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The INCLUSIVE system: A general framework for adaptive industrial automation

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***Abstract*—While modern production systems are becoming increasingly technologically advanced, the presence of human operators remains fundamental in industrial workplaces. To complement and enhance the capabilities of human workers, approaches based on adaptive automation have been introduced. They consist in adapting the behavior of the system according to the user's capabilities and effort. In this paper, we present a general holistic framework for adaptive automation, called INCLUSIVE, that assists the operator during working tasks. The system consists of three modules. First, a thorough characterization of the operator's constitutional and situational condition is provided; based on this, proper tailored adapation is given and, if necessary, further training and support are provided. The framework has been implemented and tested considering three industrial use cases, selected as representative of a wide area of interest for the industry in Europe, in terms of both production requirements and involved operators. Tests have been carried out in real production environments, considering real production tasks carried out by 53 shop floor workers. Results have shown that workers' satisfaction when using the INCLUSIVE system and their performances were increased with respect to customary interaction systems currently used in industries. Moreover, the achieved results were used to formulate a set of recommendations for the design and implementation of an adaptive interaction system in relation to ensuring worker satisfaction and system usability in an industrial environment, as well as performance requirements.**

***Note to Practitioners*—This article was motivated by the fact that, despite modern advanced automation, human operators are still central in the manufacturing process. However, technological progress often causes challenging interaction with complex industrial systems. The goal of this paper is to introduce a complete framework for adaptive automation, with the ultimate goal of facilitating the interaction of human operators with complex industrial systems. The framework relies on three modules: measurement of human capabilities, adaption of the interaction system, and additional teaching and support. The three modules are discussed at high level, independently of the target application. Moreover, to facilitate their application in specific working contexts, examples are provided with respect to three different industrial applications. Results of tests carried out with shop floor operators show that implementing the proposed framework allows better working performance and increases worker satisfaction with the use of automation.**

***Index Terms*—Human-machine interaction, User centered automation, Adaptive interaction systems, Human factors.**

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I. Introduction

With the advent of Industry 4.0, a striking feature of modern manufacturing systems is the focus on advanced automation. This combines technological progress and diversified needs of market, such as product customization and small batches production [1]. This trend adds to human-centricity of the factories of the future, where humans and automated systems cooperate and work in symbiosis [2]. Human operators are being placed in the center of attention, in the sense that automation is seen as a complement and enhancement of the cognitive capabilities of humans by advanced sensing and the higher precision of machines. In this regard, Romero *et al.* [2] have introduced the term Operator 4.0, to refer to operators of human cyber-physical systems who perform work aided by machines if and when needed. The results are more flexible, inclusive and safe workplaces, as well as better work conditions, increased productivity and improved quality. Moreover, this means increased worker satisfaction and work wellbeing, more empowered and engaged workers and increased interest towards factory work as a career, attracting young talented people [3].

The design of automatic machines that dynamically adapt to the cognitive and physical demands of users falls in the domain of the so-called adaptive automation, which goes back several decades [4]–[6]. The goal is to overcome common problems in automation, such as over-reliance, skill degradation, and reduced situation awareness [7]. This can be achieved by adapting the behavior of the system, for example dynamically allocating functions, simplifying the task or changing the level of autonomy of the machine [8]. A variety of frameworks for adaptive human-automation systems have been suggested along these lines. Classical approaches are technocentric [9], [10]: the level of adaptation to introduce is decided based on context features and enabling technologies, such as tasks, environmental conditions and hardware [11]–[13]. In particular, Lee and Martinez Lastra in [11] consider the case of adaptive interfaces of industrial monitoring systems, whereas Jammes and Smit refer to process industries in [12], and cognitive production environments are considered by Wallhoff *et al.* in [13]. In [14], Mourtzis and Vlachou propose a cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance. The system aims to support adaptive scheduling by taking shop floor monitoring data and information related to maintenance into consideration.

Other approaches to adaptive automation are anthropocentric, since they resort to user-centered design and adapt the behavior of the system considering user's capabilities and comfort during the interaction [15], [16]. In this regard, Romero *et al.* in [17] propose an anthropocentric architecture for adaptive automation that takes into account various criteria in the operating environment such as time-lapse, performance degradation, age-, disability- and inexperience-related limitations of operators to increase their working capabilities. Carpanzano *et al.* introduce an automation framework for improving workers' well-being in [18], by exploring the dynamic real time interactions among closed loop control functions and human workers. The works by Michalos *et al.* in [19] and Tsarouchi *et al.* in [20] consider assembly applications and propose dynamic task allocation between the robot and human worker based on information coming from cameras and other similar devices. Vision systems have been used to assess task-required motor skills of a worker [21] and to track a worker's motion and inform the robot about what the worker is currently doing and what they will be doing next [19], [20], [22], [23]. Further, eye tracking has been considered for personalized gaze interaction and gaze behavior analysis [24].

Other approaches propose to adapt the interaction collecting more detailed information about the human subject. This can be done by monitoring a worker's cognitive and emotional conditions and exploiting physiological parameters that allow for retrieving insights such as anxiety, fear, boredom, fatigue or exhaustion, as proposed by Arai, Fujita and Kato in [25] and [26] and by Talignani Landi *et al.* in [27]. An adaptive human-aware cell for collaborative robotics for robotized injection molding has been developed by Bettoni *et al.* in [28]. The activity is characterized by such a high production pace that it forces the operator to work under an external and very fast pace determinant, with consequent effects on the cognitive demand and on the output quality. To overcome this, it has been proposed to dynamically allocate tasks to the robot or to the worker, based on the worker's mental and physical fatigue and progress in the process [28]. In [29] Haslgrübler *et al.* present a framework for adaptive human-in-the-loop assembly tasks. Specifically, the system estimates worker's skills, cognitive load and visual attention to provide the best possible assistance with the least necessary disruption. However, in some cases, information about cognitive and emotional condition of the user is used to assess acceptability of human-system interaction in an industrial environment without providing adaptation of system behavior [25], [30], [31]. Building upon this, Villani *et al.* in [32] the ethical, legal and societal implications related to adaptive automation have been discussed and the concept of *MATE* systems has been proposed. Specifically, *MATE* systems represent an instance of adaptive automation, which is achieved by the interconnection of three modules: measurement of user's capabilities, adaptation of interaction, and teaching of the lacking competence [32].

Moving along these lines, in this paper we present a general framework for adaptive automation, called INCLUSIVE system, that assists the operator during working tasks. The system adapts the interaction in terms of information load of the HMI and automation capability of the machine, and provides specific guidance when needed, as preliminarily presented by Villani *et al.* in [33]. As a consequence, the INCLUSIVE system can be seen as an instance of *MATE* systems [32]. The aim is to provide a smart interaction system for compensating workers' limitations (e.g., due to age or inexperience), while taking full advantage of their knowledge. The ultimate goals are threefold: the first objective is to increase operator's satisfaction towards their job; the second is to increase overall job efficiency; the third to allow an inclusive work environment accessible to any operator, regardless of age, education, impairments and working experience. This would allow, for example, elderly, disabled, inexperienced and other vulnerable operators to access working positions they would be otherwise barred from.

The proposed framework has been implemented considering three industrial use cases, found to be representative of a wide area of interest for the industry in Europe in terms of both production requirements and involved operators. The INCLUSIVE system has, hence, been tested in real production environment with 53 shop floor workers. The effectiveness of the approach has been assessed with subjective and objective measurements. In particular, feedback from test participants was collected with a questionnaire on their satisfaction and system usability [34]. Moreover, objective measurements of users' mental strain were collected and these were correlated with subjective feedback information.

