Exploring the potential of Operator 4.0 interface and monitoring

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PROOF

# Exploring the potential of Operator 4.0 interface and monitoring

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ABSTRACT

In the context of smart factories, where intelligent machines share data and support enhanced functionalities at a factory level, workers are still seen as spectators rather than active players (Hermann, Pentek, & Otto, 2017). Instead, Industry 4.0 represents a great opportunity for workers to become part of the intelligent system; on one hand, operators can generate data to program machines and optimize the process flows, on the other hand they can receive useful information to support their work and cooperate with smart systems (Romero et al., 2016). Diversely from machines, humans are naturally smart, flexible and intelligent, so putting the operators in the digital loop can bring more powerful and efficient factories. The paper aims at defining a theoretical human-centered framework for Operator 4.0, and testing its feasibility and impact on companies, thanks to the integration of human factors in 4.0 computerized industrial contexts. The proposed framework is based on data collection about the workers' performance, actions and reactions, with the final objective to improve the overall factory performance and organization. Data are used to assess the workers' ergonomics performance and perceived comfort and to build a proper knowledge about the human asset of the factory, to be integrated with the knowledge derived from machine data collection. The framework is cased on the adoption of an Operator 4.0 monitoring system, which consists of an eye tracking and a wearable biosensor, combined to a proper protocol analysis to interpret data and create a solid knowledge. Virtual prototypes are used to make the workers interact with the digital factory to conveniently simulate the human–machine interaction (HMI) in order to avoid bottlenecks at the shop floor, to optimize the workflows, and to improve the workstations' design and layout. The study represents a step toward the design of human-centred industrial systems, including human factors in the digital twin. The research approach has been successfully tested on an industrial case study, developed in collaboration with CNH Industrial, for the re-design of assembly workstations.

## 1. Introduction

### 1.1. Context

The Fourth Industrial Revolution is starting to transform the modern companies, but also the way people interact with products, machines, processes and workplaces due to the change in product smartness, machine interface, and work environment complexity, through 2025 and beyond (Lorenz, Rüßmann, Strack, Lueth, & Bolle, 2015). Based on literature review, six design principles can be identified for a successful implementation of Industry 4.0 model: interoperability, virtualization, decentralization, real-time capability, service orientation, and modularity (Hermann, Pentek, & Otto, 2017). However, there are several recent trends that increase the need for research within human-machine interaction, first of all the Industrial 4.0 revolution. It pushes the adoption of advanced digital technologies to help people to interact with products and machines, to work better and more efficiently, and return to or be incorporated into the modern workforce. Thanks to the connectivity among different production resources (machines, work stations, etc.) proposed by Industry 4.0 approach, information can be generated and shared to create self-smart system adaptation and predictive and automated decision making process. Furthermore, production systems can be potentially able to self-reconfigure themselves on the basis of the collected data (Cohen, Faccio, Mora, Galizia, & Pilati, 2017). As a consequence, Industry 4.0 could strongly impact on the actual assembly paradigms, even in the cases in which the human factor is prevailing.

Moreover, new trends in Industry 4.0 are focusing on the importance of human-machine collaboration and directly promoting a closer cooperation between people and machines, encouraging the efficiently use of workforce from both machines and people in a cooperative environment, using virtual and real representations (Rada,

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2015). In this context, the human workforce assumes a crucial role within the smart factories, especially when high precision tasks are required and the overall product volumes are low due to frequent market changes or customized production (Hadorn, Courant, & Hirsbrunner, 2015). Nowadays most of the lower skilled human jobs were eliminated and replaced through technology, leading to the remaining human jobs becoming more complex and comprehensive and increasing the importance of interdisciplinary cooperation (Bonekamp & Sure, 2015). As a consequence, numerous complex, high precision processes are and will be still managed manually, and many of them could be collaboratively executed by humans and robots cooperating, thanks to the recent technological advances in robotics and human–machine interface (HMI).

### 1.2. Scope

The research focuses on the creation of a theoretical human-centered framework for Operator 4.0 based on the analysis of human behaviours and actions within the smart factory and the digitization of such information in order to optimize the overall process and improve the human-machine interaction. The study is relevant since it merges smart industrial systems with human factors (people competences, skills and needs), which represent the strategic assets of the modern industry, instead of focusing on technologies and automation like the majority of research works about Industry 4.0. In this sense, it investigates a little explored area that can highly benefit the overall system performance if properly optimized (Mattsson, Fast-Berglund, & Åkerman, 2017).

Up to now, researches about Industry 4.0 focused attention mainly on machines, and did not consider the role of human beings in the design of the smart factory (Parrott & Warshaw, 2017). However, factories are not only made up of machines but also of human beings (i.e., operators/workers), which cooperate with the machines and collaborate each other in various ways (e.g., executing tasks, controlling the process, loading or unloading the machines, interacting the machine interfaces). Although the increasing level of automation of production lines, humans still continue to have a central role in controlling the production processes and in executing delicate and strategic tasks. As a consequence, they still are the main responsible for elevated factory productivity and high product quality (Neumann, Kolus, & Wells, 2016).

The research proposes to merge physical data and virtual items, digitalized by IoT (i.e., the digital twin), not only for machines but also for people. The factory digital twin is build up through sensor data and allows information be contextualized to create self-adapting systems able to intelligently adjust the production patterns for difference scopes (Davis, Edgar, Porter, Bernaden, & Sarli, 2012). The paper aims at including also human data into the creation of the factory digital twin.

The main paper contribution is the definition of a theoretical framework to introduce human factors into Industry 4.0, and a structured procedure to carry out pragmatic assessment of the relation between physical and cognitive measureable human factors and workplace design. The validity of this framework is tested by its application to industrial cases. The research novelty is the inclusion of human factors analysis, which has recently interested a growing number of companies to pursue higher life quality for their workers (Smith & Ball, 2012), within the Industry 4.0 scenario. In fact, sustainable industrial systems must no longer satisfy exclusively performance objectives (e.g., cost, quality, speed, productivity, flexibility, adaptability) but also human-related objectives (e.g., ergonomics, mental workload, intuitiveness of actions, usability of tools, satisfaction) (Peruzzini & Pellicciari, 2017b). As a consequence, the novel connectivity and interoperability features of systems and machines can be coupled with human monitoring technologies to integrate human-related data at the smart factory level and promote more socially sustainable, intelligent and flexible manufacturing process design.

The research questions are: Q1. Can the proposed framework improve the human-machine interaction and the Operator 4.0 performance? and Q2. How the proposed framework supports the creation of the so-called digital twin?

The answer to Q1 is yes. The study demonstrated that monitoring the workers' performances could provide useful data to improve the human-machine interaction and the workers' performance also thanks to the optimized design of the workplace. In this direction, the present research aims at presenting that the smart factory can be enhanced by human physiological response monitoring systems and the use of VR set-ups. In particular, the proposed technological set-up and the assessment methodology defined in this paper are good tools to concretely implement such framework in modern factories. The research describes how the smart factory can be enhanced by human physiological data monitoring thanks to a proper technological set-up to analyse the perceived comfort of workers in terms of physical ergonomics and mental workload, and include the assessment of the human-related aspects in the design of manufacturing systems.

The answer to Q2 can be found in the use of motion capture technologies to collect data about real workers actions and to digitalize them to integrated in the digital twin of the factory to design and program the factory itself in a dynamic way. The industrial case studies demonstrated its application and feasibility in real contexts. On the basis of the experimental results, different product configurations and activity workflows were tested to define the best one in relation to the execution time.

### 1.3. Approach

The research approach for the definition of the Operator 4.0 framework is based on three stages: (1) creation of the digital twin of the real factory, (2) monitoring of human physiological response of workers, and (3) human factors assessment.

The digital twin refers to a digital representation of physical assets, processes and systems able to replicate the behaviour of the real system, which can be used for various purposes. It integrates artificial intelligence, machine learning and software analytics with collected data and company knowledge to create living digital simulation models that update and change as their physical counterparts change (Grieves, 2014). A digital twin continuously learns and updates itself from multiple sources to represent its near real-time status, working condition or position. The human physiological response analysis is based on the, monitoring of the workers' performance, actions, reactions and well-being. Finally, the human factors assessment allows understanding how people are effectively working, how they are moving into the workspace, how they are using tools and resources, and whether they are living stressful conditions, with the final aim to better design the workspaces. For the detection of the critical conditions, the research proposes: (1) a protocol analysis to analyse the workers' perceived experience during job execution, based on a reference model for the analysis of physical and cognitive ergonomics, and (2) a technological set-up for human monitoring, suitable for industrial scopes. The target audience is represented by designers and engineers of Industry 4.0 systems.

In particular, the proposed technological set-up has been defined to achieve three main goals: (1) to monitor the operators' safety and physical and mental workload into an industrial environment, considering both the real factory and its digital twin; (2) to improve process performance and the overall process quality, taking into account the workers' actions, reactions, needs and demands; and (3) to avoid bottlenecks due to human errors or late responses causing process delay or machine downtime.

The research application particularly focuses on manufacturing processes, more specifically on assembly operations. Assembly tasks are still frequently managed by human operators, mainly because complex assembly operations are hard to automate or their automation would be very expensive and not convenient for low volumes. In this context, the workstation features and layout have a significant impact on process efficiency, overall product quality, and workers' wellbeing. Moreover, the different expertise of operators has a great influence on the results in terms of process time and product quality. In this context, designing intuitive and ergonomic workstations will help also novice workers to easily achieve the performances of expert workers by an increased usability and ad-hoc supporting system features. Actually, novices and experts are good and bad at different things and make different types of errors (Gredler, 1997). For instance, novices tend to lack awareness of errors and omissions and they need to continually check solutions and assumptions; while experts can use strong self-monitoring skills. Since the cognitive requirements for expert and novice workers are different, the proposed monitoring system allows to understand the current conditions of the specific worker, expert or novice, and to re-configure the working environment according to its specific needs.

In the smart factory context, the proposed approach can be used for real-time monitor the workers actions and to intelligently reconfigure the machine behaviours (e.g., process regulation, alarms, physical interaction effectors) or information provided to the workers themselves (e.g., interface information, additional task demand) to optimize the human-system cooperation and to generate more efficient processes. The digital twin is useful not only for system design and optimization, but also for continuously simulating the systems and providing real-time feedback during real manufacturing process. The proposed approach is presented in details in Section 3.1.

### 1.4. Equipment

The monitoring system consists of an eye tracker, to investigate the visual interaction with the working environment, tools and interfaces, and a biosensor that monitors the multiple vital parameters providing a synthetic overview of the health status (i.e., heart rate, heart rate variance, temperature, breathing rate) and physical stress conditions (i.e., activity type, trunk flexion angles ± 180°, body acceleration on the 3 axes). The proposed set-up can be also merged with digitization trends and hardware/software-in-the-loop approaches, according to which industrial system features can be easily simulated, tested and optimized virtually, before the real system creation (Harrison, Tilbury, & Yuan, 2012).

## 2. Related works

### 2.1. The Industry 4.0 background

Collaboration between humans and machines tends to include workers, robots, and other intelligent entities to originate a sort of holistic integration, along different levels of abstraction and coordination (Hadorn et al., 2015). Several recent works focused on the definition of symbiotic industrial frameworks, in which human workers and artificial systems dynamically adapt to each other and cooperate to achieve common goals (Romero et al., 2016).

According to this view, machines and algorithms become the means for workers to continue to work instead of being replaced (Ferreira, Doltsinis, & Lohse, 2014), to accommodate issues related to ageing (Peruzzini & Pellicciari, 2017a), disabilities or inexperience (Romero, Noran, Stahre, Bernus, & Fast-Berglund, 2015), and to increase skill match, comfort and wellbeing (Fiasche, Pinzone, Fantini, Alexandru, & Taisch, 2016). In this context, the analysis of how humans interact with machines and which is the quality of their work from a physical and mental viewpoint is crucial to define new working modalities, to optimize the factory flows, and to design the human-centred workplace tailored on the workers' needs and process requirements (Romero et al., 2016). The final goal is to improve process reliability and efficiency, and company productivity. Several works recently analysed the need of a human-centred approach for the future industry (Stock & Seliger, 2016). Moreover, current jobs in manufacturing are facing high risk for being automated to a large extent; the number of workers is decreasing and the remaining manufacturing jobs are containing more knowledge-based and cognitive work as well as more short-term and hard-to-plan tasks. The workers increasingly have to monitor automated equipment, being integrated in decentralized decision-making, and participating in engineering activities as part of the end-to-end engineering. In this context, Industry 4.0 holds a great opportunity for realizing a sustainable industrial value creation on all three sustainability dimensions: economic, environmental, and social, including people (Stock & Seliger, 2016).

