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Safe Assembly in Industry 5.0: Digital Architecture for the Ergonomic Assembly Worksheet

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Abstract

The evolving landscape of modern manufacturing is affected by a confluence of social challenges arising from demographic shifts and erratic market demands. The emergence of Industry 5.0 revolutionized practices, with a keen focus on harnessing the potential of the Internet of Things to digitize the workforce embracing a human-centric approach. In this research, an original digital architecture integrates sensors into manufacturing environments to evaluate the well-being of assembly operators. The core objective is to capture human-process interactions, empowering production managers to optimize assembly environments from the ergonomic perspective. Three key enabling technologies are employed: radio frequency identification smart gloves, motion capture cameras, and superficial electromyography sensors. This physical layer detects and analyzes assembly tasks, operator movements, and muscular activities. Computational algorithms mine these data streams to assess the Ergonomic Assembly Worksheet, automatically. In detail, the investigated sections of this ergonomic index are basic postures, action forces, and manual material handling. Furthermore, a supplementary set of Key Risk Indicators supports production managers in evaluating the physical resilience of the assembly systems. These operator-specific metrics provide strategic information to trigger workstation redesign, task rebalancing, and other corrective actions for enhancing the safety of whichever human-centric assembly process. Finally, an experimental campaign in a controlled industrial environment tests the architecture's effectiveness and potential to reduce the risks and enhance workforce health.

Keywords: Industry 5.0; Ergonomics; Assembly process; Wearable sensors; Operator health

1. Introduction & Literature Review

The European manufacturing industries are one of the most labor-intensive sectors, employing over 32.1 million workers in 2022 [1]. However, population aging, economic instability, and retirement scheme changes are threatening companies' productivity [2, 3]. Simultaneously, increasing occupational injuries and consumers' mass-customized expectations are posing serious threats to operational efficiencies [4]. Companies must design flexible and smart resilient processes to ensure long-term profitability [5]. This dynamic interplay between social changes and market demands triggered the modern industrial age. Advanced technologies, from robotics and automation to Internet of Things (IoT) based interconnected systems, empower industries to provide a balance between a diverse workforce and personalized production [6, 7]. In this context, the Industry 5.0 paradigm places the human operator at the forefront [8]. It emphasizes a symbiotic relationship between workers and machines, where technology supports and augments operators during working shifts [9, 10]. Industry 5.0 aims at designing human-centric manufacturing models that minimize physical hazards through ergonomic designs and IoT technologies. This novel approach reduces the risk of work-related injuries, ensuring that operators can sustainably perform their tasks over the long term [10, 11]. The scientific literature demonstrates the benefits of monitoring workers' health and well-being by leveraging IoT sensors [12]. For instance, [13] introduces a human-cyber-physical system that leverages diverse sensing data to comprehensively assess operator risk, adapting dynamically to manufacturing conditions, providing timely alerts, and optimizing work processes for enhanced safety and productivity. Furthermore, motion capture (MOCAP) technologies are widely adopted to investigate body postures in assembly systems [11]. Both inertial measurement units and marker cameras represent sensor-driven approaches to perform risk assessment and man-

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agement. Industrial supervisors can analyze time-dependent ergonomic risks of workstations along with the most exposed muscular groups [14, 15]. Production systems are either redesigned or modified accordingly. For example, the adoption of height self-adjusting workstations leads to a consistent reduction of bending activities [16]. However, solely relying on MOCAP fails to evaluate upper limbs' muscular activations [17]. Surface Electromyography (sEMG) can provide insightful information on physiological status and stamina. After conditioning the sEMG dataset, the muscular contractions are expressed as a function of the Maximal Voluntary Contraction (MVC), which represents the highest energy of the muscle in isometric contractions over a time window [18]. Following the same approach outlined with MOCAP technologies, process modifications such as line re-balancing and exoskeletons may be leveraged to achieve more inclusive manufacturing systems [17].

