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Creation of a UX index to design human tasks and workstations

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ABSTRACT

Successful interaction with complex processes, like those in the modern factory, is based on the system's ability to satisfy the user needs during human tasks, mainly related to performances, physical comfort, usability, accessibility, visibility, and mental workload. However, the 'real' user perception is hidden and usually difficult to detect. User eXperience (UX) is a useful concept related to subjective perceptions and responses that result from the interaction with a product, system or process, including users' emotions, beliefs, preferences, perceptions, physical and psychological responses, behaviors and accomplishments that occur before, during and after use. The paper proposes the creation of a User eXperience Index (UXI) to assess the quality of human-system interaction during job tasks and, consequently, evaluate both process and workstation. The proposed approach has been applied to improve the design of assembly human tasks, using a virtual simulated case study focusing on tractor assembly. Tests with users, with different levels of expertise, allowed us to validate the proposed approach and to optimize the assembly task sequence. Results showed how the proposed UXI can validly objectify the workers' experience and can be validly used to improve the design of human tasks.

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1. Introduction

Design of complex systems has to take into account numerous requirements, merging both technical and social aspects, according to a typically transdisciplinary approach (Wognum et al. 2018): from engineering issues like functionality and performance, to user requirements, business aspects, until government regulations. Indeed, systems have to work properly, but also satisfy the users' needs during the task execution. The introduction of human factors (HF) in engineering purposely aims at considering both technical and social issues in the development of complex systems, including the human perspective into engineering design (Peruzzini and Pellicciari 2017). Indeed, HF engineering (HFE) is a multidisciplinary science that involves different disciplines (e.g. psychology, anthropometry, biomechanics, anatomy, physiology, psychophysics) all related to the study of the interaction between humans and the surrounding environment. HFE suggests starting from the study of the characteristics, capabilities and limits of the users, and applies them to the design of a human-centered system as well as to the evaluation of the human-machine interaction. Human-centered approaches

have been firstly defined and adopted for product and interface design, but it is fundamental also in

working systems' design in order to guarantee the best possible work conditions, and consequently, the best performance.

This approach is valid also in the modern factories; despite automation and robots growing, human work still represents the most valuable asset of every company. Indeed, in most cases, only human manual tasks can guarantee high levels of flexibility, scalability and cognitive load that are fundamental in modern manufacturing processes, as well as in high-quality and personalized production. To promote humans' roles, it is then important to understand the workers' experience and to make the factory adapt their organisation and production systems consequently (Peruzzini, Grandi, and Pellicciari 2020).

An important aspect of any type of collaboration is interaction. Interaction strongly depends on the communication flow between the user and the system, and the generated experience. As a consequence, the design of proper interfaces and workplaces is crucial

for high-quality interaction processes. A successful human-system interaction can be guaranteed by analyzing the features of machines, equipment and workers in order to combine human skills with system features to carry out the tasks in the most efficient and effective way. On one hand, the operator can inform the system about its status and can provide some inputs; on the other hand, supporting systems and interfaces must provide clear feedback, generating an immediate comprehension and data interpretation, helping workers in their job. This new perspective brings to rethink workplaces and working tasks, which require new approaches and dedicated methods.

Moreover, radical changes are affecting modern manufacturing processes. First of all, digitization is changing the manner in which goods are designed and produced. Secondly, the conditions where the operators work are suffering from time pressure and high complexity. These trends are a challenge but also present an opportunity for organizations to develop smart, human-centred workspaces able to improve the working conditions as well as the workers' well-being. In this direction, transdisciplinary engineering (TE) methods can be successfully applied to solve complex problems linked to digital manufacturing (Rauch et al. 2018). This issue incorporates examples and applications of transdisciplinary approaches including digital knowledge management, digital prototyping, virtual simulation, collaborative practices and methods to include HF within the factory process design. According to TE, different methodologies are required to bridge the gaps between technical and social sciences. They will bring the needed intelligence into the shop floor required to provide factories with flexible and adaptive behaviours. UX design is one of the methods that can be used to move attention from systems to people inside the factory and to include people from factories into design processes. Next to different methodologies, technologies like digital manufacturing and virtual simulation can help engineers and technicians to anticipate critical conditions and to envisage possible solutions.

One of the most human-intensive processes in manufacturing is assembly. Indeed, the final assembly of complex products like vehicles is still done manually or in a semi-automated way particularly for low volume productions or high-volume productions with

customized variants (Weidner, Kong, and Wulfsberg 2013). In both scenarios, workers have to deal with an increased effort, both physical and cognitive. During the design of assembly workplaces, engineers have to apply a transversal, transdisciplinary knowledge combining different topics in order to avoid design errors, with a special consideration of work safety: from mechanical design, to physics, materials technology, process management, to ergonomics. Innovative approaches like UX design and virtual prototyping could effectively help designing modern manufacturing workplaces, solving problems related to their complexity. In particular, Virtual Reality (VR) has been proved to have a real potential in improving workstation design for different purposes, including assembly process design and validation (Grajewski et al. 2013). Indeed, VR can include users in the validation of human-centered workplaces before their realization, considering both the quality of working conditions and user performance. As a result, the digital transformation does not only imply a mere technological advancement, but also a renewed attention to the people. However, only in a few cases was there a clear understanding of human-system interaction and a real planning of human activities, based on the analysis of the generated UX. It is due also to the lack of structured methods to measure and objectify UX during virtual simulations.

This paper presents a transdisciplinary approach to improve workplace design, based on the collection of postural, physiological, performance and subjective data during VR simulations for the analysis of the human-system interaction quality. Postural data consists of analysis of main anthropometric human parameters; physiological data is based on heart rate parameters and eye pupil dilation; performance data is based on time to accomplish the tasks; and finally subjective data is based on the perceived workload assessment. Such an approach has been specifically defined for industrial assembly processes, but it is pretty general and applicable also to different contexts.

The research focuses on the design of the assembly process of an after-treatment system for tractors. It is a complex activity, carried out manually due to high product customization and the high precision required. The assembly procedure has been analyzed and replicated by VR simulations involving real users. During simulation, the proposed protocol analysis has been applied to define the UXI and to validate the

best design solutions. The experimental data confirms how the proposed method is able to objectify UX and graphically represent the generated UX to support engineers to design the workplace and the assembly tasks.

The paper is structured as follows: [section 2](#) refers to the research background and deepens the role of VR simulation and design as well as the importance of adopting UX-based design methods; [section 3](#) presents the research approach and how to define the UX; [section 4](#) describes the experimental testing on the industrial case; finally, [section 5](#) contains the conclusions and future works.

2. Research background

HFE aims at ensuring human comfort and safety, and consequently improving global work performance. Indeed, there are many factors, both physical and cognitive, that affect the users' performance and the quality of manufacturing processes: from physical workload, due to uncomfortable postures, to task complexity, overload of information, or time pressure (Peruzzini et al. 2018; Biondi et al. 2020; Young et al. 2015). Cognitive workload analysis is more frequently used in complex human-interaction systems in which human errors have a crucial importance, such as railways and aerospace fields (Krehl and Balfe 2014; Alaimo et al. 2020). Workload can be defined in terms of experienced load; it is not only task-specific, but also person-specific (Rouse, Edwards, and Hammer 1993). It means that the response to the same stimuli is not equal among different users, since every user will reply according to his/her own capabilities. Therefore, workload depends upon the individual, depending on the interaction between the user or operator and the task structure. Task complexity increases with the increase in the number of processing stages that are required to perform a task and influences the amount of effort that is required by the individual for task performance. The perceived experience is dependent upon user state and context, as well as user capacity and allocation strategy of resource, that differ from experts and novices (Wickens et al. 2015). In this direction, analysis of the UX allows taking into account the users' variability, focusing on the user's personal perceptions and responses that include emotions, beliefs, preferences,

perceptions, physical and psychological responses, behaviours and accomplishments. UX is not only subjective, but also strongly depending on the workspace features, and dynamic as it can change along the lifecycle, depending on what occurs before, during and after use (International Organization for Standardization 2019).