A. Contribution and organization of the paper

The main contributions of this work to the state-of-the-art are the following:

1) we propose a general approach to adaptive automation that is not limited to the considered use cases (as done in [18]–[20], [22], [23], [28], [35]) and we provide concrete instructions about how to implement it in other applications;
2) the proposed approach consists in a holistic framework that fully supports workers, thus enabling an inclusive work environment, as opposed to approaches based on technocentric adaptive automation [11]–[14];
3) with the *Measure* module, we provide a thorough characterization of workers, thus taking into account all human characteristics and capabilities that may affect interaction with a complex system, as opposed to [29]–[31], [35] where few aspects are typically considered;
4) with the *Adapt* module, we provide general rules to adapt any interaction task of industrial automation specifically to a complete set of worker's characteristics;

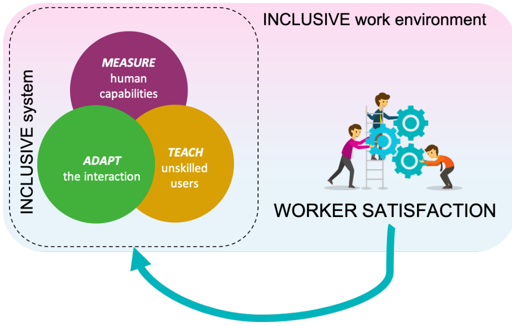


Fig. 1. Concept of the INCLUSIVE system: to achieve an inclusive work environment, the system relies on the three modules *Measure*, *Adapt* and *Teach*.

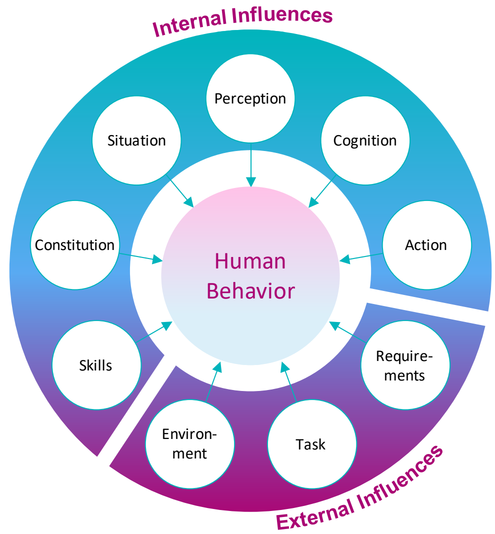
5) with the *Teach* module, we combine preliminary instructions with guidance integrated in the interaction system, thus providing the correct balance between worker's need for support and autonomy, similarly to [29];
6) we provide an extensive validation of the proposed adaptive automation framework in industrial use cases, with real shop floor operators, working tasks and machines, differently from most of the literature in the domain;
7) finally, we leverage our results to propose some general recommendations for the design of adaptive automation.

The rest of the paper is organized as follows. In Sec. II we present in detail the INCLUSIVE system and its components. Sec. III introduces the considered use cases, describes how the system has been implemented and provides details about validation tests. The results of the tests are reported in Sec. IV and in Subsec. IV-A the outcomes of tests are used to provide general recommendations for the design and implementation of a *MATE* system, such as the INCLUSIVE system. Finally, Sec. V follows with some concluding remarks.

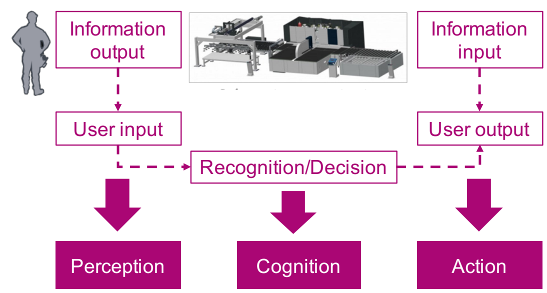
II. Methodology: the INCLUSIVE system

The rationale behind the INCLUSIVE system is that, benefiting from adaptive and anthropocentric automation, the interaction of workers with complex systems is tailored to the specific characteristics and needs of each worker. To this end, it is fundamental to build a precise thorough representation of the worker. Moreover, for least-skilled users specific guidance and training become advantageous. To achieve this, the INCLUSIVE system relies on three modules: *Measure*, *Adapt* and *Teach*.

The first set of capabilities is assessed offline, once before the beginning of interaction tasks, whereas the second set of information is continuously assessed online, during interaction. The second module, *Adapt*, consists in adapting the interaction to human capabilities. In other words, the system adapts the organization of the information, the means of interaction and the automation task that can be carried out by the user based on the outcome of the *Measure* module. Finally, the third module, *Teach*, provides unskilled users with adequate teaching support when needed. The system teaches the correct way to interact with the machine to the unskilled users, also by means of simulation in virtual and augmented environment. The main components underlying the INCLUSIVE system are shown in Fig. 1.



(a) Internal and external influencing factors in human-machine interaction. More specific attributes are reported in [36].



(b) Information processing in human-machine systems.

Fig. 2. *Measure* module: human capabilities model.

A. *The* Measure *module*

The design of this module followed two steps. Firstly, we isolated human capabilities that are relevant for human-machine interaction and might cause individual barriers to an efficient interaction. Then, we analyzed how to assess such capabilities.

Factors on human-machine interaction related to operator's strain can be distinguished between external and internal, as shown in Fig. 2(a). External factors are specified by characteristics of the technical system, such as task requirements or design of graphical user interface. Internal factors are specified by the individual characteristics of the working subject. Accordingly, the goal of the *Measure* module is to assess internal influencing factors that influence the operator's strain. Internal influences are determined by the subject's characteristics, which may vary due to the current situation, and how they processes information.

Regarding information processing, three dimensions constitute a barrier to human-machine interaction: perception of the machine information input, cognition (recognition and decision about information), and translation of decision into action [37]. These are reported in Fig. 2(b). These processes require effort based on a certain amount of available cognitive capacity. Cognitive effort arises if the available resources extend the required amount of capacity either positively or negatively. In this case, performance is likely to decrease with regard to the work task. Hence, the measurement of human capabilities relies on the assessment of perception, cognition and action. More specifically, relevant perception capabilities to be measured include visual, auditory and haptic capabilities. Cognition might be affected in terms of changed attention, memory and intelligence capabilities. With regards to action, human-machine interaction mainly influences it in terms of motoric and verbal function. These parameters have been identified and further specified in [36].

Moreover, following Fig. 2(a), other influences to human-system interaction come from the user's constitution or skills and situational factors. Specifically, constitutional factors mainly refer to culture, age and health, whereas the current situation affects interaction due to changing fatigue levels, physical and mental stress, emotions and user performance. As a consequence, permanent and/or long-lasting user capabilities can be measured before interaction, whereas current cognitive effort and performance have to be measured during interaction.

Building upon this analysis of human capabilities relevant during human-system interaction, it is important then to understand how they can be measured. With regards to capabilities related to information processing, these can be measured through established tests. Some examples are reported in Table I. In the case of constitution and skills, simple questionnaires can be used; they have to be tailored to the expertise and knowledge required by the system at hand. With respect to situational factors, they include cognitive effort and user performance. The most reliable way to track individual cognitive load of the user is the analysis of physiological parameters, such as pupil dilation, eye activity, Galvanic skin response, cerebral activity, body temperature and heart rate variability [38]–[40]. The measurement is done by means of proximal and distal measurement techniques. Proximal measurements rely on wearable devices, which do not limit the user's freedom of motion. On the contrary, distal techniques mainly rely on the use of cameras, implying on the one hand that this kind of measurement is transparent to the user, but on the other that the user has to be in the camera's field view.

