Human Work Sustainability Tool

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Abstract

The work environment influences workers' well-being and contributes to the growth of personal experiences. In fact, working in an unhealthy workplace can cause stress, frustration, and anxiety. Therefore, companies have to deal with the workers' well-being in the work environment, making the management of human factors a crucial aspect. In this context, the introduction of Industry 4.0 technologies can support workplace monitoring and improvement. Some researchers propose structured methods that consider several ergonomic domains together; however, it is necessary to create platforms that support data collection, elaboration, and correlation in an integrated way. Accordingly, this paper presents a tool that supports the monitoring of operators' activities, the data analysis, and the implementation of corrective actions to make the workplace socially sustainable. Preliminary tests were conducted to assess the functionality of the tool architecture and two use cases are presented. They focus on posture analysis and stress detection by inertial sensors and unsupervised machine learning algorithms, respectively.

Highlights

- Tool for sustainability assessment and management of human work
- Comprehensive ergonomic evaluation to prevent work-related disorders
- Unsupervised learning for stress detection in a real working context

Keywords

Human factors, Human-centered manufacturing, Worker well-being, Stress detection, Unsupervised learning, Industry 4.0.

1. Introduction

For every employee, the company is not just the place where he carries out his job, but also a living environment, since there he spends more than half of the awake hours doing his job and establishing relationships with other people, who in the end turn out to be more than colleagues. The work environment contributes to the growth of positive personal experiences, such as satisfaction, well-being, and success, as it can generate negative ones, such as frustration, stress, and anxiety.

Working in a healthy environment positively influences workers' well-being [1] and contributes to the improvement of performance and productivity [2]. When workers enjoy going to their workplace, an important increase of individual and organizational benefits (e.g., reduction of work-related stress, more satisfaction, accidents reduction) can be generated [3]. On the other hand, a worker, who performs his tasks in an unhealthy workplace, could not be able to complete them perfectly. The job activities could be carried out in an unfocused and inaccurate way and costs could increase. Workers are stressed when their workload is excessive and too difficult compared with their skills and knowledge.

Therefore, well-being in the workplace is a crucial topic that companies have to deal with. They should achieve two goals closely related: company performance (e.g., productivity, quality, efficiency) and workers satisfaction. In these last few years, the attention to workers' well-being is increasing in manufacturing industries and managers are aware of the related risks for workers.

The European Survey of Enterprises on New and Emerging Risks (ESENER) claims that 79% of managers are concerned about stress levels in their workplace, however, less than 30% of European companies have proper procedures for managing and dealing with stress [4]. This lack is the cause of work-related diseases for several million employees, with a significant social and business cost. More than one in three workers report that their work negatively affects their health and around three of five workers suffer from musculoskeletal disorders (MSDs), especially in the back, upper limbs, and/or lower limbs [5]. MSDs are one of the most common work-related health problems [6]; in Europe, they affect millions of workers in all sectors, and they lead to high costs to the enterprise. MSDs develop over time and can be caused by several risk factors: physical, organizational, psychosocial, and individual factors.

In the last few decades, the world of work has been significantly modified by these major forces: demographic shifts, increased economic globalization, and rapid technological change [7]. These changes have affected health and safety at work with the emergence of the psychosocial risks, defined by Cox and Griffiths as 'those aspects of work design and the organization and management of work, and their social and environmental contexts, which have the potential for causing psychological, social, and physical harm' [8]. ESENER highlighted how over 40% of European companies believe that psychosocial risks are more difficult to manage than traditional ones and the exposure to them at work should not be underestimated. A survey reports that 27.9% of the workers declare exposure affecting mental well-being [4].

Another crucial aspect to be considered is the aging population and consequently the aging labor force. Nowadays, fewer and fewer young people enter the labor market, while the percentage of older workers (between 55 and 64 years old), within the workforce, is increasing [9]. People enhance their skills, experience, and knowledge over the years, but at the same time, some functional and physical capacities are reduced due to the natural aging process. As people work longer, managing Occupational Safety and Health (OSH) for the workforce has become even more of a priority. Companies have to implement a new approach to human factors management in the workplace and should not ignore the impact of the aging workforce on their productivity and competitiveness. Hochdörffer et al. highlighted the importance of proper staff planning to reduce or prevent occupational injuries and absenteeism from work [10]. They proposed a system that generates job rotation schedules based on workers' qualifications, the workplace's ergonomic exposure, and the most recent allocations of each worker. They also suggested the incorporation of stress and mental fatigue assessment and motivational aspects as future research directions.

In this context, a comprehensive approach for work sustainability should be adopted. Sustainability generally refers to systems, behaviors, and activities aimed at maintaining a particular entity or resource. Specifically, work sustainability involves specific goals, strategies, and methods implemented to preserve and improve the quality of work regarding productive, social, environmental, and economic aspects. Managers need methods and tools able to support them in the human resources management also from the health and safety point of view. For this aim, this paper proposes the Human Work Sustainability (HWS) tool aimed at monitoring and improving working conditions by pursuing psychophysical well-being, satisfaction, and synergistic collaboration of workers, as well as fitting with the surrounding environment.

The rest of the paper is organized as follows. Section 2 provides a critical analysis of the most relevant scientific literature on tools for the work sustainability assessment with a particular focus on stress detection and assessment in the real context. Section 3 presents the HWS tool architecture and functionalities. Section 4 describes the general workflow of the HWS tool and its application to two use cases. Section 5 shows the main results and Section 6 discusses them in relation to the existing literature by highlighting strengths, limitations, and proposals for future work.

2. Research background

In the smart and social factory environment, there is a strong collaboration between humans, machines, and software systems. Since products and manufacturing processes are becoming increasingly complex, several Key Enabling

Technologies (KET) of Industry 4.0 could be integrated into the factory of the future to support the operator. Even shop-floor operator has changed during the fourth industrial revolution, he needs high technical knowledge and extensive social skills [11]. Providing the operator with assistance systems could represent an efficient strategy to guarantee a high level of quality products and ensure workers' well-being necessary to protect company competitiveness in the actual market [12].

The roles and the responsibilities of the worker changed, and smart manufacturing systems need to be designed and developed placing his needs at the center [13]. Romero et al. examined the role of social operator 4.0 in this context [14]. They presented a high-level social factory architecture based on an adaptive, collaborative, and smart multi-agent system. This architecture allows the design and the evaluation of the social interactions of the production system. They defined theoretically the social interaction between workers and production systems, however, the implementation in a real scenario is necessary to test if the architecture considers all the possible social interactions. Peruzzini et al. proposed a theoretical framework to introduce human factors in the industrial context and define the relationship between physical and cognitive measurable human factors and the workplace [15]. However, this framework presents some limitations: the lack of a detailed protocol for stress detection and the difficult applicability in a real industrial environment.

2.1. Tools for the work sustainability assessment

Nowadays the control and the management of human factors are essential for a company since they allow preventing accidents, enhancing quality and efficiency, ensuring safety and well-being for workers, and even achieving cost reduction. To reach these goals, it is necessary to use tools that support the data collection, elaboration, and correlation. The traditional approach for physical and cognitive ergonomics assessment is mainly based on the observation of operators at work and the manual compilation of standard analyses by experts. Nowadays, the new Industry 4.0-enabling technologies can support the development of integrated platforms for monitoring workers' physical and psychological well-being [16].