Furthermore, numerous researches focused on the description of the technological solutions enabling interoperability and data sharing (i.e., smart products and connectivity issues, smart machines, Internet of Things (IoT) applications for industry (Whitmore, Agarwal, & Da Xu, 2015), cyber-physical systems (CPS) (Brinzer, Banerjee, & Hauth, 2017), embedded technologies to enable product-related services and methods of data acquisition and elaboration (Toro, Barandiaran, & Posada, 2015). They demonstrated how advanced digital technologies could validly help people to interact with products and machines, to work better and more efficiently, and return to or be incorporated into the modern manufacturing workforce. Meanwhile, technical developments and interaction technologies among components, machines and people will make the production systems more lean, integrated, agile, traceable, and adaptable (Romero et al., 2015).

In the modern industrial scenario, manufacturing enterprises, and in particular the smart factories, should pay a greater attention to socio-technical aspects through interconnections at different levels (Jantsch, 1972), including the assessment of the human-machine interaction (Wittenberg, 2016) and dynamic organization of work roles through adaptive and proactive behaviours (Griffin, Neal, & Parker, 2007) However, there is a lack of structured methodologies and guidelines to transform ideas into practice and concretely apply human factors to the design of industrial workspaces (Peruzzini & Pellicciari, 2017b). Therefore, the socio-technical transformation towards the smart factory will need new design reference models according to this new human-centric perspective focused on the assessment of the workers' actions, behaviours, perceived comfort, and quality of work from a physical and cognitive point of view (Chen, Khoo, & Chen, 2015).

### 2.2. Analysis of human factors for sustainable industrial system design

Human factors are fundamental in industrial engineering, especially when human-system interaction occurs. However, traditional human-centred approaches are based on the late assessment of ergonomic performances, rather than on a proactive analysis able to effectively support engineers during system design and workers' decision-making during operations.

Conventional human-centred design (HCD) approach emphasizes on the inclusion of human factors in machine and system design in order to respond to physical, psychological, social and cultural needs of human beings (ISO 9241–210, 2009). HCD concept is based on a framework that puts the user at the centre of the design process and aims at developing creative solutions to problems by involving the human perspective in all steps of the problem-solving process. Human involvement typically takes place in observing the problem within context, brainstorming, conceptualizing, developing, and implementing the solution, so that HCD refers to research about how human psychological, social, physical, and biological characteristics, influence the interaction between the users, specifically the workers, and the surrounding environment, represented by tools, machines, systems, tasks, jobs, and workspaces. The final scope is to design them for a safe, comfortable, and effective human use.

In this context, adopting a HCD approach means analysing human factors to understand human behaviours and performances while interacting with socio-technical systems, and the application of the understanding to the design of interactions (Wilson, 2000). More specifically, the design of human–machine interface (HMI), defines several parameters to evaluate in order to guarantee workers' safety and wellbeing and to avoid health problems as suggested by the ISO 11228 standards (ISO 11228–1, 11228–1, 11122, 2003; ISO 11228–2, 11228–2, 21122, 2007; ISO 11228–3, 11228–3, 1122, 2007). ISO 11228 standards give a good reference on ergonomics and comfort evaluation and its parameters can be synthesized in a postural load index that represents the ergonomics level of each examined posture. In this context, workplace wellbeing relates to all aspects of working life, from the quality and safety of the physical environment, to how workers feel about their work, their working environment, the climate at work and work organization (ILO, 2016). The aim of assessing the workplace wellbeing is to make sure workers are safe, healthy, satisfied and engaged at work. Indeed, workers wellbeing is a key factor in determining an organisations' long-term effectiveness and assuring high productivity levels.

Enterprises and organizations are increasingly recognising the need to take the wellbeing of their workers seriously. A lack of recognition on the need to promote workers wellbeing may give raise to workplace problems, such as stress, bullying, conflict, alcohol and drug abuse and mental health disorders (ILO, 2016). The literary review suggests different methods to investigate human-machine interaction. Ergonomic analyses are traditionally founded on objective or subjective evaluation methods. Objective methods are based on direct observation of users and task analysis, through which experts evaluate the assumed postures step by step and provide an objective assessment of physical exposures. The well-known adopted methods are: NIOSH lifting equation (Dempsey, 2002), Ovako Working posture Analysis System (OWAS) (Karhu, Harkonen, Sorvali, & Vepsalainen, 1981), OCRA (Occhipinti, 1998), Rapid Upper Limb Assessment (RULA) (McAtamney & Corlett, 1993), Rapid Entire Body Assessment (REBA) (Hignett & McAtamney, 2000), Loading of the Upper Body Assessment (LUBA) (Kee & Karwowski, 2001) or the most recent Workplace Ergonomic Risk Assessment (WERA) (Rahman, Rani, & Rohani, 2011). Subjective methods focus on the analysis of the physical response of workers' involved in the tasks by the subjective evaluation of efforts and discomfort during task execution. The most common adopted methods are: the Rated Perceived Exertion (RPE) method, based on the Borg's scale (Kim, Martin, & Chaffin, 2004), and the Body Part Discomfort (BPD) (Lin, Wang, Drury, & Chen, 2010). However, these methods do not provide any information about the wellbeing perceived by workers and the related stress caused.

In this direction, the concept of perceived comfort can be defined as the measure of the "level of wellbeing perceived by humans when interacting with a working environment" (Kuijt-Evers, Groenesteijn, De Looze, & Vink, 2004). This is a combination of postural comfort, physical stress, and cognitive workload. The mixture of outputs is usually hard to detect and measure because of the reciprocal effect of each item and the influence of multiple factors: the characteristics of the surrounding working environment, the task complexity, the individual capabilities, and the subjective impression and judgments. Over the past 15 years, a lot of papers dealt with comfort and discomfort of industrial workstations, as presented in a recent review (Manivel, Arun, Sedhu, & Arjun, 2017). On one hand, it has been demonstrated the relationship between subjective perception of comfort or discomfort feeling and the external factors (Galinsky, Swanson, Sauter, Hurrell, & Schleifer, 2000); on the other hand, some works tried to quantify the relation between the environmental and physiological factors and the perceived comfort (Hamberg-van Reenen et al., 2008). Quantification of this relation is usually due to the combination of behavioural and cognitive responses in the perceived comfort. According to the human-machine interaction theories, information and meanings flow from the machine/system to the users in different ways (Norman, 1998). Recently, Vink and Hallbeck (2012) proposed an interesting schematization of the mechanism of comfort/discomfort perception that comes from the Moes' model (Moes, 2005). The model considers the sensory input, the type of activities (tasks), the effect on different bodily regions, the effect of the system environment on comfort, and the physical loading. According to this model, human-machine interaction can be seen as the result of the "contact" (also a non-physical contact, like a signal or a procedure) between the worker, the system and the task. As a consequence, the perceived wellbeing can be defined only by directly monitoring human actions and feelings, and relating them with task execution, environmental features, and their change over the time.

About visibility aspects, the SAE J817 standard can be validly considered (SAE J817, 1991). It mainly refers to serviceability and maintenance task assessment, but it well fits also assembly tasks and can be successfully used, with minor adjustments, also by manufacturing companies which assembly their machinery or other manufacturing tasks of various engineered products. According to SAE J817, systems are assessed in terms of location, access, operation and other miscellaneous considerations. The operation category has several subcategories (e.g., component checking, lubricating and cleaning) and each operation needed is given different scores (the easier the maintenance operation the better score it will get). The SAE regulation indicates the maximum points for each category. To obtain the maintainability score, all the scores from performing the maintenance operations must be multiplied by a quantity multiplier and a frequency multiplier according to the maintenance interval (e.g., 10 h – daily, 50 h – weekly, 100 h – semi-monthly, 250 h – monthly, 500 h – quarterly or as required, 1000 h – annually). Finally, the human interaction is assessed according to four factors: location reachability, object accessibility, operation type, and use of supporting devices.

To sum up, comfort is a subjective output, but it strongly depends on external conditions and interaction with interfaces, tasks and workstation features. In this context, monitoring and objectifying the interaction environment and the human behaviours allow to match objective data with the subjective comfort impressions, expressed by users, in order to find a correlation with the workstation features and to define the design guidelines for improving the workers' comfort level.

Several experimental set-ups based on motion capture have been defined for real-time monitoring of workers' ergonomic performances (Battini, Persona, & Sgarbossa, 2014; Vignais et al., 2013). Nevertheless, usually data are captured and workers' postures analysed when design has been completed on physical prototypes or final workstation in order to verify the achievement of the expected performance. If targets are not achieved, long and iterative optimization loops are usually generated in order to converge to an optimal solution, according to the traditional design cycle (Abras, Maloney-Krichmar, & Preece, 2004). As a consequence, they usually require a great deal of effort and an expensive physical mock-up, since at that stage modifications are time-consuming and expensive. A valid method to anticipate the analysis of human factors to the design stages is based on the use of virtual prototypes by the so-called digital human models (DHMs). DHMs are 3D anthropometric manikins consisting of an interior model of the human skeleton and an exterior model of the human body shape, which are usually integrated into 3D software toolkits for ergonomic analysis. They usually adopt forward and inverse kinematics algorithms for simulating postures and movements according to the given position of the manikin in the space. Quite similar human models for structure and functioning included into different software tools are available on the market, for general or specific purposes. The most common tools for industrial applications are Dassault Systemes' SAFEWORK model, included in CATIA and DELMIA products (Chang & Wang, 2007; DELMIA ERGONOMICS, 2017), and JACK model available on Siemens/Technomatix products (JACK, 2017). They allow biomechanical analyses and include some of the objective ergonomic methodologies for postural analysis (e.g., RULA, OWAS, etc.). RAMSIS model is specifically oriented to automotive product ergonomics (RAMSIS, 2017), while MADYMO (MAthematical DYnamic Models) to automotive crash simulations (MADYMO, 2017) and SANTOS model to military purposes (SANTOS, 2017). Other tools like 3DSSPP (3D Static Strength Prediction Program) (3DSSPP, 2017) and Anybody Modeling System (ANYBODY, 2017) specifically address biomechanical data for manual material handling. These tools allow simulating the realistic sequence of tasks on virtual prototypes even before the facilities are physically in place, and promoting a preventive ergonomic assessment. However, a lot of effort is required for preparing reliable simulations, since software handling is complicated and time-consuming and the accuracy of results highly depends on the position assumed by the virtual manikins and the simulated interaction with the virtual world (Chaffin, 2007).

More recently, virtual reality (VR) technologies can provide immersive simulating environment, reproducing the real factory, where users can also interact with digital objects by peripheral devices such as motion tracking systems and haptic interfaces. VR technologies to easily support reachability and visibility analysis, as well as visual inspection by using virtual models in immersive modality to make users directly simulate task execution. Several VR set-ups have been created to simulate and assess different aspects of manual operations in manufacturing workplaces (Jayaram, Jayaram, Shaikh, Kim, & Palmer, 2006; Wang et al., 2007). Honglun, Shouqian, and Yunhe (2007) used a virtual human model to reproduce the real human characteristics in virtual environments for product ergonomics analysis and demonstrated that digital simulations allow to detect design problems in advance, with the reduction of time and cost in prototype making; Hu et al. (2011) demonstrated the effectiveness of VR simulations for industrial workplace simulation; Abidi, El-Tamimia, Al-Ahmaria, Darwisha, and Rasheeda (2013) performed ergonomics analyses of a sport utility vehicle in a semi-immersive virtual environment to make users aware about their own feeling inside the real car; Aromaa and Vaananen (2016) proved the importance of using virtual prototypes in human-centred design supported by virtual reality environment to assess visibility, climbing, postures, space, reach and use of tools. From the various studies, it can be proved that VR offers flexibility to designer to test the different design alternatives, without the building of physical prototype, saving time and cost of product design. VR is demonstrated to be useful to replicate the interaction environment when data about tasks execution and users' behaviours can be collected easier than on real workstations and on virtual prototypes. Although VR supports qualitative evaluations based on direct observation of workers and interviews and represents a valid method to anticipate the analysis of human factors from the design stages, it lacks of structured evaluation methodologies and procedures to measure and assess the perceived comfort in the users involved.