The concept of UX has been defined in product design, firstly considering the overall experience of a person using a product such as a website or computer application, especially in terms of how easy or pleasing it is to use (Hassenzahl and Tractinsky 2006). However, UX is a strange phenomenon: from product interaction it readily moved to technology assessment, from traditional usability to beauty, hedonic, affective or experiential aspects of technology use. In this context, it has been largely applied to human-computer interaction (HCI) and, more generally, to human-system interaction. More recently, it has been also applied to define specific evaluation models for manufacturing processes and tasks (Peruzzini and Pellicciari 2018): they considered both behavioural and cognitive aspects in executing manufacturing tasks to estimate the UX impact on sustainability for a certain product and its related processes. More generally, during manufacturing tasks it can be stated that UX could be analysed by a set of objective parameters. For instance, the analysis of the postures assumed during the interaction can express the level of postural comfort. In addition, interaction data such as time to accomplish the tasks, errors, requests of assistance, number of actions or clicks on an interface, are important to understand the users' actions and reactions and to complete the UX analysis including the interaction with controls and equipment. Moreover, measuring the user's physiological response during task execution allows creating knowledge about how he/she is interacting with an industrial machine, interface or equipment, thanks to objective data (Peruzzini, Grandi, and Pellicciari 2018). Such knowledge could be used to design human-centered, ergonomic, and more usable systems.

As far as the postural comfort is concerned, there are several well-known methods in literature that can be applied also in a wider UX perspective, focusing on different types of human actions. Such methods are mainly based on user observation and analysis of

anthropometric data and joint angles. For instance, the National Institute of Occupational Safety and Health (NIOSH) allows measuring the user parameters relating to the level of musculoskeletal comfort considering also the intensity, frequency, and duration of the particular task (Dempsey 2002). There are also specific methods, to be used according to the specific context of use and type of tasks: Ovako Working posture Analysis System (OWAS) (Karhu et al. 1981), Rapid Upper Limb Assessment (RULA) (McAtamney and Nigel Corlett 1993), Rapid Entire Body Assessment (REBA) (McAtamney and Hignett 2004), or the most recent Workplace Ergonomic Risk Assessment (WERA) (Rahman, Rani, and Rohani 2011). More generally, single joint angles of the diverse body parts can be analysed and compared with a set of predefined comfort angles, according to the Dreyfuss 3D study (Tilley 2001). Such comfort values have been defined from a variety of sources, from academic and NASA studies, to evaluate the range of comfortable bending of every joint for specific tasks (e.g. driving a machine in a determined position, working with upper arms on a table, seating in front of a computer). About ergonomic analysis, traditional practice is based on user observation and paper-based or excel-based checklists. In the last ten years, ergonomic methods have been gradually introduced also in process modelling systems and digital manufacturing platforms (e.g. Siemens Jack, 3DS Delmia) to fasten physical ergonomic analysis. Such tools can validly support the creation of human-centred virtual simulations to improve ergonomics of the workstation and more generally the social sustainability of human tasks by enhancing system design and improving its serviceability, thanks to virtual mock-ups (Peruzzini et al. 2017).

As far as interaction analysis, a useful investigation technique is Video Interaction Analysis (VIA) (Jordan and Henderson 1995): it is an interdisciplinary method for empirical investigation of the interaction of human beings with each other and with objects in their environment, based on recording sessions of task execution and expert evaluation of what happened, facilitating data collection. It is low-cost, easy to perform, and validly supports ergonomic analysis of human postures, choosing the most proper ergonomic methods. VIA can be used in a variety of contexts, analysing interaction with interfaces, systems, as well as workstations. It has been proved to be

a valid method to collect data about human interaction also at the shop floor, as well as to include ergonomic aspects and work performance in the analysis and understanding of human-system interaction during manual assembly work (Engström and Medbo 1997). VIA is also useful to collect performance measures by observing the user ability to perform the task at an acceptable and safe manner: these measures can focus on both primary and secondary tasks (e.g. driving and controlling some machine features; handling parts and taking to someone else) and monitoring time, errors, number of actions required. Moreover, it may also consider how performance on the primary task is affected by the introduction of a secondary task, and the related impact on the performance. The basic idea underlying the use of performance measures is that an increase in workload may be accompanied by a decrease in performance efficiency. Today, VIA is generally recognized as a transdisciplinary technique to study human interaction in different fields, from medicine, to sociology, psychology, until manufacturing processes and human-robot interaction (Kissmann 2009).

About physiological analysis, it is based on monitoring biomedical signals, such as cerebral, muscular, cardiovascular and eye activity indicative of the activation of the nervous system. The basic assumption of physiological measures is that as workload varies (increases or decreases), operators invest a different (more or less) effort to keep performance at an acceptable level (Kramer and Weber 2000). Such change can be detected by biomedical signals' variation. However, for every specific context, it is necessary to define those human parameters that are relevant to detect stressful conditions or risky activities. The scientific literature review revealed the most reliable techniques to be used to measure workload, and consequently UX: electrocardiography (ECG), electroencephalography (EEG), and electro-oculography (EOG). ECG-based techniques record the heart's electrical activity and provide two main indicators which have been shown to be sensitive to mental workload: Heart Rate (HR) and Heart Rate Variability (HRV). HR is defined as the number of heart beats per minute, while HRV is defined as the temporal variation between sequences of consecutive heart beats. Results of recent studies seem to suggest that these parameters may be used to detect changes in workload during several activity executions, such as driving (Peruzzini, Tonietti, and

lani 2019a), assembly (Nardolillo, Baghdadi, and Cavuoto 2017) and precision tasks (Tsao et al. 2020) in modern manufacturing context (Argyle et al. 2021). Nowadays, ECG-based data measuring is quite simple and cheap thanks to low-intrusive and low-cost wearable sensors, like wristbands or chest bands, with the aim to detect non-normal conditions during task execution. Previous research showed the correlation between HR and HRV with the physical and mental workload (Mulder et al. 2004). EEG-based techniques record frequency bands and even-related brain potentials. They are time-locked responses to specific events, and their latency and polarity have been shown to reflect specific perceptual, motor and cognitive processes under different conditions (Brookhuis and de Waard 2010). However, EEG-based data recording procedures are complex, and the methodology is quite intrusive, and can hardly be used on the field to monitor users during real task execution. EOG-based data are based on recording the electrical potential difference between the cornea and the retina of a human eye, which can be used to monitor users' alertness level (Hu and Zheng 2009). Generally, variation in pupil dilatation (PD) can detect changes in the individual subject to stress, so that an increase in pupil size is caused by fatigue conditions (Wenhui Liao et al. 2006). In addition, the increase of the eye blink frequency and latency, that can be deduced together with PD analysis using an eye-tracker, can highlight an increase in the human workload (Marquart, Cabrall, and De Winter 2015). Based on eye activity recording and analysis, PD can be defined during task execution to provide information on the individual's attention source and stress (Martin, Cegarra, and Averty 2011; Sharma and Gedeon 2012). It has been found that PD changes under stress situations and can be measured by the dilation mean value. Today, pupillometry and electrooculography are well diffused, due to the increased performance of eye-trackers, the improved ergonomics of devices (e.g. glasses) and the gradual cost reduction.

As UX is strongly individual, a complete evaluation of the perceived UX needs to also include the subjective impression. For this purpose, self-reported questionnaires are frequently used before and after task execution with two different purposes. Pre-questionnaires aim at providing an ex-ante evaluation of the users' data, habits as well process knowledge and level of expertise, in order to create a baseline to

properly interpret the analysis of objective data collected during task execution. Post-questionnaires aim at self-reporting the perceived level of comfort and stress after task accomplishment, in order to rate the perceived workload and properly assess the given performance. There are different types of workload assessments, using unidimensional or multidimensional scales. Regarding the unidimensional scales, the Modified Cooper-Harper Scale (MCH) and Overall Workload Scale (OW) are useful as a screening tool to identify potential workload issues (Hill et al. 1992). Among self-reported multidimensional scales existing in literature, NASA Task Load Index (NASA-TLX) and Subjective Workload Assessment Technique (SWAT) are widely used to provide a subjective, multidimensional assessment of the perceived workload. In particular, NASA-TLX (Hart and Staveland 1988) evaluates six aspects, namely: mental demands, physical demands, temporal demands, performance, effort, and frustration. It is applied to a variety of domains, including aviation, railway sector, healthcare and other complex socio-technical domains. It is characterized by low-cost, high validity and, most importantly, lack of interference with on-going task performance, as it is filled in at the end. As all subjective measures, it presents some limitations, mostly linked to the difficulty that individuals may encounter when trying to quantify the mental effort invested in a task.