Savino et al. developed a tool for ergonomic analysis considering both postures and physical efforts; the methodology included a visual management approach that can provide immediate feedback for the operator about his ergonomic risk [17]. In this way, it is possible to both maximize productivity and minimize physical ergonomic risk for workers. Moreover, the high variability of tasks in a multi-purpose workstation could make the physical ergonomic risks evaluation difficult, highlighting the need to develop an appropriate framework that integrates complementary approaches used in the assessment of physical ergonomic risk factors and prioritizes the necessary improvements. Lasota presented a framework that integrates standard observation methods for the physical ergonomic assessment in the multi-purpose workplace. The integration of complementary approaches involves a more structured analysis and allows the definition of risk factors and the prioritization of the improvements [18]. To manage MSD risks in the context of manual handling, Rose et al. proposed an accessible, easy-to-use, and complete tool with a method for risk assessment and risk management [19]. Anyway, the tool is limited to specific analyses and does not take into account other ergonomic assessments. The aforementioned research works focus on physical ergonomic risks and a few of them present a structured method that considers several ergonomic domains together. Moreover, a lack of integrated tools emerges. For these reasons, the main novelties of this paper are: (i) a tool that integrates the analysis of the operators' well-being and the working environment within the adoption of advanced digital technologies; (ii) the correlation of the data (ergonomic and productive) from heterogeneous sources; (iii) the identification of risks and intervention strategies to make the workplace socially sustainable.

2.2. Stress assessment in the real context

Biomechanical stress on the worker, which refers to the physical ergonomic domain and includes internal and external forces exerted on the human body, has been extensively addressed over the years and several established methods have been developed for its assessment. On the contrary, the detection and evaluation of mental stress is still an open challenge. Subjective evaluations based on rating scale techniques and task/performance-based techniques are still the most widespread assessment methods in the manufacturing context [20]. Moreover, the analysis of cognitive load is usually limited to certain sectors due to its complexity. However, the enabling technologies of Industry 4.0 can offer new opportunities for the monitoring of work-related stress.

Outside the working context, several studies exist; they use above all machine learning techniques for the stress event classification and analyze several physiological parameters such as skin temperature, heart rate, breathing rate, electrodermal activity, etc. [21]. In most of them, participants underwent a stress induction procedure in controlled environments [22] and their performance in terms of accuracy detection was very high [21]. In the real context, the supervised learning approaches also prevail [23][24], despite their further necessity of training. Indeed, they have limits in application related to the ground truth collection, that must be addressed [21]. To overcome this issue, it could be considered an unsupervised machine learning scheme, that does not require a training phase and it can be more suitable in a real-world scenario. For this reason, in recent years unsupervised solutions for the assessment of human stress have been explored. However, in the literature there are limited studies on this topic [25][26][27], and, to the best of our knowledge, few works have been tested in real working scenarios [28].

So, in this paper it is presented an unsupervised machine learning system for worker stress assessment; it is validated in simulated conditions, and preliminary testing in real context has been performed. The attention was focused on the analysis of electrodermal activity: it can be successfully used in stress detection, without adding other physiological parameters [25][29], but its use in unsupervised systems has been poorly investigated. To reduce the invasiveness of the system and increase the acceptability level of workers, comfortable, wireless, and wearable smart devices were selected.

3. Material and methods

The proposed tool supports the monitoring of operators' activities, as well as the implementation of corrective/improvement actions to make the workplace socially sustainable. The idea is to integrate the analysis of the working environment and the operator's needs within a factory evolving toward the industry 4.0 paradigm, in which the operator is asked for new skills and is exposed to new stressors. As shown in Figure 1, the architecture is made up of three main layers that are described in the following paragraphs.

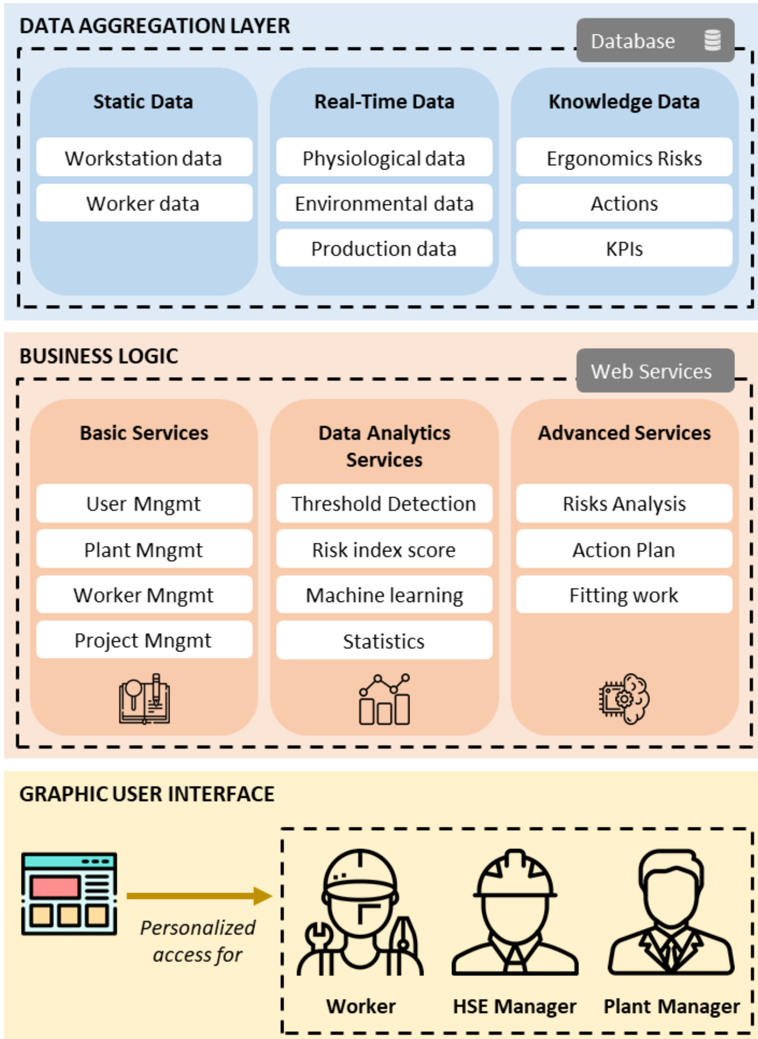


Figure 1. The architecture of the tool for human work sustainability.

3.1. Data Aggregation Layer

The data aggregation layer contains all the data useful for the ergonomics analysis considering all its domains: physical, cognitive, organizational, and environmental.

Static data include the workstation characteristics (i.e., layout, golden zone, strike zone, tasks) and workers information (i.e., demographic data, anthropometry, functional capabilities, knowledge). They are collected once and then updated when a specific event occurs (e.g., workstation redesign, a new skill acquired by the operator). Company managers are responsible for entering and managing these data on the tool.

Real-time data refer to the monitoring of workers' activities, health, and safety in terms of physical and cognitive effort, environmental comfort, and production requirements (e.g., work rhythm, products/components characteristic). These data are acquired by IoT devices (i.e., chest band, wristband, smart glasses, inertial measurement units) or retrieved from company DBs (e.g., Manufacturing Execution System). According to the domains of human factors the following data can be managed by the HSW tool:

- Physical ergonomics: movement of body segments and the relative anatomical joint angles (e.g., shoulder and elbow), steps, force, load, vibrations, etc. Their monitoring can reveal and prioritize the physical hazards within the components of occupational tasks that contribute to the risk of work-related musculoskeletal disorders such as awkward postures, fatigue, stereotypy. These issues usually have workplace design implications.

