures classification + global ergonomic risk assessment	OWAS and MHT	5 MetaMotionC IMUs (3-axis acc and 3-axis gyr)	Head, chest centre, right upper arm, right thigh and right calf	N/M	Visual (every 30 min and terminal) and auditory (concurrent)
Zhao and Obonyo (2021)	Qualitative postures classification + global ergonomic risk assessment	OWAS and MHT	5 MetaMotionC IMUs (3-axis acc and 3-axis gyr)	Forehead, chest centre, right upper arm, right thigh and right crus	25 Hz (subject 1); 50 Hz (others)	N/A

N/A: Not Applicable; N/M: Not Mentioned; IMU: inertial measurement unit; acc: accelerometer; gyr: gyroscope; mag: magnetometer;RULA: Rapid Upper Limb Assessment; LUBA: Postural Loading Upper Body Assessment; REBA: Rapid Entire Body Assessment; OWAS: Ovako Working Posture Analysing System; MHT: Maximum Holding Time.

only on the sagittal plane. In connection with this, Carbonaro et al. (2021) pointed out some gaps in the RULA tool, namely, the lack of angular thresholds to evaluate torsion and lateral bending. In order to mitigate that, they chose a threshold of three times the precision of the IMUs, for robust recognition, and Cerqueira et al. (2020) combined two ergonomic methods, with RULA assessing the sagittal plane and LUBA the coronal plane.

3.2. Hardware and system characteristics

With regard to the sensors used to record body movement, all reported studies used IMUs, containing 3-axis accelerometers and 3-axis gyroscopes (Cerqueira et al., 2020; Zhao & Obonyo, 2021; Zhao et al., 2021), or combining those with a 3-axis magnetometer (Carbonaro et al., 2021; Huang et al., 2020; Martinez et al., 2022; Martins et al., 2023; Merlo et al., 2023; Valero et al., 2017; Vignais et al., 2013; Yan et al., 2017). There is no agreement about the number and location of sensors. The number of sensing units varied between 2 and 9, except for 3 studies that used commercial systems which contain 17 IMUs: Xsens MVN Link, which embeds the sensors in a suit (Huang et al., 2020), and Xsens MVN Awinda (Martins et al., 2023; Merlo et al., 2023). The IMUs were incorporated into a personal protective equipment by Yan et al. (2017). Cerqueira et al. (2020) developed a smart garment to embed the sensors, actuators and remaining hardware. Fig. 2 displays the sensor placement in the studies, where it stands out that all but one placed a sensing unit on the head. Regarding limbs, 6 studies placed inertial sensors on both left and right limbs, whereas 3 collected data from the right limbs only. Two goniometers on the hands were added in a study to record wrist angles (Vignais et al., 2013), in order to complement the inertial system, since distal segments are the most challenging segments to achieve a lower joint angle estimation error. The sampling frequency also varies across studies, with the smallest value being 10 Hz and the highest 100 Hz.

Table 2
Summary of the studies included on postural ergonomics monitoring, regarding their algorithms, validation protocols, ground truths, and metrics.

Reference	Algorithms	Experimental protocol	Ground truth	Metrics
Yan et al. (2017)	- Joint angle estimation using tilt–twist method; - Calculation of MHT for real-time warning threshold	- N = N/M; - Typical operations of construction workers on a construction site	**Technical validation:** N/A. **Ergonomic tool validation:** N/A	N/A
Cerqueira et al. (2020)	- Joint angle estimation using a Kalman filter; - Computation of the risk level through joint angles' discretisation based on thresholds (state machine)	- N = 5; - 5 general tasks, containing different working postures; - Each trial performed 4 times: 2 without biofeedback and 2 with it	**Technical validation:** - Collaborative robot arm. **Ergonomic tool validation:** N/A	**Technical validation:** - RMSE. **User performance:** - Trial execution time; - Time spent at each risk level. **System usability:** - Questionnaires following SUS
Merlo et al. (2023)	- Joint angle estimation: N/M; - Computation of the risk level through joint angles' discretisation based on thresholds; - Calculation of an index that integrates the present and past risk scores	- N = 1; - Assembly of a corner joint with three aluminium profiles	**Technical validation:** N/A. **Ergonomic tool validation:** N/A	**User performance:** - Kinematic wear index
Martins et al. (2023)	- Computation of the risk level through joint angles' discretisation based on thresholds; - Calculation of an index that integrates the present and past risk scores	- N = 3; - Isolated postures, construction task circuit, and agriculture task circuit	**Technical validation:** N/A. **Ergonomic tool validation:** N/A	**User performance:** - LUBA scores; - Time spent at each risk level; - Kinematic wear index
Vignais et al. (2013)	- Biomechanical model of the upper body; - Joint angle estimation through loosely coupled extended Kalman filters; - Computation of the risk level through joint angles' discretisation based on thresholds	- N = 12; - Industrial manual task, composed of 4 subtasks; - 6 subjects without real-time biofeedback and 6 with it	**Technical validation:** N/A. **Ergonomic tool validation:** N/A	**User performance:** - Trial execution time; - Time spent at each risk level; - Frequency of threshold breaching. **System usability:** - 5-point Likert scale questionnaire; - Subjective observations
Carbonaro et al. (2021)	- Joint angle estimation: N/M; - Time window segmentation, and joint angles' discretisation based on thresholds; - Computation of the risk level considering a time threshold	- N = 1 (surgeon); - Real laparoscopic surgery operation	**Technical validation:** N/A. **Ergonomic tool validation:** - Camera recording	**User performance:** - RULA score; - Time spent at each risk level
Huang et al. (2020)	- Joint angle estimation: N/M; - Computation of the risk level through joint angles' discretisation based on thresholds; - Estimation of joint contact forces and moments; - Computation of lower-back compression force and joint strength percent capable	- N = 20 (healthy); - 15 experimental tasks derived from three common jobs in the shipbuilding process (manual handling, painting and welding)	**Technical validation:** N/A. **Ergonomic tool validation:** - For posture: expertise assessment through video camera recordings; - For biomechanical analysis: 3DSSPP	**Ergonomic tool validation:** - For posture: ICC; absolute difference between scores; accuracy; - For biomechanical analysis: CMC; relative error. **User performance:** - RULA and REBA scores; - Time spent at each risk level
Martinez et al. (2022)	- Joint angle estimation: Xsens proprietary sensor fusion; - Computation of the risk level through joint angles' discretisation based on thresholds	- N = 10; - Material handling task	**Technical validation:** - Camera-based MoCap (Vicon). **Ergonomic tool validation:** - EMG (Trigno, Delsys)	**Technical validation:** - RMSE; - Cohen's Kappa coefficient. **Ergonomic tool validation:** - Spearman correlation coefficient. **User performance:** - REBA and K-score scores
Valero et al. (2017)	- Joint angle estimation: N/M; - Computation of the risk level through joint angles' discretisation based on thresholds (state machine)	- N = 6 (not seriously injured in the last year); - Bricklaying routine tasks, replicating real working environments	**Technical validation:** N/A. **Ergonomic tool validation:** - Expertise assessment through video camera recordings	**User performance:** - Productivity score; - Posture score
Zhao et al. (2021)	- Deep neural network model for posture recognition; - Time threshold-based application of the ergonomic rules	- N = 30 (18 construction workers + 12 managers); - Routine construction tasks (6 trades)	**Technical validation:** N/A. **Ergonomic tool validation:** - Postures manually labelled through video camera recordings	**User performance:** - Count of MHT breach; - Total duration of MHT breach; - Detected MHT time; - Posture frequency and proportion. **System usability:** - 5-point Likert scale questionnaire

(*continued on next page*)

Table 2 (*continued*).

Zhao and Obonyo (2021)	- Incremental learning model for posture recognition; - Time threshold-based application of the ergonomic rules	- N = 9 (construction workers); - Routine construction tasks (5 trades)	**Technical validation:** N/A. **Ergonomic tool validation:** - Postures manually labelled through video camera recordings	**User performance**: - Count of MHT breach; - Total duration of MHT breach; - Detected MHT time; - Posture frequency and proportion; - OWAS ergonomic risk level

N: number of participants; RMSE: root mean squared error; SUS: System Usability Scale; ICC: intraclass correlation coefficient; CMC: coefficient of multiple correlation.

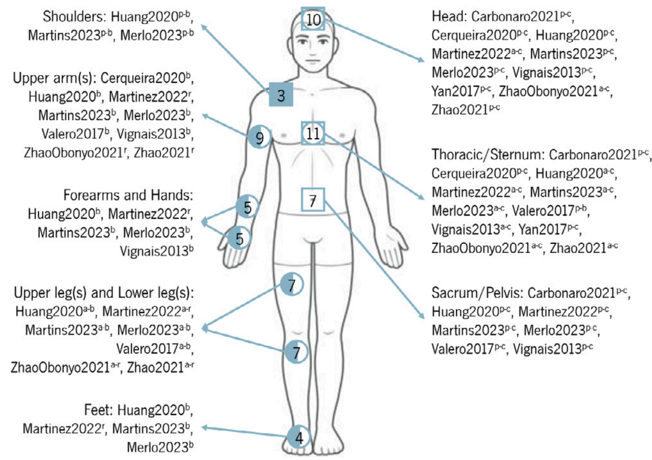

Fig. 2. Body locations of the sensors and number of included studies that chose them. Circles represent sensors in the anterior (^{a}) part of the body, squares the ones in the posterior (^{p}) part of the body, filled symbols the ones placed bilaterally (^{b}), and empty ones unilaterally (either left, ^{l}, centre, ^{c}, or right, ^{r}).

3.3. Algorithms for ergonomic assessment

Concerning the algorithms used to estimate the risk considering the collected inertial data, the majority of the studies applied angular thresholds to discretise the joint angle values, because the assessments were based on ergonomic methods that provide predefined angle ranges (Carbonaro et al., 2021; Cerqueira et al., 2020; Huang et al., 2020; Martinez et al., 2022; Martins et al., 2023; Merlo et al., 2023; Valero et al., 2017; Vignais et al., 2013; Yan et al., 2017).