The above-mentioned measures are usually collected before, during and after task execution in real, operative environments. In this way, they provide a corrective UX analysis. Different protocols for both physical and workload assessment have been recently developed to comprehend how they can affect user performance in different contexts: from driving (Izquierdo-Reyes et al. 2018) and rail tasks (Fowler et al. n.d.), until assembly and manufacturing (Gregori et al. 2018). However, they aren't able to provide a unique, consolidated index to drive workspace or workstation improvement. Moreover, such approaches are not fully suitable for design purposes since they provide a late, corrective UX assessment. In order to support designers and engineers in designing optimized human tasks and workstations, such approaches should be anticipated during the design phase. Recent examples of research works which combine multiple aspects and methods in the assessment of human comfort and wellbeing

can be found in literature (Papetti et al. 2021; Peruzzini, Toniatti, and Iani 2019a; Czerniak et al. 2021). They mainly combined physical, physiological and subjective data to have an overall assessment of the human conditions. However, they do not propose a consolidated index able to quantify the global UX considering both cognitive and physical issues.

In this direction, virtual simulation is an effective method to early detect design problems during product development (Bordegoni and Ferrise 2013). More specifically, VR is nowadays being regularly used in numerous industries to support many different industrial processes and promote human-centered design practices, from product design (Makris et al. 2012), to industrial systems design (Stark, Kind, and Neumeyer 2017), process design (Peruzzini et al. 2020), until training (Pedram et al. 2020). In all cases, VR-based simulations are useful to improve the design of human tasks optimizing user comfort, task efficiency, and related workload. The main advantage of VR is the early virtual prototyping of the workspace and the involvement of real users in testing the workspace features, simulating interactions with the different parts of the system. Different examples can be found in literature demonstrating the utility of VR-based simulation to support design practices, and in particular user-centered design, from automotive (Gong et al. 2020) to medicine (Javaid and Haleem 2020), until product-service system design (Bu et al. 2021). In addition, various studies have recently demonstrated the benefits of VR simulations to design ergonomic workstations (Caputo et al. 2018; Peruzzini, Pellicciari, and Gadaleta 2019; Dimitrokalli et al. 2020). Only a few studies have also implemented human monitoring devices during VR-based simulations to deepen the UX (Alam et al. 2017; Grandi et al. 2019). However, also in this case, UX is not quantified by a clear index.

3. The UX-based approach

3.1 The multidimensional UX analysis

The research approach is based on a multidimensional UX analysis that integrates four classes of data to objectify the UX and the perceived workload: postural, physiological, performance and subjective. Postural analysis focuses on the physical workload, physiological data focuses on the assessment of mental workload, performance data gives a measure of the efficiency and effectiveness of the interaction considering the execution time, and finally subjective data provides an individual measure of the perceived workload, using the NASA-TLX questionnaire. In particular, subjective data is used to weight the other values collected by physical, physiological and performance analysis, as defined by the following equations.

Postural analysis is based on the REBA method. REBA provides a synthetic indicator to rapidly evaluate the risk of work-related musculoskeletal disorders (WRMSD) associated with the execution of certain job tasks. It is particularly useful and indicated for industrial tasks since it considers the entire body and uses a systematic process to evaluate both upper and lower body parts for biomechanical and risk analysis. REBA analysis is carried out by video analysis (VIA). Postural data can be extracted and analysed manually by experts or automatically, using a motion analysis system (e.g. (Altieri et al. 2020)). Moreover, users are asked to fill in pre-questionnaires focusing on users' demographic data (i.e. age, gender, height, weight) and level of expertise in executing assembly tasks (low experience, medium experience, high experience). For each user, gender, height and weight data are used to define the specific user's percentile according to ANSUR database (Gordon et al. 2014). This parameter is useful to guarantee that all representative percentiles of a certain population are covered by the sample of users. In addition, experience information will be used to compare final results among users and to have average values among users with the same level of expertise. From the postural data analysis, the REBA score parameter is calculated, for each user, considering the mean value of the REBA score during the task simulation (*REBA user*), while the minimum value (*REBA min*) is considered as baseline. In order to normalize this parameter, the

REBA range is extracted from the maximum value during the assembly simulation for each user, to calculate the Postural Comfort (PC) parameter as follows:

$$PC = \frac{REBA_{user} - REBA_{min}}{REBA_{max} - REBA_{min}} \quad (1)$$

Physiological analysis is carried out by merging different parameters, from ECG activity such as HR and HRV, and from eye activity analysis, such as pupil diameter (PD). ECG data can be easily collected by wearable low-cost fitness belts or multi-parameters smart-watches and are useful to detect postural and mental stress conditions. Similarly, eye data can be collected by eye tracking systems such as glasses, or embedded into a HMD for VR/AR. Both data are collected during task execution and post-processed after testing. Before data monitoring, a rest phase of approximately 5 minutes is required in order to calculate the baseline values of the physiological parameters. During this phase, users are asked to watch a relaxing video, standing in a comfort position. Baseline values are then useful to calculate specific parameters. From physiological data analysis, two parameters are defined as Heart Activity (HA) and Pupil Activity (PA). HA is calculated as follows:

$$HA = \frac{HR_{user} - HR_{baseline}}{HR_{max} - HR_{baseline}} \quad (2)$$

where HR_{user} is the mean value of the specific user's HR as recorded during the task simulation, $HR_{baseline}$ is the mean HR value as recorded during the user's baseline phase, and HR_{max} is the maximum HR value as recorded for each user during the entire test.

Similarly, PA is calculated as follows:

$$PA = \frac{PD_{user} - PD_{baseline}}{PD_{max} - PD_{baseline}} \quad (3)$$

where PD_{user} is defined as the mean value of the specific user's PD as recorded during the task simulation, $PD_{baseline}$ is the mean PD value as recorded during the user's baseline phase, and PD_{max} is the maximum PD value as recorded for each user during the entire test.

Performance analysis is mainly based on recording the time to accomplish the task, evaluating the operator performance. Time is collected from both video analysis and VR simulation recording. About performance analysis, the User Time (UT) parameter is calculated considering the user time performance. The time to accomplish the task is clocked for each user

(T_{user}) and compared with the expert time (T_{expert}) accomplished by a senior assembly operator and the longer time performed by the less experienced user who performed the test (T_{max}), as shown in the following equation:

$$UT = \frac{T_{user} - T_{expert}}{T_{max} - T_{expert}} \quad (4)$$

Finally, subjective data is collected by a post-questionnaire based on NASA-TLX, providing a subjective assessment of the perceived workload according to six questions, for each user, on a 21-graduations scale. For this study we considered the Physical Demand judgment to weight the PC parameter, the Mental Demand judgment to weight the PD parameter, the Frustration Level judgment to weight the HA parameter, and finally the Overall Performance judgment to weight the UT parameter. Each judgment is then normalised to a 5-point scale (e.g. judgements from 0 to 4,2 fall to 1, judgements from 4,3 to 8,4 fall to 2, judgements from 8,5 to 12,6 fall to 3, judgements from 12,6 to 16,8 fall to 4, and judgements from 16,8 to 21 fall to 5). According to this, a set of weights ranging from 1 to 5 (where 1 means very positive score, 5 means very bad) can be defined to take into account the user's subjective experience. The sum of the above-mentioned parameters, properly weighted as described, generates the Weighted WorkLoad (WWL) summing both physical and cognitive aspects, as shown in equation (5):

$$WWL = \omega_1 * HA + \omega_2 * PA + \omega_3 * PC + \omega_4 * UT \quad (5)$$

where, for each individual, ω_1 is the weight related to HA as normalized judgment for the Frustration Level of NASA-TLX questionnaire, ω_2 is the weight related to PA as normalized judgment for the Mental Demand of NASA-TLX questionnaire, ω_3 is the weight related to PC as normalized judgment for the Physical Demand of NASA-TLX questionnaire, and ω_4 is the weight related to UT as normalized judgment for the Overall Performance of NASA-TLX questionnaire.

The overall UXI score is calculated in percentage as follows:

$$UXI = 100\% - (WWL/20) * 100 \quad (6)$$

A scale of UXI target values is defined as reference targets to judge if the measured parameters can guarantee a positive UX. The research considered a set of 40 different design projects, developed in the last

5 years by the University research group in collaboration with companies, to define the acceptable level of such an index to guarantee a good UX level. Experience based on such studies made us define the following ranges:

- Green mark (UXI up to 80%) = the UXI target is guaranteed, good design!
- Yellow mark (UXI from 40% to 80%) = the UXI target is close; design could be improved to achieve the comfort level until the green mark;
- Red mark (UXI down to 40%) = the overall comfort is compromised, with risk of excessive physical and cognitive workload. Design could be urgently improved.