- Cognitive ergonomics: heart rate (HR), heart rate variability (HRV), R-R intervals, breathing rate, eye-related parameters (electrooculogram, blinks, fixations), electrodermal activity (EDA), etc. Their analysis can highlight issues related to the psychological and mental response of workers such as the detection of stressful events, errors, and unintentional mistakes due to a reduction in concentration, or inadequate capabilities to work demand.
- Organizational ergonomics: breaks, shifts, co-workers, tasks and product scheduling, deadlines, skills, etc. These aspects are essential to contextualize work-related risks, identify and interpret their causes, and mitigate them. The main implications refer to job design and work schedules.
- Environmental ergonomics: temperature, humidity, particulate matter, volatile organic compounds (VOCs), average maintained illuminance, noise level, etc. These data make it possible to assess how comfortable and healthy the work environment is. Ensuring optimal environmental conditions has positive repercussions on the psychophysical effort of workers and their performance.

Another database is dedicated to the knowledge management concerning ergonomics risks (e.g., awkward posture, repetitive movements, breaks management), actions (e.g., exoskeleton, workload balancing, work-life balance, digital assistant), and KPIs (e.g., productivity, job satisfaction, accident rate). This database is based on several sources: the thorough review of the literature, the consultation of the main Workplace Health & Safety national DB, and the scouting of commercial solutions. It aims to support the identification of risk factors, the suggestion of improvement strategies, and the cost-benefit analysis.

3.2. Business Logic Layer

The business logic layer is the core of the tool and provides all the web services, from simple authentication to advanced data analyses. In particular, basic services include:

- User management service that aims to guarantee access to the tool to users with different roles, responsibilities, and skills. In this regard, a set of rules are defined (access control list and access control entry), which establishes who can access certain information and what operations he is enabled to perform, in compliance with the privacy requirements. Each operator is identified through an ID number automatically generated by the HWS tool when the worker sheet is created. Only company managers with the specific authorization can view the association between the ID and the operator's personal data, for all other users, it is not possible to trace the identity of the operator.
- Workstations and workers management services that allow populating and managing the related databases, i.e., performing the following main operations such as create, read, update, and delete.
- Project management service, which allows scheduling and managing the monitoring campaign, which is defined as the set of all the monitoring events that will be conducted in a certain context and with a specific goal. It includes the period and the shift to be monitored (when); the plant, department, production line, and workstation to be observed (where); the operator to be involved (who); the main goal of the analysis (why) and the devices, methods, and surveys to be adopted (how). The monitoring campaign can aim at identifying new risks or assessing the effective mitigation of known ones. In the second case, the corrective actions implemented, whose effects are to be assessed, must be specified.

Considering the heterogeneity of the aspects covered by the various ergonomics domains, the assessment of the production process from the operator's point of view can be quite complex and burdensome. Consequently, a wizard mode to support companies in the monitoring campaign design was implemented. It consists in selecting a specific objective from a list and consulting the technical proposals suggested by the HWS tool according to a set of correlations and related priorities. The correlation matrices were created based on which elements, devices, standard methods, and surveys could be useful for achieving a specific goal. Twenty-eight goals were classified and grouped into five categories: factory performance, perceived workload, work-related diseases, knowledge, and workplace [30]. A technical proposal was defined for each goal and it includes the elements that could be evaluated or monitored, the device to use for data collection, the structured method to follow for data analysis, and the self-assessment technique (survey) that allows considering the subjective component (operator perception). The definition of priorities, based on how strong the correlation is, enables a user-friendly visualization of the suggestions. It is possible to view both only the elements with the highest priority and all the selected ones related to the chosen goal.

Data analytics services include a series of algorithms that allow the analysis of the collected data. They are based on the scientific literature (i.e., standardized methods), knowledge, and legislation about health and safety in the workplace. The raw data (pre-)processing to extract significant information belongs to this module. The aim is to detect the exceeding of specific thresholds, calculate risk indices, or correlate different parameters (e.g., heart rate variability, activity level, galvanic skin response) through machine learning techniques. The first case mainly refers to environmental conditions (e.g., noise exposure level, average maintained illuminance, VOC). The second case mainly involves the physical ergonomic assessment tools, which allow the evaluation of work impact on different body segments. The third case is related to the cognitive domain with a specific focus on stress detection.

Statistical analyses allow analyzing historical data, comparing different case studies, monitoring progress, and gaining useful insights toward continuous improvement. They include:

- Descriptive Analytics, which examines what happened in the past and offers a clear mapping of occupational risks and interventions impacts.
- Diagnostic Analytics, which aims to understand the origin of the risks observed in the past.
- Predictive Analytics, which forecasts occupational risks using specific trends and behavior patterns as predictors.
- Prescriptive Analytics, which recommends possible actions to prevent the onset of occupational risks based on awareness, knowledge, and experience.

Advanced services aim to assess the exposure of an operator to a certain risk, define the best action plan able to mitigate risks and do not affect production performance, and fit the work to the worker. The latter is mainly based on job matching, which means the process of matching the right person to the right workstation to execute the right task based upon the individual's inherent characteristics, skills, and needs.

The corrective actions suggestion is based on a set of correlation matrices between risks and actions based on [31]. The creation of the correlation matrices was driven by the following question: Which corrective actions can be used to manage any individual risk? Firstly, a knowledge base was populated with strong correlations, which are the evident logical correlations that exist “a priori”. Then, the hypotheses of correlations that reached unanimity in dedicated brainstorming sessions with experts were added. In reverses, in the case of controversial opinions, uncertain correlations were established based on the majority influence. The strength of the correlation determines the order in which the actions are suggested by the tool.

3.3. Graphic User Interface

The last layer is the graphic user interface that allows different stakeholders to interact with the tool and access different contents according to the access permissions. The access control entries in the access control list contain the access rights of each group of users, which have to log into the tool with their own credentials. Permissions affect both the tool content that can be accessed and the actions that are enabled (e.g., read-only vs read/write). They are set according to the company policy and the roles of the involved managers. For example, the plant manager can create and manage the workstations sheets and have read-only access to worker sheets, unlike the human resources manager. In general, company managers can manage the database, the ergonomics analyses, and easily elaborate and interpret the collected data. A more user-friendly interface is provided for workers, which can interact with the system on their own to fill in questionnaires, multidimensional self-analyses (e.g., NASA-TLX [32]), and self-assessment rating scales (e.g., Borg scale [33]) or visualize the results related to the ergonomics of their work. The direct involvement of workers aims to favor the implementation of a participatory approach toward a win-win strategy. A joint analysis of the results by managers and workers is recommended to define best practices and evaluate possible corrective actions from different perspectives.

4. Tool workflow

As shown in Figure 2, the HWS tool workflow is divided into three main steps: monitoring campaign design, monitoring, and action plan.

The first step is based on the goal defined by the company that is the specific objective to be achieved (e.g., improve quality, increase job satisfaction, reduce accident rate). Accordingly, a set of guidelines have been implemented to support the monitoring campaign design. All the possible devices, methods, and surveys that can be used during the analysis have been inserted into the platform. It allows the planning of the IoT infrastructures to be adopted to achieve specific objectives. The company manager, supported by the wizard, has to select all the information related to the monitoring campaign: workers, workstations, devices, methods, and surveys. At first, the work area has to be identified according to the analysis goal (e.g., the most labor-intensive or the one with the greatest number of operators). Then, within the work area, it is possible to choose whether to monitor all the operators or select a subset of them based on specific criteria: for example, if the analysis is focused on assessing physical ergonomics, workers who performed manual lifting tasks have to be monitored, whereas those who interact with monitors and automatic machine can be excluded. The related information can be retrieved automatically from the tool database. The platform proposes the devices that can be used during the monitoring (e.g., inertial sensors for motion capture, chest band, and wrist band for vital parameters), the surveys to be filled out by the worker (e.g., NASA-TLX, for subjective workload assessment, STAI for measuring trait and state anxiety [34]), and the methods with which the collected data will be analyzed (e.g., RULA for evaluating the exposure of individual workers to ergonomic risk factors associated with upper limbs MSD [35], OCRA for assessing the risk of MSDs caused by repetitive movements of the upper limbs. [36], MURI for evaluating workers' activities that involve awkward and unnatural postures and movements [37]).