Starting by the way the joint angles were obtained from the inertial data, Yan et al. (2017) employed the tilt–twist method for angle estimation. In turn, Cerqueira et al. (2020) and Vignais et al. (2013) used a Kalman filter. However, Vignais et al. (2013) also included a biomechanical model of the upper body composed of ten rigid segments connected by anatomically restricted articulations. Martinez et al. (2022) applied a sensor-to-segment transformation to the orientation data obtained from the Xsens proprietary sensor fusion, aligning the IMUs' technical frame to the corresponding segments' anatomical frame. Martins et al. (2023) directly used the angles computed by the commercial MoCap system. The remaining manuscripts did not provide information about sensor fusion algorithms.

Cerqueira et al. (2020) implemented a real-time upper-body ergonomic risk assessment by following a RULA-LUBA-based finite state machine approach and assigning one of four risk levels to each joint movement continuously. In turn, Carbonaro et al. (2021) and Vignais et al. (2013) calculated both local scores and a global one, by means of RULA scale. However, Carbonaro et al. (2021) used a time window approach, where the risk level assigned was the highest value maintained for more than a time threshold. Huang et al. (2020), in turn, included not only a postural ergonomic analysis (RULA or REBA) but a two-dimensional static biomechanical analysis, addressing the issue of oversimplification by those ergonomic methods in the assessment of some critical anatomical body segments, such as the lower back, which plays an important role in inducing WRMSDs. The authors calculated the lower back compression force, a particularly important and useful indicator of lower-back risk. Martinez et al. (2022) introduced a novel index, K-score, which is the sum of an upper-limb posture score and a lower-limb one. This method differs from the typical ones in that it has higher resolution to joint angle changes, providing a greater sensitivity to the posture assessment.

Based on a state machine, Valero et al. (2017) combined the primary states defined by ISO 11226 for trunk inclination, knee flexion and arm elevation into twelve whole-body postures. Moreover, they defined a global metric to condense postural information, the posture score (or risk score), computed as a weighted average of the states for all measured body parts, considering the angle values and the elapsed time. Furthermore, the authors introduced a productivity score to highlight worker performance more objectively, considering the actual work performed.

Merlo et al. (2023), inspired by the RC circuit-like behaviour of muscle fatigue, presented a joint kinematic wear index that reflects not only the current risk, based on RULA criteria, but also the previous ones, thus, having memory of the time previously spent in hazardous postures as well as the repetitions. The index increases during work time and decreases during recovery (when the robot is performing the task and the worker is resting). Martins et al. (2023) replicated this idea but they separated the joint assessment into different plans, defined by LUBA method, unlike Merlo et al. (2023). Besides that, Martins et al. (2023) established that the user's joint recovers when it is assigned the minimum LUBA score and accumulates posture hazard otherwise.

Other works used time thresholds, in order to identify the maximum time during which each posture can be held (Yan et al., 2017; Zhao et al., 2021), or to assign the risk level considering a certain minimum accumulated time (Carbonaro et al., 2021). Zhao and Obonyo (2021) and Zhao et al. (2021) used deep learning-based approaches, in specific, Zhao and Obonyo (2021) built an incremental model based on the deep neural network of Zhao et al. (2021), to recognise qualitative postures, which were decomposed and associated with an OWAS classification. Each body part had an associated threshold concerning the maximum posture proportion in working time, and the criterion adopted for the risk assessment was the strictest threshold among all the affected parts, with three levels of ergonomic risk for awkward postures. Furthermore, another ergonomic method was used, in which the prolonged postures should not be maintained more than 20% of the MHT (30 s for uncomfortable postures and 3 min for comfortable postures). Yan et al. (2017) conducted a real-time local ergonomic assessment of the head, neck and trunk, following the standard ISO 11226. According to the joint angular values and the accumulated MHT, three ergonomic zones were defined for each joint plane of motion: an "acceptable" zone, where the user could be for an unlimited time; a "not recommended" zone, where an auditory warning was given; and a middle zone, where the accumulated MHT was determined by a linear relationship between the joint angle and the holding time. A different alarm sound was sent when that accumulated MHT was reached.

3.4. System's validation

The systems projected for ergonomic monitoring were validated with experimental protocols where the tasks performed were, in most cases, related to construction (Huang et al., 2020; Martins et al., 2023;

Valero et al., 2017; Yan et al., 2017; Zhao & Obonyo, 2021; Zhao et al., 2021) since it is one of the leading activity sectors in WRMSD reports (De Kok et al., 2019). In the cases of Yan et al. (2017), Zhao and Obonyo (2021) and Zhao et al. (2021), the participants were actual construction workers, whereas in the others they had no construction experience. Besides simulating construction task circuits, Martins et al. (2023) also designed an agriculture task circuit and a set of trials with isolated postures. One of the studies evaluated posture during a real surgery operation, with an experienced surgeon (Carbonaro et al., 2021). In others (Martinez et al., 2022; Merlo et al., 2023; Vignais et al., 2013), the subjects performed industrial tasks; in particular, the experiment carried out by Merlo et al. (2023) was integrated into an ergonomic role allocation framework for dynamic human–robot collaboration. Cerqueira et al. (2020) chose more general tasks, containing different working postures from several professions besides industrial ones. None of the authors chose participants with musculoskeletal disorders to carry out the trials. The number of participants varied between 1 (Carbonaro et al., 2021; Merlo et al., 2023) and 30 (Zhao et al., 2021); and Yan et al. (2017) did not mention this number.

Regarding metrics, in this review, they were separated into four different types: *technical validation*, *ergonomic tool validation*, *user performance* and *system usability* metrics. *Technical validation* metrics are mostly associated with sensor accuracy and joint angle estimation (benchmarked against a ground truth). Only two studies did this kind of validation of the results, by calculating the root mean squared error (RMSE) between their estimated angles and a ground truth — the angles from a collaborative robot arm in a controlled movement (Cerqueira et al., 2020), or the ones computed with a camera-based MoCap system with reflective markers (Martinez et al., 2022). Cerqueira et al. (2020) reported a RMSE between 2.57° and 4.95°, corresponding to an error between 1.43% and 2.5% in relation to the full angle range. Martinez et al. (2022) obtained mean RMSE values below 4° for all joint angles except for the neck. The authors also demonstrated that the ergonomic scores obtained with IMUs' were in substantial agreement with the ones obtained with Vicon (mean Cohen's Kappa coefficient of 0.67 or higher). This study, contrary to Cerqueira et al. (2020), performed this technical validation during the experimental tasks. Huang et al. (2020), who used the joint angles and segments' positions provided by a commercial inertial MoCap system (contrary to Cerqueira et al. (2020) and Martinez et al. (2022)), underlined that the results were highly influenced by the accuracy of the collected motion data and that the same type of input data acquired from other systems, like low-cost inertial sensors combined with sensor fusion algorithms, could lead to worse results.

Ergonomic tool validation metrics measure how trustworthy the presented tools are in the assessment, i.e., in the computed ergonomic score. From the selected studies, five recorded the trials with a video camera (Carbonaro et al., 2021; Huang et al., 2020; Valero et al., 2017; Zhao & Obonyo, 2021; Zhao et al., 2021), and, excluding Carbonaro et al. (2021), they mentioned an expertise assessment of the postures based on those videos as a ground truth for the *ergonomic tool validation*. Furthermore, Huang et al. (2020) calculated the intraclass correlation coefficient, to evaluate the level of consistency, and also the absolute difference between the ergonomic scores from the system and experts' ratings, and the accuracy, whose results were, respectively, around 0.83, below 1.0, and above 88%, demonstrating a high consistency with experts' ratings. Additionally, the intersystem coefficient of multiple correlation and relative RMSE were the metrics used to validate the computation of the lower-back compression force, by comparing to a commercial program, 3DSSPP (VelocityEHS, 2020), which was in good agreement with the reference system since the values of these metrics were above 0.89 and below 9.5%, respectively. Martinez et al. (2022) inspected the potential relationship between electromyography (EMG) amplitude and REBA/K-score, through Spearman's correlation coefficient. The results showed no significant correlation between the changes in the REBA score and the EMG amplitude induced by fatigue, a significant correlation with fatigue-induced change of EMG amplitude, but K-score showed a significant correlation with fatigue-induced change in EMG amplitude, meaning that K-score may also be used for fatigue detection. In turn, Valero et al. (2017) concluded that basic harmful postures were correctly classified by the state machine, although they did not provide a specific metric, which was the case of Carbonaro et al. (2021) too. Four studies (Martins et al., 2023; Merlo et al., 2023; Vignais et al., 2013; Yan et al., 2017) did not compare their approaches either regarding the ergonomic assessment or the angle estimation, so there was no ground truth.

User performance metrics, on the other hand, were used to quantify how well or poorly the subject performed ergonomically; usually, these were defined by the ergonomic methods used, e.g., RULA, LUBA or REBA scores (continuous or averaged), and other derived and the percentage of time spent at the ergonomic risk levels, or the risk distribution over time, were computed by Carbonaro et al. (2021), Cerqueira et al. (2020), Huang et al. (2020), Martinez et al. (2022), Martins et al. (2023) and Vignais et al. (2013). Conversely, Martins et al. (2023) and Merlo et al. (2023) used a kinematic wear index which takes into account the joints' ergonomic history. The trial's execution times with and without biofeedback were also recorded and compared by Cerqueira et al. (2020) and Vignais et al. (2013). Additionally, Vignais et al. (2013) computed the frequency of threshold breaching. Valero et al. (2017) introduced a productivity score, which seemed to improve with the worker's experience, but the posture score, which relied on the joint angles and on the finite-state machine score, did not show such a correlation. Zhao and Obonyo (2021) and Zhao et al. (2021) calculated how many times MHT was breached for each posture, the total duration of that breach, the detected time, posture frequency, and posture proportion; additionally, Zhao and Obonyo (2021) calculated the OWAS ergonomic risk level. These authors reported that the application of the ergonomic rules on the recognised and on ground-truth postures yielded comparable risk assessment results. Because of the misclassification of the awkward postures as normal postures, MHT assessment was sensitive to recognition errors, the total duration of awkward postures breaching MHT was underestimated by the deep learning model; for the same reason, a tendency to underestimate the OWAS risk related to awkward postures was verified, but, overall, the estimation was similar to the ground truth regarding posture proportions; hence, most of the risk levels using OWAS rules were correctly identified based on the proportion thresholds.

