Journal of Ergonomics
ISSN: 2165-7556
OPEN ACCESS Freely available online

Review Article

Input Variables for Manual Material Handling Assessment Methods Obtained Using Body Worn Sensors

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ABSTRACT

Quantifying the workplace risk factors such as body inclination angles, load weights, and vertical and horizontal reaching distances is essential to prevent work-related musculoskeletal disorders. Most of these factors need to be measured during the task. Assessing the work performed using a direct observation approach is time consuming and the study can encounter observational errors as well as disturb the workers. Wearable sensing technologies could replace the use of optical motion capturing systems. No review study was conducted to discuss the use of wearable technology as a means for providing input variables for various manual material handling job assessment methods. The current study provides a review about wearable technologies that can be used to provide input variables for different ergonomic assessment methods. The validity of diverse wearable sensors in quantifying different biomechanical measures is included. Also, the synchronization of those measures with various ergonomic assessment methods is discussed.

Keywords: Wearable sensors; Manual material handling; Risk assessment methods

INTRODUCTION

Occupational Low Back Disorders (OLBDs) such as lumbar degenerative disc, herniated disc, muscle strain, and ligament sprain, among others, have been a costly issue due to the impact they have on workers' health, productivity, and absenteeism, among others. In the United States, a study estimated the direct OLBD medical costs to be between $12.2 to $90.6 billion annually [1]. Another study estimated the annual cost of total productive time lost due to OLBD in the US workforce to be about $19.8 billion [2]. Workers' exposure to various physical factors in manual material handling (i.e., extreme torso bending, torso twisting, lifting heavy objects, etc.) needs to be assessed in order to make the required interventions to reduce the risk of injuries.

Several approaches such as direct observations, checklists, worker interviews, and questionnaires are used to identify risk factors and unsafe work conditions. However, these approaches are subjective and may differ from one evaluator to another. Optical motion capture, force plates, and Electromyography (EMG) systems were shown to effectively assess manual material handling jobs [3-6]. However, the use of optical motion captures and force plate systems are limited to use in controlled laboratory environments. Therefore, there is a need for wearable sensors that collect physiological (e.g., heart rate, muscle forces, etc.) and biomechanical (e.g., joint angles, ground reaction forces, etc.) data in free-living environments with no to minimal disturbance to the worker's movements. Also, some of the collected data such as load weight, hand position (horizontally and vertically) during lifting, torso asymmetry, task frequency, and task duration can be used in the assessment of various Manual Material Handling (MMH) jobs such as lifting, lowering, pushing, and pulling using the available MMH activities assessment methods. Examples of most popular assessment methods include the National Institute for Occupational Safety and Health (NIOSH) Lifting Equation, American Conference of Governmental Industrial Hygienists (ACGIH) Threshold Limit Values (TLVs), (WA L&I) lifting calculator, Ohio Bureau of Workers' Compensation (BWC), Snook tables, Lifting Fatigue Failure Tool (LiFFT), Ovako Working Analysis System (OWAS), and Rapid Upper Limb Assessment (RULA) [7-15]. Input variables (i.e., exposure factors) to each assessment method are tabulated in Table 1.

To the best of the author's knowledge, no review study has focused on the use of wearable technologies during various MMH activities to measure the different MMH activities risk factors (e.g., load weight, vertical lifting height, horizontal reach distance) and then use these variables as inputs into various MMH activities risk assessment methods. The current study aims to review the use of the wearable technology in the MMH activities ergonomic assessment

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Received: January 12, 2022, **Accepted:** January 12, 2022, **Published:** February 02, 2022

Citation: Hafez K (2022) Input Variables for Manual Material Handling Assessment Methods Obtained Using Body Worn Sensors. J Ergonomics.S1:001.

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methods. The current review adds to the body of knowledge the need for reliable and accurate wearable technologies that provide measurements of the workplace and working factors to be used as inputs in various MMH activities risk assessment methods without disrupting the worker.

Methodology

The current review was based on an electronic search using Google Scholar, Scopus, and PubMed. The keywords used for searching the literature included "wearable technology," "wearable sensors," "wearable devices," "wearable computers," "ergonomic," "assessment," "manual material handling," "lifting," and "occupational risk." More than 400 articles were found from the three search engines. By reviewing the titles, abstracts, and conclusions, 52 articles were included. Finally, after reading the full texts, 32 articles were included in the current review.

The article selection criteria were as follows:

- Articles related to wearable sensors.
- The wearable sensors were used to measure MMH risk factor variables.
- The measured variables were used (or could be used) as inputs into various manual material handling risk assessment methods such as NIOSH Lifting Equation, ACGIH, OWAS, etc.
- Articles were written in English.

In the next section, four elements are discussed for each wearable technology; including the technology description, validation efforts, application in MMH activities risk assessment methods, and strengths and limitations. Also, the summarized findings are tabulated at the end of this study.

WEARABLE SENSORS

The Lumbar Motion Monitor (LMM)

LMM technology description: The lumbar Motion Monitor (LMM) is a wearable system that was developed by Marras's team to collect three-dimensional torso position, velocity, and acceleration [16]. Moreover, instantaneous movement of the spine in the three-dimensional space can be assessed through the triaxial electrogoniometer that is built into the LMM device [17]. Additionally, the device is an exoskeleton of the spine that can be attached to the individual's torso using a chest harness and a waist harness. The LMM is used to assess MMH jobs in almost all occupational environments since the torso kinematics data can be wirelessly transmitted from the LMM to a portable computer *via* the digital telemetry system. The design of the device enabled for data collection with minimal obstruction to the user's movements.

LMM validation and application in MMH risk assessment methods: Previous studies have utilized the LMM along with other systems (electromyography (EMG), force plate, and goniometer) to estimate spinal loadings during lifting [18,19]. Another study has utilized the LMM and EMG sensors to evaluate torso kinematics and maximum compressive forces [20]. Several studies have validated the accuracy of the LMM and its associated model (i.e., Ohio State University (OSU) OLBD risk assessment model) [16,21,22]. The OLBD Risk model determines the job's high-risk group membership probability using torso kinematics data collected from the LMM as well as other user input variables including load weight, moment arm (horizontal distance between the L5/S1 disc and the load being handled), and lift frequency. LBD Risk probability of 0-29%, 30-69%, and 70-100% represent a low, moderate, and high risk of LBD, respectively [22].