At this point, it is possible to monitor the selected operator that performs certain tasks in the associated workstation. The platform allows creating a section dedicated to the monitoring in which all the data can be collected and organized. If the monitoring has been designed, the tool enables to refer to it by automatically retrieving the defined information (e.g., when, where, who, and why). In particular, the system is developed for considering information about the worker and workstation that are useful for the analysis, such as operator's anthropometric measures and workstation layout for ergonomic analysis. Some relevant information related to the production can be added to make a more comprehensive analysis. For example, it could be interesting to correlate how the task difficulty affects the way of working and the operator cognitive workload, or how the product shape and dimensions impact the operator posture. Even the production schedule may condition the worker's stress level. In this section, it is possible to upload output data recorded by wearable sensors during the monitoring. To make the upload more intuitive and user-friendly, a section, in which a specific structure for each type of output file can be created, has been developed (each device used in the monitoring phase has its own). All the characteristics of the output file can be defined such as format, description, timestamp, the character used as field separator, etc. Moreover, the structure of the output file has to be specified: all the measured parameters can be added, their units of measurement, minimum and maximum value, the corresponding row and column in the output file. The tool automatically stores the data in the database and analyzes them by a series of developed algorithms.

The last step is the aggregation of the collected data according to the logic of the analysis previously selected. The tool automatically identifies the risks related to the results of the performed analyses. For this aim, specific correlations between methods and risks have been defined in the HWS tool. For each method that can be used for the analyses, a threshold value, above which the analyzed activity is classified as risky, has been specified. Moreover, two levels of threshold values have been set in order to detect also the average risks if no high risks have been found out. The output will be a classification and an evaluation of risk factors. Depending on the relevance of the resolution of risks, the high risks will be firstly addressed by identifying and implementing corrective actions to be applied in the short term. Based on the correlation matrices between risks and corrective actions, the tool can suggest a series of corrective actions with different ergonomic effectiveness, costs, and implementation time. Since this is a high risk, it is necessary to find a solution as quickly as possible. Once the corrective action has been adopted, subsequent monitoring should be performed to verify the effective risk mitigation. Then, the average and low risks can be examined and, in this case, the application of the identified corrective actions can take place in the medium-long term. Moreover, the tool allows evaluating a specific intervention implemented in a certain workstation to assess its real efficacy. All data collected during the analysis will be saved in the tool database. Once all the risks have been mitigated, the tool allows concluding the analysis with the evaluation of the KPIs. In this way, it is possible to verify the effectiveness of the corrective actions implemented by monitoring the KPIs significant for the company.

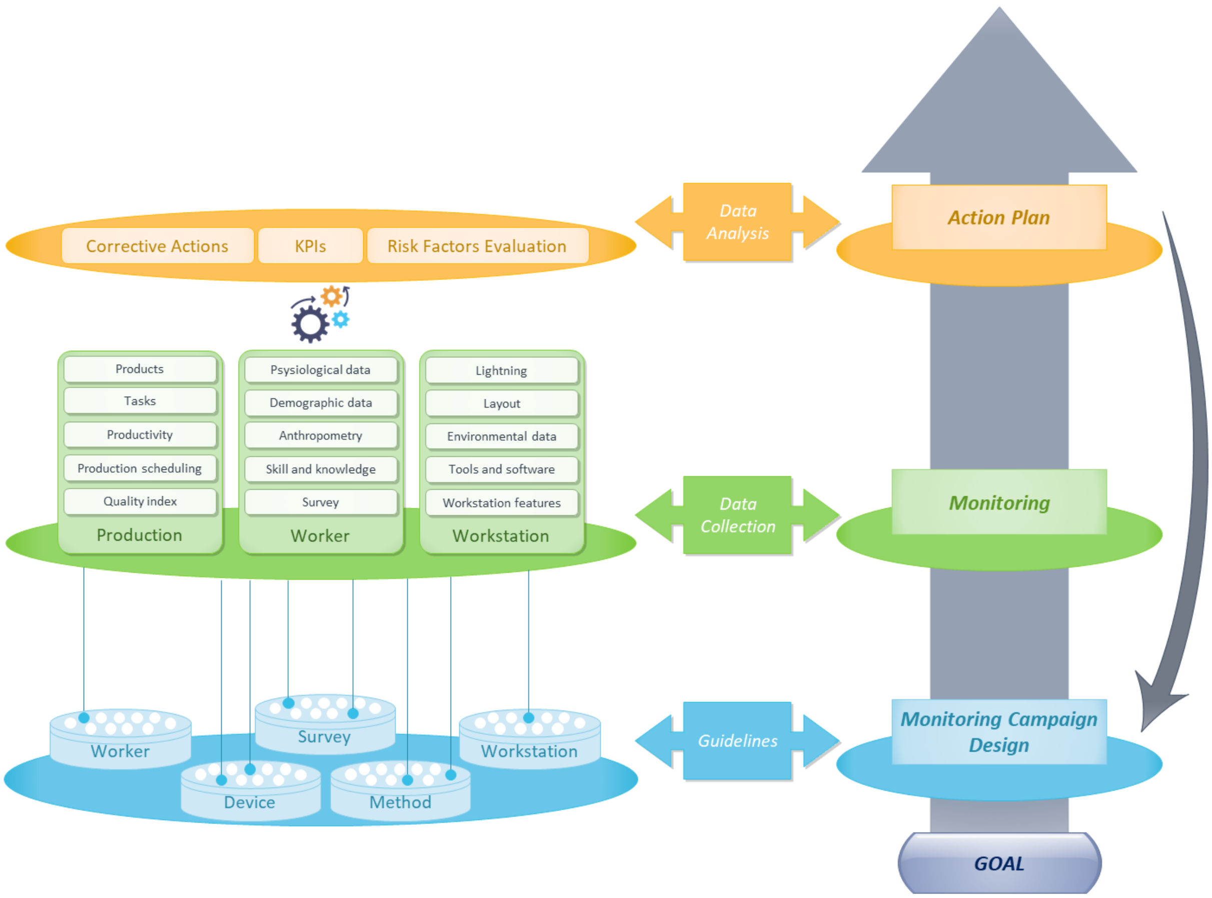


Figure 2. Tool workflow.

The HSW tool has been tested in a manufacturing company of high-performance carbon fiber parts for the automotive market. The next sessions present two case studies as examples to evaluate the tool workflow for the ergonomic analysis. According to the selected goals, the former focuses on the physical ergonomic analysis, the latter examines the workers' stress detection. Involved users freely signed the informed consent based on the EU GDPR (General Data Protection Regulation) requirements where it was made clear who had access to their personal data, the data processing activities, the purpose of the data processing, and that they could withdraw their consent at any time.

4.1. Case 1: Xsens

As a first step, the plant manager created and populated the workstations sheet within the HWS tool, reproducing the configuration of the plant. For each workstation, all the requirements for assigning a worker were identified in terms of skills, training, use of specific tools, compatibility with reduced work skills, etc. In this way, the tool is able to suggest all workers who could potentially work in that workstation and support the job rotation. Adding information related to the tasks categories and products foreseen in the specific workstation, the design of the subsequent monitoring campaign within the HWS tool is guided and some method suggestions may be disabled (e.g., NIOSH applies only in case of manual handling of loads over 3 kg).
Similarly, the worker sheet was created and populated by the Health, Safety and Environment (HSE) manager. Once the demographic information was entered, the login credentials for the operator were generated. The insertion of operator skills and training allowed enabling the matching worker/workstation. The collection of anthropometric measures, on the other hand, supports the assessment of physical ergonomics and the definition of ad-hoc corrective actions.