Finally, *system usability* metrics are related to the subjective point of view of the users and are based on questionnaires. Namely, Cerqueira et al. (2020) used the System Usability Scale (SUS) guidelines, and Vignais et al. (2013) and Zhao et al. (2021) the 5-point Likert scale questionnaire. In both cases, the participants showed satisfaction, highly accepted the wearable sensors and considered them comfortable and non-intrusive.

4. Biofeedback strategies

Biofeedback cues should be delivered with the utmost clarity so that the user perceives and distinguishes them without interference with work execution. The latter aspect is particularly relevant when choosing the biofeedback type. Visual feedback is inconvenient for tasks that demand continuous visual control because the visual cues may act as a distraction (Kim, Garate, Gandarias, Lorenzini, & Ajoudani, 2021; Lind, Diaz-Olivares et al., 2020; Lorenzini et al., 2022); also, Fani, Ciotti, and Bianchi (2021) showed no statistical differences in guidance performance between haptic and visual feedback. On the other hand, auditory feedback, despite not requiring visual attention (Lee et al., 2021), may not be heard in noisy work sites or, if delivered by earphones, it may even damp external warning signals related to safety (Cerqueira et al., 2020; Kim et al., 2021; Lee et al., 2021; Lind, Diaz-Olivares et al., 2020); on top of that, users may feel embarrassed, which may have a negative impact on their task performance (Bootsman, Markopoulos, Qi, Wang, & Timmermans, 2019). Hence, the present section focuses on biofeedback systems, mostly the ones capable of providing haptic biofeedback, which mitigates some of the issues of visual and auditory types.

Table 3 compiles information concerning the study goals, feedback modalities and actuation systems of the indicated studies, and Table 4 shows an overview of the information related to the algorithms reported in the reviewed articles, as well as the protocol followed in the trials, and the metrics considered to evaluate the solution performance.

The included articles were mainly targeted to industry (Cerqueira et al., 2020; Fani et al., 2021; Kim et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Lins et al., 2018; Lorenzini et al., 2022; Vignais et al., 2013), whereas one was directed for health care delivery (Bootsman et al., 2019), one for robotic teleoperation (Aggravi et al., 2018), and the other did not specify the target of the study (Dunkelberger et al., 2018).

From the articles included in this review, six had the purpose of providing biofeedback for posture correction (Bootsman et al., 2019; Cerqueira et al., 2020; Kim et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Vignais et al., 2013). Another report focused on the study of the optimal vibration parameters, regarding pulse length and repetitions, through the accuracy of the location-dependent perception (Lins et al., 2018). Four authors aimed at providing directional feedback (Aggravi et al., 2018; Fani et al., 2021; Kim et al., 2021; Lorenzini et al., 2022), and, from these, Kim et al. (2021) and Lorenzini et al. (2022) compared diverse strategies. Three authors developed haptic multi-cue systems to inspect the advantages of rendering perceptually different cues at the same time (Aggravi et al., 2018; Dunkelberger et al., 2018; Fani et al., 2021).

4.1. Biofeedback types and modalities

Different feedback types were explored in the included studies. As already mentioned, this literature review mainly focused on haptic feedback, which was found in several modes (in all cases, feedback cues were presented throughout the trial execution): vibrotactile (in ten publications) (Aggravi et al., 2018; Bootsman et al., 2019; Cerqueira et al., 2020; Dunkelberger et al., 2018; Fani et al., 2021; Kim et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Lins et al., 2018; Lorenzini et al., 2022); pressure/squeezing (in four studies) (Aggravi et al., 2018; Dunkelberger et al., 2018; Fani et al., 2021; Lorenzini et al., 2022); and tangential forces/lateral skin stretch (in three studies) (Aggravi et al., 2018; Dunkelberger et al., 2018; Lorenzini et al., 2022). Two of the studies combined the three haptic feedback modalities (Aggravi et al., 2018; Dunkelberger et al., 2018), and one combined squeezing and vibrations (Fani et al., 2021). Other feedback types were utilised in combination as well: auditory (Bootsman et al., 2019; Vignais et al., 2013) and visual (Bootsman et al., 2019; Cerqueira et al., 2020; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Vignais et al., 2013). Despite (Vignais et al., 2013) not including haptic biofeedback in their system, their study was included since it was pioneer in the use of biofeedback for posture correction and a core paper to demonstrate the effectiveness of biofeedback.

4.2. Hardware and system characteristics

In this section, the sensing component of the included studies' systems was not subject to analysis, only the actuation part.

In terms of haptic actuators, the most reported type (seven articles) was eccentric rotating mass vibration motor (Aggravi et al., 2018; Cerqueira et al., 2020; Kim et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Lins et al., 2018; Lorenzini et al., 2022), whereas linear resonant actuators were present in two studies (Dunkelberger et al., 2018; Fani et al., 2021), also for providing vibration cues; two studies used DC motors to control a fabric-band wrapped around user's skin (Fani et al., 2021; Lorenzini et al., 2022); another two used servomotors (Aggravi et al., 2018; Dunkelberger et al., 2018). The vibrotactile devices used by Kim et al. (2021), named ErgoTac, were wireless (Bluetooth Low Energy) and were developed in a previous work (Kim, Lorenzini, Kapıcıoğlu, & Ajoudani, 2018). Two studies (Fani et al., 2021; Lorenzini et al., 2022) used a multi-cue system developed by Casini et al. (2015) (CUFF), comprising a fabric-band actuated through two DC motors to provide tangential (slide) and normal (squeeze) force stimuli on the user's skin. Aggravi et al. (2018) and Dunkelberger et al. (2018) developed wearable devices capable of providing concurrent skin stretch, pressure and vibrotactile stimuli: in the study of Aggravi et al. (2018), the first two stimuli were yielded by servomotors similar to CUFF and the latter provided by four vibrotactile motors positioned 90° apart; in the case of Dunkelberger et al. (2018), the radial squeeze band and an haptic rocker (which encompasses a rubber-coated semi-circular interface that is pressed against the arm skin and induces a shear sensation when rotating) were mounted on the same frame to make the wearable more compact. Although all the studies presented wearable solutions for providing the cues, two developed a smart vest to integrate and embed all the hardware (Bootsman et al., 2019; Cerqueira et al., 2020). The actuators spread across the body provided cues mostly in the upper body, with only two studies providing feedback on legs, as depicted in Fig. 3. Regarding limbs, three studies placed actuators on both left and right limbs, one placed only on the dominant arm, and four on the right limb. With respect to the parameters of the haptic cues, the vibration frequency ranged between 121 Hz and 280 Hz. The choice of ON and OFF periods was mentioned only in five manuscripts: Lind, De Clercq et al. (2023) employed either intermittent or continuous vibrations, depending on the trunk angle; Lins et al. (2018) studied the ON and OFF periods between 25 and 150 ms; Kim et al. (2021) chose a duration of 400 ms; Fani et al. (2021) adopted an ON period of 100 ms and an OFF period that decreases proportionally as the error magnitude increases; and Aggravi et al. (2018) defined a duty cycle of 50%, i.e., percentages of ON and OFF time equal.

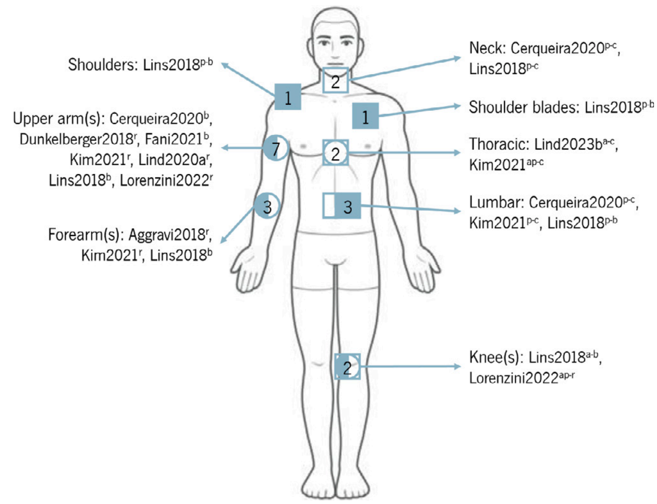

Fig. 3. Body locations of the haptic actuators and number of included studies that chose them. Circles represent actuators in the anterior (^{a}) part of the body, squares the ones in the posterior (^{p}) part of the body, filled symbols the ones placed bilaterally (^{b}), and empty ones unilaterally (either left, ^{l}, centre, ^{c}, or right, ^{r}).

For providing visual biofeedback (a summary report) after the trial, Cerqueira et al. (2020) developed a graphical user interface, whereas Lind, De Clercq et al. (2023) and Lind, Diaz-Olivares et al. (2020) developed a smartphone application connected through Bluetooth Low Energy to the sensing system and to the vibration motor. A different approach was reported by Bootsman et al. (2019), where a smartphone application provided auditory, vibrotactile and visual biofeedback; but it also asked the users to record the activity they were performing when bad posture was detected, and, with that information, it produced an overview of activities associated with poor posture episodes, giving relevant tips per activity. Vignais et al. (2013) used a see-through head-mounted display to deliver auditory signals and a visual representation of the upper-body assessment, regarding global and local assessment, respectively.

Table 3
Summary of the included studies on biofeedback, regarding their goals, feedback modalities, and actuators' type, location and parameters.