LMM strengths and limitations: The wearable LMM has several strengths. First, the LMM device can accurately measure torso kinematic data in various workplaces. Also, the collected torso data can be interpreted using the OLBD risk assessment model to assess the required job by determining the risk level in MMH jobs. Furthermore, using the resulted OLBD risk level, the necessary interventions (either on the performed job or the physical workstation) can be carried out to reduce the spinal loadings, and thus, the risk of OLBD. Finally, the LMM is portable, lightweight, and easy to use.

On the other hand, some limitations may restrict the use of the LMM device. First, it is an expensive device that may limit its use, especially in small and medium scale industries. Also, wearing the LMM on the back may restrict the worker's movement which may not represent accurate torso kinematic data, and thus, under or overestimate the LBD Risk probability. Third, the LMM does not measure the moment arm which is an input variable to the LBD Risk model. Thus, a tape measure or other means need to be utilized to measure the moment arm. Finally, the LMM does not measure the load weight which is also another input variable into the LBD Risk model. This may limit the device use in worksites with high variability in weights being lifted or lowered, such as in warehouses.

Electromyography (EMG) sensors

EMG technology description: The electrical signal measured from a muscle contraction is called an "electromyogram" [23]. Electromyography (EMG) sensors were developed to evaluate the action of the muscles during various human activities. EMG sensors indirectly quantify muscle activity using surface (wireless) or wire electrodes. These electrodes determine muscle contraction timing and the intensity of muscle contraction through the detection of voltage potentials [24]. Several factors can influence the EMG signal including fatigue, muscle shortening or lengthening velocity, rate of tension build-up, and reflex activity [23]. Wireless EMG enables muscle activity capturing beyond the laboratory.

EMG Validation Efforts: Wong, et al. review study showed that by positioning the sensor on the optimal location on the muscle, one could monitor muscle activity with a classification accuracy range of 77%-97% [25]. EMG sensors can be used to assess the physical demand of a job, which then can assist in classifying jobs as having a high or low risk of injury. Granata and Marras have developed an EMG-driven model for lower back loading prediction during isokinetic and free lifting [19]. The model effectively estimated the loading on the low back with a coefficient of determination (R^2) of 0.81. Another study has developed a framework for low back pain exposure assessment [26]. The framework included various assessment approaches including EMG and four other methods based on direct observations and questionnaires to evaluate postures. Spinal compression was used as a common metric for all the measurement methods. The EMG was utilized to collect erector spinae muscles data bilaterally at the T9 and L3 levels [26]. Painting, part assembly, and manual material lifting jobs were assessed. The authors agreed that using the EMG approach would provide a more accurate estimate of the exposure, and thus, a better estimate of the risk [26]. Also, EMG sensors can be used to classify an individual's spine as healthy or injured. Several studies have examined the sensitivity of surface Electromyography (sEMG) sensors in differentiating between healthy individuals and individuals with low back pain [27-31]. Results from these studies showed that measurements from surface EMG (e.g., greater muscle recruitment over time, lack of muscle symmetry, unbalanced muscle activity) can effectively be used as objective markers of low back pain cases. Loading on the human body's lower extremities can be quantified using EMG-assisted models. Kadaba, et al. quantified lower limb muscle forces using EMG sensors [32]. The collected forces were combined with joint kinematic data (using an optical motion analysis system) and ground reaction forces (using force plates) to predict knee flexion/extension moments.

EMG application in MMH risk assessment methods: Cabeças presented the use of surface EMG data as an alternative to the observational methods for the Strain Index (SI) computations [33]. EMG data was collected from 20 participants while performing 40 different cleaning activities. Moreover, EMG data was analyzed in the right and left wrist flexor and extensor muscles. Mean values of the percent of maximum voluntary exertion (%MVE) (normalized values) were calculated for each hand and each muscle. Cabeças considered the exertion level of (P10) %MVE from as the static load level in the muscle for the cleaning activities [33,34]. The selected level represents the amplitude probability distribution analysis of EMG signals of the estimated exertion level in the event of the muscular loading [34]. Moreover, defined trigger levels that represent the amount of exertion in the evaluated cleaning activities [33]. Also, exertions are considered when the amplitude of the signal is above the trigger level for at least 0.5 s [33]. Exertion duration was then quantified as the percentage of time the muscle is contracted above the trigger level. This was achieved using the Amplitude Probability Distribution Function (APDF) developed by [35]. Additionally, the authors utilized MegaWin v.2.3 software (MEGA Electronics Ltd.) to process the exertion intensity and frequency. The developed SI evaluation method used these quantified variables to compute the SI score [33]. The results showed the effectiveness of using the EMG data to quantify hand exertion intensity, frequency, and duration for jobs that are associated with hand/wrist exertions. However, the author stated that the usefulness of the proposed model depends on defining the appropriate trigger levels for the muscular activation in the examined activity.

Another work utilized two EMG systems (i.e., a custom and Shimmer3) [36]. Measurements from the EMG signals were also used in the SI assessment method. The intensity of exertion, duration of exertion, frequency of exertion, and wrist posture were estimated using the EMG systems. The results showed that EMG systems could be used to obtain muscle activities data to use in the assessment of MMH activities using the SI ergonomic assessment method.

A recent study by Mudiyanselage, et al. utilized 2 wireless sEMG muscle sensors attached to the upper back muscles to assess the muscles' contractions during various MMH activities [37]. Additionally, a webcam was used to help with the synchronization of the collected data. A male participant lifted various weights (5-15 kg) from different horizontal and vertical locations corresponding to NIOSH Lifting Equation $LI \leq 1.2$, $1.2<LI \leq 2.4$, and $LI>2.8$ to represent the lifting tasks with nominal, increased, and high risk, respectively. Four different machine learning classification algorithms were used to identify the various risk levels. The results showed that the developed sEMG system can be used as an automatic ergonomic assessment method by classifying the risk levels based on the NIOSH Lifting Equation. The highest accuracy levels were 97.70%, 99.35%, and 99.05% for the three time-segmentations 1 second, 0.5 second, and 0.25 second, respectively, using the Decision Tree machine learning model.