At this point, following the flow shown in Figure 3, it was possible to design a monitoring campaign by selecting an operator associated with a specific workstation that performs certain tasks. The goal of this use case was the reduction of MSDs according to which the HWS tool suggested 11 technical proposals based on the following five elements: flow; manual handling in terms of lifting and/or lowering; manual handling in terms of pushing, pulling and/or carrying; posture; and workstation layout. Filtering by posture analysis, 4 technical proposals remained from which the combination of the motion capture system, and RULA was selected. Then, monitoring took place as scheduled. The operator 13 was equipped with 18 Xsens MTw (Wireless Motion Tracker) for full-body monitoring. The following production data were collected: product, difficulty level, time, and co-worker presence. Once the Xsens output file has been uploaded on the tool the RULA score has been calculated automatically.

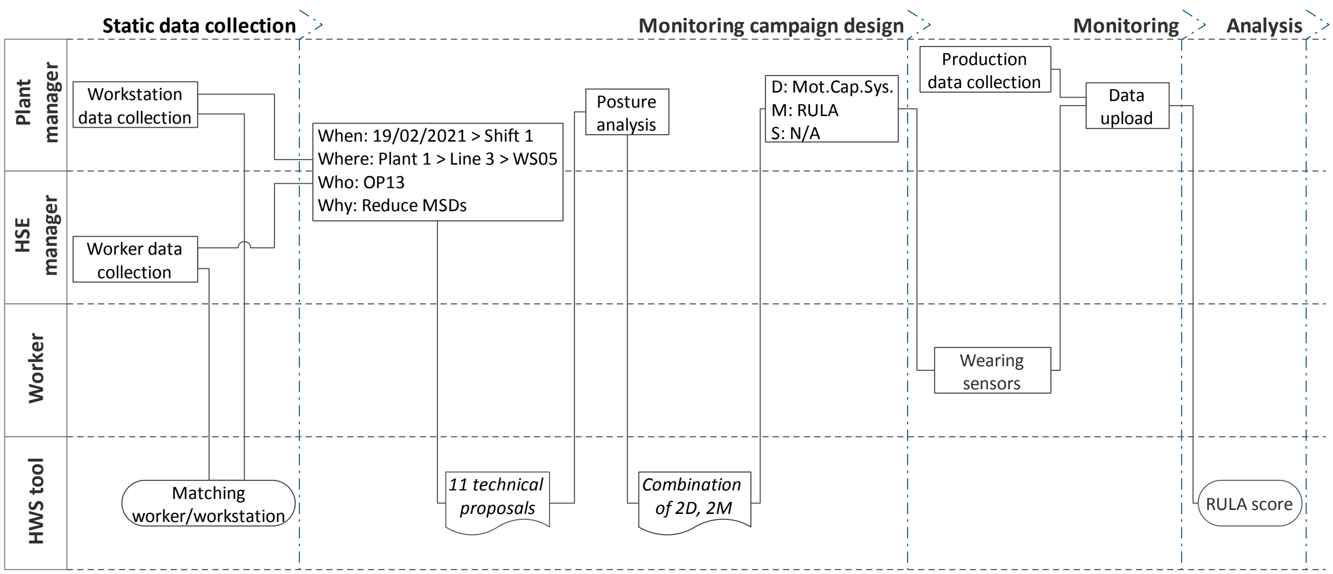


Figure 3. Workflow case 1.

4.2. Case 2: Machine learning-based system for workers' stress detection

As shown by Figure 4, the first steps are the same as the first use case. The main difference originates from the goal selection. The reduction of stress and mental health disorders (MHDs) involves the suggestion of 16 technical proposals based on the following elements: workload; shift and break; roles and responsibilities; physiological parameters and human-machine interaction. Filtering by physiological parameters, 4 technical proposals remained from which the combination of a bracelet, machine learning algorithm, STAI, and NASA-TLX was selected. Then, monitoring took place as scheduled.

Anytime, the operator sheet can be updated with the score related to the questionnaire to assess trait anxiety (STAI-Y2), which is filled in by the operator by logging in with his credentials on the HWS tool. The STAI questionnaire is used for stress assessment, comparing the operator's perception with what is resulting from the vital parameters measured with wearable sensors. The STAI-Y2 is not administered on the same day of the monitoring to prevent the operator from being influenced during the compilation by state anxiety. By administering the STAI-Y2 and STAI-Y1 questionnaires on different days, the operator's propensity to provide the same answers is limited.

Operator 4 completed the questionnaire STAI-Y1 before wearing the sensor to prevent operator anxiety from being associated with the start of monitoring. Then, he was equipped with the Empatica E4 wristband. At the end of the shift, the operator was required to fill in the questionnaire STAI-Y1 again to assess state anxiety after monitoring and the NASA questionnaire to evaluate the workload. They are administered before removing the bracelet to evaluate any changes in the physiological parameters during their compilation. Once the monitoring session was complete, all the files of the measured variables (e.g., HR, EDA) were uploaded to the HWS tool to be processed using the ad-hoc algorithms, described below, and calculate the stress level. The anxiety score and the perceived workload score were automatically calculated based on the questionnaire answers.

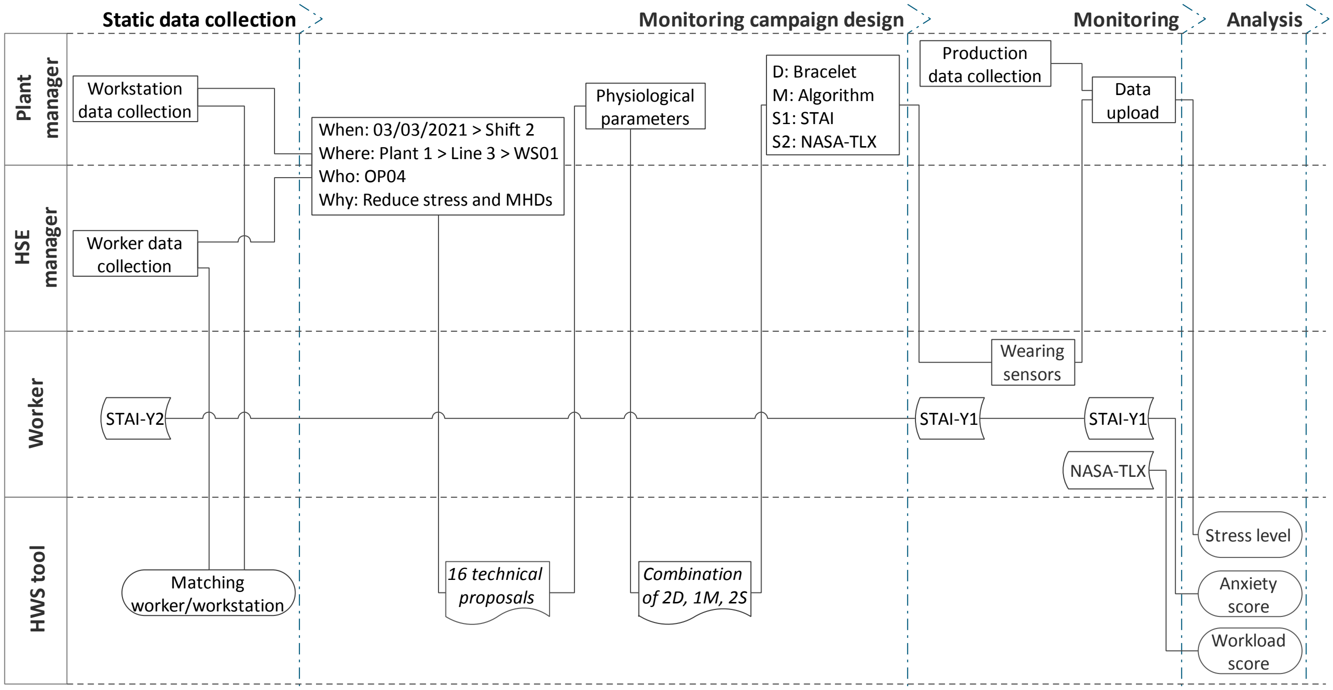


Figure 4. Workflow case 2.