Finally, with respect to user performance, it is needed to track or observe user behaviour while using the system. For instance, in eye tracking technique, user pattern and performance can be tracked in the gaze positions [41]. Recorded information can be adopted for the development of structural knowledge maps, such as registering the training evolution to give support to the operator in the future. Performance indicators include execution time, reaction time, time for decisions, execution steps, mistakes and redundancies. Their suitability strongly depends on the system and the task at hand.

A summary of the proposed model of human capabilities for interaction systems is reported in Table I. The specific implementation of the above mentioned concepts for the *Measure* module in the INCLUSIVE system is described in Subsec. III-B.

TABLE I
Measure MODULE: SUMMARY OF THE MODEL OF HUMAN CAPABILITIES FOR INTERACTION SYSTEMS.

CONSTITUTIONAL	Information processing	Perception	– Landoldt's rings tests [43] – Ishihara test [44] – Audiometer
		Cognition	– see review in [45]
		Action	– Functional-Independence-Measure questionnaire [46] – Fleishman factors [47] – Purdue Pegboard test [48]
	Knowledge		– Work experience – Specific expertise related to the system
SITUATIONAL	Cognitive effort		– Eye activity [38], [39], [40], [41] – Brain activity [38], [39] – Heart rate variability (HRV) [38], [39] – Galvanic skin response (GSR) [38], [39]
	Performance		– Execution time – Reaction time – Time for decisions – Execution steps – Mistakes – Redundancies

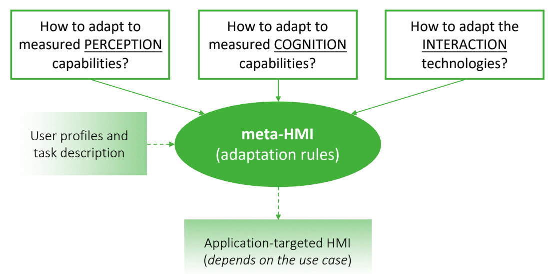


Fig. 3. *Adapt* module: overall organization.

The result of the model is a multidimensional measurement of human subjects facing an interaction system. In turn, such measurements identify groups of users that, despite having different individual capabilities and features, have common needs and response to the interaction with complex production systems, as discussed in [42]. As a consequence, this allows to define clusters of users that have the same need for adaptation and, hence, general adaptation rules for these clusters.

B. *The* Adapt *module*

The goal of the *Adapt* module is to provide general rules for the design of industrial HMIs that adapt to the skills and capabilities of operators and compensate their limitations. Building towards this goal, the first task is to define general guidelines for adaptive industrial HMIs, which extend established principles for the design of HMIs. Being general, such guidelines define a methodological approach that has general validity for any industrial application. Adding information about the application and the operator, it is possible to instantiate such rules to implement the context-dependent adaptive HMI.

Providing adaptation in the user interface turns out to be advantageous to the operator if, as a result, they can achieve a better understanding of the working task, thus feeling more confident with the entire system and acting more efficiently on it. In other words, an adaptive HMI should increase the user's situational awareness, by helping them to better perceive important data, comprehend the current situation and predict the future status [49]. To achieve this, we provide adaptation according to three different levels, namely perception, cognition and interaction, as proposed by Villani *et al.* in [50]. First, adaptation to operator perception is considered, which consists in accommodating their sensorial capabilities and presenting information accordingly. This level of adaptation refers to how information is presented. Then, cognition adaptation has to be taken into consideration: it accounts for the user's ability to understand information, which is influenced by skills and current emotional status and the kind of interaction task. This level of adaptation refers to what information is presented to the user. Finally, depending on user sensorial and physical capabilities, the best interaction means need to be selected to allow a smooth interaction: this level of adaptation refers to how interaction is enabled. The whole process underlying the *Adapt* module is depicted in Fig. 3.

The definition of perception adaptation rules was started from the universal design approach. This consists in a methodology for the design of objects that are accessible to all users, regardless of their age, ability and disability [51]. In particular, some of the guidelines of universal design are relevant in the context of perception adaptation, since they allow to address the special needs of subjects with perception limitations and physical impairments. As regards cognition adaptation, we have first identified some rules that guide on how to change the information according to the (current) cognitive capabilities of the user. These rules refer to the need to: i) select the most suited quantity and kind of information, by, for example, showing aggregated data in the presence of cognitive difficulties; ii) organize and prioritize alarms; iii) let some users explore the interface, while guiding those with cognitive difficulties; iv) enable or disable advanced functions according to cognitive capabilities [50]. To identify the most appropriate way for the HMI to adapt to the user's cognitive capabilities, their constitutional and situational characteristics need to be taken into account, as well as the kind of task at hand. Indeed, the adaptation rules apply differently to different tasks and, in some cases, do not apply at all to specific tasks. Finally, as regards adaptation of interaction modality, the specificity of industrial environment makes visual, physical and auditive interaction the only viable alternatives. Criteria have been given in [50] to identify which among them is the most suited according to user constitutional and situational characteristics, task requirements and work environment.

A summary of the levels of adaptation considered in the *Adapt* module is reported in Table II.

Receiving input from the *Measure* module, the *Adapt* module provides both constitutional and situational adaptation of the interaction system. Indeed, constitutional adaptation is dictated by constitutional measurement and accounts for quasi-static worker profile, mainly linked to their role in the company. Situational adaptation accounts for temporary variations around the quasi-static user profile, such as the worker getting fatigued towards the end of the work shift or puzzled when facing a new working task. These conditions are detected by situational measurements of cognitive effort

TABLE II
Adapt MODULE: LEVELS OF ADAPTATION

Perception adaptation: *how* information is presented		
Universal design	+	Common physical impairments
Cognition adaptation: *what* information is presented		
General design rules	+	Task characteristics
Interaction adaptation: *how* interaction is enabled		
Interaction modalities	+	User characteristics Task characteristics Environment

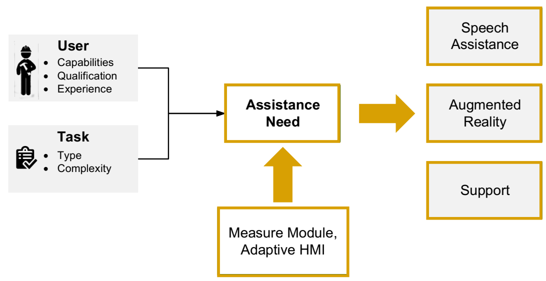


Fig. 4. *Teach* module: overview of the online assistance.

and performance and elicit a change in the behavior of the system, thus leading to situational adaptation (upon worker's acceptance).

Finally, it is noteworthy that the adaptive interaction that can be achieved by means of the proposed levels and rules can be described in terms of the level of automation [52]. In particular, depending on application context, they allow to move from the condition in which "*the computer offers no assistance; human must do it all*" (level 1), when there is no adaptation, to higher levels in which "*the computer offers a complete set of action alternatives, and*" (level 2) "*narrows the selection down to a few, or*" (level 3) "*suggests one, and*" (level 4) "*executes that suggestion if the human approves*" (level 5). Indeed, the proposed adaptation is suited for applications where the interaction is always controlled by the human operator; occasionally, based on the outcome of the *Measure* module, control is shared for relief, since the system helps the human so that her/his burden may be reduced [53]. When this is the case, cognitive automation is implemented by automating cognitive activities, such as situation assessment, monitoring, and fault management [54].