Reference	Study goals	Feedback modality	Actuators		
			Type	Location	Actuation parameters
Bootsman et al. (2019)	Biofeedback for posture correction	Concurrent (with latency) auditory, vibrotactile and visual (summary)	Smartphone application	Smartphone	N/M
Vignais et al. (2013)	Biofeedback for posture correction	Concurrent auditory and visual (representation of the upper body)	See-through head-mounted display	Head	N/M
Cerqueira et al. (2020)	Biofeedback for posture correction	Concurrent vibrotactile (all motors can be activated at the same time or one at a time) and visual (GUI)	- 4 coin-style ERM motors; - GUI	Upper arms, cervical and lumbar region	Frequency of 200 Hz; strength of 2.2 g
Lind, Diaz-Olivares et al. (2020)	Biofeedback for posture correction	Concurrent vibrotactile and visual (app)	1 coin-style ERM motor	Dominant upper arm	Duration of 1 s; 2 different levels (2 lower-intensity pulses or 4 higher-intensity pulses)
Lind et al. (2023)	Biofeedback for posture correction	Concurrent vibrotactile and visual (app)	1 coin-style ERM motor	Sternum	Intermittent or continuous vibration, depending on the trunk forward inclination angle
Lins et al. (2018)	Optimal range of vibration parameters	Concurrent vibrotactile	13 cylindrical ERM motors	Neck, shoulder blades, left and right of lumbar spine, shoulders, elbows, wrists and inner knees	1 to 3 pulses; length and pause interval of 25, 50, 100 or 150 ms; frequency of 167 Hz
Kim et al. (2021)	Comparison of distinct directional feedback strategies for posture correction	Concurrent vibrotactile, one motor activated at a time, 3 different modalities: - SPOT: 2 UPJ; desired direction given as a repulsive vibration; - RAMP: 1 UPJ; desired direction given by a variation in vibration level; - PATTERN: 3/2/2 UPJ; direction given by pattern	Coin-style ERM motors	Torso, upper arm and forearm	Frequency of 121 Hz; 3 different amplitudes determined by risk level
Lorenzini et al. (2022)	Comparison of distinct directional feedback strategies	Concurrent vibrotactile (SPOT modality from (Kim et al., 2021)) vs. tangential force (providing direction of posture correction) and squeezing (information about error amplitude)	- 2 coin-style ERM motors per joint; - 1 fabric-band actuated through 2 DC motors per joint	Right upper arm and right lower part of calf	- Vibration: frequency of 121 Hz; - Squeezing: force between 3 and 20 N, proportional to error
Fani et al. (2021)	Wearable multi-cue system with directional feedback	Concurrent squeezing (guiding along x-axis) and vibrotactile (along y-axis)	- 2 fabric-bands actuated through 2 DC motors each; - 4 coin-style LRA motors	Upper arms	- Squeezing: force between 3 and 20 N, proportional to error; - Vibration: pattern with decreasing OFF periods proportional to error (from 500 to 0 ms) and ON set to 100 ms
Aggravi, Pausé, Giordano, and Pacchierotti (2018)	Wearable multi-cue system with directional feedback	Concurrent squeezing (normal force), skin stretch (shear force) and vibrotactile providing directional information	- 2 servomotors; - 4 cylindrical ERM motors, 90° apart	Right forearm	- Squeezing: force between 2.5 and 10 N; - Skin stretch: belt displacement between 15 and 10 mm; - Vibration: maximum frequency of 280 Hz, duty cycle of 50%

(continued on next page)

Table 3 (*continued*).

Dunkelberger et al. (2018)	Wearable multi-cue system	Concurrent vibrotactile, radial squeezing and lateral skin stretch	- 4 coin-style LRA motors, 90° apart; - Strap connected to a servomotor; - Haptic rocker (servomotor + end-effector)	Right upper arm	- Vibration: frequency of 265 Hz, duration of 50 ms or 150 ms; - Squeezing: maximum torque of 588 mNm, duration of 350 ms; - Haptic rocker: maximum torque of 375 mNm, duration of 150 ms

N/M: Not Mentioned; GUI: graphical user interface; ERM: eccentric rotating mass; UPJ: units per joint; LRA: linear resonant actuators.

4.3. Algorithms to determine feedback triggering

As far as algorithms are concerned, for posture risk assessment, angle values were compared to angular thresholds to determine the application of the cues in five studies (Bootsman et al., 2019; Cerqueira et al., 2020; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Vignais et al., 2013), whereas a decision support system assessed posture with an OWAS-based classifier in one study (Lins et al., 2018). The computation of the centre of pressure (CoP) position was mentioned in two studies (Fani et al., 2021; Kim et al., 2021). Moreover, in the work of Kim et al. (2021), this calculation of the CoP was part of an optimisation problem to obtain the body configuration that minimises overloading joint torques, which is based on the displacement of the CoP. Regarding the studies which were not applied in postural ergonomic correction, the error magnitude between the current and the desired angular configurations were continuously calculated, as well as the corresponding actuation parameters, in four studies (Aggravi et al., 2018; Fani et al., 2021; Kim et al., 2021; Lorenzini et al., 2022). One manuscript did not explain what algorithms were developed (Dunkelberger et al., 2018).

4.4. Haptic biofeedback strategies

In this section, the strategies employed for transmitting the haptic cues are exploited, concerning factors such as what information is transmitted, how the intensity is related to the user deviation, or when biofeedback is activated (after how much time or how many times). Distinct approaches were followed when using haptic biofeedback.

For example, Bootsman et al. (2019) provided biofeedback in a non-localised manner, detached from the body segment to be assessed (the back). The authors mentioned three parameters to be key choices in the user experience: allowed deviation from neutral posture (which can be set by the user in the app), minimal duration of poor posture episodes (to avoid sending too many notifications), and the minimum time interval between two notifications (to prevent saturation of the user), which were set, in field studies, as 20° (maximum), 1.5 s, and 5 min, although these were intended to be personalised by the user.

In the remaining studies that employed haptic cues for posture correction, these were provided on the target body segments. Whereas Cerqueira et al. (2020) and Lins et al. (2018) provided localised vibrations in the monitored segments with the vibration motors able to be activated alone or in combination (according to the computed risk) but without providing information about the risk level or the error amplitude, Lind, Diaz-Olivares et al. (2020) delivered two different vibration levels, ordered in intensity, for upper-arm elevation angles of at least 30° and 60° relative to the upper-arm reference position, which is set by the user using the smartphone application. These two angles were chosen because upper-arm elevations exceeding 30° and 60° for more than 50% and 10% of the work time, respectively, have been associated with increased risk of musculoskeletal disorders in the neck and shoulder. In another publication, Lind, De Clercq et al. (2023) established two thresholds for vibrotactile biofeedback regarding the trunk forward inclination angle: above 30° the vibration was intermittent, and above 45° continuous.

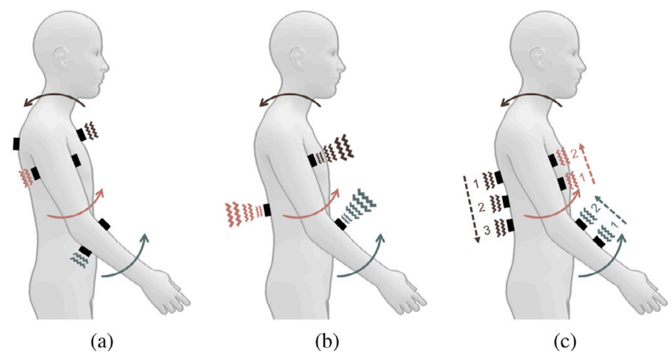

Fig. 4. Representation of the vibrations (triangular waves) provided by the motors (black boxes), in each of the three directional feedback modalities described by Kim et al. (2021): (a) SPOT, (b) RAMP, and (c) PATTERN, where the solid arrows represent the desired movement of each segment.
Source: Adapted from Kim et al. (2021).

In two studies (Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020), the biofeedback cues were given immediately when risky postures occurred and, in the others (Bootsman et al., 2019; Cerqueira et al., 2020; Vignais et al., 2013), after they had been maintained for more than a fixed maximum consecutive time period. Cerqueira et al. (2020) and Vignais et al. (2013) defined that the higher the risk level, the lower the maximum time before triggering biofeedback cues.

Inspired by the concept of directional haptic cues introduced by Tappeiner, Klatzky, Unger, and Hollis (2009), several studies have implemented haptic guidance. Kim et al. (2021) gave directional information for the torso, shoulder, and elbow but only one joint could be guided at a time (the one with the highest error magnitude). The error magnitude between the actual and the desired angular configurations was provided to the user by three distinct vibrotactile amplitudes, ordered by the risk level from an ergonomics perspective. Three different directional feedback strategies were implemented and compared regarding comfort, convenience and intuitiveness: SPOT, RAMP and PATTERN. The first one, SPOT, in Fig. 4(a), uses two vibrotactile units per joint, on opposite sides; and the direction of correction is given as a repulsive cue (in the opposite side to where the joint has to move). The RAMP modality only entails one unit per joint; in this case, the desired direction is given by an increasing or decreasing vibration, as shown in Fig. 4(b). In the PATTERN modality, multiple vibrotactile units at a certain distance (5 cm) within each segment were needed to guide each joint; the vibration sequence gives the direction in which the joint has to be moved, as illustrated in Fig. 4(c).

By addressing the guidance of shoulder and knee angles, Lorenzini et al. (2022) compared the effectiveness of SPOT modality from Kim et al. (2021) and a different feedback modality where the direction of the posture correction was implemented by a tangential force, where the rotation indicates the desired direction of correction, and the amplitude of the error is given by a normal force (squeezing) whose intensity is proportional to the error.

Table 4
Summary of the included studies on biofeedback, regarding their algorithms, validation protocols, and metrics.