EMG Strengths and Limitations: EMG systems can be used to objectively assess the muscles forces. Also, using the sEMG sensors is considered a safe and non-invasive method to obtain information about the muscle's contractions. Such information can be obtained without disrupting the workers or the workflow. Finally, through the EMG filtered data, ergonomist can determine the occupational risk factors using information such as muscle activation, muscle effort in the various body segments, and peaks and cumulative exposure [36].

On the other hand, several drawbacks related to the EMG sensors can be identified. High accuracy EMG sensors are expensive, which may limit their use. Also, precise placement of the EMG sensors is required. Data from EMG systems might vary across different subjects and placement. Also, since these sensors are attached to the body, they may become loose, and thus, result in inaccurate data collection. Finally, the EMG signals are sensitive to sweat and hair, which also may result in errors in the retrieved signals.

Inertial Measurement Units (IMUs)

IMUs technology description: Another wearable technology is the inertial measurement unit (IMU). IMU sensors are commercially available such as Shimmer3 IMU and Xsense sensors. These wearable sensors allow for quick and easy measurements of body parts' angles, velocity, and acceleration. The IMU sensor contains a low noise accelerometer, both wide range accelerometer and magnetometer, and a digital gyroscope. IMUs sensors can be effectively used in various working environments.

IMUs validation efforts: A study has developed an algorithm called Online Sparse Estimation-based Classification (OSEC) that enables for online body posture monitoring during MMH jobs using IMU sensors [38]. The results showed that the proposed system could effectively be used to monitor various joint angles during different MMH activities, and thus, can be utilized to suggest the necessary ergonomic interventions to eliminate or reduce the risk of injury [38]. Another study has utilized four IMU sensors to estimate the acceleration, the rate of change in the acceleration (i.e., jerk level), inclination angles, movement durations, and repetitions [39]. The included body parts were the ankle, wrist, hip, and torso. This data was then utilized to determine the fatigue level for individuals performing MMH jobs. It was found that the IMUs are effective in determining the above mentioned kinematics data that allowed for determining the fatigue state [39]. A later study by Koopman, et al.

was conducted to estimate the L5/S1 extension moment using IMU sensors [40]. Also, they examined the effect of reducing the number of IMU sensors on the accuracy of the estimated L5/S1 moment. Lab-based systems including The Optical Motion Capture (OMC) (i.e., for full-body kinematics measurements) and force plates (FP's) (i.e., for ground reaction forces measurements) were used as a reference for the IMU measurements. It was revealed that a set of 6 IMU sensors is optimal when considering accuracy and simplicity. The 6 IMU set consisted of sensors on the pelvis, sternum, upper arms, and forearms. It was concluded that the L5/S1 extension moments can be alternatively estimated at the workplace using the IMU systems with only 6 IMU sensors with no need to use OMC and FP systems, in case of utilizing the pressure insoles that can result in sufficient ground reaction force accuracy [40].

IMUs application in MMH risk assessment methods: Peppoloni, et al. developed an automatic assessment system consisting of 8-channel surface EMG sensors to estimate the muscular exertion efforts as well as the frequency and duration of each exertion [41]. An EMG sensor array was attached to each participant's forearm to monitor flexor carpi radialis, the palmaris longus, and the flexor carpi ulnaris. Also, the system included 4 IMU wearable sensors to assess the posture of the worker's upper limb (i.e., upper arm flexion, forearm flexion and pronation/supination, and wrist flexion/abduction). IMUs were attached to the participant's back, upper arm, forearm, and hand. Measurements from these sensors were then used as inputs into RULA and SI assessment methods (Table 1). The author's assessed 10 participants (7 males and 3 females) while performing various grocery cashier cycles. The cycles are composed of reaching for the item, grasping it, scanning, and releasing the item. The automatic RULA action level and SI scores were compared with the manual evaluation carried out by two human evaluators. Their results showed that the developed automatic system provides accurate RULA score estimation (i.e., about 95%) when compared to the mean score given by the human evaluators. The SI score given by the system, on the other hand, showed lower accuracy (i.e., about 45%) when compared with the evaluators' assessments [41]. It should be noted that the developed system does not track the neck, torso, and leg positions nor provides information about the load weight. Thus, one can expect limited capabilities of the system as for RULA assessment.

Another study by Battini, et al. developed a full-body biomechanical model linked with 17 IMUs that collect motion data integrated with several data-analysis tools developed by the authors [42]. The model was designed to be used for real-time ergonomic assessment based on the various available ergonomic assessment methods including RULA, OWAS, NIOSH lifting index, and Occupational Repetitive Action (OCRA). Moreover, the model was designed to provide real-time ergonomic-based feedback on the required interventions in the assessed workplace. The model evaluated warehouse workers while performing MMH activities (i.e., refilling, picking, and packing) in two warehouses. The variables measured using the IMU sensors included angles of head, neck, right and left shoulders, upper right and left arms, right and left forearms, right and left hands, spine, and hip. Also, IMUs determined the travel distance as well as the position of the two hands (i.e., horizontally and vertically) with respect to the center of the body. Task frequency and duration were also quantified. The hip movements were further analyzed to quantify the travel distance and the task frequency [42]. On the other hand, the authors explained that the load weight could be manually added to the model during the post-processing phase and included in the final evaluation. The OWAS assessment method was used to assess the refilling activity. The inputs to the OWAS method included full-body postures, traveled distance, duration and frequency of lifting and lowering, and the percentage of the hand positions in the unsafe lifting and lowering zones. RULA and OCRA methods were used to assess the workers' upper body while they are in a fixed position performing activities in packing workstations. Battini, et al. explained that the feedback from the developed model enabled for defining proper workplace interventions such as defining safe reachable zones (with respect to the body) and reducing the transportation distance between working places [42].