C. *The* Teach *module*

The *Teach* module is composed of two separate parts, namely offline and online training subsystems, which provide different kind of support to the user and assist them in different working moments. To comply with diversification of the workforce, the two systems adapt their characteristics to performance-influencing factors of the trainee, such as constitution, disposition and qualification, as measured by the *Measure* module.

The aim of the offline training subsystem is to prepare the operation personnel for their tasks. To this end, it provides a training environment based on a virtual simulation of the machine that allows to simulate working procedures. In virtual

TABLE III
Teach MODULE: TARGET AUDIENCE FOR EACH ASSISTANCE DEVICES (✓: ADAPTED /✗: UNSUITABLE).

		Speech-based assistance	**AR-based assistance**		**HTML support**
			Head-mounted display	**Tablet**	
User characteristics	Low-literate	✓	with non-verbal instruction		
	Age > 50	✓	adaption of the visualization (contrast, font size) + audio-annotation		
	Visually impaired	✓			
	Deafness	✗	✓	✓	✓
	Upper limbs	✓	✓	✗	✓
	Novice	with additional visual aids	✓	✓	✓
	Qualified	✓	✓	✗	✓
Task	*Do-task*	✓	✓	✓	✓
	Comprehend-task	with additional visual aids	✓	✓	✓
	Manual task	✓	✓	✗	✗
	UI task	✓	✓	✗	integrated into the pre-existent interface

training systems, adaptation describes the extent to which the training system can be adapted. Adaptation can be classified in terms of "adaptivity" and "adaptability" [55]. "Adaptivity" is initiated by the system and describes the components of the training system that can be adapted automatically, while the "adaptability" is initiated by the user and includes components of the teaching style that users can adapt. Adaptation is provided in terms of interaction, presentation and complexity, and training is adapted based on feedback collected during the training to assess the state of the trainee [56]. To maximize the effectiveness of this kind of training, the whole interaction system is fully integrated in the virtual environment. In particular, it includes the adaptive user interfaces developed in the framework of the *Adapt* module, so that the user has access to a reliable replica of the interface running on the machine to configure or control the virtual machine. As a result, the virtual training system propagates a gradual reduction of the instructions with an increasing qualification of the trainee. This increases the complexity of the training and increasingly requires the user to remember the worksteps of the trained procedure. This should support the automation of the procedure and the transformation to skill-based behavior [57].

With respect to the online assistance system, it supports employees while carrying out the procedure at the industrial machine. The teaching system is triggered by the *Measure* module or the adaptive HMI to provide assistance. The offered assistance consists in instructional methods that reduce the demand placed on the user's working memory, according to the cognitive workload theory [58]. Such methods adopt various modalities and are adapted to the task to perform and to the characteristics of the user. Fig. 4 displays an overview of the approach of the online teaching subsystem. The assistance system identifies first the assistance need of the user and, then, selects the best assistance modalities for the specific cases. Three systems were examined to offer a wide range of assistance modalities: an augmented reality (AR) and speech-based assistance for support during the procedures and HTML-based support to provide separate teaching units. In addition, in [59] haptic interaction assistance was considered as another assistance system for manual procedures in virtual training system.

With respect to user characteristics, a novice operator receives assistance that is more detailed and targets bigger parts of a task. Structured online teaching with separate lessons or a detailed description of the tasks, such as with 3D-animations, should be offered to novice operators. Experienced operators receive less advice, like in the form of pop-up messages. A speech-based assistance system could be a suitable solution for an experienced operator [60].

Furthermore, the kind of assistance to provide depends also on the characteristics of the task. In particular, we consider tasks consisting in either an action to perform (*Do-task*, physical manipulations) or a state to observe or comprehend (*Comprehend-task*, e.g. verifying the machine state). Visual representations are appropriate for *Comprehend-tasks* since they allow comparing the desired state that is represented by the assistance system with the real state of the machine.

Tasks are also distinguished by whether they are manual tasks or user interface (UI) tasks. A manual task typically requires the use of both hands. The assistance device should not require manual actions, except haptic assistance to help the operator to get the feeling of physical properties of the tools in manual tasks. Indeed, introducing physical components can improve the efficiency of virtual training systems by transporting a sense for haptic properties of components. It can facilitate the transfer of manual skills to the real environment, as shown in [59]. Moreover, the assistance device should reduce visual indications in order not to distract the operator. For UI tasks, it is recommended to avoid the use of an additional computerized device to not overload the user.

Combining these considerations, Table III displays the task- and user-specific selection of these devices under consideration of the limitation of the previous section as well as the adaptation(s) to be made when not entirely unsuitable.

To summarize, the modules constituting the modules of the INCLUSIVE system and their main features are reported in Fig. 5.

III. SYSTEM INTEGRATION AND VALIDATION

A. Use cases

To validate the proposed INCLUSIVE system, we selected real use cases that depict the scenario of human-machine systems currently utilized in industrial environments [33]. Specifically, we considered the industrial use cases in Fig. 6,

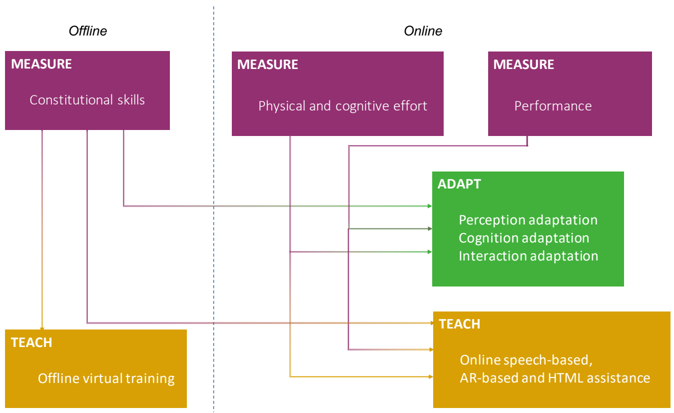


Fig. 5. Summary of the modules in the modules of the INCLUSIVE system.

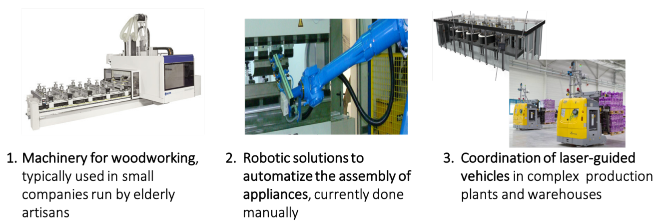


Fig. 6. Use cases considered to validate the INCLUSIVE system.

since they are representative of a wide area of interest for industry in Europe. These are:

1) woodworking machinery for small companies, typically run by elderly owners (https://youtu.be/H2UoYpfdM_I);
2) automation solutions made for developing countries (https://youtu.be/ovjeyxITEkM);
3) management of large industrial plants and warehouses (https://youtu.be/Ms3Flj8xihc).

The first use case refers to machinery used for woodworking in artisans' shops. The second one considers a robotic solution to be applied in a company located in a developing country, where operations are mostly performed manually. In particular, the considered robotic solution is for panel bending. Finally, the third use case refers to the manufacturer of laser-guided vehicles (LGVs) for coordinated movement of goods in production plants and warehouses and automated management of intralogistics flows.