Table 1 synthesizes the multidimensional analysis proposed, presenting the classes of analysis considered, the related parameters and data collection strategy, the adopted monitoring tools and the parameters related to the UXI calculation. Such an approach can guarantee to take into account the main aspects characterizing the UX during job task execution, merging both objective and subjective data as well as physical and mental workload analysis. The proposed approach is generic and could be adopted to analyse UX both in physical and virtual environments. In the specific work, it has been applied using virtual simulation testing sessions, as described in the following paragraph.

3.2 The VR set-up for UX analysis during virtual simulations

In order to perform the proposed UX analysis during virtual simulation, a VR set-up has been defined to create an immersive, interactive

environment where users can manually execute tasks, and contemporary can be monitored to collect the necessary data as presented in Table 1. In the specific research, the VR set-up combines several technologies, integrating a HMD with a hand tracking device to replicate a realistic interaction experience within a consistent factory layout. Moreover, human monitoring devices are integrated in the simulations in order to extrapolate objective data about the real user experience. Finally, video analysis is used to retrieve human postural data and carry out an expert-based postural assessment. More specifically, the VR set-up consists of the following hardware and software technologies:

- HTC Vive Pro Eye: HMD with dual-OLED displays with a combined resolution of 2880×1600 pixels, equipped with 32 infrared sensors for 360-degree tracking, a gyroscope, an accelerometer, and a laser position sensor to track its position with 6 DOF. The integrated eye tracking system is used for eye data collection. In this study, four base stations are used for a 360-degree tracking into a 4×4 meters area, in which the user can move freely;
- Leap Motion: controller with three infrared cameras that allows the user's hand gesture recognition in order to interact with objects in the virtual scene with bare hands and create realistic virtual hand gestures such as grasping or pinching. In this study, the Leap Motion sensor is placed on the centre of HTC Vive with a 3D-printed support;
- Zephyr Bioharness 3: physiological telemetry device intended for human monitoring, defined for fitness and medical purposes. The device

Table 1. Multidimensional analysis and data considered in the proposed UX-based approach.

Analysis	Collected data	Data collection strategy	Monitoring tools	UXI related parameters
<i>Postural</i>	REBA (Rapid Entire Body Assessment) User percentile	VIA (Video Interaction Analysis) Matching with posture ANSUR database	RGB cameras (e.g. GoPro) Pre-questionnaires	PC (Postural Comfort) eq.3
<i>Physiological</i>	HR (Heart Rate) and HRV (Heart Rate Variability) PD (Pupil Diameter)	Continuous monitoring during task execution using wearable sensors	Biosensor (e.g. Zephyr BH3) Eye tracking (e.g. Tobii Glasses or embedded into a VR HMD)	HA (Heart Activity) eq.1 PA (Pupil Activity) eq.2
<i>Performance</i>	Time	VIA (Video Interaction Analysis)	RGB cameras (e.g. GoPro) and VR simulation	UT (User Time) eq.4
<i>Subjective</i>	Perceived workload	NASA-TLX	Post-questionnaires	-

- consists of a chest strap and an electronic module attached to the strap, able to collect different data about heart activity, breathing, and posture;
- GoPro Hero+: RGB camera for user recording and video analysis, useful for postural assessment and time analysis;
 - Unity 3D: cross-platform game engine developed by Unity Technologies used to create VR environments and the interaction with objects in the scene;
 - Steam VR: software toolkit that manages the use of HMD and other controllers and their tracking into the virtual scene. During the simulation, Steam VR streams the user position in Unity 3D in order to perform the job tasks to be analysed;
 - Leap Motion SDK: Unity plug-in that controls the user hands and coordinates they with the HMD;
 - Specific packages for HMD ET control: Unity plug-ins to manage eye tracking and measure pupil diameters (i.e. TobiiPro.SDK and TobiiXRS SDK);
 - OmniSense Analysis: software for human monitoring data post-processing, such as heart rate, heart rate variability and postural flexion.

Thanks to this equipment, the user can simulate an assembly task acting with bare hands into a realistic, immersive environment, moving freely into the virtual workplace, grasping virtual objects and releasing parts. The sense of touch is not implemented into the proposed set-up, but it has been replaced by

visual feedback (e.g. grasped objects change colour, interference is shown with arrows). This solution makes the simulation environment cost-effective, easy scalable to different cases, and easier to program. During the simulation, the user wears the HMD and the above-mentioned parameters (i.e. postural, physiological, performance and subjective) are collected as defined by the adopted tools. The proposed general framework for the UX assessment within virtual simulations is presented in Figure 1.

Finally, in order to execute the proposed multidimensional analysis as presented in 3.1 during virtual testing with users, a 6-phase protocol analysis has been defined to carry out tests with users, as shown in Figure 2. It consists of the following steps:

- Phase 1: at the beginning, the user is asked to fill in an anamnestic pre-questionnaire to collect data about age, gender, height, weight and level of expertise in executing assembly tasks. Gender, height and weight data are used to define the specific user's percentile (according to ANSUR database), while age and expertise information allows to define the knowledge about the process under investigation and find out any significant deviation due to the user's skills;
- Phase 2: the user is asked to wear the monitoring tools and to stay relaxed for 5 minutes watching a video, standing with arms along the body. During this phase, physiological data are collected in order to create a baseline for HR, HRV

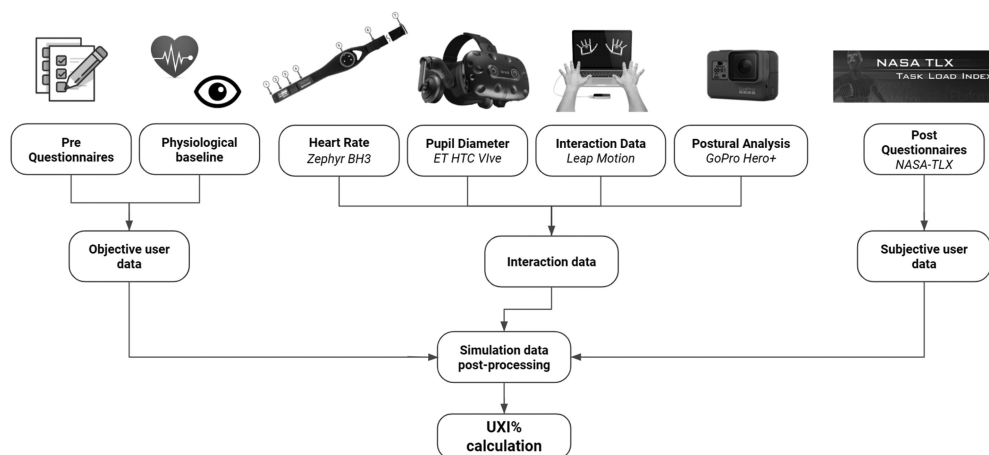


Figure 1. UXI (User eXperience Index) framework for human-machine interaction analysis.

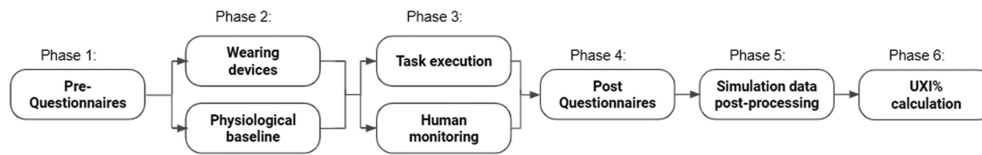


Figure 2. Workflow of the proposed protocol analysis.

and PD (heart rate and pupil diameter) to be compared with recorded data collected during the testing phase for data post-processing;

- Phase 3: users are asked to perform a specific assembly task in a VR scenario. Simultaneously, heart activity is registered by BH3 band while pupil diameter is collected by the eye-tracking system integrated in the HMD. Besides, GoPro is used to record the user's body postures and Leap Motion records the time performance by elaborating the user interaction with the objects in the scene;
- Phase 4: after the simulation, users have to compile a NASA-TLX questionnaire in order to understand the effort and the perceived faithfulness of the VR environment for UX purposes. These data are used for the definition of the specific weights, for each user, to be applied in the calculation of the User eXperience index. NASA-TLX has been integrated with a further question about the user's VR tools acceptance.
- Phase 5: data collected from pre-questionnaires and adopted devices are post-processed in order to obtain for each measured parameter a mean value to compare with the baseline value (phase 2).
- Phase 6: all the collected data are processed to calculate UX evaluation indexes.