### *2.3. Human physiological response monitoring*

The Operator 4.0 response during a specific task execution can be analysed and objectified by monitoring his/her physiological response in term of the so-called user experience (UX). ISO standards defined the UX as "a person's perceptions and responses that result from the use or anticipated use of a product, system or service", including users' emotions, beliefs, preferences, perceptions, physical and psychological responses, behaviours and accomplishments that occur before, during and after use (ISO 9241–210, 2009). The ISO standard also lists three factors that influence UX: system features, user's characteristics, and the context of use. The research proposes to monitor workers during task execution and interaction with systems and machines in order to correlate the perceived UX with objective parameters, in order to find out some relations and to detect and prevent possible discomfort and stressful conditions for the workers. Measuring workers' physiological response allows creating knowledge about how they are interacting with the industrial workplace thanks to objective data. Such knowledge can be used to design a novel human-centred smart factory, suitable to interact with the Operator 4.0.

According to the scientific literature review, the main set of physiological parameters to be used to measure the UX are: heart rate (HR), heart rate variability (HRV), breathing rate (BR), pupil dilatation, eye gaze, and eye blinks.

Heart monitoring is one of the most common methods used in medical and fitness contexts. Nowadays, it is quite simple and cheap thanks to the simplicity of measurement and low cost sensors. In particular, the measurement regards heart rate (HR) and heart rate variability (HRV). Previous researches showed the correlation between HR and HRV with the physical and mental workload (Mulder, De Waard, & Brookhuis, 2004).

Also the breathing rate (BR) has been found as a good indicator for stress detection in conjunction with other physiological measures (Labbé, Schmidt, Babin, & Pharr, 2007).

About eye tracking, pupillometry and electrooculography are nowadays widely diffused, due to the increased performance of eye-trackers, the more ergonomic devices (i.e., glasses) and gradually cost reduction. The most frequently parameters used are Eye Gaze (EG) and pupil dilatation (D), which provide information on an individual's attention source and stress (Sharma & Gedeon, 2012). Several studies focused on eye tracking application for human workload analysis and the correlation between eye-based signals and human factors. Martin, Cegarra, and Averty (2011) applied eye tracking to analyse mental workload characteristics in air traffic controllers' activity; Sharma and Gedeon (2012) found out that eye gaze and pupil dilatation provide useful information on the individual's attention source and stress; also Marquart, Cabrall, and De Winter (2015) found that the human workload increases with the increase of the blink latency and, on the contrary, decreases with the increase of blink duration and gaze variability. Results confirmed that eye tracking technique is a powerful approach to study mental workload during a complex activity.

Looking at the literature, other indicators could be included, but they were not considered in the present study due to intrusiveness of the monitoring devices and the lack of robust solutions to be used in industrial application. Among them: analysis of the electro-dermal activity (EDA), also called galvanic skin response (GSR), consisting of the measurement of electricity flow through the skin of an individual that causes continuous variation in the conductance of the skin; electro-encephalography (EEG) based on brain activity measurement; and electro-myography (EMG) that shows electrical activity produced by active muscles, and respiration measurements.

In addition, thanks to sensors' miniaturization and affordability, body worn activity recognition has gained popularity, especially using inertial measurement units (IMUs) and, in particular, accelerometers. These sensors demonstrated good potentiality in the recognition of the activities typology. However, the number of sensors to be worn has to be minimized to limit the intrusiveness and not to interfere with activity performance. Existing devices already include accelerometers and gyroscopes, like smart watches and smartphones (Moschetti, Fiorini, Esposito, Dario, & Cavallo, 2016). A review of different classification techniques used to recognize human activities from wearable inertial sensor data was presented by Attal et al. (2015).

However, due to its complex nature, it has been found that the subjective stress can be investigated more precisely by the combined measurement of multiple parameters, to achieve a reliable evaluation of both physical and mental stress in an objective way (Popovic, Stikic, Berka, Klyde, & Rosenthal, 2013). For instance, a workload assessment tool (i.e., PHYSIOPRINT) based on the combination of EEG and ECG has been introduced to distinguish between different workload types relevant for driving by incorporating complementary sensor modalities recorded in real-time on a realistic driving simulator. In this direction, also Zongmin, Damin, Xiaoru, Chen, and Huan (2014) developed an ergonomic evaluation model applied for mental task design of aircraft cockpit display interface, which seems able to effectively discriminate and predict the levels of mental workload, preserve the selected indexes by avoiding information loss, and obtain a stable discrimination result. Ohtsuka et al. (2015) suggested a method for mental workload

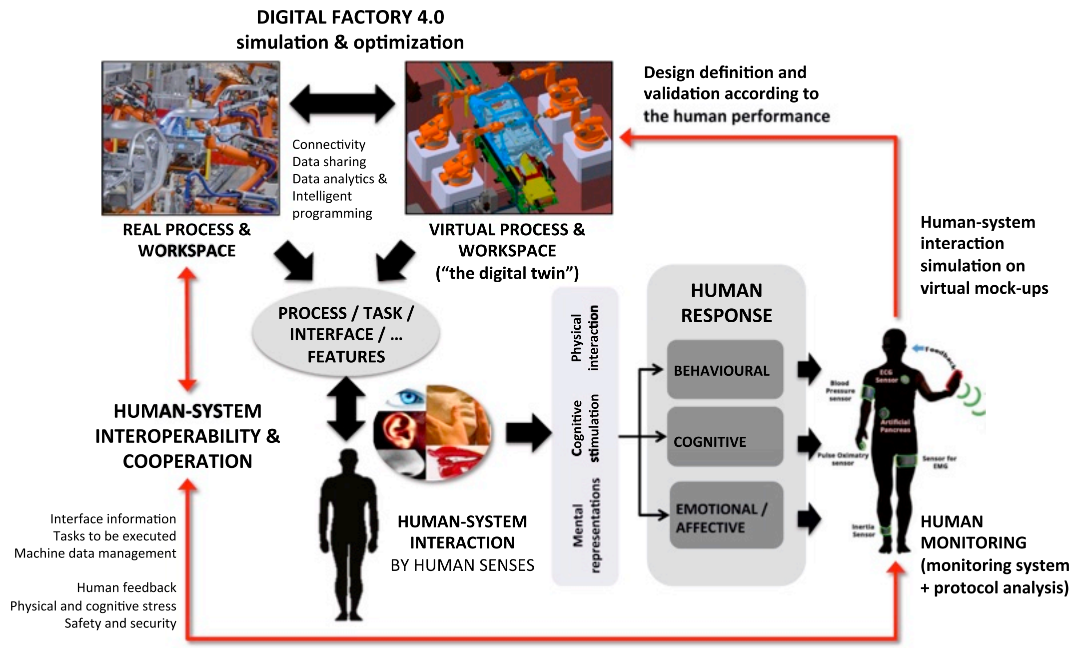



**Fig. 1.** The overall framework of the Operator 4.0 approach.

estimation during motorcycle driving, based on eye tracking and, specifically, the monitoring of saccades (duration and amplitude) and fixation. Finally, Paletta, Pittinoa, Schwarza, Wagnerb, and Kallusb (2015) used eye tracking for the analysis of the navigation paths in retails during shopping activity, finding that the specific context and the cause of arousal lead to different reactions of human psychophysiological system as well as in eye movements.

On the other hand, information about the users' behaviours and physical reactions should be coupled with the individual cognitive workload and situation awareness (Endsley, 1995). For this purpose, behavioural and cognitive methods can be usefully considered to understand how to aggregate the information collected about users' actions and relate to their perceptions and hidden cognitive processes. One of the most common methods is the NASA task load index (NASA-TLX) (Hart & Staveland, 1988). It is a subjective workload assessment tool to perform subjective workload assessments on operators working with human-machine interface systems. It incorporates a multi-dimensional rating procedure to derive an overall workload score based on a weighted average of ratings on six subscales (i.e., mental demand, physical demand, temporal demand, performance, effort, frustration) (Hart & Staveland, 1988). In the present research it is used at the beginning of the study, to "calibrate" the system to take into account the specific personal attitudes of each user and to set the system in order to find out a correlation among the monitored vital parameters and the subjective workers' experience.

As a conclusion, human physiological response monitoring has the potential to be integrated into the evolved smart factory architecture, to effectively receive data about the production plants. Data can be collected from machines, but similarly also from human beings and be merged with system data. The consolidated amount of data can create unique factory knowledge able to drive process configuration and smart adaptation of manufacturing systems, according to the humans' behaviours and stress conditions (Peruzzini, Mengoni, & Raponi, 2016). Furthermore, quantitative analysis methods can be adopted both in real and into virtual environments, representing the factory digital twin, with the purpose of real-time and continuous ergonomic evaluations. Further developments of VR tried to overcome the lack of perception of weight or collisions, providing users with a multisensory feedback, that has been proved as essential for simulating certain manufacturing tasks (Lawson, Salanitri, & Waterfield, 2016).

As far as industrial applications, technologies require to be relatively cheap, un-intrusive, and robust enough to be wired into an industrial environment (Sharma & Gedeon, 2012). The number of parameters has to be optimized according to the specific measurement objectives. Specific industrial survey and technological benchmarking have to be carried out to define the suitable set of parameters to be monitored.

## 3. Research approach

### 3.1. The Operator 4.0 general approach

The present study focuses on defining an Operator 4.0 framework where the human-system interaction is studied and understood by monitoring the physical and cognitive workload of workers by objective and subjective measures. For this purpose, a structured procedure for the human monitoring in the context on Industry 4.0 has been defined according to the main parameters defined in literature. Moreover, a proper technological set-up has been recommended to apply the proposed approach to modern factories. The set-up includes a biosensor for physiological parameters monitoring, an eye-tracker for visual interaction analysis, a motion capture system for physical movement analysis, and subjective questionnaires. Stress analysis is not included in this study for the complexity of the integration of stress-related measuring tools in an industrial context (e.g., EEG, EDA-GSR). For instance, EDA can be suitable in industry, however this is more connected to ethical concerns more then that it is complex to assess.

Fig. 1 shows the overall framework of the proposed Operator 4.0 approach.

In the Operator 4.0 framework workers and operators can interact with real and digital systems. During this process, operators' physical and mental workloads are affected by system and process features as well as by external factors (e.g., task typology, frequency and duration; type of information or data to be processed or generated; type of supporting devices and tools). Workers produce a subjective experience depending on surrounding environment, individual skills and characteristics, task features, etc. Human beings generate a 3-layer response (behavioural, cognitive, and affective/emotional) according to the Norman (1998) model of interaction. Interaction responses are hard to detect and analysed, but they could be investigated and objectified by human physiological response monitoring by available technologies. In this context, the use of virtual objects is particularly useful when new workspace features, already not existing, have to be tested. The users' feedback generated during the interaction with the virtual world is used to define the most suitable workspace design, to validate different alternatives and to generate a socially sustainable workspace. Subsequently, the monitoring technologies are used also to monitor human interaction with real objects as a part of the industrial IoT. In this context, the human physiological response monitoring allows to understand the users' workload to leverage interoperability and cooperation with smart systems and to intelligently optimize process programming. For instance, it could help to define which, when and how information has to be provided, or to optimize task sequence or workspace features (i.e., geometrical layout, tool availability, lighting or thermal conditions) according to the human feedback (Cenni, 2003; ISO 10075–3, 10075–3, 1007, 2004). This architecture includes the workers as an active part of the Industry 4.0 scenario to promote process flexibility and realize real-time smart system configuration considering social sustainability.

