RECENT NOVELTIES IN THE FIELD OF THE ERGONOMICS RISK ASSESSMENT METHODOLOGY: SHORT REVIEW

Renato Pinho[1], J. Santos Baptista[2], Sara Ferreira[3], J. Torres Costa[4]

[1.] DemSSO, University of Porto, Portugal.

[2.] Faculty of Engineering of the University of Porto, Portugal.

[3.] Faculty of Engineering of the University of Porto, Research Centre for Territory, Transports and Environment, Porto, Portugal.

[4.] Faculty of Medicine and Faculty of Engineering of the University of Porto, Porto, Portugal.

Abstract

Objective: The authors make a short literature review of the evolution of the postural risk assessment during the last decades. **Background:** Work-related musculoskeletal disorders are prevalent in the current industrial work scenario. The authors make a literature review of the evolution of the postural risk assessment during the last decades. The present study aims to analyse if any update novelty has been published in the postural risk assessment methodology field. **Method:** Exploratory research was performed in Scopus, Web of Science, Springer, Pubmed, Taylor, and Francis. **Results:** A summary of extracted data from included papers is provided. **Conclusion:** The authors concluded that few researchers foresee novelties for biomechanical risk assessment, and the recent research points to an algorithm that allows automatisation and online real-time ergonomics risk evaluation.

Keywords: Musculoskeletal disorders, postural risk, workplace.

Introduction

Work-related musculoskeletal disorders (WMSDs) are a significant problem in personal suffering and the costs associated with loss of production, sickness benefits, and health care (Bevan.,2015). Due to the high direct and indirect cost of musculoskeletal disorders (MSDs), there is a strong motivation for all stakeholders (e.g. employers, workers, and researchers) to identify factors that cause a work-related disease and eliminate worker exposure to these risk factors (Bevan., 2015).

An increasing number of studies have shown that adverse ergonomics factors at workplace constitute substantial risk (Bernard, 1997; Rijn et al., 2010; Molen et al., 2017). In particular, awkward posture, high loads, rapid movements, repetitious tasks and lack of adequate recovery time have been identified as harmful, separately and or in combination (Rijn et al., 2010; van der Molen et al., 2017).

To determine an exposure-response relationship, reliable information regarding exposure is necessary (Rijn et al., 2010). Several methods and tools have been designed in the last decades for ergonomics risk assessment, and these can be classified as follows (David., 2005; Vignais et al., 2017):

- Self-assessment, where workers assess themselves using specifically designed forms (Borg., 1998).
- Expert observation, where qualified personnel objectively estimates workers' body measurements through on-site observations and offline video analysis (Bao et al., 2005).
- Direct measurement, where anthropometric tools and devices are attached to a worker's body, automatically collects data for ergonomic analysis (Koppelaar et al., 2005).

The results obtained by self-reporting questionnaires are biased. Modelling human performance is challenging, as diverse influential factors have complex interactions (Waldman and Spangler., 1989).

The Expert observations of the work performed are more objective compared to self-assessment. Several observations tools for performing MSDs risk assessment have been proposed in the past. Although each of the existing observational-based ergonomic risk assessments offers advantages, no one seems superior to the others (Takala et al., 2010). Also, there is no comprehensive method that can be used to evaluate the whole range of ergonomic risks (Roman-Li., 2014).

Observational methods suffer from two significant weaknesses: First, in current industrial practice, workers' posture needs to be manually observed, coded, and inputted into a standardised form which is time-consuming and less practical for long-term observation workers rotating among multiple tasks. Second, it is dependent on the technical observer and experience. Many research studies have revealed problems with the existing posture assessment tools due to their dependency on observers' capabilities for approximating interest angles and difficulties related to inter-rater reliability between measurements (Golabchi et al., 2015).

In recent studies (Manghisi et al., 2017), the direct measurement applied different technologies, such as wearable sensors and computer vision, to infer the risk of MSDs through automated observational methods.

Availability of wearable sensor technologies and the development of data mining approaches offer new opportunities to evaluate operator performance in field settings (Taso et al., 2019). For example, kinematics obtained using inertial measurement units can be used with traditional or advanced machine learning techniques for manufacturing task classification (Kim and Nussbaum., 2014), daily activity recognition (Koping et al., 2018), fatigue detection and prediction (Maman et al., 2017), and recognition of chronic low back pain populations (Hu et al., 2018). Surface electromyographic (SEMG) sensors have also been widely applied to monitor muscle activity (Bosch et al., 2012; Ranavolo et al., 2018), and features extracted from SEMG have been used as inputs to machine learning models to classify lifting tasks that pose different levels of risk (Brandt et al., 2018). Heart rate and heart rate variability can also be obtainable from wearable sensors and used in conjunction with other sensors to assess operator exertion and fatigue levels (Nicoletti and Laubli., 2018).