Although data-driven investigations facilitate timely and effective process modifications, they may not comprehensively cover the digitization of ergonomic indicators. Among these, the Ergonomic Assembly Worksheet (EAWS) [19] evaluates the workers' safety on a wide spectrum of parameters compared to other indices such as the Key Indicator Method, which limits the analysis to manual handling tasks [20]. The EAWS tool is structured into risk assessment sections and adopts a multidimensional approach to evaluate the sustainability of assembly activities by considering different physical features. Each task performed by the operator falls into an EAWS section depending on the force exerted or the weight lifted during its execution. The first EAWS section evaluates the operator's posture to identify strenuous movements that could lead to injuries or long-term musculoskeletal disorders. This investigation evaluates parameters such as body positioning, joint angles, and ranges of motion. The resulting score is weighted on time and is higher depending on the effort required to perform the specific movement. The second section investigates muscular forces since operators often use their upper limbs to perform assembly tasks. Having as input parameters the operator's postures, grip types, and thrust directions, the score is computed as a function of force intensity and duration. Upper limb exertions are assessed for both hands and arms independently, and the calculated points are then aggregated to yield an overall score of motion application dynamics. The third section considers the physical demands placed on workers during material handling activities such as lifting, carrying, and pushing. The relevant parameters to compute the final scores are the products' weight, body posture, and frequency. The score for each section is obtained by summing the points related to all the analyzed actions, and the final EAWS score is obtained by summing the points of all the individual sections. A low score means that the industrial task and system design do not pose risks to workers' health and well-being, while a high score highlights potential weaknesses that may require process adjustments [19].

Although the EAWS assesses the ergonomics of assembly systems with different levels of detail, its application is based on evaluators' experience and commitment rather than being data-oriented. Therefore, this research develops a digital architecture to automatize this screening tool by leveraging three IoT technologies as a physical layer. First, a Microsoft Azure Kinect camera captures the 3D positions of body joints during assembly tasks. Second, four channels of sEMG sensors acquire muscular activations in workers' upper limbs. The third technology targets instead the detection of human-process interactions. The monitored worker wears a wearable Radio Frequency IDentification (RFID) based smart glove that enables the automatic recognition of components and tools. Benefitting from these data streams, algorithms digitize the first three EAWS (i.e., Basic Postures, Action Forces, and Manual Material Handling). In particular, the RFID data permits an activity segmentation of the assembly process and thus the evaluation of Key Risk Indicators (KRIs) within each task performed. Finally, this work is organized as follows. Section 2 outlines the proposed architecture to evaluate the EAWS during manual assembly working cycles. While the technologies acquire workers' body movements, muscular contractions, and process interactions, algorithms automatically and quantitatively evaluate the mentioned sections of the ergonomic index. The applicability of the digital system is demonstrated during an extensive industrial experimental campaign (Section 3) focusing on how the obtained preliminary results can be beneficial to safeguard the workforce's well-being and physical resilience. Section 4 ends this work by outlining the conclusions and further research opportunities.

2. Digital Architecture for EAWS Assessment

This section describes the developed digital architecture to automatically evaluate the EAWS index in human-centric assembly systems (Fig. 1). This framework combines RFID data with a MOCAP camera and sEMG measurements to trigger operator and assembly task-driven ergonomic analysis. Therefore, line supervisors can analyze the physical well-being of workers through several KRIs and, if necessary, trigger process modifications (e.g., assembly line re-balancing).