Reference	Algorithms	Experimental protocol	Metrics
Bootsman et al. (2019)	Angular threshold-based for poor posture notification	- N = 28 (nurses, non-sedentary job, no lower back pain); - Four-phased (A-B-A-C), where condition A has no biofeedback, B only has notifications of poor posture occurrences, and C has notifications, activities self-recording and overview	**User performance:** - Number of poor posture episodes. **System usability:** - Credibility and expectancy questionnaire; - Intrinsic Motivation Inventory; - UTAUT questionnaire; - Semi-structured interview
Vignais et al. (2013)	Angular threshold-based for ergonomic risk assessment	- N = 12; - Industrial manual task, composed of 4 subtasks; - Half of the subjects without real-time biofeedback and half with it	**User performance:** - Trial execution time; - Time spent at each risk level; - Frequency of threshold breaching. **System usability:** - 5-point Likert scale questionnaire; - Subjective observations
Cerqueira et al. (2020)	State machine (angular threshold-based) for ergonomic risk assessment	- N = 5; - 5 general tasks, containing different working postures; - Each trial performed 4 times: 2 without biofeedback and 2 with	**User performance:** - Trial execution time; - Time spent at each risk level. **System usability:** - Questionnaire following SUS
Lind, Diaz-Olivares et al. (2020)	Angular threshold-based for risk assessment	- N = 16 (novices, healthy); - Mail sorting in letter trays; - 2 experimental conditions: with and without predetermined positions of the workstation; verbal ergonomic instructions solely or in combination with haptic biofeedback	**User performance:** - Accumulated time in upper-arm elevations; - 50th, 90th, 95th and 99th percentiles angles. **System usability:** - Borg CR10 scale; - Discomfort/pain body map; - Semi-structured interview
Lind, De Clercq et al. (2023)	Angular threshold-based for risk assessment	- N = 15 (real warehouse workers, healthy); - Manual sorting of packages in a warehouse, for 5 workdays within 4 weeks; - 2 sessions with vibrotactile biofeedback and 3 without (baseline, post-training and follow-ups weeks later)	**User performance:** - Accumulated time in forwarding trunk inclinations; - 90th, 95th and 99th percentiles angles; - 10th–90th percentile range. **System usability:** - Copenhagen Psychosocial Questionnaire II; - Comfort Rating Scale; - Semi-open questions; - Self-rated work ability; - Borg RPE scale for physical exertion; - Productivity demands
Lins et al. (2018)	Decision Support System analyses posture using OWAS and generates pulse sequences at appropriate locations	- N = 11; - Standing upright on two legs; - Determine position perceived as the most prominent vibration; - Sequence of stimulations defined randomly	**System usability:** - Perception accuracy
Kim et al. (2021)	- Continuous calculation of error magnitude between the current configuration and the desired one, and subsequent vibration amplitude; - Ergonomics framework: desired postures determined based on overloading joint torques method	- Directional modalities evaluation: N = 15; torso and arm feedback considered separately; moving according to vibrotactile guidance, towards three assigned configurations. - Ergonomic postural adjustment: N = 5; 3 joints simultaneously; holding a heavy object in non-ergonomic postures, guided by the haptic cues to the optimal configuration	**User performance:** -[a] Confusion index; success ratio; -[b] Reaching time; angular distance; reaching velocity; -[c] Final error; - Decrement ratio. **System usability:** - Single Ease Question; - SUS
Lorenzini et al. (2022)	- Calculation of vibration amplitude similar to Kim et al. (2021); - Calculation of squeezing force through the error	- N = 12 (healthy); - 2 blocks (randomised order): one guided by normal and tangential force cues and the other by vibrotactile cues, each with 3 sub-blocks: upper and lower limb guidance separately and also jointly; three reference angles (combinations) for each	**User performance:** -[a] Confusion index; success ratio; -[b] Reaching time; angular distance; reaching velocity; -[c] Final error. **System usability:** - 7-point Likert scale questionnaire; - NASA-TLX questionnaire
Fani et al. (2021)	- Computation of CoP position; - Calculation of errors; - Calculation of force (input for squeezing device) and duration of OFF/ON periods (for vibrotactile motors)	- N = 11 (healthy); - Movements guided along two perpendicular directions; - 3 experimental conditions: no guidance, haptic cues and visual cues	**User performance:** - Success rate; - Completion time. **System usability:** - 7-point Likert scale questionnaire; - NASA-TLX questionnaire

(*continued on next page*)

Table 4 (*continued*).

Aggravi et al. (2018)	- Computation of torque cues, frequencies for vibrotactile motors and angles for servomotors; - Calculation of end-effector velocity	- N = 34; - Two human subjects' teleoperation experiments in a virtual environment: control the motion of a robotic manipulator for grasping an object, and the motion of a quadrotor fleet along a given path	**User performance:** - Completion time; - Trajectory length; - Haptic actuation; - Gripper rotation error. **System usability:** - Perceived effectiveness
Dunkelberger et al. (2018)	N/M	- N = 8 (healthy); - Identification of a set of 32 haptic presentations, with three concurrent cues, both in multimodal and unimodal approaches	**System usability:** - Perception accuracy

N/M: Not Mentioned; N: number of participants; UTAUT: Unified Theory of Acceptance and Use of Technology; SUS: System Usability Scale; CoP: centre of pressure.

[a] For all the trials.

[b] For the successful cases.

[c] For the failed trials.

Fani et al. (2021) conveyed squeezing stimuli and vibrations with a different aim: aiding in posture balancing along the user's frontal and sagittal planes, respectively. The device, which integrated both motor types, squeezes the arm on the side towards which the users have to move their weight, with a force proportional to the error between the current position of the CoP along the users' frontal plane and the desired one; regarding the vibrotactile motors, synchronised in both arms, they vibrate on the back or on the front side, considering the direction in which the body weight has to be moved, following an ON/OFF pattern with the OFF periods decreasing as the error increases, proportionally.

4.5. System's validation

The trials for the validation of these systems were conducted in different conditions. In one study Bootsman et al. (2019), the experiment took place in hospitals, where the subjects were nurses, carrying out their normal duties (real working conditions). Lind, De Clercq et al. (2023) carried out the validation in a real warehouse with actual workers performing manual sorting of packages. The experiments of the remaining studies were conducted in controlled lab environments. In two studies, the subjects were placed in task scenarios where they had to perform different work activities and postures from industry (Cerqueira et al., 2020; Vignais et al., 2013) and other professions too (Cerqueira et al., 2020; Lind, Diaz-Olivares et al., 2020) while receiving cues that warn against ergonomically hazardous postures. In particular, Lind, Diaz-Olivares et al. (2020) simulated mail sorting (repetitive manual handling), in two different conditions: with the positions of the letter tray stack predetermined or adjustable. But, in the vast majority of the cases (six studies), the subjects did not perform manual tasks: in some of them, subjects were asked to identify the haptic cues they felt, without performing any subsequent action (Dunkelberger et al., 2018; Lins et al., 2018); in other cases, participants had to move in accordance with the vibrotactile feedback instructions towards an assigned configuration (Kim et al., 2021; Lorenzini et al., 2022) (Kim et al. (2021) carried out a second protocol where the subjects had to lift and hold a heavy object in a non-ergonomic posture and received cues to guide them to the configuration that minimises the overloading joints torques); in the case of Fani et al. (2021), the users had to follow the feedback cues to control their CoP location on a balancing board; and Aggravi et al. (2018) conducted teleoperation experiments in a virtual environment. The number of participants in the experimental protocols varied between 5 (Cerqueira et al., 2020) and 34 (Aggravi et al., 2018). Some studies explicitly mentioned the absence of musculoskeletal discomfort or disorders or other physical limitations as inclusion criteria for participant selection (Bootsman et al., 2019; Dunkelberger et al., 2018; Fani et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Lorenzini et al., 2022), others also required no psychological impediments that could affect their capabilities of understanding and performing the tasks (Dunkelberger et al., 2018; Lorenzini et al., 2022); two studies explicitly required naive participants or with little experience (Fani et al., 2021; Lind, Diaz-Olivares et al., 2020).

The ground truth of the experiments was a control group who performed without feedback in one study (Vignais et al., 2013). In others, it was composed of the baseline trials that all the subjects performed (no division of participants into groups): without any kind of feedback (Aggravi et al., 2018; Bootsman et al., 2019; Cerqueira et al., 2020; Fani et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020), or with a type of feedback other than the one proposed by the authors (Aggravi et al., 2018; Fani et al., 2021; Lind, Diaz-Olivares et al., 2020). Two studies included post-training sessions after one trial with biofeedback on the same day (Bootsman et al., 2019; Lind, De Clercq et al., 2023), and Lind, De Clercq et al. (2023) also designed follow-up sessions weeks later. Different feedback strategies were compared by Kim et al. (2021) and different haptic modalities by Lorenzini et al. (2022). Dunkelberger et al. (2018), who combined vibration, squeeze, and lateral stretch cues, used as ground truth for comparison a system equivalent to the one they developed, where the squeeze and stretch actuators were replaced by vibrotactors that rendered the cues in the same way (ON or OFF) and for the same amount of time as the corresponding ones on the multi-modality system, in order to check how accurately these multi-cues were perceived by users and how distinguishable they were.

Several metrics were used to assess the system effectiveness through *user performance* in baseline (the ground truth) and in feedback conditions, or in different feedback modalities: number of poor posture episodes (Bootsman et al., 2019), percentage of time spent at ergonomic risk levels/above certain angles (Cerqueira et al., 2020; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Vignais et al., 2013), angular percentiles (Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020), angle error in relation to the target angle (Aggravi et al., 2018; Kim et al., 2021; Lorenzini et al., 2022), reaching/completion time (Aggravi et al., 2018; Cerqueira et al., 2020; Fani et al., 2021; Kim et al., 2021; Lorenzini et al., 2022; Vignais et al., 2013), confusion index (Kim et al., 2021; Lorenzini et al., 2022), success ratio (Fani et al., 2021; Kim et al., 2021; Lorenzini et al., 2022), travelled angular distance (Kim et al., 2021; Lorenzini et al., 2022), average velocity (Kim et al., 2021; Lorenzini et al., 2022), decrement ratio (reduction rate of overloading joint torque) (Kim et al., 2021), trajectory length (Aggravi et al., 2018), and percentage of time in which the feedback was ON (Aggravi et al., 2018).