According to the Norman's model of interaction (Norman, 1998), any human response is automatically generated in unconscious way during task execution, during information interpretation, or during physical activities, independently from activity type and nature. The human response depends on objective factors (e.g., environment layout, task features, available time) and subjective factors (e.g., human characteristics, skills, expertise, stress condition). Anytime a human being performs an action, his/her body and his/her brain generate behaviours, cognitive, and emotional feedback, as a combination of physical postures, actions, mental workload, impressions and usability, which affects his/her physical and cognitive workload contributing to the task performance as well as the mental stress (Wilson, 2000). The behavioural response generates the physical workload, which can be assessed by the analysis of the postural comfort, the physical stress and the muscular fatigue as proposed by Ma, Chablat, Bennis, Zhang, and Guillaume (2010). The cognitive response generates the cognitive workload, which can be assessed by the analysis of the mental stress that comes from numerous causes (e.g., environmental stressors, psychological stressors, life stress, fatigue and sleep disruption, work overload and pressure) according to Wickens, Gordon, and Liu (2004). The correlation between subjective feelings and objective data monitoring can be made by the NASA-TXL method (Hart & Staveland, 1988). As a consequence, the inclusion of human factors in production system design helps to understand human behaviours and performance interacting with socio-technical systems, and the application of that understanding to design of interactions. In a nutshell, the proposed approach is based on three main entities:

1. the creation of the digital twin of the real factory in order to anticipate system validation (e.g., machine design, functioning and performance; software development and control system management; machine and layout design; social aspects based on physical and cognitive ergonomics assessment and analysis of human-machine and human-human interaction);
2. the definition of a proper set-up for human physiological response monitoring to analyse the human behaviours, actions and reactions, and objectify the workers' experience. This set-up can be used both within real factory for real-time monitoring, and immersive virtual environments for preventive assessment of new design solutions;
3. the definition of a structured protocol analysis to assess human factors based on the correlation of the monitored human physiological parameters and the operators' behavioural and cognitive response and well as health conditions. This protocol includes: a set of metrics able to objectify human performances, a set of tools to be used for collecting data (e.g., vital sensors, eye-tracking, motion capture and localization devices), and a set of data analysis techniques (e.g., simulations on DHM, heuristic evaluation, video analysis).

The integration of human monitoring devices within the industrial IoT framework enables a wider data sharing among machines, control systems and workers, to enhance interoperability and cooperation. According to this approach, the generated cyber-physical factory model (i.e, the "new" digital twin) will include both machine and human data to better couple the real production system with its digital representation as a base for programming and optimization (Uhlemann, Lehmann, & Steinhilper, 2017). The model could be validly used to represent real processes and optimize their features.

### *3.2. The human physiological response set-up*

The research considers a set of parameters related to the selected available technologies, chosen on the basis of integration features with typical smart factory architecture.

The following vital parameters to be monitored have been chosen:

- Heart activity by heart rate (HR) and heart rate variability (HRV), to investigate physical and mental stress conditions;
- Respiration activity by breathing rate (BR) to detect physical stress and fatigue;
- Skin temperature (ST) to analyse the general physical comfort;
- Eye Gaze (EG) and pupil Dilation (D) to investigate the operators' visual interaction processes with devices, interfaces, machines or people;
- Postural acceleration devices (P) to monitor the body movements.

The study did not consider EMG and ECG due to the highly intrusive modalities of application (based on wearable sensors in numerous body areas) and the high probability of interference into industrial environments. Also EDA – GSR have not been considered since their measure is highly affected by environmental variables and changing conditions and reliable results can be obtained only in controlled environments such as labs (Boucsein, 2000), not suitable for industrial applications.

The technological set-up is composed by the following devices:

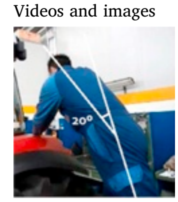
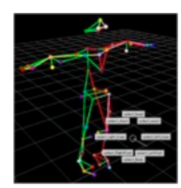
- a high-quality eye tracking system (i.e., Glasses 2 by Tobii);
- a multi-parametric wearable sensor for real-time vital parameters monitoring (i.e., BioHarness 3.0 by Zephyr);
- a video camera for video recording of operators' actions in the surrounding environment (i.e., GoPro Hero3). Issues like informed consent, confidentiality, and security were properly considered.
- a digital human modelling software (i.e., Tecnomatix Jack) for modelling the virtual environment and create the digital twin of the monitored operators;
- an optical motion capture systems (i.e., VICON Bonita cameras) and related software tools (i.e., VICON Tracker) supported the full body tracking of the operators' position and the digitalization of the tracked movements to be processed by software tools.

Table 1 shows the selected parameters and technologies for workers' monitoring. Such list of parameters merges together physical comfort, physiological response, and mental workload.

Concerning eye tracking, obtained data are considered very useful to monitor the human-system interaction and to correlate the eye-related data with human stress, mental workload and emotions. Furthermore, eye tracking technology has several advantages: the camera records the user point of view, it can be used on both real and virtual environments, and collected data can be integrated with EEG data to have a more compressive cognitive workload analysis. Obviously, the quality of the obtained results depends on the users' head movements and mental load have to be interpreted according to the specific field of application.

The multi-parametric wearable sensor allows to directly record human behaviours and physiological data, it is cheap and less intrusive for the user. In particular, it measures a set of useful parameters (i.e.,

**Table 1**
Selected tools for workers' monitoring in industry 4.0.

| Monitored parameters | Tool typology | Selected tool | Collected data |
|---|---|---|---|
| Eye Gaze (EG)<br>Pupil Dilatation (D) | Eye Tracker | Tobii Glasses 2  | Gaze plot, Heat maps, Pupil diameter  |
| Heart Rate (HR)<br>Heart Rate Var. (HRV)<br>Breathing Rate (BPM)<br>Skin temperature (ST)<br>Activity (VMU)<br>Posture angle (°) | Multi-parametric wearable sensor | Zephyr BioHarness 3.0  | HR diagram<br>HRV diagram<br>HR max<br>BR diagram<br>Activity diagram<br>Stooping on x-y-z axes |
| – | Video camera | GoPro Hero3 | Videos and images  |
| RULA score<br>OCRA index | Digital human modelling and simulation | Technomatix Jack | Digital human movements  |
| Human positions, postures and movements | Motion capture system | VICON Bonita cameras (no. 10) and VICON Tracker  | Sequence of movements on a virtual manikins  |

HR and HRV), which were found to be the most important markers to identify human stress in various conditions (i.e., mental task, high physical workload, stressful driving) and other common daily activities (Marquart et al., 2015). Furthermore, it also measures breathing activity by breaths per minute (BPM), body skin temperature (ST) to provide a more complete analysis of the health workers' conditions, and body activity level by means of the vector magnitude units (VMU) and the postural angular inclination (°) measured by means of accelerometers and gyroscopes. The VMU is the vectorial sum of activity counts in three orthogonal directions, while the postural angular inclination helps to define the physical comfort of the posture assumed by the worker.

Finally, the workers' video recording adds useful information about the executed actions and the surrounding environment. An external camera is used and recorded video is synchronized with the head view obtained by the eye tracker camera. Motion capture can be easily carried out into a virtual or a mixed environment, where simulation are carried out, while its adoption at the real shop floor is more difficult due to optical interfaces and the calibration issues into an industrial environment. Video analysis is also used to create a set of virtual images to be converted into a 3D human model by a DHM system. Issues like informed consent, confidentiality, and security were properly considered for video analysis.

The proposed technologies have pros and cons. On one hand, they are low cost and available, since they are properly of the research lab involved in the research. On the other hand, they are wearable, so they imply that the operators wear them, and this can cause a sense of annoyance or disturbance. However, the future real system industrialization can monitor the same parameters with less intrusive technologies, also embedded in the already adopted tools or in the personal protective equipment (e.g., safety helmets, protection glasses, gloves).

### 3.3. *The protocol analysis for human factor assessment in industry*

On the basis of the research background as presented in the previous paragraphs, a structured protocol analysis has been defined. It describes in a structured manner the types of analysis considered, the evaluation metrics, the collecting data methodologies, and the adopted technologies and tools for human physiological response monitoring.

Three main analyses have been defined:

1. *Postural analysis:* it measures the physical interaction and physical workload during task execution;
2. *Visibility and Occlusion analysis:* it measures visibility and accessibility conditions, considering both physical objects and delivered

**Table 2**
Protocol analysis for human physiological response assessment.

| Analysis | Evaluation metrics | Tools for data generation | Elaboration data technique |
|---|---|---|---|
| *Posture* | Biometrics measures (VMU)<br>RULA, OWAS, REBA | Video recording<br>Motion capture<br>Tecnomatix Jack | – Video task analysis<br>– Heuristic evaluation<br>– NASA-TXL questionnaire (1–7 score) |
| *Visibility & Occlusion* | – Heat Map, Gaze Plot<br>– Accessibility SAE assessment<br>– View Cones, Head Forward View | Tobii eye tracking<br>Motion capture<br>Video recording<br>Tecnomatix Jack | – Video task analysis<br>– Eye Tracking<br>– Heuristic evaluation<br>– NASA-TXL questionnaire (1–7 judge) |
| *Mental Workload* | – Biometrics measures (HR. HRV, BPM, ST)<br>– Perceived comfort (ease of use, mental workload)<br>– Heat Map, Gaze Plot, D | Zephyr Biosensor<br>Tobii eye tracking | – Vital parameters real-time monitoring<br>– Heuristic evaluation<br>– NASA-TXL questionnaire (1–7 judge) |

information on devices;

3. *Mental Workload analysis:* it measures the ease of use, cognitive workload, and simplicity of the tasks.

In order to carry out the above-mentioned analyses, a set of metrics have been selected:

1. Postural ergonomic measures carried out by RULA, REBA and OWAS techniques (properly selected according to the specific context of use and task typology);
2. Eye movement measures by heat maps and gaze plot;
3. Biometrics measures, such as Heart Rate (HR), Heart Rate Variability (HRV), Postural comfort (as angle of body inclination °), Breathing Rate (BPM), and the Activity level (expressed by VMU);
4. Perceived comfort level, expressed by a subjective questionnaire according to a 1–7 point scale.

As far as the postural measures are concerned, OWAS (Ovako working posture analysis system) is a time-driven field measure that provides a general assessment of the complexity of the task and its impact on the human posture. It considers the position of the main sections of the body (i.e., legs, arms, back) and the weight involved in the task. It provides a synthetic score identified with a colour according to the level of risk of the specific task, in four levels: acceptable risk (green colour), low risk (yellow colour), medium risk (orange colour) and high risk (red colour). In case of low risk you can improve the task to reduce the postural load; in case of medium risk some changes are required; in case of high risk, corrective actions are recommended urgently. REBA (Rapid Entire Body Assessment) provides a more detailed risk assessment with respect to OWAS, and is particularly suitable for standing working positions. It considers the position of legs, arms (upper and lower), trunk, wrists, and in addition the load or force involved, how manipulated are hold and the position stability. Also in this case, we obtain a score from 1 to 15, connected to an increasing risk level. From 1 to 3 the risk is very low, from 4 to 7 the risk is medium, from 8 to 10 the risk is high, from 11 to 15 the risk is very high and urgent actions are required. Finally, RULA (Rapid Upper Limb Assessment) is a posture-targeting method that allows easily calculating the musculoskeletal loads on the upper limbs. It measures the position of legs, arms (upper and lower, right and left independently), trunk, wrists, and neck. The RULA score ranges from 1 to 7 and, similarly to REBA, indicates the postural risk and need for corrective actions. RULA is more specific for the analysis of the upper part of the body with respect to REBA. The combination of the three measures was proved to effectively assess the quality of postural stress for workers involved in manufacturing industry.

Visibility and occlusion issues are jointly addressed by eye tracking and digital simulations. Heat maps and gaze plots are generated by a proper software toolkit. They are data visualizations able to communicate important aspects of visual behaviours of the users. Gaze plots show the location, order, and time spent looking at specific locations on the stimulus, whether physical or digital interfaces, printed documents, or videos. So the primary function of the gaze plot is to reveal the time sequence of looking or where we look and when we look there. Time spent looking, most commonly expressed as fixation duration, is shown by the diameter of the fixation circles. Heat maps show how looking is distributed over the stimulus. In contrast to the gaze plot, there is no information about the order of looking in a static heat map. Neither is the focus on individual fixations. Rather, heat maps are a visualization that can effectively reveal the focus of visual attention for dozens or even hundreds of participants at a time. Contemporarily, digital simulations allow visualizing view cones by proper tool functions. Results from both eye tracking and simulation are evaluated according to SAE accessibility guidelines, according to the specific context of application. SAE standards provide guidelines for accessibility evaluation in different fields; they were defined for vehicle industry but can be transferred also to other sectors. For instance, SAE J817 (1991) refers to serviceability and maintenance guidelines and well suited maintenance task analysis also for manufacturing products and systems; SAE J2364 refers to recommended practice navigation and guidance function accessibility while driving, and can be used for any driving activity, not only on on-road vehicles; SAE J287 refers to driver hand control reachability; SAE J1050 refers to field of view analysis. Each of them suggests which aspects have to be monitored and which scores have to be assigned. A matrix can be created where all scores for all aspects are summed up in order to highlight the most critical tasks.