For each use case, a specific working scenario has been analyzed in order to derive what are the concrete limitations of currently implemented solutions in terms of human-system interaction. Specifically, for the first use case we focused on the activities related to tuning of the machine, to make it ready for woodworking (tuning of the tools warehouse, tuning of the worktable area components) and routine maintenance procedures. For the second use case, we considered the standard activities performed by a user for bending a part, and replacing malfunctioning tools. The working scenario for the third use case referred to the management of a fleet of LGVs operated along the production lines and in partially structured and highly dynamic warehouses. In particular, the possibility to monitor the status of the fleet was tested, together with maintenance procedures for encoder recalibration and oil change.

As regards system architecture, the three modules of the INCLUSIVE system (*Measure*, *Adapt* and *Teach*) communicate among each other and with the proprietary systems of the use cases through an adaptive automation middleware[1], which allows for hardware independence and modularity. Specifically, the middleare is connected to the INCLUSIVE system via the OPC UA protocol[2] and to the proprietary HMIs via (Fast Ethernet) TCP/IP connection.

B. Implementation of the Measure *module*

The rationale behind the *Measure* module described in II-A is general and does not take into account the specificity of industrial working systems. To instantiate it in the INCLUSIVE system, a concept was developed consisting of different assessment approaches. For this purpose, user data were assessed within three time levels: static, real-time, and longitudinal analysis. In this regard, individual resources were considered in the static analysis, specifically focusing on users characteristics of the target groups (see Table III). This analysis addressed constitutional user characteristics and consisted in a questionnaire, which was integrated in the HMI and examined the user's general computer skills, work experience, experience with the machine and the presence of visual impairments. The answers given to the questionnaire are combined to determine the default settings for the initial user profile, according to the guidelines provided by Villani *et al.* in [42].

Cognitive effort was considered by measuring physiological parameters (real-time analysis). A combination of proximal and distal measurement techniques was consider to jointly achieve continuous measurement without interruption of the task (proximal) and contactless measurement able to capture any user in front of the sensor (distal). Results of empirical studies showed that pupil dilation, Galvanic skin response and heart rate variability were most sensitive to different levels of cognitive workload (e.g. [40], [61]). In accordance with the literature (e.g., [38], [39], [62]), physiological signals were analyzed computing standard indices. The commercial software ThingWorx Analytics[3] was used to identify meaningful patterns in the data, leveraging a set of predictive analytic algorithms and machine learning techniques. A generalized prediction model for cognitive stress detection was generated, after training and validation on physiological data from 25 test subjects who were exposed to cognitive stressors: in other words, they were asked to perform a task demanding significant mental engagement and attention. Physiological data were measured with a wearable device, namely Empatica E4 wristand[4]. For those working tasks that did not require the operator to move around the machine, pupillary response was recorded using FOVIO eye tracking system[5].

[1]https://www.kepware.com/en-us/products/kepserverex/
[2]https://opcfoundation.org/about/opc-technologies/opc-ua/
[3]https://www.ptc.com/en/resources/iiot/product-brief/thingworx-analytics
[4]https://www.empatica.com/research/e4/
[5]http://www.eyetracking.com/Hardware/Eye-Tracker-List

TABLE IV
OVERVIEW OF THE USE CASES AND THE CONSIDERED WORKING SCENARIOS (HRV: HEART RATE VARIABILITY; GSR: GALVANIC SKIN RESPONSE).

	Participants	Evaluation scenarios	Human measurement	Performance metrics
Use case 1	18 (SCM, IT)	***Machinery for woodworking*** – Tooling of the tool warehouse – Maintenance operation due to error message about locked spindle	– Constitutional questionnaire – HRV and GSR via Empatica E4 – Time needed to perform actions	– Usability questionnaire – Worker satisfaction questionnaire – Physiological parameters – Time needed and mistakes occurred
Use case 2	18 (Silverline, TR)	***Robotic bending system*** – Setting of working parameters – Maintenance procedure for sensor replacement	– Constitutional questionnaire – HRV and GSR via Empatica E4 – Time needed to perform actions	– Usability questionnaire – Worker satisfaction questionnaire – Physiological parameters
Use case 3	17 (Elettric80, IT)	***Management of fleets of LGVs*** – Assessing the status of the fleet – Maintenance procedure for motor wheel encoder calibration	– HRV and GSR via Empatica E4 – Pupillary response via FOVIO eye tracker – Time needed (*only for non-expert operators*)	– Usability questionnaire – Worker satisfaction questionnaire – Physiological parameters

The longitudinal profile contains data about the user performance, which aims at deriving additional online and offline training measures in the *Teach* module. For this purpose, the user's performance when using the system was recorded over a certain period of time.

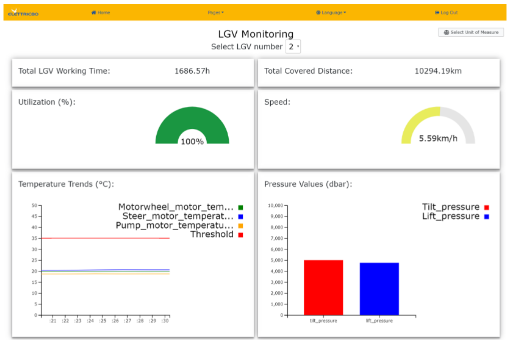
All these data were used as input parameters for the *Adapt* module, based on which the INCLUSIVE system was individually adapted. The implementation of the *Measure* module for the considered use cases is summarized in Table IV. The human measurements regarded both constitutional (static analysis) and situational factors; moreover, situational factors were investigated with respect to both cognitive effort (real-time analysis) and performance (longitudinal analysis). These analyses represent the subset of the methodologies proposed in Table I that were identified as the most appropriate for our use cases. A couple of remarks are noteworthy for use case 3. First, the questionnaire about constitutional capabilities was not included in the HMI since tasks and responsibilities charged to expert and non-expert operators are substantially different, as described in Subsec. III-C. Expert operators are in charge of monitoring the status of the fleet and setting new interventions, who are then typically performed by non-expert operators. As a consequence, the static profile in this use case is set based on employee's profiling by human resources department. Second, given the nature of tasks charged to expert operators, longitudinal measurement of performance according to Table I does not apply to this class of operators since they need to explore the HMI, as described in Subsec. III-C.

C. *Implementation of the* Adapt *module*

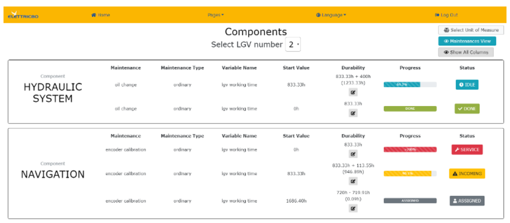
The *Adapt* module was implemented following the guidelines discussed in [50]. In particular, with reference to Table IV, it was implemented for the first task of the evaluation scenario of each use case, while the second task was implemented in the online *Teach* module. It was included in the user interface to guide in performing maintenance activities, providing offline and online step-by-step guidance, when needed by the user. These functionalities are enabled adaptively based on the outcome of the *Measure* module.

As regards use case 1, the *Adapt* module was applied for tooling the tool warehouse, which is a procedural task for setup, according to the classification in [50]. Perception adaption was implemented to accommodate for reduced vision capabilities by adapting font size to maximize legibility and providing pictorial representations of tools for redundant presentation of information, following the principles in Table IV in [50]. Cognition adaptation was implemented considering guidance (rule R3 in Table V in [50]), being a procedural task. Then, as regards interaction adaptation, visual interaction was considered, since it is a setup task (Table VII in [50]). More detailed description is reported in [50]. The same rules were considered for the task related to setting of the working parameters of the robotic bending system of use case 2.

