Internet of Things 21 (2023) 100673

Contents lists available at ScienceDirect

Internet of Things

journal homepage: www.elsevier.com/locate/iot

Review article

Towards a cognitive assistant supporting human operators in the Artificial Intelligence of Things

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ARTICLE INFO

Keywords:
Cognitive skills
Artificial intelligence
Internet of things
Assistive systems
Human-centred
Cyber–physical systems

ABSTRACT

Internet of Things (IoT) systems are becoming increasingly complex due to heterogeneity of devices and requirements for real-time processing and decision making. In this context, Artificial Intelligence (AI) technologies provide powerful capabilities for endowing IoT devices with intelligent services, leading to the so-called Artificial Intelligence of Things (AIoT). The operator is in the middle of this complexity, trying to understand the situation and make effective real-time decisions. Hence, human factors, especially cognitive ones, are a major issue to be addressed. The human cognitive part must be framed together with intelligent artefacts, requiring a systematic approach in the domain of joint cognitive systems. New software development methods in the form of assistants and wizards are necessary to help operators to be context-aware and reduce their technical workload regarding coding or computer-oriented skills, focusing on the task or service at hand. Building on previous research on the role of the human worker in an AIoT environment, this article analyses the described situation in terms of human cyber–physical systems, with the aim of proposing a conceptual framework for these assistance systems at the cognitive level. Two illustrative examples are described to validate the effectiveness of the proposed framework in collaborative tasks.

1. Introduction

Internet of Things (IoT) systems are increasingly becoming complex. Heterogeneity in terms of hardware, software, computing capacity, and connectivity is a source of complexity. Embedding IoT systems into more general cyber–physical systems (CPS), including devices that are able not only to collect but also to process and take decisions in real-time is a second source of complexity [1]. Moreover, not only sensors should be considered but also actuators, especially collaborative robots (cobots) in the industry domain [2].

In this context, Artificial Intelligence (AI) technologies provide powerful capabilities to endow IoT devices with intelligent services, leading to the so-called Artificial Intelligence of Things (AIoT) [3], an IoT-oriented version of CPS. Furthermore, collaborative human–AI systems are expected to play a key role in the future of work as elements involved in Industry 5.0. This shift towards more resilient, sustainable, and human-centred industries requires that models and governance structures be adjusted [4].

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https://doi.org/10.1016/j.iot.2022.100673
Received 20 November 2022; Received in revised form 14 December 2022; Accepted 15 December 2022
Available online 21 December 2022

The introduction of disruptive technologies in Industry 5.0, such as AIoT, integrated through cyber–physical systems [5], causes operators to face new challenges [6]. The operator is in the midst of this complexity, trying to understand the current situation and make effective real-time decisions. These challenges are reflected in the increased demands on the operator's physical, sensory, and cognitive skills [7] — identifying, judging, attending, perceiving, remembering, reasoning, deciding, problem solving, and planning. Hence, human factors, especially the cognitive ones, are a major issue to be addressed in this context.

Cognitive skills of the operators are more required than physical strength [8]. However, operators are generally not trained in the cognitive skills and abilities needed in the workplace, leading to situations of increased mental load, low performance, and reduced efficiency and effectiveness of the process [9]. In order to address these challenges and make complex processes manageable, it is necessary to provide support to operators. Support can be provided through digital assistance systems, which help operators in their tasks by dealing with a diverse range of systems [10]. Beyond simply being a software tool, these systems can also consist of a set of functions that enhance human capabilities, such as exoskeletons and collaborative robots for physical capabilities, or virtual and augmented reality for sensory capabilities. The effectiveness of digital assistance systems would be improved by a better understanding of human teams and human–technology interactions.

In this article, we conduct a survey on the need for cognitive assistants to support human operators in factory work environments. However, a sole focus on automation is not sufficient to address cognitive issues; a socio-technical perspective is also necessary. We therefore introduce the domain of cognitive systems engineering, which is dedicated to the careful study of human–machine interaction as the meaningful behaviour of a unified system, and present joint cognitive systems (JCS) [11] as a principled approach to studying human work with complex technology. In this context, we analyse cognitive assistants from the perspective of AIoT embedded in a human-centred CPS. We provide several examples from previous research to illustrate our analysis, and propose a conceptual framework, adapted from human–robot interaction, for the design of cognitive assistants.

Therefore, this article is organised as follows: firstly, the role of the human worker is analysed in the perspective of Industry 5.0 as a socio-technical system. Next, this analysis leads to the concept of human cyber–physical systems, which is introduced from the special focus of joint cognitive systems. Previous examples developing these ideas for the authors are then briefly presented. A conceptual framework is then proposed for cognitive assistants design and two illustrative examples are depicted. Finally, some conclusions and future work are provided.