Biometric measures are recorded and elaborated by a proper software toolkits, made available by Zephyr (https://www.zephyranywhere.com/resources/developer-user-tools). They allow to visualize data by charts or diagrams as needed and to synchronize the different feedback.

Finally, the subjective measure of the perceived comfort is defined by the NASA-TLX questionnaire. Users are asked to rate the six NASA-TXL categories for each executed task within a 7-points scale. These ratings are then combined to the task load index. The questionnaires is structured in six questions:

- How mentally demanding is the task?
- How physically demanding is the task?
- How hurried or rushed is the pace of the task?
- How successful are you in accomplishing what you are asked to do?
- How hard do you have to work to accomplish your level of performance?
- How insecure, discouraged, irritated, stressed, and annoyed are you?

The proposed metrics can be measured by different technologies and techniques, specifically:

1. Digital human modelling software;

2. Eye tracking;
3. Multi-parametric biosensor;
4. Video analysis;
5. Heuristic evaluation by experts;
6. Questionnaire/direct interview.

Table 2 describes how the proposed protocol is structured: for each analysis, the collecting data methodologies, the evaluation metrics, and the adopted tools for data generation are indicated. About data collection, postural analysis is based on biomechanical and anthropometric data which are inferred by combining different techniques: video recording and motion capture (when possible) in the real factory, software simulation by Tecnomatix Jack and motion capture in the virtual or mixed environment. Visibility and occlusion data are collected by video recording, motion capture, and software simulation as well, but also eye tracking can be added to have more specific data about visualization maps and interface/object navigation modalities (when exactly operators look at during their work). The combination between eye tracking and biometrical data monitoring from the biosensor supports mental workload analysis, while data from the biosensor are also useful to detect specific emotional states of the workers in combination with the NASA-TXL questionnaire results (e.g., anxiety, physical stress, comfortable conditions).

Once data are collected, workers' behaviours and reactions are investigated by the most common investigation techniques used in HCD: heuristic evaluation based on users' observation and experts' assessment (Nielsen, 1994), direct interview and/or questionnaire, video task analysis by experts (Jordan & Henderson, 1995). Heat maps and gaze plots about eye tracking and biometric measures are also added. The combination of objective data with subjective data from NASA-TLX allows to calibrate the system and to find a correlation between objective facts and subjective impressions. For a specific workers' population, this correlation can be found at the beginning of the study as a sort of system calibration and can be avoided in the following analysis.

The combination of different techniques allows objectifying the workers' observation by capturing moment-to-moment interactions and supports experts in the analysis of human interactions. Not all techniques have to be necessarily used at the same time; for the specific context of use, only some of them can be used. Experts in ergonomics and human factors are involved in techniques and tools selected, case by case, in user observation and data interpretation on the basis of the protocol metrics.

### 3.4. The virtual simulation set-up for socially sustainable workplace design

In order to assess human physiological response before the creation of the real factory or to optimize an existing factory according to social sustainability principles, a high-fidelity virtual prototype of the workspace under investigation has to be created, simulating the entire production line or a specific workstation to be analysed. First of all, a 3D digital model is necessary. At the same time, human actions and task sequences have to be analysed. Analysis can be based on real users' observation at the shop floor or on virtual simulation within an immersive virtual or mixed environment. A mixed environment offers the advantage to combine real objects and virtual data in order to test design changes to existing systems, workstations or products. Virtual environments are used when the activity focuses on a completely new design. For the specific research, the Tecnomatix Jack software has been used for creating the virtual factory prototype merging the workspace digital mock-ups and virtual manikins replicating the operators' actions. A Vicon optical tracking system with 10 Bonita cameras has been used to track the users' movements both at the shop floor and in the University laboratories, and to virtually reproduce the users' movements. Tasks have been reproduced and simulated by virtual manikins of real workers monitored by motion capture. In the first case, generic manikins representing the target population based on the software libraries and considering different percentiles of the analysed population (i.e., 5p, 50p and 95p) are used. In the second case, personalized virtual manikin replicating the real user's features and actions. The DHM software was used in both desktop-based modality and VR-based immersive modality, where the virtual scene can be projected with active stereoscopic view and users can navigate into the virtual scene by having a more impressive simulation of the task execution. Video analysis was useful for task analysis and simulation, to support understanding the interaction modalities.

The virtual set-up used for simulation has been equipped with a Stewart large screen for rear projection (6x2 meters), two high-performance Barco Galaxy NW-7 projectors, active stereo glasses with active Volfoni Edge RF, two Nintendo Wiimote devices for interactive navigation, a Denon AVR sound system with Dolby surround. The system is managed by two powerful workstations with advanced Nvidia graphics cards and different software toolkits. The created virtual simulation set-up is shown in Fig. 2, arranged at the Virtual Prototyping Lab of the Modena Technopole, in Modena.

The combination of advanced simulation tools with high-quality immersive stereoscopic viewing and interaction devices allows reproducing virtual objects into a 1:1 scale, creating highly realistic simulations, and validating static and dynamic behaviours of systems from the preliminary design. Two or more users can be tracked in the virtual space to simulate also human-human interaction. In the meanwhile, users interacting with the virtual mock-up can be monitored by the human data monitoring systems and collected data (according to the proposed protocol) are used to observe the human behaviours, feelings and performances. The collected data about human behaviour can be used to in a twofold manner:

1. to improve the workspace design (e.g., layout reconfiguration, task sequence modification, different location of specific objects or parts to be assembled, different product configuration to support the design for assembly);
2. to compare data collected on real factory to validate the impact of corrective actions.

In the present research, the use of a virtual large-screen immersive set-up allows having a collaborative workspace involving multiple users and combining the analysis of physical and cognitive aspects by analysing virtual and real users' behaviours, and measuring data according to the proposed protocol. The same application could be also visualized by an Head Mounted Display (HMD).

## 4. The industrial case study

### 4.1. Case study description

The case study has been developed in collaboration with CNH Industrial, a global manufacturer of agriculture and industrial vehicles, with more than 64 manufacturing plants and 50 research and development centres in 180 countries. It designs and produces tractors, trucks, buses, on-road and off-road powertrain solutions, and marine vehicles. The use case focused on the application of the proposed approach to assembly workspace, in order to optimize the operators' sequence of tasks and workload, with the final scope to realize a socially sustainable working environment. The agricultural market was selected for the research, since it was considered one of the most promising business areas of CNH Industrial for the near future. A specific product and a specific workstation were selected for the study. In particular, one of the most widespread tractors produced by the company has been chosen, and a set of assembly workstations were selected on the basis of three main indicators: time of execution, frequency of bottlenecks and criticalities, and variability in task execution. We choose the longest tasks, during which the highest number of problems is statistically registered, and where operators can follow different task sequence. In particular, the paper presents the results achieved on one specific task,