The computer-based assessment, where human body models are automatically estimated from cameras by computer vision (CV) applications, provides systematic and objective model-based ergonomic measurements (Mehrizi et al., 2019).

Over the last few years, several disruptive technologies related to the Industry 4.0 (I4.0) paradigm enabled fruitful ergonomics applications (Kadir et al., 2019). More specifically, the impact of automated data collection and analysis is shaping a new group of data-driven applications where technological advances in hardware sensors and machine learning (ML) open novel roads for Ergonomics.

With the advancement in ML, image recognition, deep learning, computer vision, some researchers have made significant progress in posture recognition by improving algorithms.

The development of deep learning, in recent years, and the more powerful graphical processing units (GPUs) has allowed a significant number of researchers to adopt the convolutional neural network (CNN), a form of deep neural structures, for vision-based human pose reconstruction and improved the accuracy of the reconstructed pose (Newell et al., 2016). The advent of Tensorflow Lite makes deploying deep learning-based methods on mobile possible (Manning et al., 2018), so postural risk assessment can be performed on a hand-held cell phone.

There is now the potential to develop methods that provide rapid (or even real-time). We decided to review from January 2020 until March 2021 novelties published in the field of postural risks assessment methodology.

Material and Methods

The variable of interest in this literature review was "novelty in the postural risks assessment methodology".

The review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology (Moher et al., 2009), and exploratory research was done.

The review search for studies that report novelties in the postural risks assessment methodology related to occupational disorders. Therefore, studies focusing on the ergonomic risk assessment were pursued in five electronic databases: Scopus, Web of Science, Springer, Pubmed and Taylor and Francis. The search strategy selected studies from January 2020 to March 2021 (both included) because our purpose was to know any UpToDate scientifically article referring to new methodology or novelty in the field of postural related to worker's exposure.

The various combinations of keywords were used to generate maximum articles from multiple sources, including journal publications, book publications, study reports of national societies, conference proceedings, etc. The combinations used in the search were "musculoskeletal disorders", "risk ergonomic", novel, novelty, "new methodology", and similar combinations using the Boolean operator "AND" and the Boolean operator "OR".

After removing duplicates and screening, a total of 8 full-text papers were identified and included in the review report in this paper.

Results

Overall Papers' Analysis

The eight selected papers were primarily analysed for their geographical distribution. The United States was the most dominant country in the included studies with three studies (Bani et al.,2021; Asadi et al.,2020; Li et al.,2020) and two (Li Ze et al.,.2020; Tsao et al.,.) in association with China and one (Mumati et al., 2021) in association with Jordan. India with one (Bhatia et al., 2021) study and Spain and Argentina with one (Fernández et al., 2020) study in association.

Articles using camera/video recordings to evaluate risk ergonomics exposure

Eight articles (Mumani et al., 2021; Bani et al., 2021; Li Ze et al., 2020; Bhatia et al., 2020; Tsai et al., 2020; Asadi et al., 2020; Fernández et al., 2020; Li et al., 2020) used data obtain from picture/video recordings to observe and assess risk ergonomics exposure. Seven of those (Bani et al., 2021; Li Ze et al., 2020; Bhatia et al., 2020; Tsai et al., 2020; Asadi et al., 2020; Fernández et al., 2020; Li et al., 2020) were in a laboratory or experimental environments and one consist of an empirical model based fuzzy-logic set theory (Mumani et al., 2021).

Main Findings

Among the eight studies included in the review, five studies report a novel in the field of the risk assessment in the context of rating of standard methods; two studies report a novel in the field of the risk assessment in the context of the direct instrumental evaluations and one (Bani et al., 2021) make the report of a new tool based in the principles of the fatigue failure theory.

Mumani et al. (2021) studied an empirical model based on fuzzy-logic set theory that applied the Monte-Carlo simulation in which joint angles are represented in distributions. The authors pretend to automatise the standard observational method RULA and REBA. The proposed approach exhibited a higher degree of sensitivity concerning joint angles associated with variability and uncertainty.