4. Experimental testing on an industrial case study

4.1 The case study and user testing

The proposed approach has been applied to a real industrial use case, focusing on a specific phase of the assembly line of tractors. Tractor assembly is an interesting process to study, since the complexity is similar to automotive assembly, but it is usually characterized

by lower production quantities and higher personalization and variants. As a result, the most part of the tractor assembly line is executed manually by operators and only a few phases are generally supported by automation and robots. In this context, workers' ergonomics is a relevant issue, also due to the hard tasks to execute, both physically and mentally.

In particular, the research focuses on the hood assembly of a medium-size agricultural machine (i.e. the New Holland T5 Utility tractor commercialized by CNH Industrial), which is currently a completely manual procedure. This case provides a valuable example of the adoption of the proposed approach and allows showing how the UXI can be used to validate a specific assembly sequence. The current task sequence of the hood assembly, as considered in this study, is detailed below and presented in 10 steps:

- Step 1: Pick up the hood from the conveyor with a hoist;
- Step 2: Lower the hood with the hoist onto the tractor body;
- Step 3: Climb the ladder and guide the hood with hands in order to centre the four threaded pins in the holes of the hood support bracket;
- Step 4: Go down the ladder and pick up n.2 bolts from the box storage;
- Step 5: Climb the ladder and manually tacking the bolts;
- Step 6: Go down the ladder and pick up n.2 nuts from the box storage;
- Step 7: Climb the ladder and manually tacking the nuts;
- Step 8: Go down the ladder and pick up electric screwdriver from the trolley;
- Step 9: Climb the ladder and tighten the nuts with the electric screwdriver;

- Step 10: Go down the ladder and place the electric screwdriver on the trolley.

Moreover, precise indications were submitted regarding boundary conditions such as:

- Maximum hood's opening angle of 50°;
- Hood collected from the right side of the tractor body;
- N.1 operator per side to perform each operation.

The experimental study was developed at the University Lab on the current task sequence with the aim to validate the proposed method, in collaboration with CNH Industrial. The final scope was to subsequently apply the proposed approach within the company virtual Lab, to objectively measure the human activity and have precise feedback to improve the UX of the operators during assembly tasks, supporting the definition of proper redesign actions.

Five users with different levels of expertise were involved in the experimental tests. For each user, physiological reference values were defined during the baseline analysis. Data collected from all users were analysed and synchronized. Each testing session was structured as follows:

- Phase 1:
 - Pre-questionnaire (1 mins);
- Phase 2:
 - Monitoring tools wearing and tools set-up (5 mins);
 - Tools calibration (5 mins);
 - Baseline in VR scenario standing relaxed (5 mins);
- Phase 3:
 - Task execution according to the above-mentioned 10 steps (5–7 mins, depending on user performance);
- Phase 4:
 - Post-questionnaire (2 mins);
- Phase 5:
 - Data Post-processing
- Phase 6:
 - UXI calculation

About data post-processing, during the VR simulation the eye tracker integrated in the HTC Vive gave a .xml file as output that was converted into a .xlsx file for the extraction of PD values. The PD baseline was

calculated averaging the initial 5 minutes values in relax pose before starting the test. The OmniSense Analysis software allowed the export of HR data during the simulation in a .xlsx file format. Furthermore, Excel was used for data post-processing and correlation. Thanks to video analysis, it was possible to assess the REBA average score during the virtual assembly simulation, extracting the most critical postures. Finally, to assess the user's performance such as the time to accomplish the overall process, a chronometer in the virtual scene was implemented, enabling the start button with the Leap Motion controller. All these parameters were therefore considered as input of the UXI as the comfort final value, calculated as indicated by equation (6). Moreover, the use of post-questionnaires was found remarkably useful, as they provide support to correct data interpretation. Indeed, the subjective impressions represented a valid support to correctly judge the UX target value taken during the simulation.

Figure 3 shows the virtual environment as implemented in unity 3D to carry out the simulation. Figure 4 presents how users are equipped with human monitoring technologies, according to the model presented in Figure 1. Finally, Figure 5 shows test execution with users.

4.2 Experimental results and discussion

According to the proposed UX approach, both subjective and objective data collected during tests with users were elaborated, as Phase 5 and 6 of the testing sessions. Parameter evaluation is shown in Table 2. For each user, HA, PA, PC and UT parameters were calculated according to the previous equations (from 1 to 4). In the same way, weights were extracted from the post-questionnaires and normalized; in particular, each weight was associated with one of the specific calculated parameters, as shown in equations (5) and (6).

On the basis of such data, a critical analysis can be carried out. Generally, the analysis of physiological parameters (HA and PA) and the relative weights (ω_1 and ω_2) showed a low physical demanding assembly process. It means that the original process is not particularly burdensome for the operators, promoting visibility and reducing the physical stress. Indeed, all PC parameters related to REBA scores showed a good level of user comfort during the simulation, in

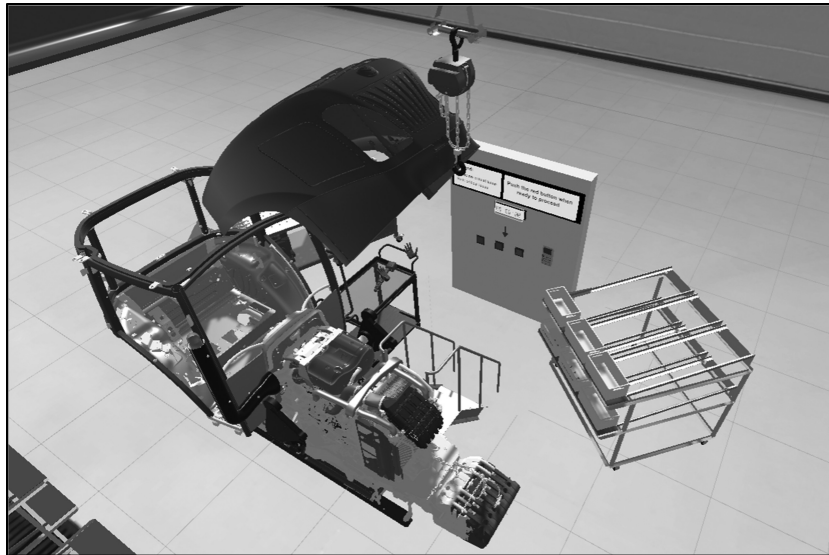


Figure 3. Hood assembly virtual scenario created in Unity 3D.

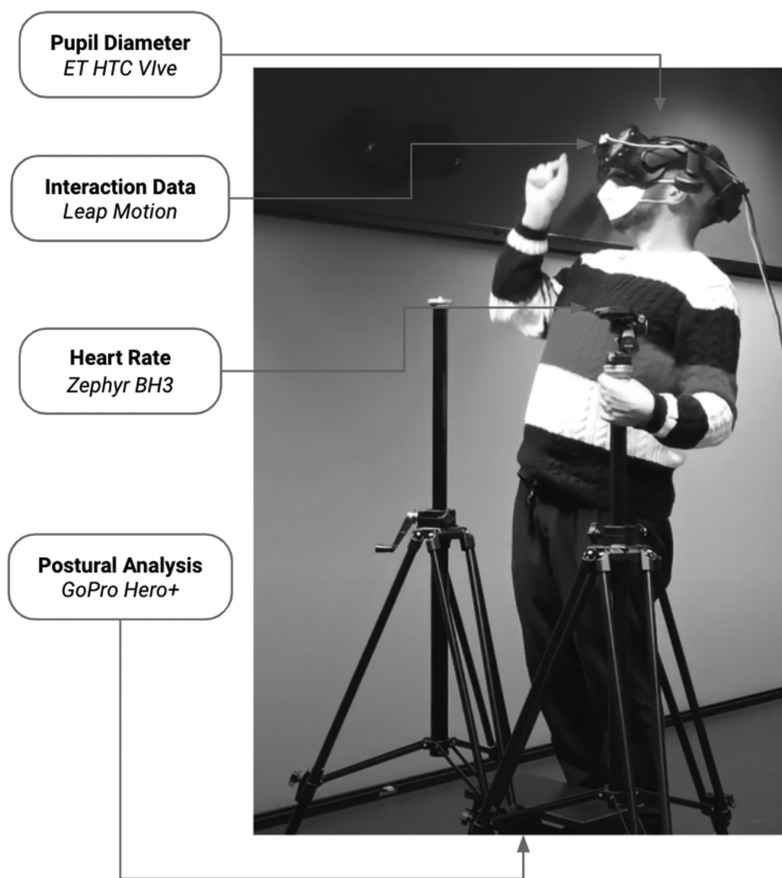


Figure 4. User equipment for human monitoring during virtual simulation.