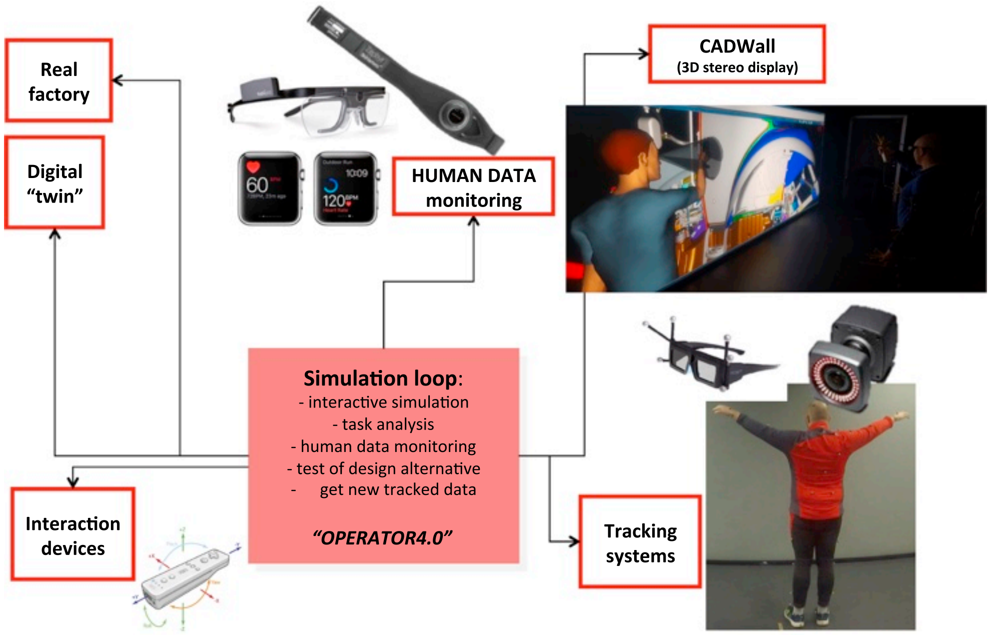



**Fig. 2.** The virtual simulation set-up for socially sustainable workplace design.

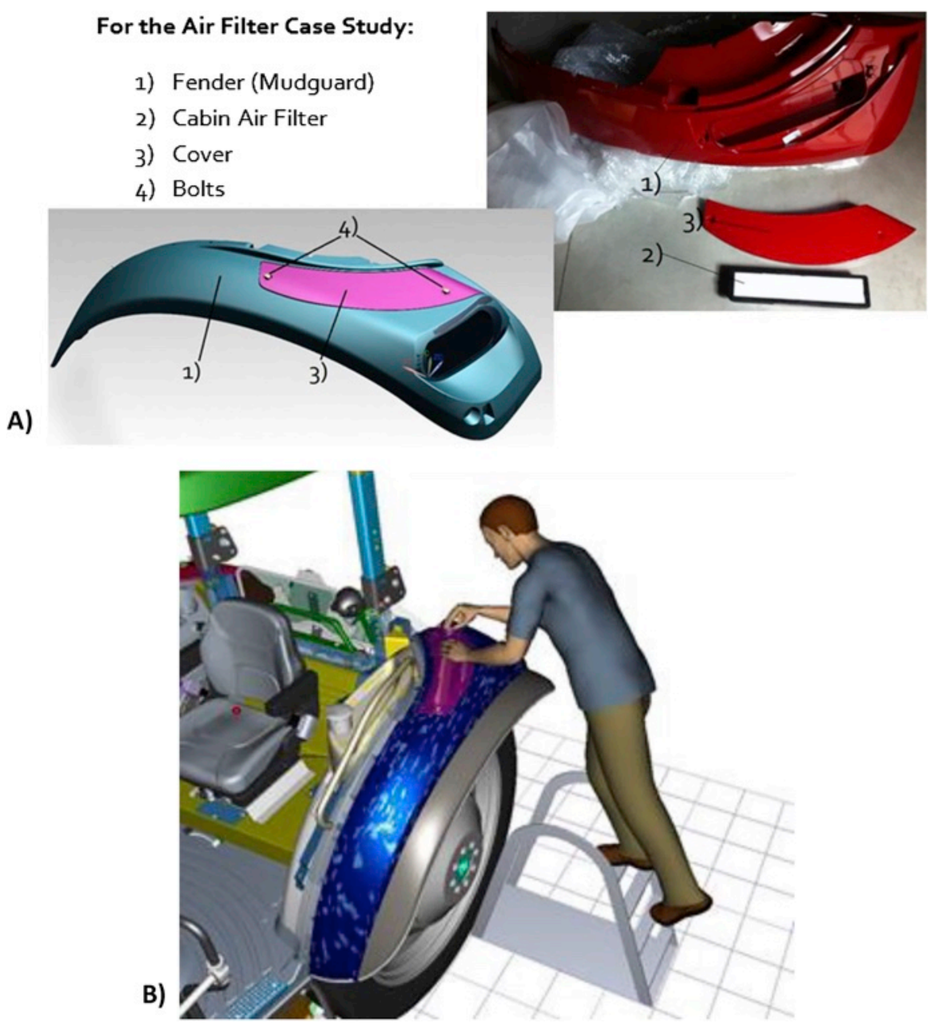



**Fig. 3.** The case study – assembly of the air cabin filters (A. components involved, B. position of the operator).

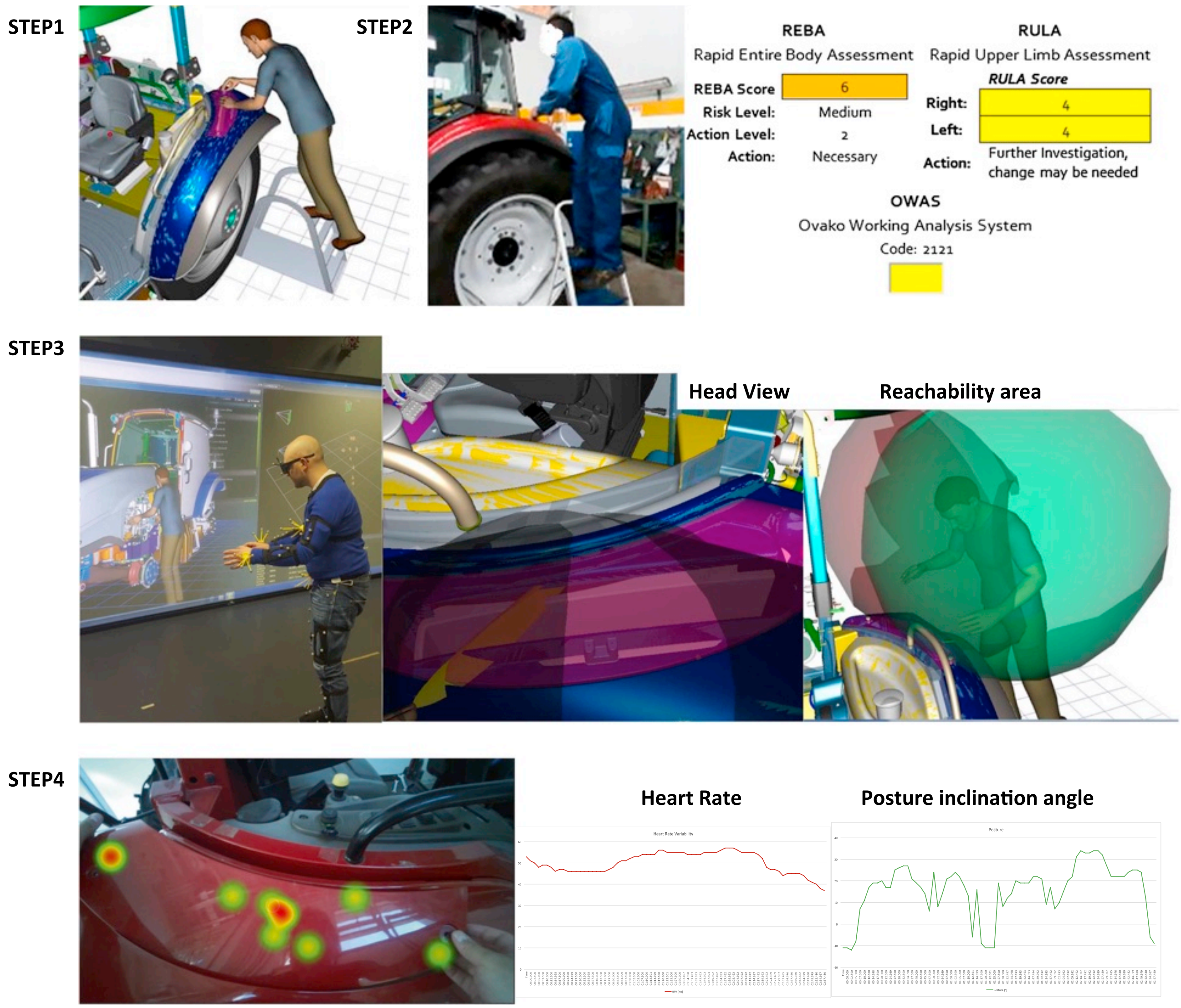



**Fig. 4.** Experimental testing for the case study (step 1–step 4).

related to the assembly of the air cabin filters: it requires a ladder, the operators' movements are complex and affected by the uncomfortable position, a huge quantity of components are involved, and it take a long time. Fig. 3 shows the components involved in the case study related to the air cabin filters' assembly.

### *4.2. The experimental procedure*

Experimentation was based on the adoption of the procedure described in section 3 to the above-mentioned case study. In particular, the workspace virtualization, the implementation of the proposed human monitoring data set-up (described in Section 3.2), and the adoption of proposed protocol analysis (described in Section 3.3). The experimental procedure can be synthetized in the following steps:

Step 1. Creation of the digital twin of the real workstation: the digital model was realized on the basis of the analysis of the real tasks on the real factory;
Step 2. Task analysis: real users were observed with the aim to find out the human-system interaction flow and the interaction modalities;
Step 3. Task virtualization and virtual simulation on digital mock-ups: virtual simulation allowed to emulate the real users interaction thanks to virtual mock-ups and virtual manikins, reproducing the users' actions into the virtual world;
Step 4. Human physiological response monitoring by the proposed set-up within both the real environment and the virtual environment: operators were monitored during task execution and their physical and mental workload was inferred by vital parameters' monitoring in order to understand how comfortable they are working and how stressful the interaction is;
Step 5. Application of the proposed protocol to assess the social performance quality according to the protocol metrics, referring to four areas of investigation: posture, visibility and occlusion, mental workload, and emotional analysis;
Step 6. Simulation of design alternatives on the digital mock-up: a variety of design alternative were validated in a quick and easy way in order to define the more sustainable design (see Fig. 4).

According to posture analysis, all three proposed assessment techniques (i.e., RULA, REBA and OWAS) were used. They were calculated on both real users and virtual manikins, reproduced by the motion capture. Visibility and occlusion assessment has been carried about by SAE J817 Standards (1991), even though the tasks referred to assembly tasks.

Four experts carried out the assessment based on the proposed

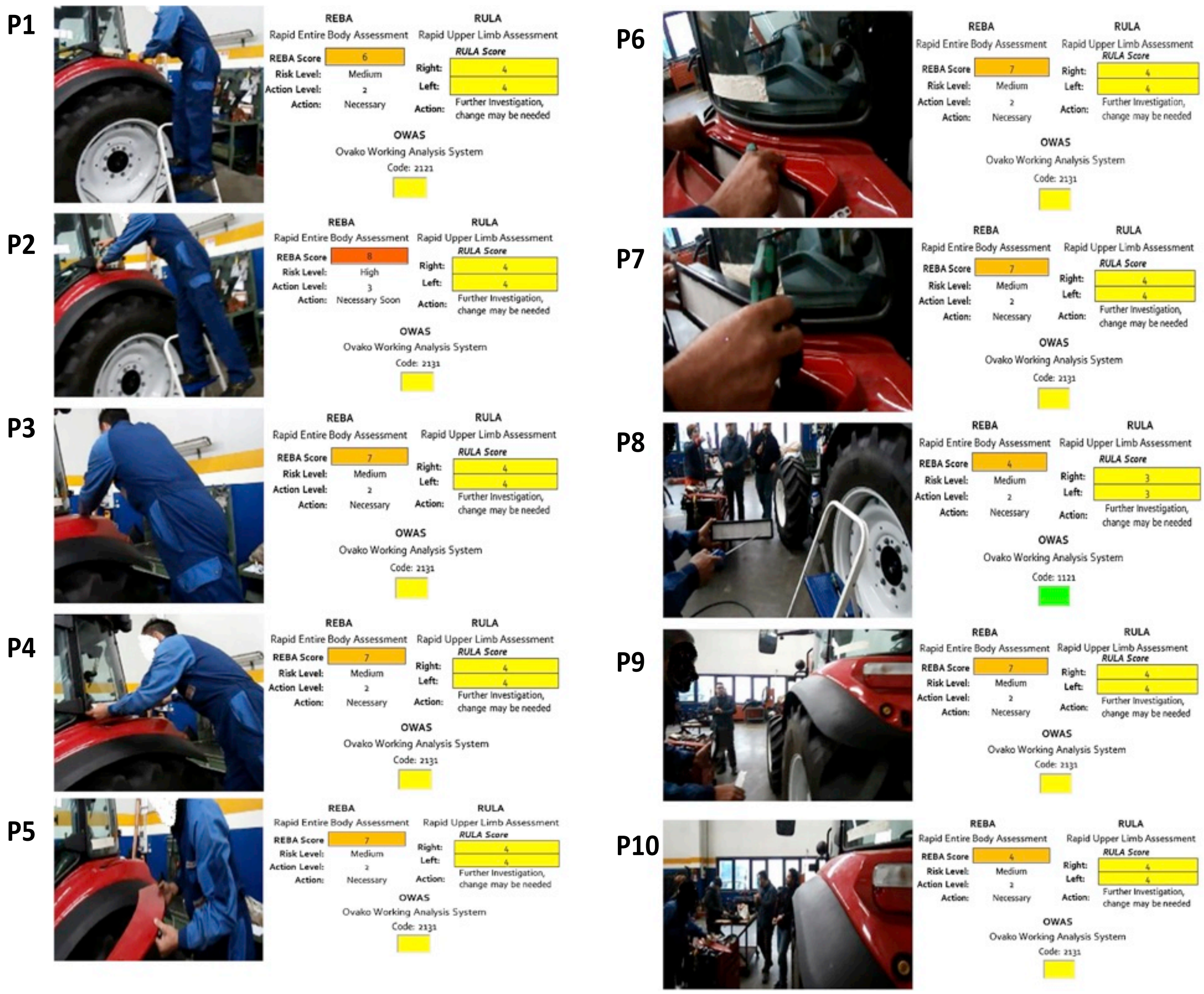



**Fig. 5.** Results about posture analysis on real user observation at the shop floor (on 10 postures).

protocol: visibility and accessibility assessment was based on both virtual manikins and real users' video observation, and results were merged with the direct interview during task execution.

### *4.3. Results and discussion*

Data analysis was structured according to the proposed protocol in four categories (posture, visibility and accessibility, and mental workload). A preliminary task analysis divided the entire task into 10 single postures (P) like "frames" of the entire task sequence. Postural analysis was carried out from real users observation at the shop floor (Fig. 5) and the digitalized environment (Fig. 6). Personalized digital manikins were created from motion capture, but analyses were replicated using the same software libraries for European population for three percentiles (i.e., 5p, 50p and 95p).

Similarly, the virtual mock-ups were used on the 10 postures for visibility and accessibility analysis. Main results are shown in Fig. 7. Finally, mental workload analysis and emotional analysis were based on the combination of eye tracking data and vital parameters monitoring. Fig. 8 synthetized the main results collected along all the task duration.

At the beginning, NASA-TXL allowed to determine how to interpret the information collected by the human monitoring system, as a sort of calibration, on a sample of target users. After that, specific users involved on the analysis were study with the defined protocol. Finally, subjective questionnaires were adopted at the end of the experimentation and involved users were asked to express their subjective impressions about perceived comfort. The questionnaire was prepared in Italian and four questions related to the different aspect of the protocol, which users are asked to judge according to a 1–7 Likert scale (1 = not at all/extremely negative, 7 = extremely positive). The questions are as follows:

Q1. Visibility (i.e., Are you able to clearly see all you need during task execution?),
Q2. Accessibility (i.e., Are you able to reach all you need during task execution?),
Q3. Mental Workload (i.e., Are you feeling an high concentration or pressure during task execution?).

Four experts in ergonomics and human factors were involved, two of them from Academia and two of them from Industry. Eight users were involved during experimental testing: four of them belonged to the company and four from them were researchers from the University, not participating into the present project. Data collected from software simulation were merged with human data monitoring, eye tracking results as well as heuristic evaluation and questionnaire judgements to investigate behavioural and cognitive metrics.