Bani et al. (2021) report a new shoulder risk assessment tool based on fatigue failure theory principles. The authors describe a method based on analysed exposure assessment video and model-based logistic regression, adjusted in database epidemiologic. The study revealed a strong association between the Log CD (cumulative damage) measure generated by The Shoulder Tool and multiple shoulder MSD, providing evidence that fatigue failure may be an essential aetiological factor in developing MSDs.

Li et al. (2020) proposed a novel intelligent REBA system based on a convolutional pose machine, using the Quick Capture system that enables smartphone application. They report a Human skeleton recognition algorithm based on an image and data acquisition scheme and output the REBA assessment report.

Bhatia et al. (2020) applied a Kinect sensor as a markerless technique to assess ergonomics risk in the dental practice, and they introduced a slow-motion real-time task assessment to analyse posture. The authors concluded that postural analysis of slow-motion tasks like dentistry using the Kinect V2 system proved to be discreet and efficient.

Asadi et al. (2020) proposed a novel computer vision based on an automating approach based on a deep neural network that estimates the perceived forceful exertion obtained by the inputs from facial videos and photoplethysmogram from wearable devices. The Deep Neural Network classifier performed the best with 96% and 87% accuracy for two and three-level classification. The authors concluded that implementing the integrated approach on electronic devices (smartphones, tablets) would simplify biomechanical risk at the workplace.

Tsao et al. (2020) present a real-time, online, data-driven approach to evaluating repetitive precision task performance using wearable sensor data (kinematics, electromyography and heart rate). Then, these features were used as input variables of an artificial neural network to predict WMSDs. Models using all data types (i.e., sEMG, IMU and H.R.) and the linear discrimination analyses (LDA) outperformed the other models. Furthermore, the findings show that a tool based on these machine-learning techniques and sEMG features, choosing a proper combination of input features and the exemplary network architecture, can improve biomechanical risk classification. Moreover, the authors concluded that implementing the integrated approach on electronic devices (smartphones, tablets) would simplify biomechanical risk at the workplace.

Li et al. (2020) report a "novel end-to-end implementation algorithm for RULA" based on a real-time Vision-based algorithm that monitors workers with RGB cameras and two different depth neural networks to estimate the RULA action levels. The system gives a score congruent to the expert observation as far as the RULA grand score is concerned. Overall, the algorithm achieved 93% accuracy and 29 frames per second to detect the RULA action level.

In Li Ze et al. (2020) study, a novel intelligent rapid entire body assessment (REBA) system based on convolutional pose machines, entitled the Quick Capture system, was applied to determine the risk levels. The results show that the Quick Capture system is robust in limb angle recognition and dramatically improves the calculation of the REBA scores. In the angle analysis, the average correlation of the posture was 0.915 (correlation ranged from 0.988 to 0.731), and for the scores, 83,33% of the scores were consistent with those from the experts.

Fernández et al. (2020) present a novel method that performs accurate, ergonomic risk assessment, automatically computing rapid upper limb assessment (RULA) scores from snapshots or digital video using computer vision and machine learning techniques. The processing workflow uses open-source neural networks to detect the workers' skeletons, after which their body-joints positions and angle are inferred, with which RULA scores are computed. The computer RULA scores were in close agreement with the assessment of the expert.

Discussion

Several methods have been developed to reduce the risk of work-related musculoskeletal disorders, accepted by the international literature, and used in the workplace (Ranavolo et al., 2018). Over the last few decades, various rule-based postural assessment systems have been ideated and widely used to facilitate the measurement and evaluation of risks related to WMSDs.

Previous researchers have attempted to address WMSDs by identifying their risk factors. A consensus has been established that working postures and motions are associated with WMSDs risks (NIOSH, 2014). Therefore, different postural assessment systems have been developed and utilised for that purpose as early as the 1970s. The design of these rule-based assessments is based on the pen-and-paper-based observational approach, which allows a rapid and straightforward on-site evaluation (Li and Buckle., 1999).

As primary input, the rule-based assessments require a quantitative description of working posture. Thus, the reliability of the assessment results directly depends on the input posture information collected (Andrews et al., 2008b). However, the current practice to collect and estimate posture is heavily reliant on a manual assessment (e.g. human observer and estimation of projected angle in recorded videos/photo), which is subjective and qualitative (Li and Buckle., 1999). As a result, the manual assessment may decrease reliability due to the high intra- and interobserver variability (Plantard et al., 2017).