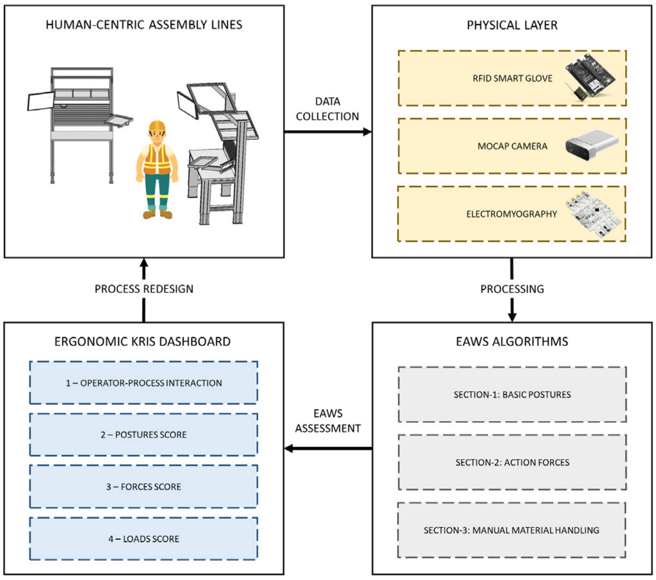


Fig. 1. Qualitative overview of the digital architecture to evaluate the EAWS

2.1. Physical Layer

As depicted in Fig. 1, the physical layer is built upon three IoT technologies: (i) an RFID smart glove, (ii) the MOCAP camera, and (iii) the sEMG data acquisition system. The RFID smart glove utilizes the PyScan device [21], which incorporates the NXP MFRC63002 RFID/NFC reader and a Wi-Fi transceiver. For every scanned RFID tag, it transmits the RFID tags of tools and components storage cabins along with the timestamps to the Server using the Message Queuing Telemetry Transport (MQTT) protocol. The MOCAP camera is based on the Azure Kinect [22], which integrates an RGB-D (Red, Green, Blue - Depth) camera with a 1 MP depth sensor and a 12 MP RGB video camera. RGB images and depth time-driven measurements are streamed to a PC via USB at a frame rate of 15 fps and then are post-processed to provide the position and orientation of 32 body joints [11]. The sEMG data acquisition system comprises the BITalino evaluation kit [18], which includes the Atmega 328P Microcontroller and the HC-6 Bluetooth transceiver. The board is configured for acquiring four sEMG signals from the right and left forearm and bicep, respectively. These sEMG signals are acquired at a sampling rate of 1000 kHz and transmitted to a PC via Bluetooth. The measurements from these three systems are synchronized in post-processing based on the timestamps.

2.2. EAWS Algorithms

The first computational step is to detect the production sequence based on the scanned RFID tags. In particular, the activity segmentation is reconstructed from the dataset tuple composed of a unique tagID and timestamp. Following the same approach, the system keeps track of tools' usage within assembly tasks. For each time window, the digital architecture identifies the measurements of the other two IoT technologies during the respective temporal interval. A parallel computation triggers the evaluation of three EAWS sections (Fig. 2), namely basic postures (Section 2.2.1), action forces (Section 2.2.2), and manual material handling (Section 2.2.3). While the first two subsubsections consider the MOCAP and sEMG data streams as independent, the third one combines them to evaluate the score.

2.2.1. EAWS Section-1: Basic Postures

This algorithm branch has as input data the time-dependent 3D positions of the operator body joints. According to the developer documentation, these geometrical points are embedded into a tree structure [23]. This framework facilitates punctual evaluations of the operators' postures during the execution of assembly activities, forming a hierarchical representation of the human joint configuration. The developed algorithms calculate the angles between body joints based on arccosines. For instance, the back inclination postures involve the ratio between the dot product of the back vectors and the leg vectors, and the norm cross product of the back vectors and the leg vectors. Based on these computations, the algorithms reconstruct the different EAWS basic movements and assign to each time frame the related angle. The postures section lists a wide spectrum of body motions that workers may assume during their tasks within an industrial context. These include standing, walking, sitting, kneeling, lying down, and climbing, as well as asymmetrical movements like trunk rotation, lateral bending, or far-reaching [19]. For each frame, the algorithms identify a specific posture based on both the values of the angles computed and the range they fall within. The magnitude of key angles combined with their duration determines the score of the specific movement. It is worth noting that critical postures held for longer periods contribute more significantly to the overall result. Specifically, for the same duration, each posture in the EAWS database is assigned a different scoring scale that varies depending on the level of musculoskeletal risk associated with it. The cumulative sum of movement points yields the aggregate score for any assembly task windowed through RFID-based process interactions. Scaling this approach for all the activities, the overall level of risk associated with the process is equal to the mean of the task-driven scores.