A study by Schall Jr, et al. compared thoracolumbar torso motion data measured *via* two IMUs (series SXT IMUs, Nexgen Ergonomics, Inc.) to that of the ACUPATH™ LMM™ [43]. Data provided from each IMU sensor included acceleration, angular velocity, magnetic field strength, and spatial orientation in the form of quaternion outputs obtained from a Kalman filter. Data from both systems were collected simultaneously from 36 male participants while performing material handling tasks. The LMM was worn on the participant's back while one IMU was worn on the sternum and another one at the L5/S1 body segment. The data quantified from the two systems included angular displacements of the thoracolumbar region of the torso in the sagittal flexion/extension, lateral bending, and axial rotation planes. The

Table 1: Inputs variables to various manual material handling risk assessment methods

Authors	Assessment methods	Activity	Exposure factors
Waters, et al. [7]	NIOSH Lifting Equation	Lifting and lowering	Load weight, horizontal distance, height, vertical travel distance, asymmetry, frequency, duration, and hand coupling
ACGIH [8]	ACGIH TLV	Lifting	Load weight, horizontal distance, height, asymmetry, frequency, and duration
WAC 296-62-051 (2000a), WAC 296-62-051 (2000b) [9, 10]	WA L&I	MMH	Load weight, horizontal distance, height, asymmetry, frequency, and duration
Ferguson, et al. [11]	Ohio BWC	Lifting	Load weight, horizontal distance, height, asymmetry, and frequency
Snook, et al. [12]	Snook Tables	MMH	Load weight, horizontal distance, height, and frequency
Gallagher, et al. [13]	LiFFT	Lifting	Load weight, horizontal distance, and frequency
Karhu, et al. [14]	OWAS	MMH	Load weight as well as postures of back, forearms, and legs
McAtamney, et al. [15]	RULA	Tasks performed by upper limbs	Load weight, muscle use, task duration and frequency, as well as postures of the arm, wrist, neck, torso, and legs

results showed a small RMSE difference for the mean angular displacement estimates in the flexion/extension, lateral bending, and axial rotation motion planes between the IMU and the LMM systems. Furthermore, small Bland and Altman bias estimates were observed in the flexion/extension, lateral bending, and axial rotation planes across a range of a variety of movements and speeds [43]. Finally, it was noted that processing methods that computed torso motion data obtained both from IMUs worn on the sternum and L5/S1 body segment were more equivalent to the LMM data than processing methods that computed torso motion only from the IMU worn on the sternum [43].

A later study by Schall Jr, et al. utilized three IMUs ("ArduIMU v3") to measure the physical activity of 36 registered nurses working a full shift [44]. Two IMUs were attached to the upper arms, and one was attached to the posterior torso. Measurements from the three IMUs were compared to those obtained from one accelerometer ("wGT3X-BT PA") attached to the waist. Raw acceleration information from each device was summarized into the intensity of acceleration (i.e., activity counts/min) by calculating the vector magnitude of three-dimensional accelerometer axes to convert raw acceleration values to an omnidirectional measure of acceleration. The acceleration signals were then filtered and converted to activity counts. Additionally, the duration of each physical activity was computed from each sensor for each participant. The results indicated that the IMUs attached to the upper arms both estimated about an average of 200 counts/min more than the "wGT3X-BT." On the other hand, the IMU that was attached to the torso showed a smaller difference with an average of 8 counts/min more than those obtained *via* the "wGT3X-BT" [44]. One can conclude that the variation in the activity counts can be related to the number of activities the nurses perform with their arms, in which they can be monitored using the sensors on the arms more accurately than the sensors attached to the torso or waist. It is therefore recommended that IMUs or accelerometers be worn on the body part that is involved in the required monitored movement. Additionally, the observed individual may be asked not to perform any movements other than those required in the examined activity. For instance, if one is interested in estimating the number of lifts (i.e., lift rate) MMH workers performs, wearable sensors should be attached to the arms, and they may also be instructed to restrict their arm movements during the data collection to the lifting and lowering activities only.

A study by Valero, et al. developed Activity Tracking with the Body Area Network (ATBAN) system to determine body postures and motion data, in order to detect the unsafe postures during MMH activities [45]. Moreover, the system provides real-time feedback in the form of a beep alert as well as the option of a summary report that could be generated at the end of a work session. The system consists of 7 wearable IMUs integrated into a body area network. Four sensors were worn on the arms (i.e., two on each arm) to provide information about load location from the body (i.e., horizontally and vertically). Also, one sensor was attached to the lower back to determine the torso inclination. Additionally, two sensors were worn on the shins to determine knee flexion degrees. Information from sensors worn on both the lower back and shins were used to distinguish squatting and stooping postures during low height lifting. The authors demonstrated that the system is conservative in which it wrongly detected a bending posture when the participant was, in fact, standing up. The system, on the other hand, did not miss any stooping or squatting postures. The authors related the false positives to the inclusion of one leg only (the sensor was worn on the right leg) in the experiment. Monitoring both legs may improve the system's performance [45].