To assess the work-related stress, the signals related to the EDA and HR, coming from the Empatica E4 wristband, were analyzed.

The developed software framework consists of the three main modules reported in the block diagram of Figure 5.

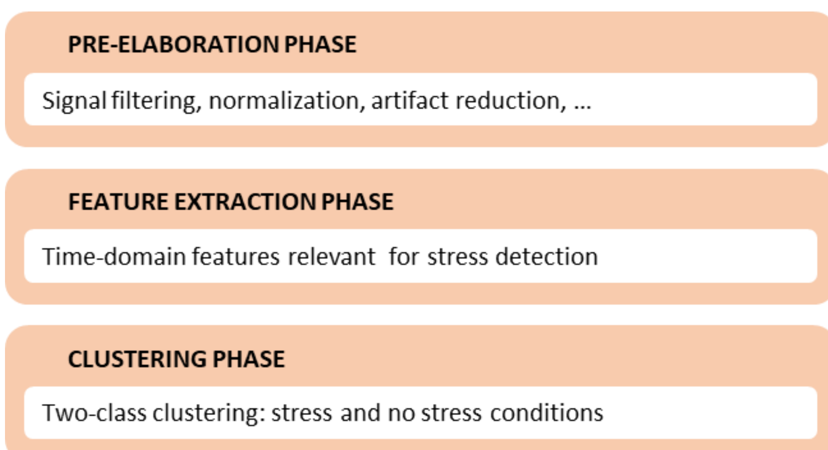


Figure 5. Main computational steps of stress evaluation software framework.

The pre-processing step reduces the environmental noise and the artifacts due to wrist movements. For measuring HR, the inter-beat interval (IBI) signals were acquired. Empatica wristband extracts IBI sequences from the photoplethysmography (PPG) data and integrates an algorithm, that removes incorrect peaks due to noise in the PPG signal. So, in the presence of a great deal of disturbance, for example, due to abrupt movements, many samples are lost. Based on the analysis of the data acquired during the working days, it was found that the sequences were very fragmented and therefore it becomes very difficult to assess short-term stress conditions. For this reason, it was decided to not consider the IBI data and to focus on the EDA signal.

For the EDA signal, the Empatica E4 provides electrical conductance (in µS) across the skin. The data were acquired and then processed in offline mode by using Mathworks Matlab software. To reduce the effect of the artifacts it was eliminated the abrupt signal changes in accordance with Kocielnik et al. [38]. Then, the signal was decomposed into phasic and tonic components. The tonic component retains baseline information about the signal and the subject's physical characteristics. While the phasic component is related to the fast response of skin conductance following a stimulus, measured over a short period of time. Since the phasic component can be associated with a specific event and used to recognize a particularly stressful work condition, only the phasic component was analyzed. It was obtained by filtering the EDA signal with a Butterworth bandpass filter with cutoff frequencies between 0.16Hz and 2Hz.

To evaluate the EDA signal in relation to individual worker characteristics and the effects on worker sweating due to environmental conditions (temperature, humidity, etc.), the EDA activity was collected during a rest period of about 5 minutes. Then, the baseline was calculated as the mean of the data measured and used to normalize the signals acquired during the regular activities.

For the feature extraction phase, several time-domain features, commonly used in the analysis of stress detection [23][25][29] were analyzed. They were calculated within a sliding window of 5 seconds.

In Figure 6 it is reported an example of the features extracted considering the data acquired during a work shift, monitoring the operator even during coffee and lunch breaks.

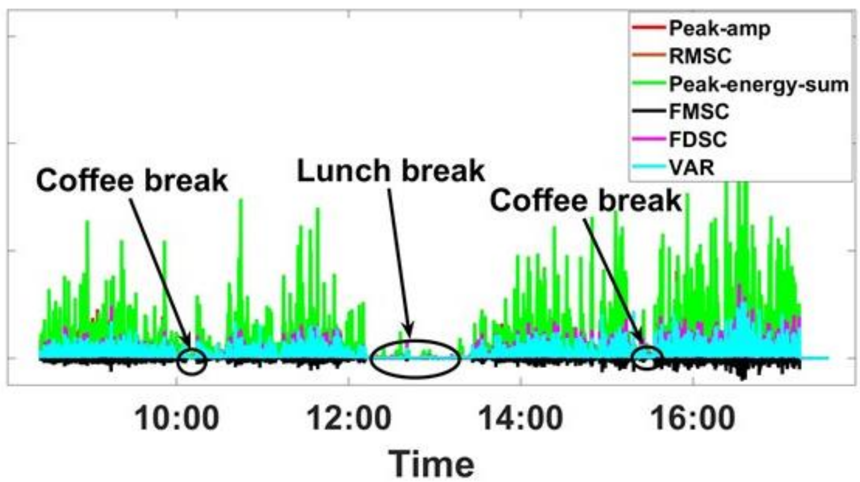


Figure 6. Example of EDA extracted features: peak amplitude sum (peak-amp), peak-energy-sum, the mean (FMSC), and standard deviation (FDSC) of the first signal derivative, Variance (VAR).

Through visual inspection of the extracted features, it is evident that there is a different trend in correspondence of the rest intervals (no stress conditions). To identify the desirable features, the Laplacian score feature selection technique was used [39]: in Table 1 the chosen features as input to the unsupervised clustering phase are reported.

Table 1. EDA extracted feature.

Signal	Feature
EDA	peak amplitude sum (time of occurrence of peak − time of point of onset)
	peak rise time sum (0.5 × peak amplitude × peak rise time)
	the mean of the first signal derivative
	the standard deviation of the first signal derivative

To cluster the two classes (no stress and stress conditions) the chosen algorithm is the commonly used and effective unsupervised K-means clustering [40]. It identifies k number of centroids, through an iterative procedure of positioning

optimization, and then allocates each data sample to the nearest cluster, based on the distance between the sample and centroid.
To evaluate the performance of the stress detection system, the average clustering accuracy was calculated in percentage according to equation (1).

$$\text{Accuracy} = \frac{\text{number of correct classifications}}{\text{number of total classifications}} \tag{1}$$

5. Results

The involved company produces high-performance carbon fiber parts for the automotive market often significantly different from each other in size and functionality to satisfy specific customer needs. This study focused on the lamination department as manual work is prevalent and determines the added value of the product. Operators must always maintain maximum concentration due to the peculiarities of each product that subjects them to a significant mental and cognitive load during the entire work shift. In some workstations, there are also significant physical efforts due to the large dimensions of the products. Consequently, both physical and cognitive well-being were analyzed in the two proposed use cases. The results are described in the following sections.

5.1. Case 1: Xsens

In general, the layout of the workstation WS05 is perfectly compatible with the anthropometric characteristics of the operator involved in the analysis. Theoretically, the height of the worktable allows the operator to perform all operations in the strike zone and the management of components behind the operator (higher risk areas) is not provided.