Recently, advanced motion capture systems have drawn attention to the possibility of replacing manual assessment with automated tools. Since these systems provide quantitative measurements of human motion, they have enabled quantitative measurements of working postures. Mainly, wearable inertial measurement units (IMU) – such as three-dimensional (3D) sensor platforms integrating an accelerometer, gyroscopes, and magnetometers – are increasingly being used for motion data acquisition (Ahn et al., 2019). Therefore, IMU-based motion capture systems are widely used to investigate ergonomic risk by integrating rule-based assessment systems (Vignais et al., 2017). Also, the most innovative wearable technologies, electronic devices, computer vision, neural network convolutional, new theoretics algorithm, with the aim of not interfering with the work activities performed by workers, have been introduced to improve the biomechanical risk assessment adapting it to all the working conditions and overcoming the limits of the current standardised methods. Indeed, these innovations will allow estimating biomechanical risk in real-time, providing direct feedback to the end-user who would be constantly monitored directly while at work.

In this review, we report on recent novels implementations in the biomechanical risk assessments to prevent WMSDs. The majority of the published article was in the field of the new algorithm and the development of neural network convolutional that will allow a real-time online technical independent assessment.

These studies show that the indices used for instrumented-based approaches correlate with the variables that determine the risks for MSDs. Two of the most promising indices/approaches proposed in the literature are mainly based on machine-learning techniques based on sEMG features (Varrecchia et al., 2018).

Although new innovative technologies for biomechanical risk assessment are only initially, the literature shows that these different approaches can better estimate the ergonomic risk and prevent occupational disease.

Furthermore, a gold standard is ideal for assessing validity, but no general gold standard is for evaluating biomechanical risk exposure (Takala et al., 2010).

Conclusions

The automated, rule-based assessment tool eliminates intra- and interobserver variability due to manual assessment.

The experimental papers' results show the system's effectiveness regarding the scores and the overall time needed to evaluate. Nowadays, the qualitative visual assessment of postural variables can be measured consistently.

The developed neural network showed to be able to classify the phases of the analysed task correctly. However, the results are insufficient to evaluate the effort necessary to extend the analysis to further workers on the same task. This is why further research activities are ongoing to devise a robust and easy to tune algorithm for automating the ergonomics risk assessment.

The analysis of the papers report in this review sheds light on the fact that too few researchers foresee novelties for biomechanical risk assessment, although the requirement to obtain increasingly quantitative evaluations, the recent miniaturisation process, and the need to follow a constantly evolving workplace scenario is promoting their use.

Implications for future research

Methods for improving exposure assessment should be focused upon in the future. These concerns increase the representativeness of technical measures for valid point estimates and elaboration of valid job exposure matrices. Continuous variables should be used in an attempt to find "safe levels" of exposure if existing. Methods should be elaborated that simplify exposure assessments and effective standardised procedures for the definition of the relevant outcome, improving the possibilities for better epidemiological studies in the future.

References

Ahn, C. R., S. Lee, C. F. Sun, H. Jebelli, K. Yang, and B. Choi. 2019. "Wearable sensing technology applications in construction safety and health." J. Constr. Eng. Manage. 145 (11): 03119007. https://doi.org/10 .1061/(ASCE)CO.1943-7862.0001708.

Andrews, D. M., A. M. Holmes, P. L. Weir, T. A. Arnold, and J. P. Callaghan. 2008b. "Decision times and errors increase when classifying trunk postures near posture bin boundaries." Theor. Issues Ergon. Sci. 9 (5): 425–440. https://doi.org/10.1080/14639220701652889.

Asadi, H., Zhou, G., Lee, J. J., Aggarwal, V., & Yu, D. (2020). A computer vision approach for classifying isometric grip force exertion levels. Ergonomics, 63(8), 1010–1026. https://doi.org/10.1080/00140139.2020.1745898

Bani Hani, D., Huangfu, R., Sesek, R., Schall, M. C., Davis, G. A., & Gallagher, S. (2021). Development and validation of a cumulative exposure shoulder risk assessment tool based on fatigue failure theory. Ergonomics, 64(1), 39–54. https://doi.org/10.1080/00140139.2020.1811399

Bao, S., and B. Silverstein. 2005. "Estimation of Hand Force in Ergonomic Job Evaluations." Ergonomics 48 (3): 288–301. doi:10.1080/0014013042000327724.