The quantitative evaluation of the effectiveness of the smart shirt developed by Bootsman et al. (2019) for tracking lumbar spine curvature proved that the biofeedback system helped to reduce the occurrences of undesired posture behaviour compared with the baseline, in the short term. The results obtained by Vignais et al. (2013) showed a significant reduction in RULA risk in the biofeedback condition, both at the segments' level and globally. Still, the group that performed with biofeedback took more time to execute the tasks. Cerqueira et al. (2020)

showed that real-time biofeedback reduced the ergonomic risk overall and the time spent at high-risk level until a maximum of 45% for the neck and 39.8% for the trunk. However, it was also noted that the participants took, on average, 30% more time to execute the trial in the biofeedback condition, compared with the baseline. Still, the authors believe that, with training, this difference would reduce. Lind, Diaz-Olivares et al. (2020) showed that, for work technique training, when the workstation was all fixed, either verbal ergonomic instructions alone or combined with haptic biofeedback were able to significantly reduce the time in adverse upper-arm postures, after short periods of training. However, the combination had significantly better results, with the accumulated times in upper-arm elevations above 30° and 60° decreasing 38% and 49%, respectively, compared with no biofeedback at all. The haptic biofeedback was also the most important input for the users to redesign the workstation. In another paper, Lind, De Clercq et al. (2023) reported significant reductions in the median proportion of time spent in high trunk forward inclinations (68% for angles above 30° and 89% for angles above 60°) when receiving the vibrotactile biofeedback compared to the baseline. Accordingly, the 95th and 99th percentiles trunk inclination angle decreased in the biofeedback condition and also in post-feedback compared to the baseline. However, for follow-up sessions, there was only a slight tendency of decline in the 90th and 95th percentile trunk angles. The results obtained by Kim et al. (2021) encouraged the use of either one of the proposed vibrotactile feedback strategies for guidance, since the overall final errors between the desired and the actual joint configurations were below 9%, indicating that the subjects could reach the desired joint angles. Overall, the angle errors registered in the torso were lower than those in the arms. SPOT modality was the most intuitive and preferable modality to provide directional guidance, thanks to its inferior final mean error for the overall joints (equal to 4.09%, whereas RAMP reported 6.89% and PATTERN 5.18%) and lower time to reach the desired joint angles (28.35 s, 60.24 s, and 54.83 s, respectively). SPOT modality integrated with an ergonomic optimisation framework, when performing a lifting task, did not show a noticeable change in the overloading joint torques at the elbow and shoulder in all cases, but led to a reduction in hip, knee, and ankle joints. Regarding the comparison between different haptic feedback modalities, Lorenzini et al. (2022) reported that, when guiding only one joint, the vibrotactile device was found to be the most befitting for the shoulder, considering that it led to higher performances regarding all the metrics, and it was generally better perceived by the users; in turn, the force cues seemed to be the effective solution for the knee, because of the faster responses and higher accuracy in reaching the desired posture. Overall, when the shoulder and knee joints were guided simultaneously, the performance of both devices got worse; even so, a good percentage of success was reached, which demonstrated the aptitude of the integration of these two feedback modalities in posture correction applications. Fani et al. (2021) showed statistically significant differences in terms of success rate and time for moving CoP position between each of the two conditions (haptic or visual feedback) and baseline (no guidance), but no significant differences between the two types of feedback: success rates of 88% and 96% and trial durations of 13.87 s and 10.57 s were reached with haptic cues and visual cues, respectively. In opposition, in the experiment of Aggravi et al. (2018), all the considered metrics but completion time improved when using the wearable feedback device instead of visual feedback, and all improved compared with wearing no device — performance on completion time and trajectory length improved of 19.8% and 25.1%, respectively.

The proposed *systems' usability* was evaluated by questionnaires like credibility and expectancy (Bootsman et al., 2019), Intrinsic Motivation Inventory (Bootsman et al., 2019), Unified Theory of Acceptance and Use of Technology (UTAUT) (Bootsman et al., 2019), SUS guidelines (Cerqueira et al., 2020; Kim et al., 2021), Single Ease Question (Kim et al., 2021), Likert scales (Fani et al., 2021; Lorenzini et al., 2022; Vignais et al., 2013), NASA-TLX (Fani et al., 2021; Lorenzini et al., 2022), perceived effectiveness (Aggravi et al., 2018), Borg scale and a body map to rate the discomfort/pain or physical exertion (Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020), Copenhagen Psychosocial Questionnaire II (Lind, De Clercq et al., 2023), Comfort Rating Scale (Lind, De Clercq et al., 2023), and other subjective reports/semi-structured interviews were conducted as well (Bootsman et al., 2019; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Vignais et al., 2013). Moreover, Dunkelberger et al. (2018) and Lins et al. (2018) calculated the accuracy between the perceived cues and the given ones in order to assess the clarity with which the cues were perceived.

Participants in the experiment of Bootsman et al. (2019) found the system overall moderately positive, and their ratings respecting credibility and motivation to use the device were encouraging, but they were not completely satisfied because of the need to interact with the app to associate activities with sustained poor posture occurrences, which was not always convenient, due to their work. Participants in the study of Vignais et al. (2013) expressed that the biofeedback system helped to support more ergonomic postures, and defended the combination of the visual and auditory feedback modalities against a single one. Cerqueira et al. (2020) reported that users highly accepted the system and its intuitiveness, and it neither restricted movements nor influenced normal working behaviour, thus demonstrating the feasibility of vibrotactile biofeedback. Lind, Diaz-Olivares et al. (2020) also revealed that biofeedback was experienced positively and useable by the participants and made them more aware of their work technique. The subjects recruited by Lind, De Clercq et al. (2023) considered that the system was very comfortable and nonintrusive, and that it did not increase the cognitive demands, indeed, the majority declared to be more aware of their postures after the biofeedback training. Besides, their perceived exertion did not vary significantly between different conditions. Participants in the experiment of Fani et al. (2021) rated the wearable haptic system as intuitive and effective. Aggravi et al. (2018) declared a 149.1% improvement in perceived effectiveness when receiving haptic feedback. The subjective data collected by Kim et al. (2021) was in agreement with objective data, showing excellent acceptance of the preferred feedback strategy among the participants. Lorenzini et al. (2022) reported that both vibrotactile and slide-and-squeeze devices achieved good acceptability and intuitiveness, although the former was preferred for shoulder guidance and the latter for the knee, which is in agreement with the performance indices. The advantages of the transmission of large sets of haptic cues against only vibrations were stated by Dunkelberger et al. (2018), who reported that more cue combinations were correctly identified in the first case (41.4% vs. 30.5%). Moreover, when stretch and squeeze were both ON, users had trouble perceiving the stretch cue. The perceptual accuracy of the vibration cues was higher for the multimodal feedback condition: despite the fact that this vibrotactile band is identical in both conditions, the researchers argued that these were concealed in the unimodal system. The qualitative assessment made by the participants also indicated a majority preference for the proposed multimodal feedback system. Regarding vibrotactile feedback, Lins et al. (2018), after testing sequences with 1 to 3 pulse repetitions and pulse lengths of 25, 50, 100, and 150 ms (with pulse intervals with these same durations), found an optimal user perception for a pulse sequence of two 150 ms pulses. Further, the accuracy of the vibration perceptions varied substantially through the body, being better perceived in the shoulders (84.7%) and wrists (78.9%), followed by the upper back (74.1%), arms (65.9%) and knees (56.4%), and very difficult to perceive properly in the lumbar region (2.2%), likely because of the loose jacket where the vibration motors where placed. Thus, vibrations generated by motors close to the skin were perceptible in most cases.

5. Discussion

Overall, this literature review demonstrated the potential of wearable technology to not only monitor and/or assess posture but also to provide biofeedback about it. The key ideas presented regarding sensing and actuation technology, ergonomic methods, and feedback effectiveness are discussed in the present section to answer the research questions. Accordingly, current gaps and future directions are pointed out.

5.1. What types, number, locations and settings of wearable devices were adopted in the literature studies?

Currently, the trendiest wearable technology in data collection are IMUs. The number of degrees of freedom (DoFs) of the sensing devices has a considerable impact on angle estimation. It is frequent to find studies that only combine accelerometer and gyroscope. However, most studies also consider magnetometer data (9 DoF). With 6-DoF IMUs, orientation data from the gyroscope is corrected only with information from the accelerometer (roll and pitch angles), whereas 9 DoF join magnetometer data, which provides a global heading direction based on a magnetic field (yaw angle), allowing a higher accuracy and robustness against drift over time (Lind, Diaz-Olivares et al., 2020; Vignais et al., 2013). Nonetheless, magnetometers can be affected by magnetic disturbances (Lind, Abtahi et al., 2023; Vignais et al., 2013), and they increase the sensing system's cost as well. Considering all studies, the number of IMUs is not consensual; it depends on the complexity of the postural assessment. Apart from that, the level of intrusiveness and inconvenience was rated as low by real workers (Zhao et al., 2021), reporting that the sensors did not reduce their productivity.

Regarding ergonomic assessment, excepting Huang et al. (2020) and Martinez et al. (2022), who employed the REBA method, the authors focused only on the upper body since most ergonomic methods do not give much relevance to the lower limbs. This is reflected in the sensors' body location: most of these studies did not collect information about lower-limb motion, but the ones that do, place one sensor on the upper leg and another on the lower leg, being able to measure knee angle. To measure head inclination, a sensor is placed on the head in most systems. Since the trunk is one of the most critical segments to musculoskeletal disorders, all studies from Section 3 measured this angle, using one or two IMUs placed in the back or chest. Almost all of the selected studies placed IMUs on either the shoulder(s) or the upper arm(s), in order to track shoulder joint movements. Few studies addressed forearms/hand movements since inertial sensors have higher angle estimation errors for extremity joint movements (Wang, Dai, & Ning, 2015). The accuracy of the collected data is dependent on the choice of the sensors' locations (Yan et al., 2017). Hoareau, Fan, Abtahi, and Yang (2023) evidenced that in-cloth IMUs can assess posture with an acceptable accuracy compared to on-skin sensors (mean errors below 4° for upper-arm and trunk angles), although this depends on the fit of the clothes. Nevertheless, the sensors must not interfere with other safety equipment, as Zhao et al. (2021) reported to happen.

From the included studies, three of them integrated the actuators in a smart garment with sensors and all the hardware embedded, ready to be worn by the users autonomously (Cerqueira et al., 2020; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020), whereas one used a commercial suit with inertial sensors (Huang et al., 2020).

The choice of the sampling frequency depends on the temporal dynamics of the activities, and this frequency must always be superior to twice the maximum frequency in the human movement's spectrum, 10 Hz, in order to respect the Nyquist theorem. Nonetheless, the frequencies that concentrate most of the energy range between 0.3 and 3.5 Hz (Sun & Hill, 1993). However, the more samples per second, the greater the demands in terms of a fast response from the orientation filter, in order to achieve real-time ergonomic assessment or, at least, online.