Possible risks can originate from the lamination of large products, which influenced the choice of the hours of the shift to be monitored. The graph in Figure 7 shows the trend of the RULA score based on the data collected with the motion capture system. It is related to the right side, which resulted in the worst one. Most of the work activity falls into a low-risk band (67% of the time) not requiring immediate corrective actions. However, the factors that expose the operator to average risk for 20% of the time were investigated and the HWS tool reported "R1 Awkward posture > 1.3 Upper limbs > 1.3.2 Wrist". In fact, lamination sometimes requires particular movements of the wrist in terms of rotation and deviation based on the product geometry. This made it difficult to identify a suitable improvement intervention except for the study, identification, and dissemination of a best practice. High risks are rarely observed (3% of the time) and often are not work-related movements.

The overall target of this case study was the pinpointing of specific latent risk activities that can lead to the onset of MSDs. The HWS tool contributed to the achievement of the objective by identifying in the movements of the wrist an incorrect habit of the operator that could not emerge from the theoretical evaluation of the workstation ergonomics. Moreover, the HWS tool automatically reported the category of the identified risk in the results section.

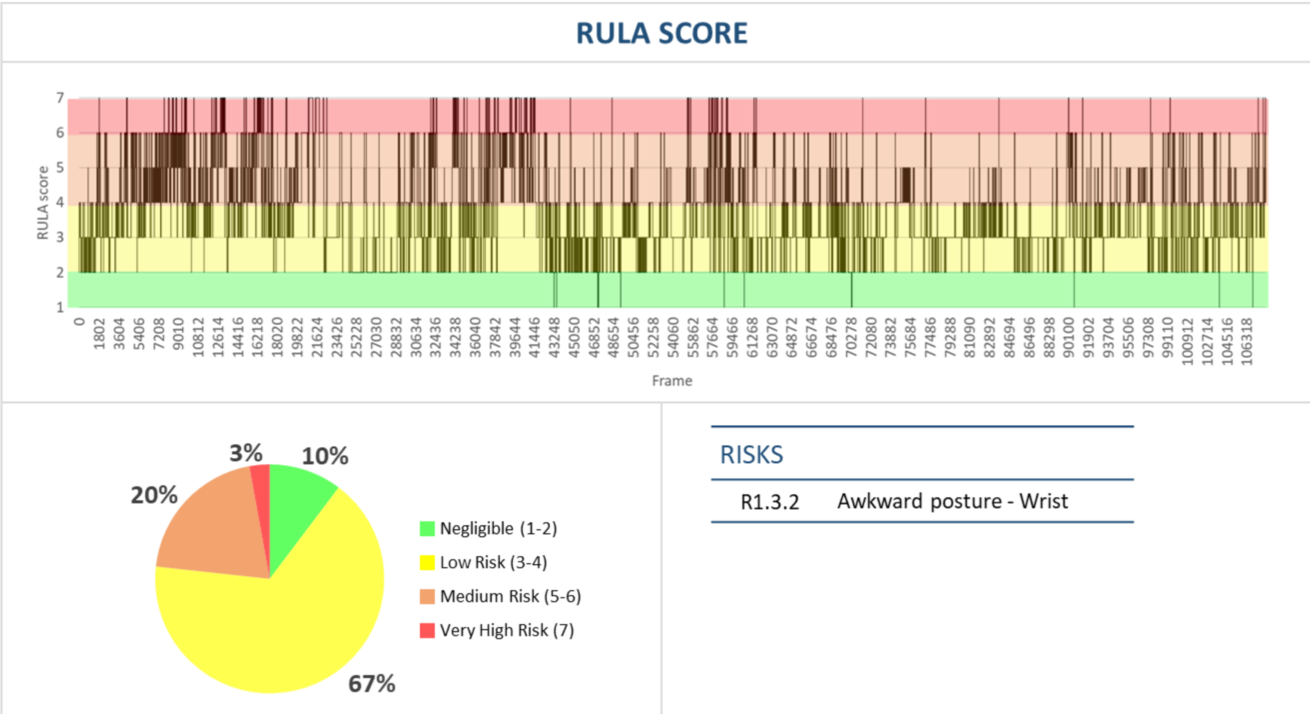


Figure 7. RULA score.

5.2. Case 2: Machine learning-based system for workers' stress detection

The framework software has been initially tested considering a dataset obtained through simulations of activities (in controlled conditions), carried out in the laboratory. A preliminary analysis was then conducted in a real context, evaluating the system response to the data described in Section 4.2.

For the analysis in controlled conditions, the dataset obtained in our previous work [41] was considered. In particular, 5 volunteers (4 male and 1 female, age 28.6±3.8) wore the E4 Empatica device and performed five tasks simulating manufacturing activities, by using LEGO bricks and a toolbox, separated by a rest period of two minutes. As described in [41], the rest periods and one of the five tasks were considered "no-stress" events, while the remaining tasks were classified as "stress" events. The analysis indicated that the best performance was obtained considering the "cityblock" k-means distance metric and the mean accuracy value was about 76%. The obtained result fits well in an unsupervised system; moreover, it was obtained considering only one physiological parameter.

The testing in a real scenario was accomplished through the analysis of data acquired during the whole work shift. From a preliminary assessment, it appears that the software framework can cluster rest conditions and potential stress conditions for the user. Figure 8 shows an example of how the EDA raw data, measured during one working day, were clustered: blue points indicate no-stress conditions, while red points represent potentially stressful conditions. As it is possible to see from the figure, the rest conditions (coffee and lunch break) belong to the same "no stress" cluster.

All work activities were videotaped allowing the identification of the operation that the worker was carrying out in correspondence with a red area. For example, focusing on the time interval shown in Figure 9, two potentially stressful conditions were detected by the tool. The relative screenshots, shown in Figure 10, demonstrate how they are due to completely different activities. The former can be defined as a high motor activity: the operator was performing the preparation and lamination of large templates on the mold. The latter can be associated with a higher precision activity as the operator is laminating smaller and more critical areas of the product.

The subjective evaluation, i.e., the operator's perception, showed a high workload (NASA-TLX score: 63) and a low and constant level of anxiety (STAI-Y2: 33; STAI-Y1_before: 34; STAI-Y1_after: 31). The perceived workload was mainly characterized by high temporal and physical demand for the operator rather than mental demand. Indeed, the operator worked on a large product with particular geometrical features that involve a significant physical strain. STAI questionnaires showed a very small reduction of the anxiety level from the beginning of the work shift to the end of the day. This could be justified by having finished the product in time and therefore by the reduction of the time pressure. However, both surveys (before and after the work shift) present scores below critical values [34] and do not point out a particular anxiety level.

In this case, the use of the developed algorithm in the HWS tool allowed the detection of some stressful activities for the monitored operator. The consequent contextualization of these stress conditions can lead the work management (e.g., task allocation, workstation rotation, co-worker assignment) towards the prevention of work-related stress.

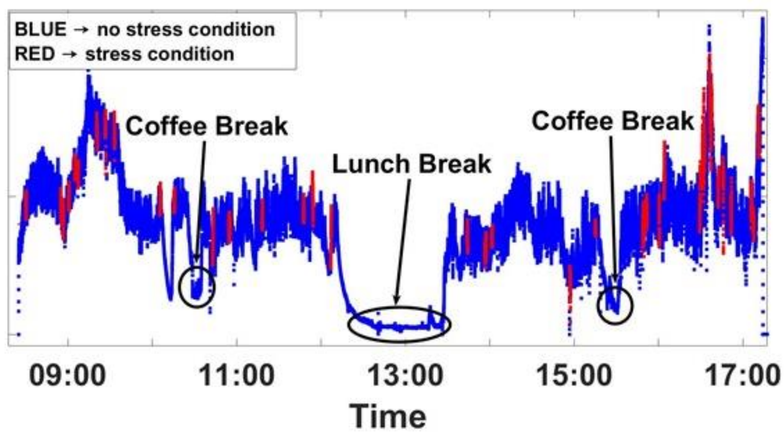


Figure 8. Example of the clustering results.