2.2.2. EAWS Section-2: Action Forces

A parallel computation is performed to evaluate the muscular activations in workers' upper limbs during assembly tasks. The sEMG data are denoised and conditioned following a three-step approach. First, the signal is decomposed to the 4th order using the Daubechies 45 as wavelet and scaling functions. Second, the dataset is conditioned through the Teager-Kaiser Energy Operator (TKEO) to evaluate the energy of the signal. Finally, a 4th-order low-pass Butterworth filter, with a cut-off frequency equal to 10 Hz, represents the third pre-processing step. However, the time-dependent acquisition of these four channels alone provides little information on the level of muscular activation during assembly tasks. Indeed, the algorithm evaluates the sEMG acquisition noise and the MVC. Both parameters are operator and muscle-specific. The acquisition noise is approximated to three times the standard deviation of the signal in resting scenarios during a fixed time window. To increase its reliability, multiple acquisitions need to be performed and the resulting noise is the mean over the N experiments. The computation of the second parameter is based on recording the isometric contractions of biceps brachii and radial flexors K times [24]. In particular, the resulting MVC is given by the sum of the signals' energy, where its amplitude is greater than the acquisition noise multiplied by the time duration of the contraction over the entire period of the recording. Similarly to the noise estimation, a unique MVC for each muscular group is obtained by performing the mean of the K maximal contractions. It's worth noting that the calculated MVC may be different from operator to operator and even between the subjects' sides. Having these parameters as input data, the algorithm defines non-overlapping sliding windows for each channel of sEMG data recorded during the assembly period. The duration of the windows is equal to the mean of the period when the MVC is evaluated. Within time windows the signal energy is thresholded using acquisition noises to assess the absolute magnitude of the muscular contraction. As seen for the computations of the maximal contraction, this activation is equal to the sum of the energy of the

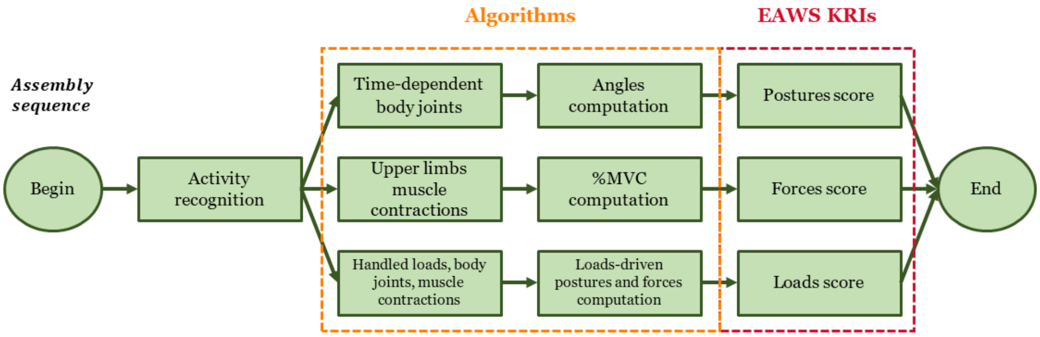


Fig. 2. Qualitative flow heuristic diagram of the digital IoT architecture

signal times the related duration over the window time. The resulting relative activation (e.g., % MVC) is given by dividing this absolute contraction by the MVC. It is reasonable to expect dynamic muscular activation in assembly tasks. Furthermore, its distribution may be sparse among muscular groups and posture-insensitive. Under the assumption that % MVC is directly correlated with exerted forces, relative activations are grouped into 5 categories and connected durations into 6 thresholded groups [19, 25]. Based on this EAWS classification, the action force assessment score is computed for each sEMG channel and assembly task. This enables highly detailed evaluation by pointing out the most physically stressed body parts. Under the assumption that % MVC is directly correlated with exerted forces, relative activations are grouped into 5 categories and connected durations into 6 thresholded groups [19, 25]. By multiplying the intensity and duration scores within each category, values are obtained and eventually summed to calculate the overall section score. Based on this EAWS classification, the action force assessment score is computed for each sEMG channel and assembly task, enabling highly detailed evaluation by pointing out the most physically stressed body parts. To obtain an aggregated risk value for the task, the explained procedure is scaled for the remaining time windows. The adoption of these time windows allows a punctual identification of the highest muscular efforts as well.

2.2.3. *EAWS Section-3: Manual Material Handling*

The last branch of the algorithm combines all measurements of the physical layer to assess hazardous events during manual material handling. Starting from the RFID-identified assembly tasks, the algorithms search for time windows where workers are not using tools. An additional data filtering technique is adopted to eliminate periods in which the assembled product weighs less than 3 kg [19]. The last window removal is performed to check the meters traveled by the workers using a threshold equal to the mean measurement error in the worst-case scenario [11]. This condition is embedded in an or-statement to investigate bending, kneeling, and arm postures as well. At this point, the sEMG-driven muscular efforts in % MVC and basic postures are computed according to the previous sub-subsections. Additional points and different scales are assigned to workers' gender, means of transport (e.g., trolleys), and floor conditions (e.g., very low rolling resistance). The final score is obtained by multiplying the sum of these points with the time window durations. Benefitting from this level of analysis, plant supervisors may re-layout the assembly system by minimizing the most dangerous traveling tasks or even assisting workers with hydraulic lifts.