Another study by Valero, et al. has developed a novel system "Activity Tracking with Body Area Network (AT-BAN)" and data processing framework to evaluate manual handling activities in construction work environments [46]. ISO 11226 posture thresholds were used for posture evaluation in the developed system [47]. The AT-BAN system included 8 IMUs to quantify body part inclination angles by measuring acceleration, magnetic heading, and angular velocity. The sensors were attached to body parts that are associated with the motion of the bricklaying activity including upper and lower back, arms, and upper and lower legs. This placement enabled the examination of torso inclination, knee flexion, kneeling, and arm elevation. Moreover, the system classifies the state of torso inclination angles (i.e., α), knee flexion angles (i.e., β), kneeling, and arm elevation degrees (i.e., γ) based on the safe ISO posture thresholds (Table 2). To evaluate the validity of the developed

Table 2: Safe body postures according to ISO 11226 standard adapted from [46]

Body part postures	Angle	Definition
Torso inclination	$\alpha<0°$	Torso backward inclination. Not recommended position
	$0° \leq \alpha<20°$	Acceptable torso inclination
	$20° \leq \alpha<60°$	Torso forward inclination. The holding time is evaluated according to $t>-0.075\alpha + 5.5$ where t is time in minutes and α is the angle in degrees. If inequality is true, not recommended
	$\alpha \geq 60°$	Torso forward inclination. Not recommended position
Knee flexion	$\beta>140°$	Acceptable knee flexion
	$90°<\beta \leq 140°$	Extreme knee flexion. Not recommended position
Kneeling	$\beta>90°$	Extreme knee flexion. Not recommended position
	$\beta \leq 90°$ (and calf parallel to floor)	Just one leg kneeling. Squatting movement considered
	$\beta \leq 90°$ (and calf parallel to floor)	Kneeling
Arm elevation	$0° \leq \gamma<20°$	Acceptable upper arm elevation
	$20° \leq \gamma<60°$	The holding time is evaluated according to $t>-0.05\gamma +4$. If inequality is true, not recommended
	$\gamma \geq 60°$	Not recommended position

AT-BAN system, an experiment was conducted with six college trainees performing typical bricklaying activities at a construction training college. Moreover, the performed activities included carrying and spreading mortar as well as moving and laying different kinds of bricks. In addition to the use of IMU sensors, the system simultaneously recorded the participant's movements using a camera video to visually distinguish the movements and provide ground truth information for the angles quantified using the IMUs and the proposed algorithms. Valero's colleagues found that the AT-BAN system correctly differentiated the basic postures and detected those that are susceptible to increase the risk of work-related musculoskeletal disorders, based on the ISO 11226 standard.

Yan, et al. developed a real-time feedback system to warn construction workers of unsafe body postures through a connected smartphone application [48]. Also, the system consists of two IMU sensors attached to the back of the participant's safety helmet and the middle-upper back to measure the head, neck, and back inclination angles. Moreover, a real-time data processing algorithm was used to translate raw unit quaternion vectors collected from the body segments by IMU sensors into meaningful data in terms of flexion-extension, lateral bending, and axial rotation. This data was obtained for the head, neck, and torso and compared with thresholds of posture angles and time spent in each posture provided in the International Organization for Standardization (ISO) 11226 to determine the safe body postures and holding time in the developed system [47,48]. If the inclination angle or the holding time exceeded the safe ISO thresholds, the alarm system would be activated to warn the worker of the unsafe working conditions and the possible risk of LBD. To examine the effectiveness of the developed system, the authors recruited a participant who was required to perform two construction tasks including brick lifting and rebar tying. Yan's team reported that the developed system had provided an adequate real-time warning for unsafe postures and the duration of time spent in these postures [48]. To further examine the system usability in the field, an experiment was conducted on a real construction site. The construction workers reported that the system enabled them to avoid working with unsafe postures and to reduce the amount of time of awkward working postures. Also, they reported that using the developed system did not disturb their activities.

Chen, et al. developed an automated approach based on 17 IMU sensors (Noitom Perception Neuron) to evaluate different body postures [49]. The study included four male college students. One IMU was attached to the head, spine, hip, and the right and left shoulders, arms, forearms, hands, upper legs, lower legs, and feet for each participant. Motion data was wirelessly transferred to a computer for further analysis. The experimental data was collected in two phases. The first phase included motion data of six predefined postures (i.e., working overhead, torso forward bending, reaching, kneeling, squatting, and neck bending) [49]. The second phase included multiple sequencing postures while performing MMH activities. A video camera was utilized simultaneously to record the performed activities for reference purposes. The results showed that the developed system could successfully and accurately distinguish awkward postures involved in construction operations. Also, the authors suggested that such a system can be integrated with the available ergonomic postures assessment methods such as RULA and NIOSH lifting equation [49].

Hischke, et al. aimed at determining the optimal sensor placement on the torso to estimate torso postures [50]. Hischke's colleagues conducted an experiment with 30 college-student participants. Participants performed three manual material handling tasks using a 0.45 kg box on a table. First, the reaching task in which the participants reached the box and pulled it toward their body. Also, participants lowered the box to the ground without releasing it and then lifted it again to the table. Third, they pushed it across the table. Seventeen IMU (Xsens MVN BIOMECH) sensors were attached to different body parts of each participant. However, Hischke, Arroyo evaluated data from IMUs on the sternum, right shoulder, and sacrum only [50]. Estimated torso flexion and extension angles were recorded in Euler angle form downloaded using Xsens MVN Studio 4.0 and converted to a measure of rotation angles using Matlab. The authors followed the manufacturer's instructions for measurement of torso flexion and extension angles using IMU estimates derived from the sternum and the relative position of sacrum. This placement was considered as a reference measure. Additionally, Hischke's team obtained torso flexion and extension information from IMU placed on the sternum only and right shoulder only. Thus, measurements of sagittal torso inclination angles were completed using three configurations including X-SST for sternum segment values with respect to sacrum segment values, X-ST for sternum segment values only, and X-SH for right shoulder values only.

Hischke's team demonstrated that the torso inclination angles obtained from the IMU attached to the right shoulder were similar to the X-SST reference measures. Also, measures from the IMU attached to the sternum were almost comparable to the reference measures. Furthermore, strong correlation coefficients (ranged from 0.5 to 0.88) were observed for torso inclination measures from IMUs attached to the sternum and right shoulder. However, it was shown that data obtained from the sternum segment was more comparable to the reference measures than data obtained from the right shoulder segment [50]. Moreover, the percent of time spent in each posture was estimated using the three sensor configurations. The authors demonstrated that the percent of time obtained from IMUs attached to the sternum and right shoulder showed moderate and acceptable, respectively, agreement when both were compared to the reference measure. Thus, the authors advocated that using a single IMU sensor worn on the sternum would perform similar to two IMUs configuration on the sternum and the relative sacrum segment.