Bhatia, V., Randhawa, J. S., Jain, A., & Grover, V. (2020). Comparative analysis of imaging and novel markerless approach for measurement of postural parameters in dental seating tasks. Measurement and Control (United Kingdom), 53(7–8), 1059–1069. https://doi.org/10.1177/0020294020932340

Bernard BP (1997) Musculoskeletal disorders and workplace factors. A critical review of epidemiologic evidence for work-related musculoskeletal disorders of the neck, upper extremity, and low back. Department of Health and Human Services NIOSH, Cincinnati

Bevan, S. (2015). The economic impact of musculoskeletal disorders (MSDs) on work in Europe. Best Practice & Research Clinical Rheumatology, 29(3), 356–373.

Borg, G. 1998. Borg's Perceived Exertion and Pain Scales. Champaign, IL: Human kinetics.

Bosch, T., S. E. Mathiassen, D. Hallman, M. P. de Looze, E. Lyskov, B. Visser, and J. H. van Die€en. 2012. "Temporal Strategy and Performance during a Fatiguing Short-Cycle Repetitive Task." Ergonomics 55 (8): 863–873. doi:10.1080/ 00140139.2012.682739.

David, G. C. (2005). Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. Occupational Medicine, 55(3), 190–199.

Golabki, A., S. Han, and A. R. Fayek. 2015. "An Application of Fuzzy Ergonomic Assessment for Human Motion Analysis in Modular Construction." Proc., 2015 Modular and Offsite Construction (MOC) Summit and 1st Int. Conf. on the Industrialization of Construction (ICIC), 257–264. Edmonton, AB, Canada: University of Alberta.

Kim, S., and M. A. Nussbaum. 2014. "An Evaluation of Classification Algorithms for Manual Material Handling Tasks Based on Data Obtained Using Wearable Technologies." Ergonomics 57 (7): 1040–1051. doi:10.1080/ 00140139.2014.907450.

Hu, B., C. Kim, X. Ning, and X. Xu. 2018. "Using a Deep Learning Network to Recognise Low Back Pain in Static Standing." Ergonomics 61 (10): 1374–1381. doi:10.1080/ 00140139.2018.1481230.

Kadir, B. A., Broberg, O., & da Conceição, C. S. (2019). Current research and future perspectives on human factors and ergonomics in Industry 4.0. Computers & Industrial Engineering, 137, 1–12.

Koppelaar, E., and R. Wells. 2005. "Comparison of Measurement Methods for Quantifying Hand Force." Ergonomics 48 (8): 983–1007. doi:10.1080/001401305 00120841.

Koping, L., K. Shirahama, and M. Grzegorzek. 2018. "A General Framework for Sensor-Based Human Activity Recognition." Computers in Biology and Medicine 95: 248–260. doi:10.1016/j.compbiomed.2017.12.025.

Waldman, D. A., and W. D. Spangler. 1989. "Putting Together the Pieces: A Closer Look at the Determinants of Job Performance." Human Performance 2 (1): 29–59. doi:10. 1207/s15327043hup0201_2

Li, G., and P. Buckle. 1999. "Current techniques for assessing physical exposure to work-related musculoskeletal risks, with emphasis on posture based methods." Ergonomics 42 (5): 674–695. https://doi.org/10.1080/001401399185388.

Li, L., Martin, T., & Xu, X. (2020). A novel vision-based real-time method for evaluating postural risk factors associated with musculoskeletal disorders. Applied Ergonomics, 87. https://doi.org/10.1016/j.apergo.2020.103138

Li, Z., Zhang, R., Lee, C. H., & Lee, Y. C. (2020). An evaluation of posture recognition based on an intelligent rapid entire body assessment system for determining musculoskeletal disorders. Sensors (Switzerland), 20(16), 1–21. https://doi.org/10.3390/s20164414

Manghisi, Vito Modesto, Uva, Antonio Emmanuele, Fiorentino, Michele, Bevilacqua, Vitoantonio,Trotta, Gianpaolo Francesco, Monno, Giuseppe, 2017. Real time RULAassessment using Kinect v2 sensor. Appl. Ergon. 65, 481–491.

MassirisFernández, M., Fernández, J. Á., Bajo, J. M., & Delrieux, C. A. (2020). Ergonomic risk assessment based on computer vision and machine learning. Computers and Industrial Engineering, 149(December 2019). https://doi.org/10.1016/j.cie.2020.106816

Mehrizi, R., X. Peng, X. Xu, S. Zhang, and K. Li. 2019. "A Deep Neural Network-Based Method for Estimation of 3d Lifting Motions." Journal of Biomechanics 84: 87–93. doi:10.1016/j. jbiomech.2018.12.022.