The *Adapt* module implemented for use case 3 is reported in Fig. 7. In particular, we have developed a smart interaction system that supports the supervision of a fleet of LGVs in production plants or large, partially structured, and highly dynamic warehouses, compensating variations in roles, skills, cognitive capabilities, disabilities, education level and age of operators. An adaptive HMI has been developed that allows to check the internal status of each vehicle and, hence, schedule and perform maintenance activities on a group of LGVs. In the case of expert operators, the HMI allows to explore any technical information of the fleet, implementing a level of automation 1. On the contrary, non-expert operator are informed only of the tasks they are responsible for and solicited when actions is needed (level of automation 3). Specifically, with reference to Fig. 7, the HMI shows specific working parameters and their trends representative of the working condition and remaining working life of each vehicle (Fig. 7(a)). Moreover, it highlights incoming scheduled maintenance activities for the fleet, giving the opportunity of assigning them to operators (Fig. 7(b)). The user interface allows expert operators also to enter new maintenance interventions or postpone existing interventions, based on the current status of vehicles. In terms of the proposed three levels of adaptation, perception adaptation was implemented to accommodate visual impairments due to reduced vision capabilities and color blindness. Indeed, for this kind of interface color blindness becomes relevant since colors are associated to alarms and difference between current values and thresholds. To this end, adjustment of font size and color scheme were implemented to maximize legibility



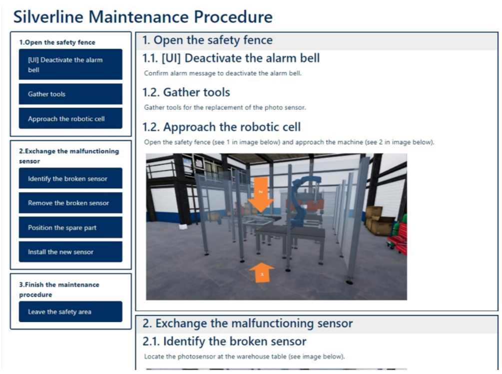
(a) View of vehicle specific working parameters (available for expert operators).



(b) View of scheduled maintenance activities for the fleet: non-expert operators can only see tasks they have been assigned to.

Fig. 7. Implementation of the *Adapt* module for use case 3.

(a) Offline *Teach* module: virtual training environment.



(b) Online *Teach* module: HTML support system.

Fig. 8. Implementation of the *Teach* module for use case 2.

and provide adequate contrast between essential information and its surroundings (Table III in [50]). Cognition adaptation was implemented in terms of information selection, alarm organization and functionality enabling, being a supervision task (rules R1, R2 and R4 in Table V in [50]). Finally, visual interaction was considered (Table VII in [50]).

D. Implementation of the Teach *module*

In Fig. 8 we report, as an example, the *Teach* module implemented for use case 2. In particular, Fig. 8(a) shows the virtual training environment reproducing the newly implemented robotic bending system. For this use case, the offline training resulted being fundamental to operators, given that they were new to the robotic system. Indeed, before the introduction of the INCLUSIVE system, a manually fed bender was used, whereas with the INCLUSIVE system it as possible to introduce a robot to feed metal sheets to the bender.

E. Testing sessions

The effectiveness of the INCLUSIVE system has been tested in sets of tests in real production environment at companies representative of the use cases, with shop floor workers. In particular, use case 1 was tested in SCM Group, in Italy, one of the world leading producers of woodworking machines. Use case 2 was tested in SILVERLINE, in Turkey, a company producing domestic appliances. SILVERLINE production process uses several kinds of very simple machines for bending metal parts and components, currently manually fed mainly because of the variability of the process itself and the lack of skilled production line personnel capable of managing automatic machines or robots. Finally, use case 3 was tested in Elettric80, located in Italy. Elettric80 produces automated solutions for warehouse management, mainly based on fleets of LGVs used for goods transportation inside production plants and logistic warehouses.

An overview of all the tests is reported in Table IV. For each use case, two evaluation scenarios were identified: these represent frequent working tasks considered to assess the effectiveness of the INCLUSIVE system at the use cases.

It is noteworthy that in the use case 1 the same evaluation scenarios were performed with both the INCLUSIVE system and the legacy user interface currently used on woodworking machines. This was not possible in the use cases 2 and 3, since there is no legacy interface currently in use that performs the same tasks of the INCLUSIVE interface. Indeed, as regards the use case 2, the INCLUSIVE system was introduced to automatize an activity currently done manually. As regards the use case 3, there is no existing user interface for the management of a fleet of vehicles.

The whole study was approved by the Ethics Committee of the Province of Modena, Italy, being the study coordinated by the University of Modena and Reggio Emilia.

1) Test protocols: Each participant was explained the overall goals of the tests and the protocol. Moreover, in compliance with the General Data Protection Regulation (EU) 2016/679 (GDPR), each test subject and the local coordinator of tests signed the informed consent form.

At the beginning of the test, participants were asked to self-assess with respect to their computer skills and knowledge of the machine, in order to identify the initial user level for the INCLUSIVE HMI [36]. To this end, the assessment of constitutional user's characteristics in the *Measure* module was used. Then, information was given to operators about working conditions of the INCLUSIVE system by using the simulated environment in the offline training system, which is part of the *Teach* module. Afterwards, operators were instructed to act on the real system, under real working conditions. In particular, tests consisted in asking participants to perform the tasks of the considered evaluation scenarios listed in Table IV. When needed, realistic details were provided, such as values for parameters to be set. With respect to maintenance procedures, the corresponding alarms were forced to appear on the user interface intermittently during the test session, in order to invite test subjects to solve them.

For use case 1, these tasks were repeated twice for each participant, considering the customary user interface and the INCLUSIVE system. In order to avoid learning effects in results, half of the users tested the INCLUSIVE HMI before the customary one, while the other half performed the test in reverse order.

After performing the tasks, users were asked to fill out questionnaires measuring system usability [63] and worker satisfaction [34].

2) Test subjects:

a) Use case 1: A total of 18 participants (17 male, 1 female), between the ages of 19 and 54 (AM = 35; SD = 13.1), were enrolled in tests. Participants have earned all education degrees from an elementary school to a master's degree. The duration of the employment also varies greatly, ranging from under six months to, in many cases, over ten years. As a result of the initial self-assessment of computer skills and knowledge of the machine, half of the participants reported average computer skills, whereas the other half reported low computer skills. Moreover, half reported they had no knowledge of the machine, whereas the other half reported being familiar with it. Finally, a test participant had mild cognitive impairments, whereas two had visual impairments.

b) Use case 2: A total of 18 male operators were enrolled in the tests. The mean age was 34.6 years (SD = 6.8). A third of the participants were working as welding operators and another five participants as bending operators. The remaining participants were working as polishing, documentation, glass preparation, or robotic systems operators. Eight of them self-assessed as expert users, while the remaining as non-expert. All participants have earned at least a high school diploma, with five participants having a secondary school diploma. Three participants graduated from a vocational college. Half of the participants were working in the current position for one to two years, two participants between 7 and 12 months, and one participant for less than six months. As regards constitutional characteristics, two participants had hearing impairments and two others impairments at the upper limbs.

c) Use case 3: A total of 17 users (13 male, 4 female) took part in the questionnaire survey conducted at Elettric80. The mean age was 29.3 years (SD = 8.2). The youngest participant was 24 years old, and the oldest participant was 51 years old. Mean job tenure in the company was 2.41 years. One participant completed a secondary school, 16 participants completed university studies with a bachelor's (6) and master's (10) degree.