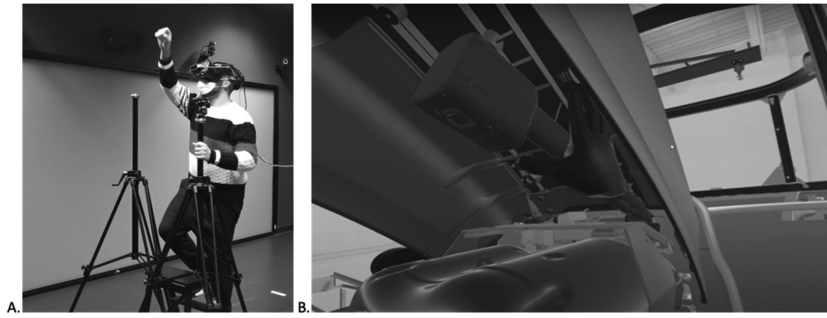


Figure 5. VR-based testing with users: external view (A) and user view from the HMD (B).

Table 2. Parameters, weights and UXI for each user.

	User 1	User 2	User 3	User 4	User 5
Recognized Percentile (ANSUR)	5	50	95	50	5
HA	0,376	0,265	0,198	0,535	0,368
PA	0,570	0,395	0,250	0,447	0,272
PC	0,667	0,556	0,444	0,556	0,667
UT	0,933	0,302	1,000	0,187	0,391
ω_1	2,5	3,0	1,5	3,5	4,0
ω_2	3,5	2,5	3,5	2,5	2,5
ω_3	4,0	3,0	4,0	2,0	4,0
ω_4	4,5	3,5	4,0	2,5	3,5
WWL	9,80	4,51	6,95	4,57	6,19
UXI	50,98	77,47	65,25	77,15	69,07
Average UXI on all users	67,98				

particular for taller users (bigger percentiles). The analysed procedure could be not highly comfortable for shorter users (e.g. users no.1 and no. 5). About the analysis of the UXI, user no.1 showed the lower result; it was effectively pretty inexperienced with the assembly process and unfamiliar with VR technologies, as demonstrated also by the performance weight (ω_4) and the performance parameter UT. On the contrary, user no. 2 scored the higher UXI, as demonstrated by data in Table 2. Finally, the last row contains the overall UXI score (almost 68%), calculated as the average value of UX on all users for the

assembly process analysed. Results obtained on the investigated assembly process were analysed together with the company design team to discuss redesign actions thanks to design changes on both the product and the workstation. In particular, the UXI analysis revealed the operator's difficulty to reach and view the hood fixing points. The following redesigned actions will focus on overcoming the main criticalities identified by the design team thanks to the proposed approach. This is a good way to define strategic redesign actions to improve the overall UX.

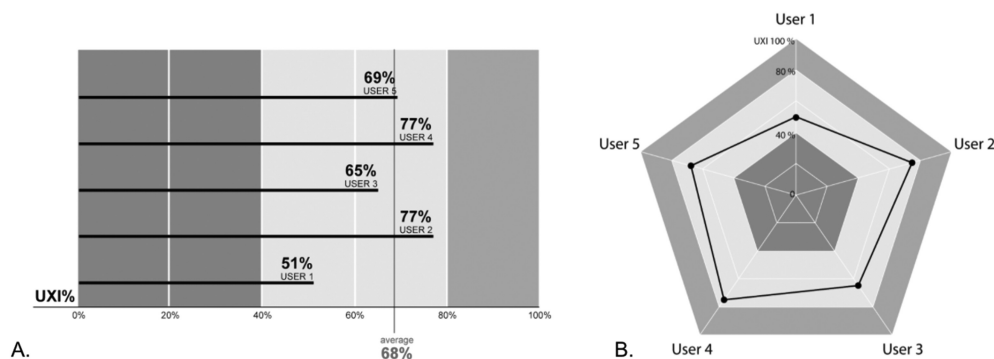


Figure 6. UXI bar graph (A) and radar graph (B) for each user and comparison with average value.

UXI results can be also analysed using a bar and radar graphs, highlighting the UXI distribution on all users. In particular, bar graphs (Figure 6A) are useful to compare results and define how the average UXI is positioned with respect to experimental data, where the average UXI supports the understanding of the global performance. In addition, the radar graph (Figure 6B) can significantly reveal the precise situation of all users and each user contemporary, showing how the average value originated. If scores are located into the red area, it means that UX has to be immediately improved and design changes are necessary soon. If scores are located into the yellow area, UX could be improved but the situation is not highly critical. If scores are in the green area, UX is already optimized. In the present study, the radar graph showed that scores are situated in the yellow area: it means that the design solution proposed is good but further design changes could be adopted. Results showed that, for all participants, the UXI is in the yellow area; it means that the expert and non-expert performance are comparable, but design changes could improve the quality of work.

Although the good results achieved, the present study has some limitations. Firstly, the proposed method has been applied to a pretty simple and short assembly procedure. It could be adopted to more complex cases, also including a longer period of time for human data collection. Secondly, the video analysis to define the REBA postural parameter is pretty simplified; it could be improved by introducing specific techniques for human posture recognition and ergonomic angles detection based on motion capture (e.g. optical VICON tracking) to be used in Lab, or RGB video analysis as proposed by [49] to be used in the field. Thirdly, the number of users involved in the preliminary testing is enough to detect usability problems (Nielsen 1994) but not statistically relevant. Future works will cover these issues.

5. Conclusion and future works

This paper presented a transdisciplinary approach to support the design of assembly human tasks based on a multidimensional UX analysis, combining different parameters and calculating a unique index to express the quality of the interaction. Such an approach has been defined as transdisciplinary as it includes both technical and social

aspects in the UX evaluation and involves people from practice. Technical science concerns the design of machines, interfaces and information systems. Social science assists in identifying the user needs in order to design comfortable and safe workplaces, combining several technologies and integrating them as integral parts of a personnel safety system to improve safety, maintain availability, reduce errors and decrease the time needed for scheduled or ad hoc interventions. About the societal impact, the presented methodology could enhance the quality of the assembly procedures, helping engineers and designers in detecting possible issues in advance and including human factors along the design process, and finally improve the human wellbeing within the factories. The proposed approach allows a holistic assessment of the interaction quality and to find out specific correlations between the collected parameters, thanks to wearable and environmental sensors. Human monitoring devices like an eye tracker and a biometric wristband are used to collect physiological data, such as Heart Rate (HR) and pupil diameter (PD); external RGB cameras are used to support interaction analysis and define a REBA score to assess the quality of the postural comfort as well as collect performance indicators, such as the time to accomplish the task; finally subjective assessment is collected by proper post-test questionnaires to measure the perceived workload, based on NASA-TLX. This approach combines different branches of knowledge in order to provide a unique index to measure the global UX (namely UXI), according to a transdisciplinary approach. The combination of human monitoring and ergonomics methods allowed the evaluation of the users' physical comfort and mental workload. Such a method has been applied to an industrial case, focusing on the design of assembly human tasks and using VR-based simulation testing sessions. Results showed that UXI is able to validly objectify the UX and quickly identify design optimization in terms of reachability, visibility and performance. The combined evaluation of mental and physical workload could enhance the quality of the assembly process, revealing possible issues before the physical implementation. Therefore, the UXI could be a useful tool that provides rapid feedback during the design stage. UXI is ready to be applied to various

industrial cases: integrating more precise postural analysis could be performed using motion capture technologies, it could be used to improve the overall user assembly experience. Despite the first satisfactory results, the UXI index has some limitations, such as a considerable amount of time for data post-processing and a perfectible postural analysis.

Future works will focus on including further physiological parameters in the UXI definition, in order to strengthen the UX analysis, such as the breathing rate or the galvanic skin response, offered by low-cost, low-intrusive devices. Furthermore, the monitoring set-up could be improved, introducing less intrusive wearable technologies to better match with industrial cases: for instance, the biometric chest band could be replaced by a smartwatch and a smartphone, with a low level of intrusiveness. Moreover, postural analysis could be improved by directly detecting the interested postural angles and automatically defining the REBA score, using a motion capture system in Lab or video analysis based on 3 RGB cameras. Finally, the proposed method could be further validated on more complex and longer assembly tasks, involving a bigger sample of users. The proposed approach could be also applied to other contexts, with the aim to assess the final UX (e.g. virtual training, on field manual tasks).