Maman, Z. S., M. A. A. Yazdi, L. A. Cavuoto, and F. M. Megahed. 2017. "A Data-Driven Approach to Modeling Physical Using Wearable Sensors." Applied Ergonomics 65: 515–529. doi:10.1016/j.apergo.2017.02.001.

Moher, D., et al., 2009. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. Ann. Intern. Med. 151 (4), 264–269.

Mumani, A., Stone, R. T., & Momani, A. M. (2021). An application of Monte-Carlo simulation to RULA and REBA. Theoretical Issues in Ergonomics Science, 0(0), 1–16. https://doi.org/10.1080/1463922X.2021.1893406

Newell, Alejandro, Yang, Kaiyu, Deng, Jia, 2016. Stacked hourglass networks for human pose estimation. In: European Conference on Computer Vision. Springer, pp. 483–499.

Nicoletti, C., and T. L€aubli. 2018. "Leg and Back Muscle Activity, Heart Rate, Performance and Comfort during Sitting, Standing, and Using a Sit-Stand-Support with Different Seat Angles." International Journal of Industrial Ergonomics 67: 73–80. doi:10.1016/j.ergon.2018.04.011.

NIOSH (National Institute for Occupational Safety and Health). 2014.Observation-based posture assessment: Review of current practice and recommendations for improvement. Cincinnati: U.S. Dept. of Health and Human Services.

Plantard, P., Shum, H. P., Pierres, A.-S. L., & Multon, F. (2017). Validation of an ergonomic assessment method using Kinect data in real workplace conditions. Applied Ergonomics, 65, 562–569.

Ranavolo, A., G. Chini, A. Silvetti, S. Mari, M. Serrao, and F. Draicchio. 2018. "Myoelectric Manifestation of muscle fatigue in Repetitive Work Detected by Means of Miniaturised sEMG Sensors." International Journal of Occupational Safety and Ergonomics 24 (3): 464–411. DOI: 10.1080/10803548.2017.1357867.

Rijn, R. M. van, Huisstede, B. M. A., Koes, B. W., Burdorf, A., & Scandinavian, S. (2010). Associations between work-related factors and specific disorders of the shoulder — a systematic review of the literature Published by : the Scandinavian Journal of Work, Environment & Health, the Finnish Institute of Occupational Health, the Danish Nat. 36(3), 189–201.

Roman-Liu, D., A. Groborz, and T. Tokarski. 2013. "Comparison of Risk Assessment Procedures

Used in OCRA and ULRA Methods." Ergonomics 56 (10): 1584–1598. doi:10.1080/00140139.

2013.829923

Takala, Esa-Pekka, Irmeli Pehkonen, Mikael Forsman, Gert-Åke Hansson, Svend Erik Mathiassen, W. Patrick Neumann, Gisela Sjøgaard, Kaj Bo Veiersted, Rolf H. Westgaard, and Jørgen Winkel. 2010. "Systematic Evaluation of Observational Methods Assessing Biomechanical Exposures at Work." Scandinavian Journal of Work, Environment & Health 36 (1): 3–24. doi:10.5271/ sjweh.2876.

Tsao, L., Nussbaum, M. A., Kim, S., & Ma, L. (2020). Modelling performance during repetitive precision tasks using wearable sensors: a data-driven approach. Ergonomics, 63(7), 831–849. https://doi.org/10.1080/00140139.2020.1759700

Van der Molen, H. F., Foresti, C., Daams, J. G., Frings-Dresen, M. H. W., & Kuijer, P. P. F. M. (2017). Work-related risk factors for specific shoulder disorders: A systematic review and meta-analysis. Occupational and Environmental Medicine, 74(10), 745–755. https://doi.org/10.1136/oemed-2017-104339

Varrecchia, T., C. De Marchis, M. Rinaldi, F. Draicchio, M. Serrao, M. Schmid, S. Conforto, and A. Ranavolo. 2018. "Lifting Activity Assessment Using Surface Electromyographic Features and Neural Networks." International Journal of Industrial Ergonomics 66: 1–9. DOI: 10.1016/j.ergon.2018.02.003.

Vignais, N., Bernard, F., Touvenot, G., & Sagot, J.-C. (2017). Physical risk factors identification based on body sensor network combined with videotaping. Applied Ergonomics, 65, 410–417.