The task was defined critical mainly due to: (1) the position assumed by the operators, since they need to stand up in a ladder to reach

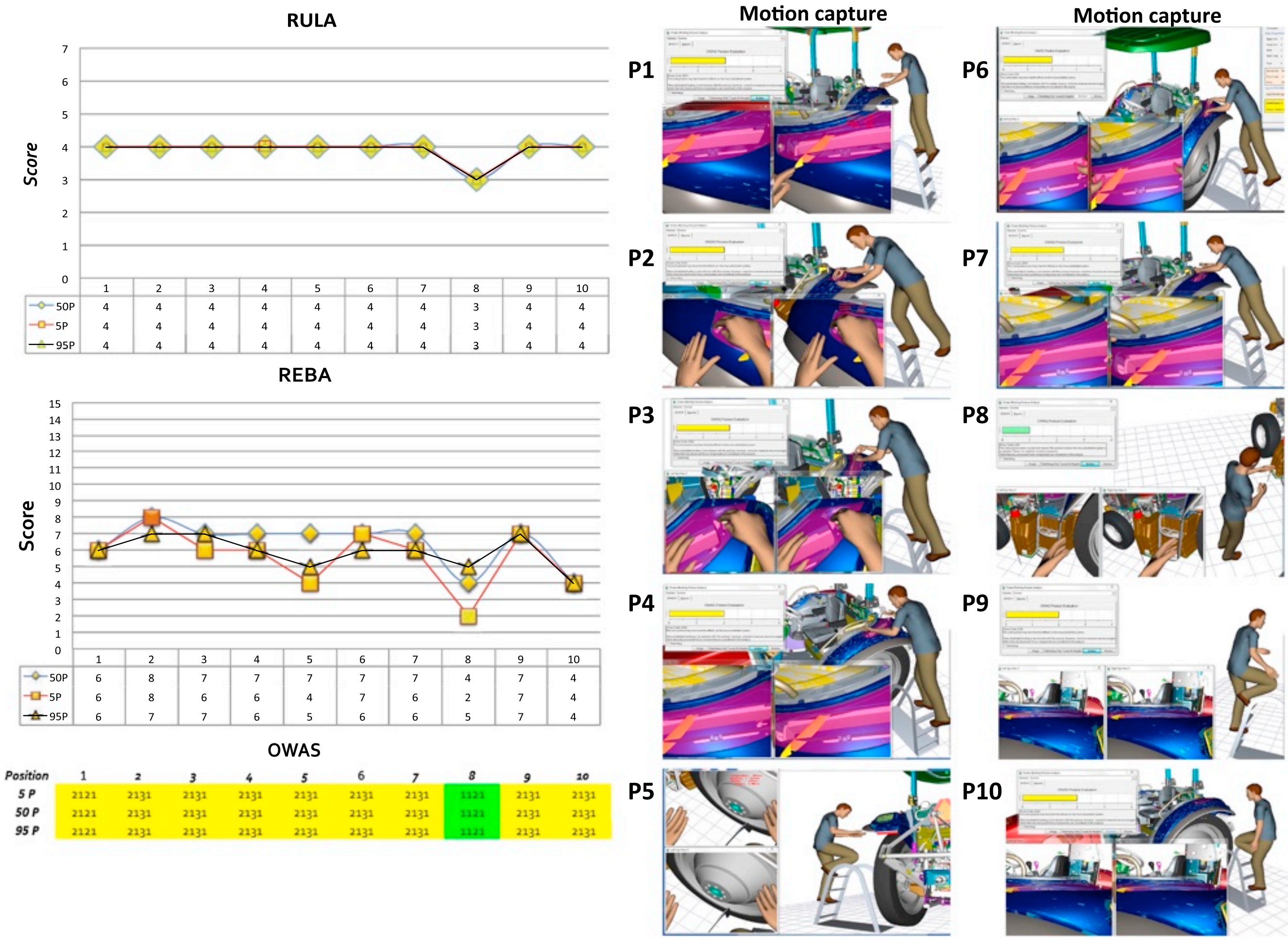



**Fig. 6.** Results about posture analysis on digital mock-ups by motion capture (on 10 postures for 5p, 50p and 95p).

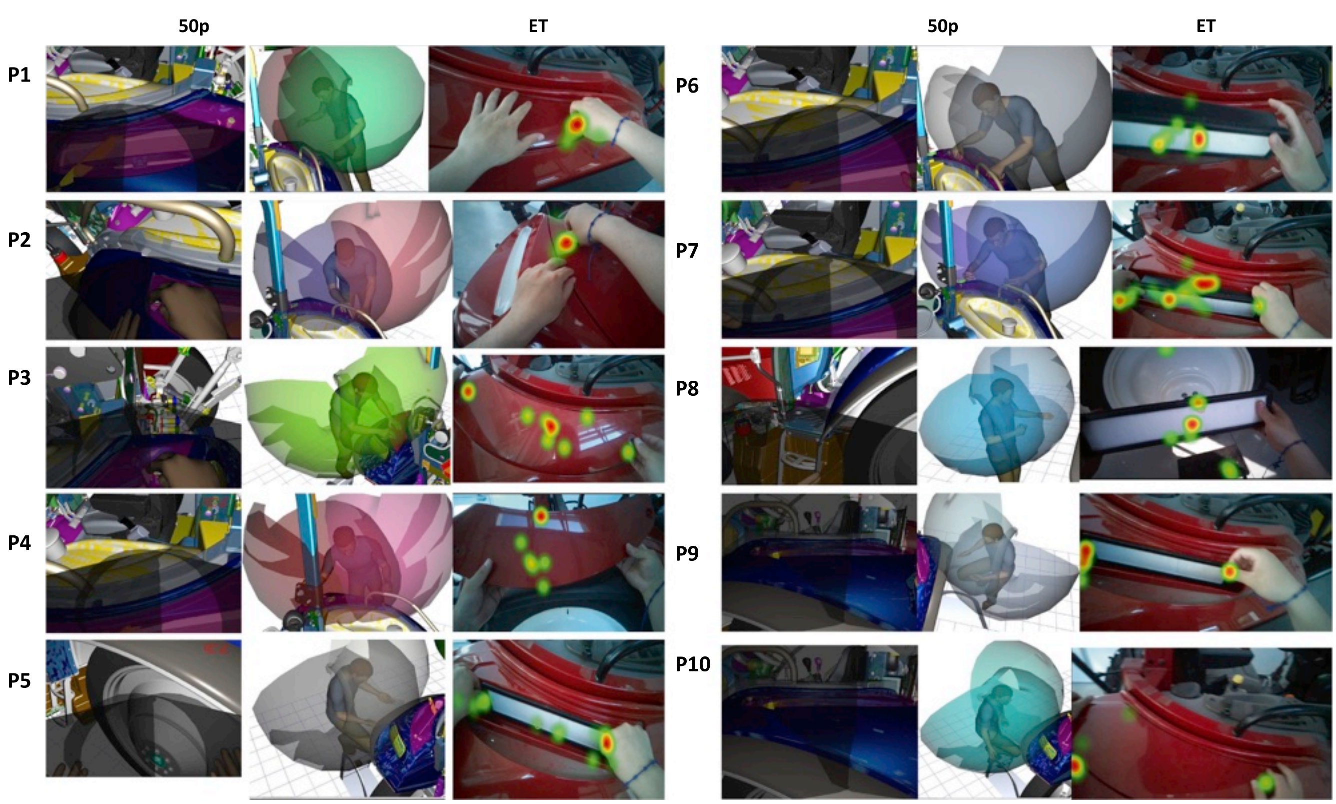



**Fig. 7.** Results about visibility and occlusion analysis on digital mock-ups and by eye tracking (on 10 postures).

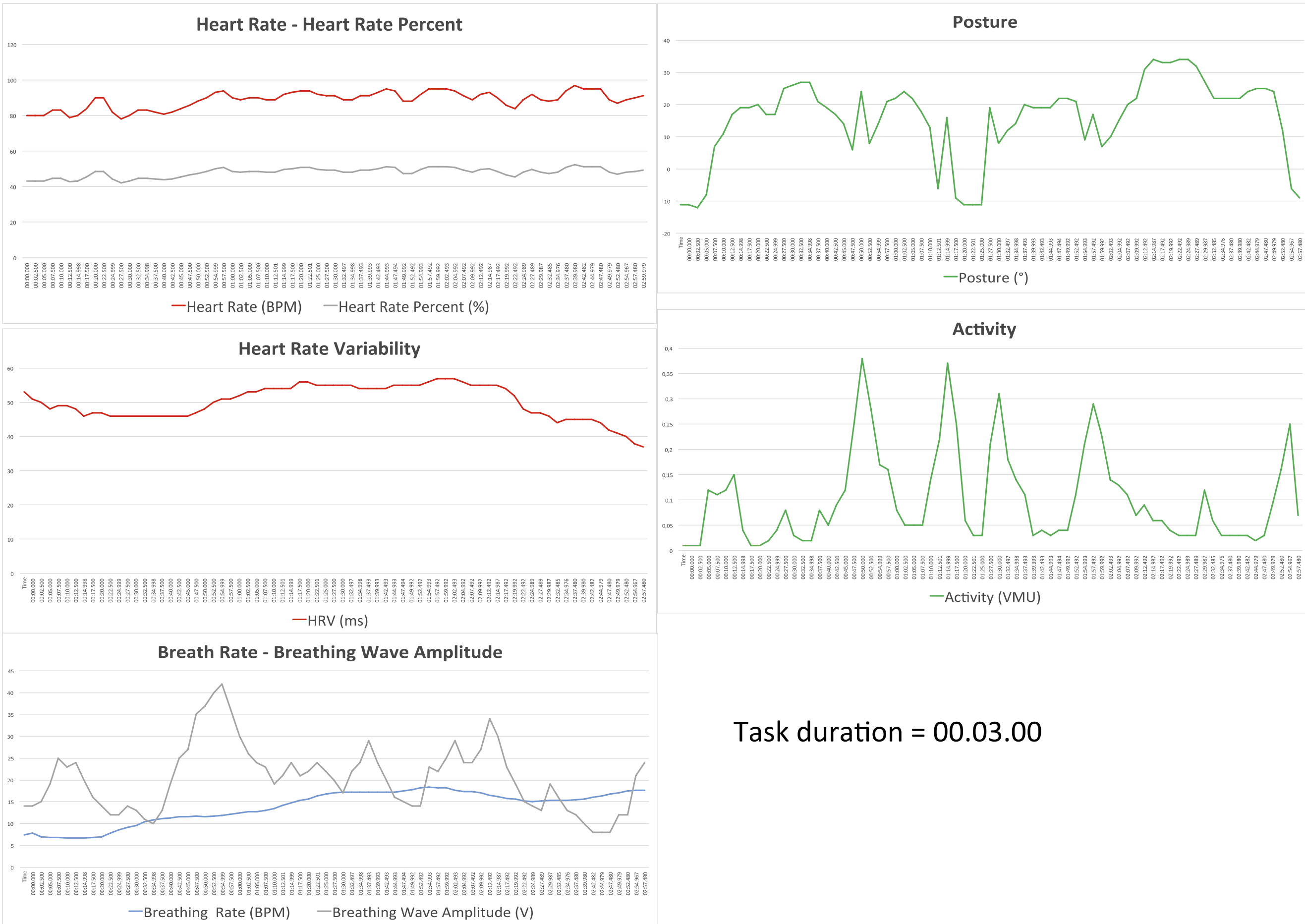



**Fig. 8.** Human physiological data collection for physical and mental workload during experimental study.

the working area, and (2) the distance between the working area and the workers' body. These facts caused a discrete pressure on operators, due to uncomfortable positions assumed and sense of risk they perceived staying of the ladder (for short operators, with one feet only with a stable anchoring).

On the basis of the experimental results, some design changes were proposed and tested, related to the following aspects:

- change of the assembly sequence in order to assembly the cabin air filter on the ground, and mount all the group later on (however, this modification implies to assembly a more complex part later on);
- creation of a special ladder with a specific shape to make the operator closer to the working area, to be reused also for other assembly tasks;
- variation of the accessibility path and to access the filter in a different way, preferable from the wheel before its assembly.