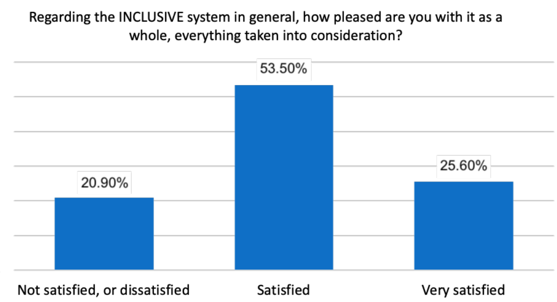


Fig. 9. Overall satisfaction with the INCLUSIVE system.

3) Performance metrics: A thorough assessment of the INCLUSIVE system was achieved by considering objective and subject performance metrics [64]. Objective metrics consist in performance related indexes measured during tests, namely time needed to perform a task and number of mistakes occurred while carrying out the procedure. As regards subjective metrics, after test sessions, participants were administered the *system usability scale* (SUS) questionnaire [63] and the *worker satisfaction* questionnaire [34]. The former is an established tool to assess the usability of a wide variety of products and services [65], while the latter was developed in the context of the INCLUSIVE project and is based on a model of worker satisfaction [34], [66]. This model constitutes a comprehensive end-user evaluation framework, accounting for the core system usability principles as well as physical and psychosocial aspects of the working environment, and, most importantly, the end-user evaluation of the INCLUSIVE HMI building modules (*Adapt*, *Measure* and *Teach*). Thus, the worker satisfaction questionnaire consists in three sections: physical working conditions, psychosocial working conditions and ethical aspects, and user's satisfaction with the INCLUSIVE system and its modules. Full details about the model and the questionnaire for worker satisfaction are reported in [34].

IV. Results

The results of the measurement of worker satisfaction with the proposed adaptive INCLUSIVE system demonstrated that the majority of the participants assessed the overall satisfaction with the adaptive system as relatively high: 79.1% of the study participants were satisfied or even very satisfied with it, as shown in Fig. 9. Equally, around 70% were satisfied with the design and ease of the adaptive HMI. Further, the largest number of the study participants (80%) felt that the HMI helped them to cooperate efficiently with the machine/robot and the same number declared that, in general, the HMI helped them to become more productive in their work. However, more than 30% declared that the amount of the HMI information was rather excessive.

The INCLUSIVE system was assessed favorably with respect to the legacy industrial interface, customarily used in industry for use case 1. Comparative assessment considered

TABLE V
RESULTS OF SPEARMAN CORRELATION ANALYSIS BETWEEN THE OBJECTIVE PARAMETERS AND THE SUBJECTIVE WORKER SATISFACTION.

	HR mean	HR T1 mean	HR T2 mean	HR max	HR T1 max	HR T2 max	LFnu	HFnu	GSR mean	GSR T1 mean	GSR T2 mean	Temp mean	Temp T1 mean	Temp T2 mean
Safety functions are readily accessible	-0.28	-0.31	-0.19	-0.28	-0.24	-0.24	0.03	-0.39*	-0.07	-0.01	0.04	0.27	0.35	0.27
Error messages and warning messages are clear	-0.21	-0.26	-0.16	-0.30	-0.25	-0.19	0.15	-0.41*	0.09	0.03	-0.02	0.03	0.10	-0.07
Characters are easy to read	-0.18	-0.18	-0.05	-0.20	-0.23	-0.11	0.27	-0.46**	0.18	0.14	0.15	0.30	0.38*	0.23
The interface buttons (options) are visible on the screen	-0.09	-0.09	0.02	-0.15	-0.17	-0.08	0.21	-0.31	0.15	0.20	0.12	0.28	0.39*	0.24
Position of messages on the screen is consistent	0.15	0.19	0.17	0.05	0.08	0.14	0.23	-0.16	0.23	0.30	0.41*	0.29	0.34	0.40*
The colors used in the HMI help to better perceive the information on the screen	0.03	-0.03	0.16	-0.02	-0.05	0.10	0.39*	-0.39*	0.17	0.20	0.21	0.34	0.45**	0.33
The HMI layout is aesthetic	-0.24	-0.29	-0.19	-0.37*	-0.36*	-0.23	0.14	-0.44*	0.03	0.10	0.09	0.21	0.27	0.20
In general. the organization of information is clear	-0.04	0.08	-0.04	0.00	0.11	-0.08	0.12	-0.03	0.37*	0.45**	0.50**	0.27	0.28	.409*
The changing interface distracts me	-0.37*	-0.31	-0.36*	-0.27	-0.20	-0.36*	0.10	-0.04	0.34	0.33	0.26	-0.01	0.01	0.11
In general. the layout of the adaptive HMI is appropriate	-0.12	-0.06	-0.12	-0.11	-0.02	-0.15	0.19	-0.25	0.25	0.28	0.46**	0.32	0.36*	0.40*
Use of terms throughout system is consistent and understandable	0.02	-0.02	0.04	-0.09	-0.05	-0.05	0.25	-0.46**	-0.07	0.12	-0.02	0.13	0.22	0.16
I can easily find all the information I need	-0.10	-0.06	-0.13	-0.18	-0.11	-0.14	0.08	-0.21	0.00	0.14	0.08	0.17	0.18	0.37*
I can easily return to the earlier steps	0.06	0.01	0.07	-0.04	-0.06	-0.02	0.23	-0.38*	-0.17	0.04	-0.03	0.20	0.28	0.21
The number of operations to perform a task/to achieve a goal/to set up a process is optimal	-0.16	-0.21	-0.08	-0.23	-0.26	-0.12	0.20	-0.53**	-0.08	0.03	-0.11	0.25	0.32	0.14
The HMI helps me to more efficiently cooperate with the machine/robot.	-0.02	-0.12	0.07	-0.18	-0.10	-0.03	0.16	-0.44*	-0.10	0.01	0.05	0.20	0.27	0.20
In general. the HMI helps me to be more productive in my work	-0.04	-0.10	0.05	-0.24	-0.15	-0.08	0.16	-0.41*	-0.03	0.11	0.02	0.17	0.25	0.26
I feel I can be easily guided when I get lost/commit an error	0.04	0.01	0.05	-0.15	-0.17	-0.01	0.36*	-0.27	-0.06	0.02	-0.10	0.33	0.29	0.33
I trust the system and that my personal data will not be abused	-0.13	-0.11	-0.08	-0.23	-0.27	-0.16	0.00	-0.46**	-0.30	-0.18	-0.32	0.26	0.33	0.25

*p<0.05; **p<0.01; ***p<0.001

Heart rate (HR): *HR mean*: mean HR throughout the test; *HR mean T1*: mean HR in the first part of the test; *HR mean T2*: mean HR in the last part of the test; *HR max*: maximum HR throughout the test; *HR max T1*: maximum HR in the first part of the test; *HR max T2*: maximum HR in the last part of the test. **Heart Rate Variability (HRV)**: *HFnu*: high-frequency normalized spectral power throughout the test; *LFnu*: low-frequency normalized spectral power throughout the test. **Galvanic Skin Response (GSR)**: *GSR mean*: mean GSR throughout the test; *GSR mean T1*: mean GSR in the first part of the test; *GSR mean T2*: mean GSR in the last part of the test. **Skin temperature (ST)**: *ST mean*: mean ST throughout the test; *ST mean 1*: mean ST in the first part of the test; *ST mean 2*: mean ST in the last part of the test.

both subjective (system usability and worker satisfaction) and objective measurements (time needed and mistakes occurred to perform requested tasks). In particular, using the INCLUSIVE system provided a reduction of 36.9% of time needed to accomplish a task and of 37.5% of occurred mistakes, on average over 18 test subjects. A thorough analysis of the results of the tests for use case 1 is reported in [66].