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

- Alaimo, A., A. Esposito, C. Orlando, and A. Simoncini. 2020. "Aircraft Pilots Workload Analysis: Heart Rate Variability Objective Measures and Nasa-Task Load Index Subjective Evaluation." *Aerospace* 7 (9): 137. doi:10.3390/aerospace7090137.
- Alam, M. F., S. Katsikas, O. Beltramello, and S. Hadjiefthymiades. 2017. "Augmented and Virtual Reality Based Monitoring and Safety System: A Prototype IoT Platform." *Journal of Network and Computer Applications* 89: 109–119. doi:10.1016/j.jnca.2017.03.022.
- Altieri, A., S. Ceccacci, A. Talipu, and M. Mengoni. 2020. "A Low Cost Motion Analysis System Based on RGB Cameras to Support Ergonomic Risk Assessment in Real Workplaces." In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, (Vol. 83983, pp. V009T09A067). American Society of Mechanical Engineers.
- Argyle, E. M., A. Marinescu, M. L. Wilson, G. Lawson, and S. Sharples. 2021. "Physiological Indicators of Task Demand, Fatigue, and Cognition in Future Digital Manufacturing Environments." *International Journal of Human-Computer Studies* 145: 102522. doi:10.1016/j.ijhcs.2020.102522.
- Biondi, F. N., A. Cacanindin, C. Douglas, and J. Cort. 2020. "Overloaded and at Work: Investigating the Effect of Cognitive Workload on Assembly Task Performance." *Human Factors* 0018720820929928.
- Bordegoni, M., and F. Ferrise. 2013. "Designing Interaction with Consumer Products in a Multisensory Virtual Reality Environment: This Paper Shows How Virtual Reality Technology Can Be Used Instead of Physical Artifacts or Mock-Ups for the New Product and Evaluation of Its Usage." *Virtual and Physical Prototyping* 8 (1): 51–64. doi:10.1080/17452759.2012.762612.
- Brookhuis, K. A., and D. de Waard. 2010. "Monitoring Drivers' Mental Workload in Driving Simulators Using Physiological Measures." *Accident Analysis & Prevention* 42 (3): 898–903. doi:10.1016/j.aap.2009.06.001.
- Bu, L., C.-H. Chen, K. K. H. Ng, P. Zheng, G. Dong, and H. Liu. 2021. "A User-Centric Design Approach for Smart Product-Service Systems Using Virtual Reality: A Case Study." *Journal of Cleaner Production* 280: 124413. doi:10.1016/j.jclepro.2020.124413.
- Caputo, F., A. Greco, E. D'Amato, I. Notaro, and S. Spada. 2018. "On the Use of Virtual Reality for a Human-Centered Workplace Design." *Procedia Structural Integrity* 8: 297–308. doi:10.1016/j.prostr.2017.12.031.
- Czerniak, J. N., N. Schierhorst, V. Villani, L. Sabattini, C. Brandl, A. Mertens, M. Schwalm, and V. Nitsch. 2021. "The Index of Cognitive Activity-Eligibility for Task-Evoked Informational Strain and Robustness Towards Visual Influences." *Applied Ergonomics* 92: 103342. doi:10.1016/j.apergo.2020.103342.
- Dempsey, P. G. 2002. "Usability of the Revised NIOSH Lifting Equation." *Ergonomics* 45 (12): 817–828. doi:10.1080/00140130210159977.
- Dimitrakalli, A., G.-C. Vosniakos, D. Nathanael, and E. Matsas. 2020. "On the Assessment of Human-Robot Collaboration in Mechanical Product Assembly by Use of Virtual Reality." *Procedia Manufacturing* 51: 627–634. doi:10.1016/j.promfg.2020.10.088.
- Engström, T., and P. Medbo. 1997. "Data Collection and Analysis of Manual Work Using Video Recording and Personal Computer Techniques." *International Journal of Industrial Ergonomics* 19 (4): 291–298. doi:10.1016/S0169-8141(96)00038-8.

- Fowler, A., D. Golightly, S. Sharples, C. Harvey, M. Wilson, and H. Gibson. n.d. "Human Performance in Rail: Current Assessment and Future Opportunities."
- Gong, L., H. Söderlund, L. Bogojevic, X. Chen, A. Berce, Å. Fast-Berglund, and B. Johansson. 2020. "Interaction Design for Multi-User Virtual Reality Systems: An Automotive Case Study." *Procedia Cirp* 93: 1259–1264. doi:10.1016/j.procir.2020.04.036.
- Gordon, C. C., C. L. Blackwell, B. Bradtmiller, J. L. Parham, P. Barrientos, S. P. Paquette, B. D. Corner, J. M. Carson, J. C. Venezia, and B. M. Rockwell. 2014. "2012 Anthropometric Survey of Us Army Personnel: Methods and Summary Statistics." Army Natick Soldier Research Development and Engineering Center MA.
- Grajewski, D., F. Górski, P. Zawadzki, and A. Hamrol. 2013. "Application of Virtual Reality Techniques in Design of Ergonomic Manufacturing Workplaces." *Procedia Computer Science* 25: 289–301. doi:10.1016/j.procs.2013.11.035.
- Grandi, F., L. Zanni, M. Peruzzini, M. Pellicciari, and C. E. Campanella. 2019. "A Transdisciplinary Digital Approach for Tractor's Human-Centred Design." *International Journal of Computer Integrated Manufacturing*. doi:10.1080/0951192X.2019.1599441.
- Gregori, F., A. Papetti, M. Pandolfi, M. Peruzzini, and M. Germani. 2018. "Improving a Production Site from a Social Point of View: An IoT Infrastructure to Monitor Workers Condition." *Procedia CIRP* 72: 886–891. doi:10.1016/j.procir.2018.03.057.
- Hart, S. G., and L. E. Staveland. 1988. "Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research." *Advances in Psychology* 52 (C): 139–183. doi:10.1016/S0166-4115(08)62386-9.
- Hassenzahl, M., and N. Tractinsky. 2006. "User Experience-a Research Agenda." *Behaviour & Information Technology* 25 (2): 91–97. doi:10.1080/01449290500330331.
- Hill, S. G., H. P. Iavecchia, J. C. Byers, A. C. Bittner Jr, A. L. Zaklade, and R. E. Christ. 1992. "Comparison of Four Subjective Workload Rating Scales." *Human Factors* 34 (4): 429–439. doi:10.1177/001872089203400405.
- Hu, S., and G. Zheng. 2009. "Driver Drowsiness Detection with Eyelid Related Parameters by Support Vector Machine." *Expert Systems with Applications* 36 (4): 7651–7658. doi:10.1016/j.eswa.2008.09.030.
- International Organization for Standardization. 2019. ISO 9241-210 - Ergonomics of Human-system Interaction - Part 210: Human-centred design for interactive systems, issued 2019.
- Izquierdo-Reyes, J., R. A. Ramirez-Mendoza, M. R. Bustamante-Bello, S. Navarro-Tuch, and R. Avila-Vazquez. 2018. "Advanced Driver Monitoring for Assistance System (ADMAS)." *International Journal on Interactive Design and Manufacturing (Ijidem)* 12 (1): 187–197. doi:10.1007/s12008-016-0349-9.
- Javaid, M., and A. Haleem. 2020. "Virtual Reality Applications toward Medical Field." *Clinical Epidemiology and Global Health* 8 (2): 600–605. doi:10.1016/j.cegh.2019.12.010.
- Jordan, B., and A. Henderson. 1995. "Interaction Analysis: Foundations and Practice." *The Journal of the Learning Sciences* 4 (1): 39–103. doi:10.1207/s15327809jls0401_2.
- Karhu, O., R. Härkönen, P. Sorvali, and P. Vepsäläinen. 1981. "Observing Working Postures in Industry: Examples of OWAS Application." *Applied Ergonomics* 12 (1): 13–17. doi:10.1016/0003-6870(81)90088-0.
- Kissmann, U. 2009. *Video Interaction Analysis: Methods and Methodology*. Lang.
- Kramer, A. R. T. H. U. R. F., and T. Weber. 2000. "Applications of Psychophysiology to Human Factors." *Handbook of Psychophysiology* 2: 794–814.
- Krehl, C., and N. Balfe. 2014. "Cognitive Workload Analysis in Rail Signalling Environments." *Cognition, Technology & Work* 16 (3): 359–371. doi:10.1007/s10111-013-0266-7.
- Liao, W., W. Zhang, Z. Zhu, and J. Qiang. 2006. "A Real-Time Human Stress Monitoring System Using Dynamic Bayesian Network." *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Workshops*. IEEE (pp. 70). doi:10.1109/cvpr.2005.394.
- Makris, S., L. Rentzos, G. Pintzos, D. Mavrikios, and G. Chrysosolouris. 2012. "Semantic-Based Taxonomy for Immersive Product Design Using VR Techniques." *CIRP Annals* 61 (1): 147–150. doi:10.1016/j.cirp.2012.03.008.
- Marquart, G., C. Cabrall, and J. De Winter. 2015. "Review of Eye-Related Measures of Drivers' Mental Workload." *Procedia Manufacturing* 3: 2854–2861. doi:10.1016/j.promfg.2015.07.783.
- Martin, C., J. Cegarra, and P. Averty. 2011. "Analysis of Mental Workload during En-Route Air Traffic Control Task Execution Based on Eye-Tracking Technique." In *International Conference on Engineering Psychology and Cognitive Ergonomics*, 592–597. Springer.
- McAtamney, L., and S. Hignett. 2004. "Rapid Entire Body Assessment." *Handbook of Human Factors and Ergonomics Methods* 31: 8@1@811. doi:10.1201/9780203489925.ch8.
- McAtamney, L., and E. Nigel Corlett. 1993. "RULA: A Survey Method for the Investigation of Work-Related Upper Limb Disorders." *Applied Ergonomics* 24 (2): 91–99. doi:10.1016/0003-6870(93)90080-5.
- Mulder, L., J. M. Ben, D. de Waard, and K. A. Brookhuis. 2004. "Estimating Mental Effort Using Heart Rate and Heart Rate Variability." In *Handbook of Human Factors and Ergonomics Methods*, 227–236. CRC Press.
- Nardolillo, A. M., A. Baghdadi, and L. A. Cavuoto. 2017. "Heart Rate Variability during a Simulated Assembly Task; Influence of Age and Gender." In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, (Vol. 61, pp. 1853–1857). SAGE Publications Sage CA: Los Angeles, CA.
- Nielsen, J. 1994. *Usability Engineering*. Morgan Kaufmann.
- Papetti, A., F. Gregori, M. Pandolfi, M. Peruzzini, and M. Germani. 2021. "A Method to Improve Workers' Well-Being toward Human-Centered Connected Factories." *Journal of Computational Design and Engineering* 7 (5): 630–643. doi:10.1093/jcde/qwaa047.