Brents, et al. utilized 17 IMU sensors (Xsens, Enschede, NT) to evaluate five male brewery workers while transferring spent kegs from two different pallet vertical heights onto a conveyor [51]. The sensors were fixed onto a full-body suit. Torso angles were assessed using sternum and pelvic sensor data where maximum values represented torso sagittal flexion angles and minimum values represented the sagittal extension angles. Data from the sensors revealed greater average torso flexion (4.2°) during low lifts compared to high lifts. Moreover, torso extension angles were greater (3.34°) when lifting from lower heights as compared with those at higher lifting heights. Also, data from the sensors showed no significant differences in lift duration between low and high lift heights.

Barim, et al. utilized wearable IMU sensors (Kinetic Inc.) attached to the upper back, left upper arm, right and left wrist, and left thigh to aid in manual material handling risk assessment [52]. Optitrack motion capture system was used as a reference system. The IMU data was used to estimate the lifting duration while lifting from the 12 ACGIH lifting zones. Additionally, the angular data of the sensors on the body segments and a body segments ratio model were used to determine multiple horizontal and vertical hand locations (according to 12 ACGIH lifting zones) during lifting. Also, the upper back sensor was used to measure the trunk inclination angle. Barim's team showed high accuracy for IMU system measurements of lifting duration and trunk inclination angle. However, the measurements of the hand horizontal and vertical locations encountered large errors. The mean errors for the horizontal and vertical measurements were 6.5 and 33 cm, respectively. These errors could be attributed to the errors in the arm angular data due to the rotations of the sensors on the arm. Moreover, using angular data measured while each body segment was on a different plane of movement might be the reason for the inaccurate estimation of the hand location. The IMU system measured the lifting duration with minimum and maximum accuracy levels of 1.032 sec and 0.386 sec. Also, the results demonstrated a high correlation (r>0.90) between the IMU and the reference systems in measuring the hand vertical height and trunk inclination angle, while it was poor (r=0.14) for the hand horizontal distance [52]. Barim's colleagues stated that the longer the horizontal lifting distance, the greater the errors in the horizontal distance measurements obtained from the IMU system.

A later study by Barim, et al. used the same IMU system used in a previous study to estimate the various ACGIH TLV lifting zones (the combination of horizontal and vertical locations) during lifting [52,53]. The new model used the same gyroscope information with ratio and the actual measured length of the body segments to improve the measurement accuracy [53]. The results showed that using the body segment length information reduced the measurement errors to be 2.2 and 14 cm, compared to the older model errors of 6.5 and 33 cm, for horizontal and vertical location measurements, respectively. However, these variables were estimated for sagittal lifting tasks, and thus, the usefulness of the proposed IMU system in assessing asymmetrical lifting tasks is unknown.

Beravs, Rebersek developed a wearable IMU system consisting of three-axial accelerometers, gyroscopes, and magnetometers to measure the different joints (i.e., hip, knee, and ankle) angles [54]. Their results showed that the IMU system could be used to measure body joint angles with a median absolute error of up to 5 degrees (Optotrak Certus was used as a reference measuring system). This error would be expected to increase with more dynamic movements due to the changes in the plane of movement of the various body segment. Thus, it might be infeasible to rely on the proposed wearable system and use the outcome measurements in the various ergonomic assessment method (e.g., RULA, REBA, ...etc.).

Conforti, et al. used eight wireless IMUs (MIMUs MTw, Xsens Technologies—NL) to record kinematic data of the upper and lower body segments [55]. These data were then used to distinguish between safe and unsafe lifting and releasing load tasks. For the upper body segments, a sensor was attached to the sternum body and another sensor was attached to the pelvis. For the lower body segments, two sensors were on the mid-thighs (laterally), two sensors on the mid-shanks (laterally), and two sensors on the instep of the feet. The results demonstrated that using the IMU system to measure the range of motion of lower limb and lumbosacral joints as well as the displacement of the trunk with respect to the pelvis, allowed for distinguishing between the safe and unsafe body postures during lifting and releasing loads. Also, Conforti's team demonstrated that the changes in the hip joint ROM could be used to distinguish between different load weights while lifting or releasing tasks. IMU measurements of the RoM of the lumbosacral, left and right knee, and left and right ankle joint angles could be used as inputs into various MMH activities assessment methods such as RULA, REBA, and OWAS.

Donisi, et al. utilized a single IMU sensor (Opal System by APDM Inc.) attached to the lumbar region to gather acceleration and angular velocity signals during lifting activities [56]. The lifting activities were designed by diversely combining lifting height, frequency, and load weight to correspond to two NIOSH LI risk levels, including no-risk class (LI<1.0) and risk class (LI>1.0). Several machine learning algorithms use time-domain features extracted from the IMU acceleration and angular velocity signals to identify the risk level (i.e., no risk or risk). Donisi's colleagues described their proposed system as a potential approach to automatically classify the biomechanical risk to which users may be exposed during lifting activities.

Giannini, et al. utilized a wearable system composed of body IMU sensors (a custom system and two commercial ones) [36]. The kinematic data was then used to implement postural assessment methods including NIOSH and REBA. The results showed that the proposed system could be used to obtain kinematic data to use in the assessment of MMH activities using the various ergonomic assessment methods. The drawback of the proposed system; however, is that assessing more complex MMH activities would require a longer time to obtain the risk level as compared to the manual assessment methods. Additionally, assessing complex activities using the proposed method requires the intervention of an expert in ergonomic assessment methods for MMH activities recognition and segmentation.