With respect to objective assessment derived from physiological parameters measured with the Empatica E4 wristband (heart rate, skin temperature, and Galvanic skin response), it was found in all the use cases that test subjects underwent sustained mental workload. A correlation analysis of these data with the results of subjective worker satisfaction was carried out to identify those objective (physiological) measures that can be used to monitor the level of satisfaction relating to the working with the INCLUSIVE system, and to identify which operations have a negative impact on worker cognitive load and stress level.

Table V reports the results of this analysis. Specifically, the first column reports the statements from the worker satisfaction questionnaire in [34]. The subject's agreement with statements were measured with a 4-point Likert scale, where 4 = "to a large extent" and 1 = "to a very small extent". The remaining columns report the physiological parameters derived from Empatica E4 wristband and used in the analysis. The r-Pearson correlation analysis was performed using SPSS 23.

The correlation analysis revealed a number of significant relationships between physiological parameters and subjective worker satisfaction indicators. In particular, spectral power in the high frequency band (HFnu, [67]) was most often correlated with subjective satisfaction with HMI. This outcome confirms that heart rate variability could be one of the most responsive factors when measuring human physiological reactions/strain [38], [39]. In particular, stress is correlated with the decrease in the high frequency band (HFnu) and increase of power in the low frequency band (LFnu). In line with this assumption, but contrary to our expectations, the results of the correlation analysis indicate that the higher the level of strain, the higher the level of subjective satisfaction. The higher levels of physiological parameters are a symptom of physiological and psychological activation/arousal and do not have to be interpreted as stress or negative strain. New, modern working methods, coupled with a new technological solution to practice could cause an activation state in the users, but it does not mean that they were experiencing negative strain or overload. It could be interpreted by every user in a different way: as a threat or a challenge, which is a positive approach related to positive psychological effects [68]. While long-lasting activation could be harmful for person's health, a short-term activation/arousal is not necessarily associated with negative outcomes, depending on stimuli and their interpretation [68], [69], or various resources [70]. It is possible that after some time working with the new HMI these physiological parameters would return to their previous levels. However, said situation could not be observed during our tests. Therefore, it may be recommended that future studies could include longitudinal tests, repeating measurement after longer period of time, for instance after 6 or 12 months. Finally, it is worthy to point out that, although the strain level was significantly higher throughout the tests, users were able to appreciate new functions of the INCLUSIVE system. It would mean that, even if the user is stressed or overloaded with work, they is able to cognitively assess new functions.

A. Recommendations to ensure worker satisfaction and system usability

The achieved results were used to formulate a set of recommendations for the design and implementation of an adaptive interaction system, rendered in the shape of a *MATE* system. The recommendations have been developed according to the model of worker satisfaction with an adaptive interface [34] and to the whole INCLUSIVE system functionalities. These assumptions are based on subjective and objective measurement of worker satisfaction: the subjective and objective measurement data have been correlated and the obtained results analyzed in order to formulate the complete recommendations for the development of an adaptive automation system applied in an industrial environment that responds to operator needs and performance requirements. Said recommendations are summarized in Table VI.

V. Conclusion

In this paper we presented a general approach to the holistic design of industrial interaction systems that adapt to the skills and capabilities of human operators. The goal is that of relieving the increasing complexity of modern production systems by providing operators with usable interfaces, enabling a smooth and easy interaction. The systems developed according to the proposed approach allow for inclusive and flexible working environments accessible to any operator, regardless of age, education level, cognitive and physical impairments and experience in the tasks to be performed. This allows, for example, elderly, disabled, and inexperienced operators, who are the most vulnerable in the interaction with complex automatic systems, to access working positions they would be otherwise barred from.

To implement the proposed methodology, three industrial use cases were selected as representative of a wide area of interest for the industry in Europe, in terms of both production requirements and involved operators. The INCLUSIVE system has, hence, been tested in real production environments at the companies leading the use cases, with shop floor workers. The effectiveness of the approach has been assessed with subjective and objective measurements. In particular, feedback from test participants was collected with a questionnaire on their satisfaction and system usability. Moreover, objective measurements of users' mental strain were collected and these were correlated with subjective feedback information.

Future work will consists in a more extensive assessment to further validate the proposed methodology for the design of adaptive interaction systems and propose their concrete application in industrial working environments. In order for this to happen, acceptance by workers and trust in the use of the system need further appropriate scrutiny.

Acknowledgment

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TABLE VI
Recommendations for design and implementation of an adaptive interaction system, in the shape of a *MATE* system.

Recommendations related to monitoring user parameters
An adaptive HMI could include the real-time measurement of physiological parameters, e.g.: – heart rate and heart rate variability – Galvanic skin response – body temperature – pupillary response
An adaptive HMI user should: – trust the system and that their own personal data will not be abused – feel that monitoring strain can benefit them – not feel that an adaptive HMI can challenge their physical comfort
Recommendations related to system adaptation
Interface functions should be modifiable with regard to a certain systems aspects based on: – task needs – user capabilities and skills – personal user preferences
User parameters (capabilities, skills, personal preferences) should be taken into account using: – a-priori user profile (containing the user's innate and evolved skills and capabilities, which can be evaluated beforehand and are applied continuously for the individual) – real-time user profile (measuring the actual state of the operator whilst working using physiological parameters measurement) – longitudinal user profile (analysis of user performance and capabilities development)
The system should maintain those settings appropriated for user when re-starting
The adaptive interface should help an user to be: – less stressed using the adaptive HMI – more confident using an adaptive HMI – make fewer mistakes/errors using an adaptive HMI
Recommendations related to online and offline training
A guided step-by-step approach would be more suited to the unskilled user
A more skilled user would work better using shortcuts
The online training might use several ways of assistance, such as: – AR-based assistance – speech-based assistance – support assistance
The online training should be: – easy to read and perceive – adequate in relation to an operator's skills and capabilities – adapted to a current work task
If there is an offline training system in the adaptive HMI it could replace or support teaching-in by a trainer for this procedure and it also should be: – easy to read and perceive – adequate in relation to an operator's skills and capabilities – adapted to a current work task
Recommendations related to psychosocial working conditions
In their work in general, the adaptive HMI operators should: – have the possibility of learning new things – have the possibility of getting help and support from the nearest superior – have enough time to perform work tasks – should not be stressed during their work – be recognized and appreciated by management
General recommendations related to measuring worker satisfaction and system usability
Subjective measurements of worker satisfaction and system usability should be carried out along with the objective measurement in order to properly interpret the latter ones (in terms of strain or excitement)
Further studies should confirm usability of other wearable devices in measuring a worker's physiological parameters in various work environments, performing different tasks
These measurement should be repeated after some time of using the adaptive HMI (e.g., several months) in order to confirm or disconfirm worker satisfaction and system usability in the long term

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