Several types of feedback were found in scientific literature, but the haptic one stood out as the most appropriate, and different actuators were found to provide it. Within haptic cues, the most common type is vibrotactile, due to the reduced weight, small size and lower power consumption of vibration motors in general, and because they can be driven at a range of different frequencies and amplitudes (Dunkelberger et al., 2018; Lorenzini et al., 2022), thus being able to alert for bad posture (Bootsman et al., 2019; Cerqueira et al., 2020; Kim et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020), to guide human joints (Kim et al., 2021; Lorenzini et al., 2022) or to give navigational cues (Fani et al., 2021). Due to the motors, the presented slide-and-squeeze devices' wearability is compromised by the larger dimensions, which almost go beyond the limits of what humans perceive as their intimate space, an aura around the body that extends only 12.7 cm off the body (Cerqueira et al., 2020). Moreover, it may limit the user's movements, which is a serious handicap for a device that should be as inconspicuous as possible.

Ideal haptic biofeedback should give the desired information promptly through tactile cues that users can sense and distinguish accurately (Dunkelberger et al., 2018). One of the crucial factors in biofeedback effectiveness is the actuators' location. In the case of vibrotactors, they must be close to the skin in order to enhance their vibration; in one study they were not directly placed in users' skin but in a loose suit, and that led to a mean perception accuracy of approximately 60%, with the authors pointing out that the vibrations triggered by vibrotactors close to the skin were perceptible more often (Lins et al., 2018). Beyond that, vibrations on bones (neck, spine, pelvis and sacrum) should be avoided since they are felt throughout the whole body segment, and they are perceived as very uncomfortable; instead, the actuation units can be placed aside (Visser, 2018). For instance, Kim et al. (2021) set the vibrotactile devices near the joints to be guided. In the majority of the addressed papers, actuators were placed in the arms, especially in the upper arm to raise awareness about the shoulder joint.

The distance between haptic units must take into account the minimum distance required to distinguish two stimuli, applied in different locations. Different values are mentioned in the literature: Kim et al. (2021) chose 5 cm for trunk and arms, Filosa et al. (2019) reported a distance of 5.5 cm for the abdomen, Visser (2018) mentioned 5 cm for the upper leg, and Lins et al. (2018) pointed out 4 cm for limbs. If the motors are placed at smaller distances, the cues may be perceived as a single vibration with a large surface (Visser, 2018).

Concerning vibrotactile cues, the vibration frequency is also a crucial aspect, because the human cerebral cortex is only capable of discerning frequencies from 80 to 250 Hz, hence the vibration frequency must lie within this spectrum (Cerqueira et al., 2020), which also avoids the tendon vibration illusion frequency (75 Hz) (Kammers, van der Ham, & Dijkerman, 2006). Effectively, in all the scanned studies but one Dunkelberger et al. (2018), the chosen frequency was between these values.

Vibration intensity plays an important role in user experience too. A trade-off between safety and perception is present in the choice of this value, as higher intensities are more readily perceived, but, on the other side, both intensity and duration of the vibration increase the risk of injury, and, besides that, higher intensities consume more energy (Kim et al., 2021).

Another aspect that contributes to the effectiveness of the feedback is the duration of each cue, or the length of ON and OFF periods when multiple pulses are given. For example, Aggravi et al. (2018) established equal ON and OFF periods for the motors when they were activated. On the other hand, Fani et al. (2021) defined an ON period of 100 ms, while the OFF period was variable, decreasing with the error magnitude. Nevertheless, Lins et al. (2018) found optimal ON and OFF periods of 150 ms, which is probably due to the fact that lower intensity vibrations require longer duration (Kim et al., 2021). However, Lins et al. (2018) pointed out that pulses longer than 200 ms would likely annoy the users; additionally, they found an optimal number of pulses equal to two. Although a third pulse could increase the perception, that was not considerable, and it would cost additional energy (Lins et al., 2018).

5.2. Which ergonomic criteria govern these postural assessments?

Ergonomic tools, like the ones exposed, can be divided into local risk assessment, global, or both when the local scores assigned to individual body segments/joints are combined to obtain an overall risk value, which is already proposed by ergonomic methods like RULA or REBA. The latter approach, i.e., the combination of local and global approaches, was the most found in literature, because it allows obtaining more information regarding the overall WRMSD risk and the body parts that are more exposed to it. All the included studies used quantitative scores to express postural risk, which is important to provide concrete information to the user or the ergonomist. Regarding the inputs for the ergonomic rules, only in the cases of Zhao and Obonyo (2021) and Zhao et al. (2021), they were nominal, qualitative postures; in the remaining, they were angular values for each articulation's DoF. It should be noted that ergonomic assessments based on angular thresholds are dependent on the posture reference, which is an initial neutral posture (standing), that is user-dependent (Bootsman et al., 2019; Cerqueira et al., 2020; Lind, Abtahi et al., 2023; Valero et al., 2017). This means that the estimated risk level may be misjudged due to an improper initial alignment of the body segments or due to bad postural habits.

Also, a gap in standards for assessing dynamic activities was pointed out, given that most ergonomic methods were developed for static postures (Valero et al., 2017).

One recurrent drawback of these systems, derived from the chosen ergonomic methods themselves, is that they pay little attention to motions in planes other than sagittal. Hence, the authors who used tools like RULA or REBA had to define on their own some angular thresholds for common movements like arm abduction, or lateral bending or twisting of the trunk or neck (Vignais et al., 2013). Despite its limitations, RULA is undoubtedly the most frequent ergonomic posture assessment tool, thanks to its good inter-observer reproducibility (Carbonaro et al., 2021). Overall, these tools usually simplify the assessment of anatomical areas like the lumbar zone, which is the body part most affected by WRMSDs (Huang et al., 2020; Vignais et al., 2013). One study tried to address this by complementing the postural ergonomic analysis with a biomechanical analysis (Huang et al., 2020).

Another weakness of most of these systems is the disregard for the influence of the time previously spent at each risk level. One research (Carbonaro et al., 2021) tried to address this issue, by using a time window approach where each window's final score was not the longest score kept, but the highest score among those maintained for more than a certain time threshold. In turn, Zhao and Obonyo (2021) assigned the OWAS risk considering posture proportions in working time. Besides that, the same study and another two (Yan et al., 2017; Zhao & Obonyo, 2021) used the concept of MHT, with Zhao and Obonyo (2021) counting the number of times and the duration each posture was kept for more than the defined MHT, and Yan et al. (2017) using the accumulated ones to classify the posture as acceptable or not, using ISO 11226 standards. Differently, Valero et al. (2017) calculated a posture score by averaging the risk levels weighted over time, but only as a final metric, non-continuously. Finally, Martins et al. (2023) and Merlo et al. (2023) presented a cumulative ergonomic index that replicates a memory effect concerning the time spent in each posture, increasing as the user continues to adopt risky postures and decreasing otherwise, inspired by the time response of a capacitor in an RC circuit.

5.3. When to trigger biofeedback cues and what information can be encoded in them?

Concerning ergonomics correction, usually, biofeedback is provided when reaching higher risk levels. Notwithstanding, there may be a time allowed (before triggering the biofeedback) for maintaining those risk levels, or a certain awkward posture, to avoid annoying the user (Bootsman et al., 2019). This was also mentioned by a manager participating in the experiment of Zhao et al. (2021), workers tended to ignore the biofeedback if the notifications were too often. Two studies considered different maximum times for holding different risk levels, shortening these times for higher risk levels (Cerqueira et al., 2020; Vignais et al., 2013). However, the choice of these values does not follow any criteria.

Meaningful information can be encoded in the haptic cues, notifying about the risk level (the magnitude of the error) and/or giving tips about how to achieve a better posture. Actually, the lack of guidance information in postural correction applications often appears as a drawback of biofeedback systems (Cerqueira et al., 2020; Lins et al., 2018). In the case of vibration cues, some of the parameters already referred can transmit information: pulse length, number of repetitions, variations in the pause interval (Fani et al., 2021; Lind, De Clercq et al., 2023; Lins et al., 2018) — the use of intermittent or continuous vibration can notify, respectively, for a medium or a high postural risk (Lind, De Clercq et al., 2023) — and vibration intensity/amplitude — the intensity of vibration itself can inform about the risk magnitude (Lind, Diaz-Olivares et al., 2020), and variations in the amplitude can provide directional guidance (Kim et al., 2021). It is possible to give this directional guidance through vibration patterns by playing with the sequence of vibration when using more than one actuator per segment, or placing two units on opposite sides of the target joint/segment to indicate the desired direction (Kim et al., 2021). It has been shown that other types of haptic feedback can also provide guidance, such as a squeezing force proportional to the error amplitude, or tangential forces indicating the direction that minimises the error (or the risk, for ergonomic applications) (Aggravi et al., 2018; Fani et al., 2021; Lorenzini et al., 2022). This simultaneous rendering of different types of information through distinct cues is recommended to the extent that it has been proven that presenting information-rich cues at a slower rate has a greater response than low-information cues at a faster rate, which means that the increase of the information content of each cue is the best solution when more information needs to be provided (Tan, Reed, & Durlach, 2009).

5.4. Has biofeedback proved to be effective in posture correction?

The research proved that biofeedback is a promising tool for ergonomic interventions, in work technique training, and in work and workplace design, increasing awareness of risky working situations, while lessening the necessity of skilled trainers and ergonomists (Cerqueira et al., 2020; Lind, Diaz-Olivares et al., 2020). It was demonstrated that, even though strong feelings of discomfort sensed by the worker during a task were an evident source of intrinsic biofeedback in changing work technique and workstation design, haptic biofeedback can be a more powerful input channel, particularly for individuals who felt no or weak discomfort (Lind, Diaz-Olivares et al., 2020). The external haptic biofeedback is able to enhance or even replace the intrinsic one (Lind, Diaz-Olivares et al., 2020). In all the studies where the performance using biofeedback was compared with no guidance, the results were positive, i.e., the biofeedback consistently reduced the time spent at non-ergonomic postures (Bootsman et al., 2019; Cerqueira et al., 2020; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020) or the deviation in relation to the neutral position (Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020); it reduced the time to accomplish the goal (Aggravi et al., 2018; Fani et al., 2021) and increased the success rate (Fani et al., 2021) relative to the baseline condition (the ground truth in the mentioned cases). Yet, one of the gaps found during the research was the lack of evidence about the limits of how much and what type of biofeedback information can be beneficial (Lind, Diaz-Olivares et al., 2020). These studies are typically cross-sectional, only one study (Lind, De Clercq et al., 2023) carried out a post-intervention session to assess the medium-term retention of improvements, and it did not find a significant reduction in the time in hazardous trunk postures in follow-up sessions (one and three weeks), despite the reduction in the short term, which means that the use of vibrotactile biofeedback during short periods may not be enough to mitigate bad postures over a longer time. Similarly, Bootsman et al. (2019) reported that, even immediately after improving posture while receiving biofeedback for an hour, participants returned to postures similar to the initial baseline when no biofeedback was given in a withdrawal condition, which may indicate that biofeedback training should last longer. However, long-term biofeedback may increase the risk of the user disregarding the body's intrinsic biofeedback system, developing an extrinsic biofeedback dependency (Lind, Diaz-Olivares et al., 2020). Besides that, vibrotactile biofeedback may lead to adaptation of the receptive channels, which translates into a deterioration of tactile sensitivity subsequent to the application of the stimulus, even after its cessation. The risk of saturation increases with continued overusage of vibrations when they occur along multiple body axes or in a distributed manner — this can be diluted by combining different types of haptic stimuli, as already referred (Fani et al., 2021).