Porta, et al. examined the accuracy of using a limited number of IMUs to predict the MMH activity type, frequency, and duration using a bidirectional long- and short-term memory algorithm [57]. Ten individuals (5 males and 5 females) were recruited to participate in the study. The participants performed multiple MMH activities including walking, load carrying, pulling, and pushing. Also, the tasks included lifting and lowering different weights from the ground and knuckle heights. Various IMU configurations were examined. The first configuration considered four different single IMU locations, including the trunk, right wrist, left wrist, and pelvis. Three other configurations included 2 IMU sensors attached on: both wrist, the pelvis and right wrist, the trunk and right wrist. Another configuration included three IMU sensors attached to the pelvis and both wrists. The last configuration was for the full-body monitoring with IMU sensors attached to the head, sternum, pelvis, and scapulae, the upper and lower arms, hands, thighs, shanks, and feet. Regarding the various task classifications and sensor configurations, the results showed that the median values of accuracy and F1-scores ranged between 97.1% and 99.7% and between 75.9% and 95.5%, respectively, compared to the reference configuration outputs (i.e., full-body set). Moreover, Porta's team stated that using a single IMU sensor placed on either of the four body segments (i.e., trunk, right wrist, left wrist, and pelvis) resulted in satisfactory results in terms of identifying the task type and estimate task duration and frequency.

IMUs strengths and limitations: The IMU system provides body posture information such as inclination angles comparable to those provided by the camera-based and marker-based motion capture systems. Thus, the technology is a promising substitute for the previously mentioned systems. Also, IMU sensors are wearable, small in size, quick, and easy-to-use technology, which makes this technology suitable to use as an assessment mean in the workplace.

However, some limitations may restrict the use of IMU sensors. First, the movement of the IMU sensors during work may under or overestimate the collected data. Additionally, IMUs generate an abundant amount of raw data that requires both a long processing time and large memory storage. Furthermore, the accuracy of the collected motion data depends on the pre-processing and the developed detection algorithms [49]. Moreover, high accuracy IMU sensors are expensive which may limit their use. Also, since the IMU sensors contain magnetometers, the IMU system performance might deteriorate if used in the presence of any magnetic material in the surrounding environment [58]. Finally, measuring hand location during MMH activity using the IMU sensors encounters large errors due to the hand movement in a different plane of movement with respect to the other body segments (e.g., feet, lumbar) plane of movement [53].

Wearable pressure sensing insoles

Pressure sensing insoles technology description: Portable force plates can effectively be used to quantify ground reaction forces for kinetic analysis. However, forces that can be estimated using these plates are limited to a small area (i.e., the size of the force plate). Thus, in-shoe pressure wearable sensors have been developed to measure ground reaction forces outside of the controlled laboratory. Liu, et al. has developed a shoe-size force plate with three triaxial force sensors, three uniaxial gyroscopes, and one triaxial accelerometer [59]. These sensors were attached to a shoe to measure ground reaction forces, the centre of pressure, angular velocity, and acceleration [59]. Another study developed a ground reaction force wearable shoe using two six degrees of freedom sensors attached to the bottom of the shoe [60]. The sensors were attached beneath the heel and forefoot.

Pressure sensing insoles validation efforts: The wearable force plate and 3D motion analysis system could measure the triaxial force under static and dynamic working conditions with adequate precision (error:<6.4% of maximum measurement force) [59]. Another study demonstrated that the ground reaction force estimated from the developed shoe sensor signals was comparable to the reference force plate measurements [60]. Veltink's team showed that the difference of RMSE between the two modules in ground reaction force measurements was 2.3 ± 0.4 % of maximal vertical ground reaction force.

Pressure sensing insoles application in MMH risk assessment methods: Hand forces during lifting can be estimated based on information about ground reaction forces and body segments acceleration using wearable pressure sensing shoes. A study by Faber, et al. utilized hand forces using instrumented Xsens ForceShoes and 17 Xsens IMUs to measure hand forces during lifting [61]. The force shoes were used to measure the ground reaction forces, while the IMUs were used to obtain full-body segment acceleration data. Each force shoe included a force sensor underneath the heel and another force sensor underneath the forefoot. Kinematic data from the IMUs was recorded using Xsens software (MVN Studio 3.0, Xsens technologies). IMU sensors were worn on the pelvis, head, scapulae, upper arms, forearms, sternum, hands, thighs, shanks, and feet. For comparison purposes, full-body kinematics (acceleration) and ground reaction forces were simultaneously measured using an optical motion capture system and 6 Kistler force plates, respectively. Hand forces were estimated based on the ground reaction forces measured using the force shoes and the ground reaction forces were estimated based on different body segment accelerations. Moreover, information about the mass and the acceleration of the center of the mass of each body segment were used to determine the estimated ground reaction forces [61]. As a reference, the 3D hand forces were calculated based on the object mass, object center of mass acceleration, and the ground reaction forces measured by the force plate the object was lifted from. The authors compared the estimated hand forces with the hand forces calculated based on the object kinematics data and ground reaction forces obtained from the force plate the object was lifted from. The results showed that the hand forces RMS differences ranged between 10-15N when using the laboratory-based measurements (i.e., optical motion capture system + force plate), 11-18N when using the IMUs and force plate, and 17-21N when using the IMUs along with the force shoes [61].

The L5/S1 moments could encounter larger errors when being estimated using the bottom-up model compared to the top-down model, for the ground reaction forces used in the bottom-up model are usually much larger than the hand forces factor in the top-down model. Thus, Faber, et al. utilized a Xsens full-body IMU system (i.e., 17 IMUs) along with force shoes to compare the 3D L5/S1 moments estimated using either a top-down or bottom-up inverse dynamics model [58]. The outcomes from these models were compared to those obtained from the optical motion capture system and force plates. Sixteen participants performed lifting tasks from a combination of various horizontal distances and vertical heights. The results from the proposed system showed that the top-down model resulted in smaller errors (average RMS errors were about 10%) compared to the bottom-up model (average RMS errors were about 20%). Faber's colleagues explained the cause of errors from the IMU system due to insufficient identification of shoulder location in the 3D space (influenced top-down model outputs) and the inaccurate anatomical calibration (influenced bottom-up model outputs).