- Pedram, S., S. Palmisano, R. Skarbez, P. Perez, and M. Farrelly. 2020. "Investigating the Process of Mine Rescuers' Safety Training with Immersive Virtual Reality: A Structural Equation Modelling Approach." *Computers & Education* 153: 103891. doi:10.1016/j.compedu.2020.103891.
- Peruzzini, M., F. Grandi, S. Cavallaro, and M. Pellicciari. 2020. "Using Virtual Manufacturing to Design Human-Centric Factories: An Industrial Case." *International Journal of Advanced Manufacturing Technology*. doi:10.1007/s00170-020-06229-2.
- Peruzzini, M., F. Grandi, and M. Pellicciari. 2018. "How to Analyse the Workers' Experience in Integrated Product-Process Design." *Journal of Industrial Information Integration* 12 (December): 31–46. doi:10.1016/j.jii.2018.06.002.
- Peruzzini, M., F. Grandi, and M. Pellicciari. 2020. "Exploring the Potential of Operator 4.0 Interface and Monitoring." *Computers & Industrial Engineering* 139 (December 2018): 105600. doi:10.1016/j.cie.2018.12.047.
- Peruzzini, M., F. Grandi, M. Pellicciari, and C. Campanella. 2017. "Virtual Maintenance Simulation for Socially Sustainable Serviceability." *Procedia Manufacturing* 11 (June): 1413–1420. doi:10.1016/j.promfg.2017.07.271.
- Peruzzini, M., F. Grandi, M. Pellicciari, and C. E. Campanella. 2018. "User Experience Analysis Based on Physiological Data Monitoring and Mixed Prototyping to Support Human-Centre Product Design." In *International Conference on Applied Human Factors and Ergonomics* (pp. 401–412). Springer.
- Peruzzini, M., and M. Pellicciari. 2017. "A Framework to Design A Human-Centred Adaptive Manufacturing System for Aging Workers." *Advanced Engineering Informatics* 33: 330–349. doi:10.1016/j.aei.2017.02.003.
- Peruzzini, M., and M. Pellicciari. 2018. "User Experience Evaluation Model for Sustainable Manufacturing." *International Journal of Computer Integrated Manufacturing* 31 (6): 494–512. doi:10.1080/0951192X.2017.1305502.
- Peruzzini, M., M. Pellicciari, and M. Gadaleta. 2019. "A Comparative Study on Computer-Integrated Set-Ups to Design Human-Centred Manufacturing Systems." *Robotics and Computer-Integrated Manufacturing* 55: 265–278. doi:10.1016/j.rcim.2018.03.009.
- Peruzzini, M., M. Tonietti, and C. Iani. 2019a. "Transdisciplinary Design Approach Based on Driver's Workload Monitoring." *Journal of Industrial Information Integration* 15: 91–102. doi:10.1016/j.jii.2019.04.001.
- Rahman, M. N. A., M. R. A. Rani, and M. J. Rohani. 2011. "WERA: An Observational Tool Develop to Assess the Physical Risk Factor Associated with WRMDs. Part 1 Development Process." *International Journal of Occupational Safety and Ergonomics*, 2011a. Submitted and under Review
- Rauch, E., D. T. Matt, C. A. Brown, W. Towner, A. Vickery, and S. Santiteerakul. 2018. "Transfer of Industry 4.0 To Small and Medium Sized Enterprises." *Advances in Transdisciplinary Engineering* 7: 63–71.
- Rouse, W. B., S. L. Edwards, and J. M. Hammer. 1993. "Modeling the Dynamics of Mental Workload and Human Performance in Complex Systems." *IEEE Transactions on Systems, Man, and Cybernetics* 23 (6): 1662–1671. doi:10.1109/21.257761.
- Sharma, N., and T. Gedeon. 2012. "Objective Measures, Sensors and Computational Techniques for Stress Recognition and Classification: A Survey." *Computer Methods and Programs in Biomedicine* 108 (3): 1287–1301. doi:10.1016/j.cmpb.2012.07.003.
- Stark, R., S. Kind, and S. Neumeyer. 2017. "Innovations in Digital Modelling for Next Generation Manufacturing System Design." *CIRP Annals* 66 (1): 169–172. doi:10.1016/j.cirp.2017.04.045.
- Tilley, A. R. 2001. *The Measure of Man and Woman: Human Factors in Design*. John Wiley & Sons.
- Tsao, L., M. A. Nussbaum, S. Kim, and M. Liang. 2020. "Modelling Performance during Repetitive Precision Tasks Using Wearable Sensors: A Data-Driven Approach." *Ergonomics* 63 (7): 831–849. doi:10.1080/00140139.2020.1759700.
- Weidner, R., N. Kong, and J. P. Wulfsberg. 2013. "Human Hybrid Robot: A New Concept for Supporting Manual Assembly Tasks." *Production Engineering* 7 (6): 675–684. doi:10.1007/s11740-013-0487-x.
- Wickens, C. D., J. G. Hollands, S. Banbury, and R. Parasuraman. 2015. *Engineering Psychology and Human Performance*. Psychology Press.
- Wognum, N., C. Bil, F. Elgh, M. Peruzzini, J. Stjepandić, and W. Verhagen. 2018. "Transdisciplinary Engineering Research Challenges." In *25th ISPE International Conference on Transdisciplinary Engineering Integrating (TE2018)*, 3–6 July, Modena, Italy (pp. 753–762). IOS Press.
- Young, M. S., K. A. Brookhuis, C. D. Wickens, and P. A. Hancock. 2015. "State of Science: Mental Workload in Ergonomics." *Ergonomics* 58 (1): 1–17. doi:10.1080/00140139.2014.956151.