3. Results

This section validates the digital architecture for assessing EAWS in human-centric assembly lines. While Section 3.1 outlines the industrial-like setup for monitoring one worker at a time using the described physical layer, the subsequent section (Section 3.2) presents the computed KRIs for the EAWS basic postures section.

3.1. *Experimental campaign*

An extensive experimental campaign has been performed in an industrial-like environment (see Fig. 3) to test the validity of the digital architecture. The objective is to automatically evaluate the EAWS ergonomic index for each operator. Volunteer workers assemble a chest of drawers in an industrial workstation. In particular, the home furniture with dimension of 67 cm×69 cm×39 cm (H×L×W) is distinguished by 22 assembly tasks. During the productive cycle, four manual tools are required: (i) hammer, (ii) Phillips screwdriver, (iii) slotted screwdriver, and (iv) hexagonal Allen key. Fine components such as fasteners are picked up by workers from dedicated bins in a supermarket. During the production cycle, the human factor is digitized with the IoT technologies discussed in subsec-

Fig. 3. Controlled Industrial Environment

tion 2.1. First, the monitored worker wears the RFID-smart glove to enable an activity segmentation of the assembly sequence. Tasks and tools are automatically recognized based on components picked from the supermarket and workstation, respectively, thanks to tagging properly with the RFID laser in the assembly environment. The RFID datasets stored in InfluxDB are imported into MATLAB, where they are timely aligned with the other two measurements. While MOCAP assembly videos are converted to 3D body joints using an executable C# script, the 4 channels sEMG data are acquired using a Python script and then imported in MATLAB using CSV formats. The muscular acquisition is based on Ag–AgCl disc-type disposable electrodes after skin alcohol washing. Based on the discussion of the EAWS algorithms (subsection 2.2), the following subsection preliminary validates the digital architecture. In particular, the postures KRIs provide valuable insights to assess the well-being of workers in human-centric assembly lines.

3.2. Postures Score

The structure of the EAWS provides different levels of detail to evaluate the potential musculoskeletal disorders in the workforce. Based on this, a top-down approach is established to analyze the root causes of processes' weaknesses during the furniture assembly activity. Indeed, the investigation starts with the aggregate EAWS score considering the 22 assembly tasks. As depicted in Fig. 4-(a), the global score is equal 30 points indicating a medium risk. Three primary basic postures influence this value. While standing postures account for 4 over 13 points, the low bending scenario weighs 23 over 40. This lean-forward posture is distinguished by a back angle to the legs ranging from 20 to 60 degrees. Additional 3 points are assigned to the trunk rotation. Despite these metrics suggesting the need for a process reconfiguration, they fail to highlight the riskiest assembly tasks.

Fig. 4-(b) fills this gap by computing the activity-dependent EAWS score. It's worth noting that no assembly tasks lay in the safe green zone. While the vast majority of scores fall within the medium risk band, 3 activities are distinguished by scores greater than 50. This RFID-based segmentation represents a valuable insight for plant supervisors from two viewpoints. First, absolute scores assist the priority identification practice. For instance, the process redesign may start with the last task (e.g., mounting white caps) due to its highest score (e.g., 66 points). Second, Fig. 4-(b) outlines task durations as an additional decision-making driver. Indeed, activities such as mounting plastic plates (e.g., the first task) may be detrimental to workers' social sustainability due to prolonged time windows of medium risks. A similar example is the insertion of wooden dowels, the 19-th assembly task of the furniture. However, this MOCAP and RFID-based KRI do not exploit the most relevant postures within each manual task. This strong limitation unfortunately does not allow in-depth process investigation and thus related corrective actions.