Matijevich, et al. utilized Xsens IMU sensors and Novel pedar-x pressure insoles along with machine learning algorithms for multiple variable regressions to determine the lumbar extension moment [62]. Ten participants (7 males and 3 females) were recruited to perform about 400 tasks that include handling boxes of 5-23 kg with various body postures (e.g., twisting, squatting, and reaching). IMUs were attached on the feet, shanks, thighs, pelvis, and trunk. The pressure insoles were placed inside the shoes. A lab-based motion capture system and in-ground force plates (AMTI) were utilized as a gold-standard reference. The results showed that data from IMUs attached on the above mentioned body segments and pressure insoles enabled the prediction of the lumbar extension moments with higher accuracy (R^2=0.92) as compared to the trunk IMU and insole pressure (R^2=0.89) and trunk IMU only (R^2=0.74). The RMSE for the distributed IMUs, trunk IMU and insole pressure, and trunk IMU only were 17 nm, 20 nm, 31 nm, respectively. Therefore, these RMSE values are about 7%, 8%, and 13% of the NIOSH Lifting Equation spine compression force limit (i.e., 3400 N). In other words, data from a single IMU on the trunk and pressure insoles can be considered as an accurate and reliable method to automate the ergonomic

Pressure sensing insoles strengths and limitations: Several other strengths can be discussed. First, pressure insoles allow for capturing detailed foot pressure information such as ground force reaction and pressure distribution [25]. Also, the technology of pressure-sensitive insoles and inertial sensors can estimate the ground reaction forces that enable kinetic analysis within a free-living environment. Moreover, the pressure insoles along with the IMU sensors could be used in biomechanical models to compute the loading on the back.

On the other hand, the commercial pressure insole system is expensive which may limit its use [25]. Also, Wong, et al. confirmed that complex movement and a vast range of activities might impact the pressure insoles' accuracy [25]. Also, measurements from the insole may encounter errors due to the possible slippage of the insole within the user's socks. The use of inaccurate insole measurements in the assessment of MMH activities may under or overestimate the risk of OLBD.

DISCUSSIONS

Increased OLBDs cases are mainly related to the exposure to various physical factors in MMH activities such as extreme torso flexion, torso twisting, and lifting heavy objects, among others. Thus, it is critical to identify these factors in workplaces to take into consideration the required interventions, and thus, reduce the OLBDs cases. Various ergonomic assessment methods are available to assess the MMH activities. The application of such assessment methods requires direct observation and manual assessment to quantify the risk factors. Direct observations, however, may not be accurate in highly dynamic jobs, and thus, influence the assessment outcomes [36,63]. Additionally, this approach is time consuming and increases the cost of the assessment [62-64]. This direct observation has the potential of interrupting the worker's performance during the assessment as the ergonomist may require to get close to the worker while he/she is performing the task [37].

Motion capturing systems provide accurate workplaces risk factor measurements that could be used as input variables into various MMH assessment methods. However, such systems are difficult to transfer and use in workplaces. Also, the long calibration procedures increase the difficulty of using such systems in workplaces. Furthermore, object movements (i.e., individuals or material) in the workplace may obstruct the camera's view, which may limit the system's ability to determine the reflective marker's location in the three-dimensional space, and thus, result in measurement errors [36,62,64].

The usability of various wearable sensors in measuring different biomechanical factors was reviewed in the current study. It was demonstrated that wearable sensors such as LMM, EMGs, IMUs, and pressure insole sensors can be effectively used to provide kinematic and kinetic information. This information could be used in the various MMH activities assessment methods. One can conclude that, besides the use of torso kinematics data obtained from the LMM in the OLBD Risk assessment model, information about torso asymmetry and task duration can be used to assess MMH activities using various assessment methods such as the NIOSH Lifting Equation, WA L&I, ACGIH, and RULA, among others (Table 1). Moreover, EMG sensors were used in multiple EMG-assisted models to estimate muscular forces, task frequency and duration, which also can be used as input variables into the SI assessment method [33,36,41].

The reviewed studies demonstrated that data obtained from IMU sensors such as various body segments inclination angles, horizontal and vertical reaching of the hands, and task frequency and duration could be used as input variables into MMH activities assessment methods such as NIOSH Lifting Equation, WA L&I, ACGIH, among other assessment methods to evaluate MMH jobs (Table 1) [36,41,42,45,46,48-53,57]. Also, variables obtained from the insole pressure sensors (i.e., load weight as well as lift frequency and duration) could be used to assess MMH jobs using NIOSH Lifting Equation; WA L&I; ACGIH, among other assessment methods.

On the other hand, the review showed that even though most of the wearable technologies can be used to estimate workplace risk factors, the estimated variables include errors, which may result in inaccurate risk assessment. Data from the EMG system may vary across different subjects and sensor placements. Additionally, errors in the EMG signals are expected during working if the sensors became lose (due to the dynamic movements) or if the user's body became sweaty.

Additionally, the accuracy of workplace risk factors measured using IMUs depends on the data pre-processing and the sophisticated prediction algorithms, which may limit their use [49]. Also, due to the use of magnetometers in IMU technology, the system performance might be negatively influenced if used near magnetic material [58]. Also, no efforts were made to show the validation of the IMU measurements for hand horizontal and vertical locations with respect to the body. Barim, Lu showed that IMU sensors provide inaccurate information about hand location with respect to the body during lifting [53]. Such information represents a critical limitation for using an IMU system to assess MMH activities, as the horizontal distance between the load being lifted and the body has been shown as a major workplace risk factor [13,65,66]. Also, another critical factor in the MMH activities risk assessment is the spinal loadings. Faber, Kingma stated that utilizing the pressure insoles to determine the spinal loadings of obese workers may influence the estimated spinal loadings [58,67]. A similar effect would be expected if the insoles were used to assess workers handling heavy objects (Table S1) [58].

CONCLUSIONS

It can be concluded that there is a need for reliable, accurate, and effective wearable technology to automate the ergonomic risk assessment in real workplaces. It is critical that such technology continuously estimate the workplace risk factors such as body segment inclination angles, hand horizontal and vertical locations during lifting/lowering, task frequency, and task duration. Future studies may improve the body movement detection accuracy by developing more sophisticated machine learning algorithms to enhance the wearable sensors' performance in detecting hazardous activities.

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