It is interesting to note that there was a tendency for the tasks performed while receiving biofeedback to take more time, thus reducing work productivity (Cerqueira et al., 2020; Lind, Diaz-Olivares et al., 2020; Vignais et al., 2013). This may be due to the actions taken to alter the work technique (Cerqueira et al., 2020; Lind, Diaz-Olivares et al., 2020). For instance, it is usual to reduce trunk inclination by squatting or semi-squatting, which may increase the physiological workload since it moves a larger mass of the body (Lind, De Clercq et al., 2023). That time gap is expected to be lessened with training, as users become more conscious of their posture and gain perception of correct ergonomic practices (Cerqueira et al., 2020). Another possible undesirable situation arising from biofeedback is the risk of worsening the ergonomics of some body parts while improving it on the target body part, although this may be solved by monitoring other body segments (Lind, Diaz-Olivares et al., 2020). Also, the guidance of multi-joint segments (with more actuators) demands more cognitive effort than single-joint ones, as shown by Kim et al. (2021), where the feedback success achieved worse rates for the arm than for the torso. This means that the correction of the arm posture possibly demands more attention from the user than the one of the torso.

Regarding the validation of biofeedback on postural ergonomic support, it is significant to note that only four of the studies demonstrated the use of localised haptic biofeedback to alert for the correction of ergonomically risky postures (Cerqueira et al., 2020; Kim et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020). Other studies presented the feedback concept for ergonomics but did not integrate it into a framework (Fani et al., 2021; Lins et al., 2018; Lorenzini et al., 2022). Additionally, the experimental protocols of the latter only included relatively simple tasks performed by novice participants. Directional feedback was not applied yet in a real context, only in controlled environments (Aggravi et al., 2018; Fani et al., 2021; Kim et al., 2021; Lorenzini et al., 2022). Hence, it is not straightforward to generalise the results for experienced workers on more complex tasks.

Also concerning the validation protocol, only one of the presented studies validated the angle estimation with other MoCap system online (Martinez et al., 2022), although Cerqueira et al. (2020) performed an offline technical validation, not with the sensors placed on the human body but on a collaborative robot arm. This is a vital step in order to trust the ergonomic assessment carried out, otherwise, it is not possible to know the associated error, which is a serious handicap of several studies, as mentioned by Lee et al. (2021). In addition, most validation experiments took place in a lab, instead of in a field environment with workers, where real conditions play a role in the postures adopted.

Besides the collected objective data, users' opinions were also registered, usually by questionnaires with discrete score scales, such as 7-point Likert scale, which measures the degree of agreement with the statements, or NASA-TLX questionnaire, which allows the self-evaluation of predefined parameters. The subjective outcomes were favourable to the use of biofeedback systems. The questionnaires revealed a good acceptance (Bootsman et al., 2019; Cerqueira et al., 2020; Kim et al., 2021; Lind, De Clercq et al., 2023; Lind, Diaz-Olivares et al., 2020; Lorenzini et al., 2022) of the technology and great intuitiveness (Cerqueira et al., 2020; Fani et al., 2021; Lorenzini et al., 2022), users found it useful (Aggravi et al., 2018; Cerqueira et al., 2020; Zhao et al., 2021), comfortable to wear (Bootsman et al., 2019; Cerqueira et al., 2020; Lind, De Clercq et al., 2023), and some studies also reported acceptable ratings regarding the credibility of the device to support posture correction and the users' motivation to use it with that intention (Bootsman et al., 2019; Cerqueira et al., 2020). Zhao et al. (2021) reported that some workers indicated that the assessment enabled them to understand what were the risky postures and how to adjust them, and one manager highlighted that it could even enhance safety planning. Real construction workers reported low physical and mental discomfort in one study (Zhao et al., 2021); however, in another one (Lind, Diaz-Olivares et al., 2020), some subjects mentioned that the biofeedback distracted or stressed them at the beginning.

5.5. Review limitations

Since this work aimed at joining two research topics, the idea was to provide an overview of each one of them and connect them, instead of analysing each of them in detail. For instance, an overview of postural ergonomics assessment was provided without considering other WRMSD risk factors such as repetitive motions, biomechanical loads or force exertions, which could provide a broader perspective of an ergonomic assessment. Cognitive ergonomics was not addressed either. Although not explored in this review, applications combining inertial and physiological data, e.g., electromyography or heart rate, could also be found for ergonomic assessment. Similarly, this work mainly explored haptic feedback as this type was shown to be the most unobtrusive, and the other types were not fully scrutinised.

Moreover, this literature search was limited to two databases, and to articles written in English, which means that articles belonging to other databases or written in other languages were not included. Since this is a narrative review, the quality of the included studies was not formally assessed. Data regarding system validation, namely, angle estimation, was scarce, for the studies that addressed posture monitoring. Hence, their results' benchmarking was limited.

5.6. Challenges and future work

This work identified some gaps in the literature, both in data processing/assessment and validation. Future studies should, in the first place, validate the accuracy of the collected inertial data and, when applicable, the angle estimation online, resorting, e.g., to commercial MoCap systems, so that the conducted ergonomic assessment can be reliable and the results benchmarked. In this sense, we also encourage the authors to report the sensor fusion and angle estimation algorithms.

With respect to posture assessment tools, one of the main open problems discovered in this literature review is linked to the adopted ergonomic methods. An interesting research advance would be the development of a continuous scale for ergonomic assessment, taking into account the cumulative effect of bad postures, instead of the classical "snapshot" tools, which pose a challenge to summarise the exposure, as pointed out by Lind, Abtahi et al. (2023). Furthermore, investigation into the maximum holding times for each joint in non-ergonomic postures is needed to decide when to trigger biofeedback cues. In this sense, Martins et al. (2023) suggested the integration of a cumulative ergonomic index into a directional biofeedback strategy. Besides, the exploration of artificial intelligence algorithms for ergonomic risk assessment was pointed out as a possibility (Cerqueira et al., 2020).

The ergonomic assessment itself can be a valuable tool, but it would be interesting to correlate the ergonomic risk with the situations that originate it, i.e., which activities or postures throughout the work shift impose a higher risk. To get an overview of the work activities in terms of posture hazard, Bootsman et al. (2019) associated the occurrences of hazardous postures with the activities, however, they relied on the workers' manual labelling in an app, which turned out to be inconvenient. In fact, three studies combined posture classification with risk assessment: Valero et al. (2017) carried out that posture classification using a state machine approach based on joint angles, whereas Zhao and Obonyo (2021) and Zhao et al. (2021) implemented automated activity recognition models based on deep learning, which guarantees generalisability, although only Zhao et al. (2021) did it in real time. These models have been gaining importance in context-aware systems in several domains, such as surveillance, or health and ambient assistive living (Martins, Ribeiro, Soares, & Santos, 2022; Ponce et al., 2016). Hence, it is necessary to develop a system able to recognise the activity in real time (or, at least, online) and perform an ergonomic assessment, which could be dependent on the activity, and provide contextual biofeedback to enhance posture self-awareness and prompt the users to correct their posture to a less hazardous one.

There is still no evidence on whether biofeedback training should be used for just some hours or continuously for entire workdays. Regarding directional feedback, so far, few studies have implemented it for the correction of non-ergonomic postures, hence, validation in real working conditions is necessary. The wearability and inconspicuousness of feedback technology like slide and/or squeeze bands should be improved too, in order to compete with vibrotactile motors. Besides, there is room for the combination of haptic feedback with other technologies, such as augmented reality glasses, as sustained by the users' opinions in one study (Vignais et al., 2013).

6. Conclusion

The current state of the art of posture monitoring systems, analysed in this review, showed the relevance of combining ergonomic risk assessment with intuitive biofeedback strategies. On the one hand, posture risk assessments were essentially based on traditional ergonomic scales, which were adapted from observational methods. Their automation relying on an inertial system proved to be an interesting tool to ergonomically diagnose risky tasks and workspaces to possibly redesign them and, then, reduce WRMSD risk. But, besides the direct application of these fixed criteria, other approaches were presented, such as taking into consideration the previous ergonomic scores, a valuable addition to the risk assessment since WRMSDs arise from the accumulation of risky postures over time. The transmission of the assessment to the users was mainly carried out with haptic biofeedback, which was given concurrently based on the amplification of error perception. Particularly, vibrotactile feedback, the simplest and most discrete haptic modality, led to a decrease in posture risk and time spent at riskier joint configurations in several studies, making workers aware of their posture. Further, graphical interfaces like the ones suggested by some studies allow a direct analysis and intuitive understanding of the risk, offering the possibility of providing objective data to ergonomists. One of the contributions of this review was the presentation of other feedback modalities besides vibrotactile, namely, pressure and stretch cues. In fact, their simultaneous use in directional feedback strategies proved to be more effective than vibration alone, at least in controlled lab environments. Hence, in this regard, further validation is needed.

CRediT authorship contribution statement

Diogo R. Martins: Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing, Conceptualization. **Sara M. Cerqueira:** Conceptualization, Investigation, Methodology, Visualization, Writing – review & editing. **Cristina P. Santos:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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