On the basis of the experimental results and design guidelines, a new design solution has been defined and tested in both virtual simulation set-up and mixed-reality environment in order to find out the optimal solution. It allowed supporting the Operator 4.0 to carry out his/her tasks in a more efficient and effective way. Fig. 9 shows the comparison between the current design solution (existing one) and the new design solution (defined on virtual prototypes) according to some of the protocol metrics. In particular, Fig. 9A shows the virtual model of the new solution, based on a special ladder and a new assembly procedure. Fig. 9B shows the comparison between the two assembly sequences for both designs, according to the OWAS technique, VMU and postural inclination collected by the biosensor for postural analysis, and the HR and HRV for the stress analysis. In the graphs, the orange line refers to the existing solution and the green line to the new solutions. On the basis of the parameters monitored during task execution, according to Table 1, it can be stated that the new procedure helps the workers and reduce the efforts from a physical and mental viewpoint.

In conclusion, the researches highlighted that:

1. the 3D immersive virtual set-up supported operators (both researchers and real workers) to evaluate the virtual workstation on 1:1 scale, to be immersed in the virtual scene, to assume the same point of view of the virtual manikin, and to reproduce the simulated actions in a realistic way;
2. the human monitoring system added useful information to the postural assessment and allowed to detect particularly critical conditions that have never been analysed in the past;
3. the adoption of human monitoring tools also at the shop floor was found not too invasive and operators accepted them in a positive way because they felt more secure and controlled;
4. motion tracking by optical cameras was not possible at the shop floor due to light interference and calibration issues. It was used only during experimental test inside the University laboratories. For users' tracking at the shop floor, video recording from multiple cameras was used;
5. data about human interaction could be validly managed by an IoT architecture to include vital parameters monitoring in the Industry 4.0 framework.

Fig. 10 shows the comparison between results obtained in the three tested set-ups. In particular, Fig. 10A reports the results of OWAS

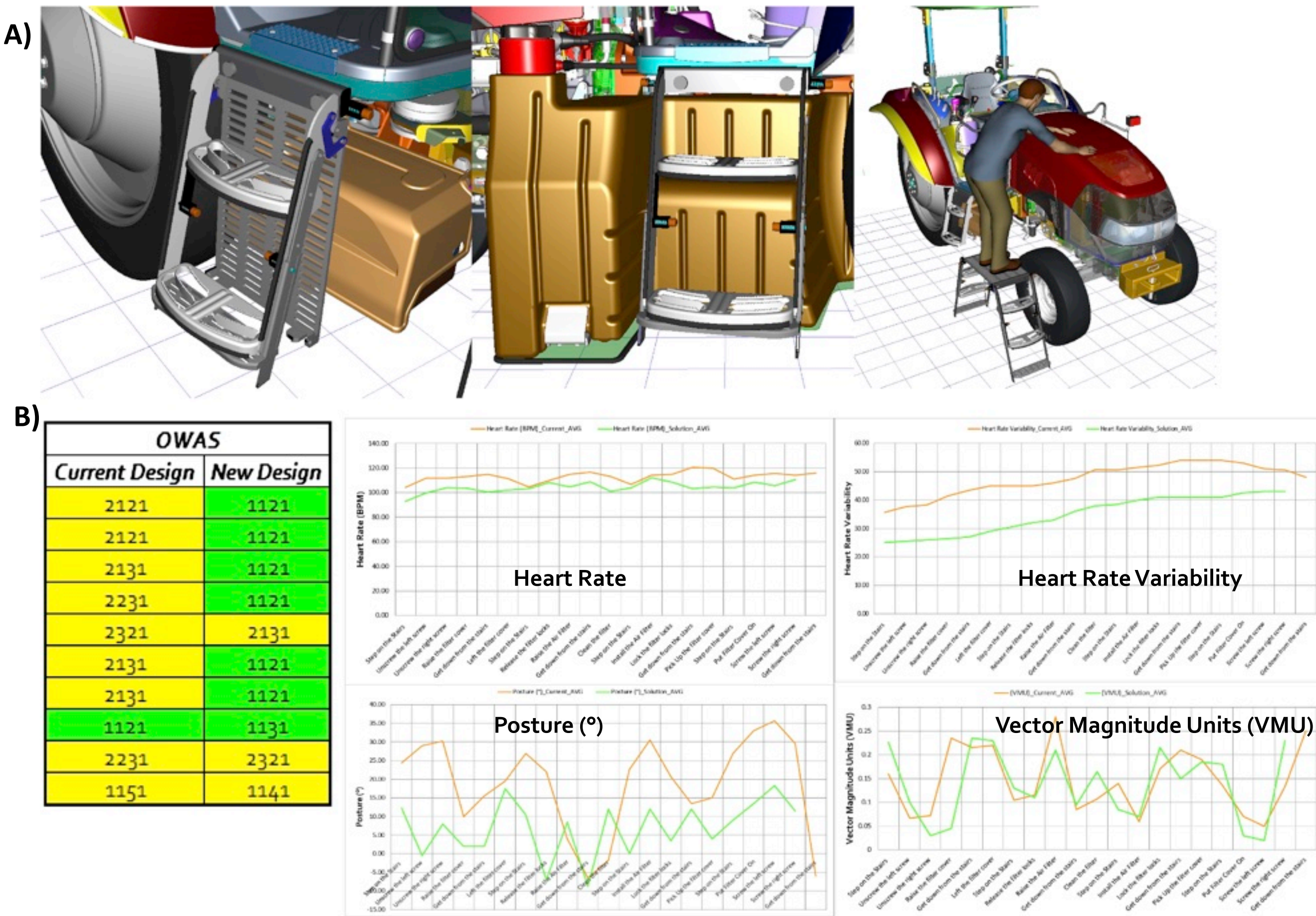



**Fig. 9.** Results for the new design solution based on a new ergonomic supporting ladder and a new assembly procedure.

postural analysis and highlights that both assessment on virtual simulations and mixed-reality environment are reliable of compared to the traditional methods, based on users' observation. Fig. 10B synthetize the comparison by analysing the adoption of the different set-ups in terms of costs, time and efforts for analysis, accuracy of collected data, possibility of scaling human-related data, re-use of virtual models and assessment of mental workload. The case study demonstrated that virtual simulation is a good compromise between time, cost and efforts for postural analysis but it lacks of mental workload assessment; while the MR set-up requires a greater effort for initial investment and environment preparation, but it provides a more complete analysis.

The main limitations of the current experimental study refer to three main points:

1. the lack of assessment of the emotional response based on human psychophysical response monitoring: in particular, a more robust interpretation protocol is required to relate eye tracking data (i.e., heat maps and gaze plots) and heart rate data (HR and HRV) with individual stress and emotions, since the initial calibration by NASA-TXL is not enough, and a more complex monitoring set-up is required with the integration of other monitoring devices. The research is going on with the definition of a more detailed protocol to determine the users' stress level and emotions, and to find out the conditions under which they are harmful or beneficial to the operator in a factory context;
2. the applicability of the proposed set-up: the present study investigated the adoption of the proposed tools for monitoring the human psychophysical response for industrial purposes and the results were promising. However, the current technologies are not ready for an immediate application at the shop floor and further developments are needed. Up to now, the protocol is effectively applicable into a laboratorial or prototyping context. To move into a real industrial environment, improvements are necessary about eye tracking technologies (they should be introduced in a less intrusive way (e.g., not wearing a pair of ad-hoc glasses, but integrated eye-tracking devices within protection glasses that operators already use)), vital parameters monitoring (they could be carried out by alternative devices (e.g., wearable bracelets or rings)), and motion capture of real workers (it could be realized with alterative systems, avoiding the reflection and occlusion problems that characterize optical tracking systems);
3. the lack of extensive empirical data: tests should be repeated involving a significant number of users in order to carry out a robust statistical analysis to validate the approach. Up to now, the research presented promising results that could be validated later on, with more users and a higher number of case studies.

Despite those limits, the research is valuable since it demonstrated the feasibility of the approach and collected positive feedback from the industrial partners. Promising results push to continue with the research and to overcome the current limitations.

## 5. Conclusions

The present research proposed the application of a human-centred design approach inspired to the Operator 4.0 concept and gave suggestions to how a structured protocol analysis considering human factors can be used into Industry 4.0 framework.

The proposed approach is based on human physiological response monitoring in order to objectify the Operator 4.0 experience and assess

**A) Air Filter Case - Current Procedure - 5P**

| | OWAS | | |
|---|---|---|---|
| | Current Procedure | | |
| | Video | Jack | Motion Capture |
| Step 1 - Step on the Stairs | 2121 | 2121 | 2121 |
| Step 2 - Unscrew the left screw | 2131 | 2131 | 2121 |
| Step 3 - Unscrew the right screw | 2131 | 2131 | 2131 |
| Step 4 - Raise the filter cover | 2131 | 2131 | 2231 |
| Step 5 - Get down from the stairs | 2131 | 2131 | 2321 |
| Step 6 - Release the left and right locks | 2131 | 2131 | 2131 |
| Step 7 - Raise the Air Filter | 2131 | 2131 | 2131 |
| Step 8 - Clean the filter | 1121 | 1121 | 1121 |
| Step 9 - Step on Stairs Safely | 2131 | 2131 | 2231 |
| Step 10 - Get down from the stairs | 2131 | 2131 | 1151 |

**B)**

| | TRADITIONAL SET-UP (USERS' OBERSERVATION) | VIRTUAL SIMULATION SET-UP | MIXED REALITY SET-UP |
|---|---|---|---|
| Cost and complexity | Low Cost<br>Cheap equipment | Investment on SW Licenses<br>Experts training | Investment on Motion Capture HW & SW (quite expensive)<br>Experts training |
| Time for analysis | High (observation, data collection and analysis, data comparison) | Medium (virtual mock-up creation and posture analysis) | Medium (motion capture system set-up and calibration) |
| Accuracy | Low (angles/distances interpreted the by observer) | Medium (angles calculated by the SW) | High (even if it strongly depends on the accuracy of the calibration and set-up) |
| Human Scaling (5P/50P/95P) | Difficult to get persons of different sizes and weights to represent a certain population | Scaling Option Available, all populations can be simulated | Difficult to get persons of different sizes and weights to represent population |
| Use of Virtual Prototypes | No, physical prototype needed. | Yes, CAD models could be incorporated to the simulation | Yes, CAD models could be incorporated to the simulation |
| Mental workload analysis | Mental and physical worklload can be hardly inferred – use only if subjective data by questionnaires | Mental and physical workload is not calculated by software | Mental and physical workload can be inferred by biosensor and eye tracking data and combined with subjective data by questionnaires |

**Fig. 10.** Comparison among the different experimental set-ups: traditional set-up based on users' observation, virtual simulation set-up and mixed-reality set-up.

physical ergonomics and mental workload by structured protocol analysis. The final aim of the research is to demonstrate the feasibility of the proposed approach for an industrial context, where human physiological response monitoring can be validly used to improve the interaction between operators and industrial workplaces, and the operators' wellbeing and quality of life within the factories. The most important contribution of the paper is the definition of a procedure to carry out pragmatic assessment of the relation between physical and cognitive measureable human factors and workplace design. The experimental study demonstrated the effectiveness of the proposed approach and the usefulness of the human physiological response monitoring in defining socially sustainable workplaces, by using virtual and mixed reality set-ups that help designers and engineers to define and validate in real time the proposed design solutions.

More specifically, the adopted monitoring system consisted of an eye tracking system and a wearable human physiological data monitoring technology collecting a set of vital parameters. The proposed set-up is combined with virtual prototyping in order to create the factory digital twin, where workspaces can be simulated to be tested and optimized before their creation, and then improved continuously and properly controlled during real processes, acting as a digital emulation of the real world in the context on Industry 4.0. The depicted framework was proved to conveniently simulate human-machine interaction, improve the perceived comfort, and avoid ergonomic problems at the shop floor. The research approach was tested on an assembly workstation in the industrial vehicle sector, in collaboration with CNH Industrial. The case study demonstrated how the approach could effectively support the simulation of the human–machine interaction in order to identify the critical conditions, improve the workers' perceived comfort, and avoid ergonomic problems at the shop floor. Future works will focus on further developments in two main areas: definition of a more detailed protocol for mental/cognitive workload and emotion assessment, and industrialization of the proposed set-up for a real monitoring at the shop floor, considering also certified devices for industrial use.

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