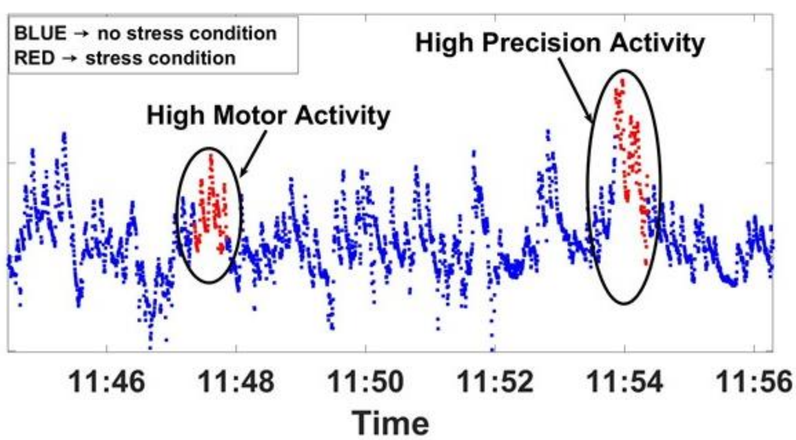
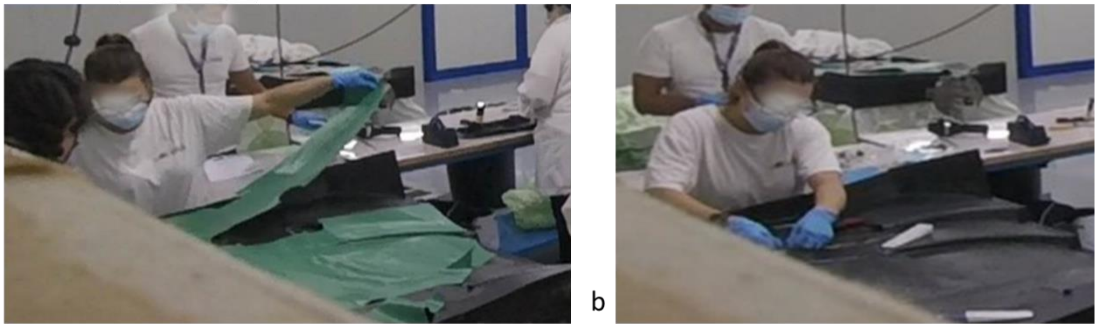


Figure 9. Zoom - example of the clustering results.



a b

Figure 10. Screenshot of activity at about a) 11:47 and b) 11.54.

6. Discussion and concluding remarks

Both case studies demonstrated that the use of the HWS tool allows enhancing both workers' well-being and business performance by a smart integration and interpretation of data. The identification of neglected risks enabled the company to deal with them and find corrective actions and solutions that have provided great benefits not only to the people involved in the analysis but also to the company as a whole. The paper presents a comprehensive approach to consider all work-related ergonomic aspects (physical, cognitive, environmental, and organizational) evaluating also the interactions between them, by addressing one of the open issues that emerged in Kadir et al. [42]. Moreover, the tool allows identifying objectively potential risk factors and suggesting the most appropriate corrective actions, as suggested by Cecacci et al. [43].

A hardware-software system was implemented to detect potentially stressful conditions for workers. To avoid a complex training phase, based on labeled datasets of simulated events that could be inaccurate and different from real-world data, an unsupervised machine learning approach was adopted. The performance achieved with this technique is lower than the most widely used supervised systems but could be more effective in a real-world manufacturing scenario. To make the system minimally invasive, a comfortable and unobtrusive device was adopted. Finally, the EDA signal was analyzed, it has been poorly investigated with unsupervised systems, but it seems to provide promising results. Only a preliminary test of the stress detection algorithm using real data was performed, so a more in-depth study, in relation to the ground truth is needed to evaluate the performance of the system in terms of detection accuracy. Moreover, to increase the performance and reliability of the system it will be necessary to apply strategies, both on software and hardware level, able to reduce the signal disturbs due to artifacts. The involvement of a larger sample of operators and the monitoring of numerous work shifts will make it possible to use the classification of activities and the results of the questionnaires for evaluating the performance of machine learning algorithms and their future optimization. The software framework will also be improved considering different levels of stress.

The review of Niknejad et al. [44] highlighted that smart wearable devices are mainly used in the healthcare sector and a limited number of studies explored their implementation in other industries to improve workers' health and safety, suggesting it as an interesting research area. The proposed tool goes exactly in this direction by foreseeing the sensors use in measurement campaigns and promoting objective ergonomic evaluations in a real industrial scenario. For example, the first use case highlighted how objective data allow detecting risks that are often not detectable by purely theoretical approaches, which do not take into consideration people's not always healthy habits. The use of the HWS tool allows identifying an awkward posture, related to the wrist position and rotation, that had not been detected by the ergonomist's standard analysis. Moreover, the second case study confirmed that the use of smart wearable devices for stress detection allows carrying out quantitative analysis in an objective way. The developed algorithm for stress detection detected two different potentially stressful conditions that actually represented two stressful activities for the operator.

As know, the participatory approach to ergonomics has a positive effect on the reduction of work-related risks [45]. For this aim, the tool provides the direct involvement of workers who can access it whenever they wish to view the scheduled monitoring and the results obtained. This increased the ergonomics awareness and perceived usefulness, stimulating proactive behaviors. Previous studies [46] showed how the focus on health and safety elicited the highest acceptance of wearable technologies by workers rather the productivity improvement. In addition, adequate information on the data analysis process (access, purposes, obtainable information, etc.) plays a key role in the acceptance.

Being transparent about the purpose of monitoring is also essential to avoid ethical issues arising. If employees do not perceive their well-being as the key driver, they may view the monitoring campaigns as an invasion of privacy, lack of trust, or dissatisfaction. It can result in demotivated workers, complaints against the company, or high turnover rates. For this purpose, it is important to define and share a standard and detailed monitoring policy; give free access to the results of the monitoring campaigns to the subjects involved; provide them with detailed and frequent reports of the results obtained; implement the defined action plans to give greater evidence of the benefits of the analyses.

One of the main limitations of the current version of the tool is the manual management of the output files from the sensors. On the one hand, it guarantees greater flexibility (i.e., the company can integrate the sensors it prefers by appropriately configuring the output files), it is not affected by data loss due to connection problems and does not require additional equipment other than the internal memory of the devices. However, on the other hand, it only allows offline evaluations. In the next future, the possibility of carrying out real-time analyses through the most common devices will be implemented.

Another limit of the tool is the use of overly general corrective actions. They fit well to different contexts, but often do not offer an effective solution to a specific risk. The use of machine learning algorithms and a knowledge base approach will be investigated to customize the tool based on the needs of the company.

Finally, the Human Work Sustainability Tool requires dedicated training for company managers to better exploit its potentialities. Moreover, to guarantee a participatory approach toward a win-win strategy, the workers themselves have direct access to the tool with their credentials. They can fill out surveys directly on the platform, control their well-being and performance, and modify their personal information. For these reasons, they have to be trained in using the tool to accomplish these activities on their own.

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