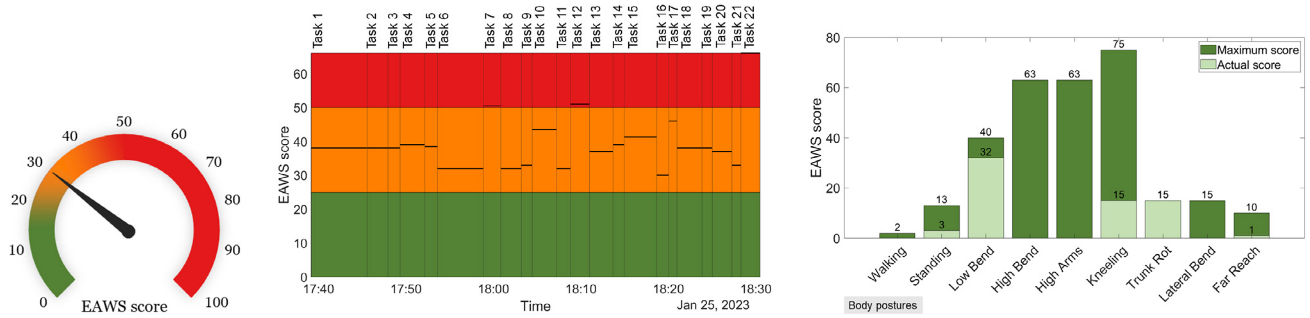
To overcome this, the third KRI narrows the analysis by depicting the activity-dependent distributions of assessment points over the EAWS postures. Fig. 4-(c) details the last task, where the operator is first positioned in front of the workstation to fix the drawer's screws and then kneels to insert it into the finished product. In particular, light and dark green represent the measured and the maximum possible score, respectively. For the sake of clarity, it should be noted that some non-pertinent postures are not included in this bar chart (e.g., kneeling upright). This level of analysis is extremely beneficial in pointing out operator-driven weaknesses of the assembly process. For instance, low bending, trunk rotation, and kneeling postures are the biggest contributors to this high-aggregated ergonomic risk. The relevance of this KRI increases when it triggers comparisons with other tasks. It's possible to focus on the most significant movements among the riskiest tasks and, following a Pareto approach, implement corrective actions to reduce the associated risk of the 80%. However, this KRI falls short of suggesting the most adequate adjustment measures to adopt.

In this context, it is strategic to enrich the decision-making process by checking how posture angles evolve. Taking low-bending and kneeling postures as examples, two distinct scenarios emerge. On one hand, the first posture shows an average back angle of 27 degrees and a duration of 23 seconds out of 131 seconds. A potential effective solution could be to implement height-adjustable assembly workstations. This investment is justified not only by the presence of even riskier bending angles in other tasks (e.g. activity 12, mounting of white caps, mean angle of 28 degrees) but also to achieve a socially inclusive assembly system for the entire workforce. On the other hand, the kneeling posture has an average knee angle of 60 degrees and a critical angle duration of 29 seconds. In this case, lean management approaches (e.g., visual instructions) combined with internal workshops can be useful tools to establish good assembly practices.

To conclude, the validated operator-centric digital architecture provides valuable insights into the safety weaknesses of assembly processes. In addition, the top-down approach guides plant supervisors to the root deficiencies of industrial procedures by suggesting a set of corrective actions (e.g., line rebalancing). Deltas of improvements after process modifications may be easily measured and discussed with workers and labor unions. Therefore, this digital IoT architecture brings a step forward the social inclusion in manufacturing systems by prioritizing long-term well-being over short-term productivity, promoting a vision of ergonomic awareness.

4. Conclusions and Further Research

In the dynamic manufacturing landscape, social challenges due to changing demographics and market demands need to be faced. Industry 5.0 has reshaped industries, emphasizing the role of IoT sensors with a human-centric approach. This research introduces an architecture that integrates electronic devices into the manufacturing environment, digitizing the activities of assembly operators. Computational algorithms process ergonomics data to automatically assess the EAWS index. This operator-specific framework digitizes the basic postures, action forces, and manual material handling sections. Different KRIs



(a) (b) (c)

Fig. 4. (a) Aggregate EAWS score with risk ranges; (b) Time-driven EAWS score over assembly tasks; (c) EAWS score for each posture (light green) on the maximum score (dark green) assignable to every category of the last assembly task

are defined to support industrial plant supervisors in developing personalized improvements to workflow and workplace design. Experimental tests validate its effectiveness in reducing health risks for workers. Further research should verify the other two sections of the EAWS index, namely the action forces and the manual material handling. Subsequently, a digital twin may be designed to achieve the concept of humans in the loop and react in real time to hazardous events.

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