2. The role of the human worker in Industry 5.0

In Industry 5.0, not only are production lines and processes changing, but the role of the human is also subject to significant changes and proves to be crucial for developing productive systems [12]. With regards to the tasks and role of the operator, an increase in the proportion of complex cognitive tasks is expected, thereby increasing the need for coordination or organization of production resources, as well as the control and monitoring of complex production systems. The literature shows that a significant change in this relationship from purely physical to cognitive refers to the human–machine interface, which encompasses the interaction between operators and a set of new forms of collaborative work [13]. Let us consider this new role of the human worker from the perspective of all involved elements: the human operator, the process, and the cognitive assistant support.

2.1. The human operator

Since the increase in automation of factories reduces costs and improves productivity, one might think that people in the production hall will no longer be needed except for secondary tasks such as repair and maintenance. Such theories of "unmanned factories" have been discussed for decades during the Computer-Integrated Manufacturing (CIM) era. In practice, however, factories will not be without humans. Humans are an indispensable resource in the workplace [14]. People will work with sensors, robots, machines, cyber–physical systems, and other humans [15]. The concept of Operator 4.0 [16] emerged as a general definition for an operator in an industrial setting assisted by technological tools.

Most standard situations can be handled by automation through cyber–physical systems (CPS) or Artificial Intelligence of Things (AIoT), however operators must monitor and tune the automated system to keep it functioning within specified bounds. Moreover, automated systems are not capable of dealing with unanticipated situations [15]; humans can learn from experience and thus compensate for incomplete knowledge. Humans can also adapt to different situations and prioritize different goals according to current demands. Thus, human workers compensate for inevitable design shortcomings by learning and acting in flexible, context-dependent ways [17].

Human operators are still key elements in manufacturing systems, but the increasing degree of automation doesn't necessarily lead to enhanced operator performance. Humans can make mistakes that, regardless of their origin, have a direct influence on the cost of non-quality and delays. Some studies have demonstrated that human-caused non-quality is due to three main reasons [18]: lack of appropriate guidelines, gaps in training, and the unavailability of documentation in production lines. As a result of disruptive technologies, workers must deal with different working situations, either due to changing work-places in the production line, or changing production schemes and software products in the same work-place. Operators must be aware of important elements in the situation and interpret it correctly according to their task of interest. Being constantly aware of all these elements is a difficult task for operators and may lead to cognitive overload that must be reduced.

2.2. The factory in Industry 5.0

On the other hand, continuous innovation in cyber–physical systems allows machines to take care of the adequate supply of material, change the production method to the optimal one for the real product, or devise a new plan themselves [9]. Therefore, this technological evolution generates, among other things, the following impacts on the operator:

- the qualification of manual tasks decreases;
- the operator has access to all the necessary information in real-time to make decisions;
- intelligent assistance systems allow decisions to be made more quickly and in a short space of time;
- co-working in the workspace between machines and people requires less effort and attention;
- human implementation and monitoring is more important than ever.

The emerging technologies in the Artificial Intelligence of Things are allowing cyber–physical systems (CPS) focused on human–machine interaction to move from a physical interaction paradigm to a cognitive one. The operator should be able to take control and supervise the automated production system. However, the increasing information and communication capabilities of these systems leads to complexity that is not understandable by the current standard user interfaces used in the industry. As a result, the operator would need support to maintain the system within stable requirements. Furthermore, the operator could get the factory's work plan and would therefore need additional information during field operation, requiring access to location-independent as well as situation-oriented and task-oriented information [19].

2.3. The cognitive assistant support

As a result of this paradigm shift, new forms of interaction appear in the field of Human–Machine Interface (HMI), in the form of intelligent user interfaces, such as Operator Support Systems (OSS), assistance systems, decision support systems, and IPAs (Intelligent Personal Assistants) [7]. In the context of smart, people-centred service systems, cognitive systems can potentially progress from tools to assistants to collaborators to coaches, and be perceived differently depending on the role they play in a service system.

Assistance systems support the operator as follows [20]:

- From a human-centred design approach, they consider the identification of the user's context, the specification of user requirements, the creation of design solutions, and their evaluation. Moreover, they provide an appropriate amount of information in a clear way.
- They are decision makers in production control, with information acquisition, data aggregation/analysis of information, and operation choice.

At this point, it should be highlighted that the final decision should always remain with the human operator, thus maintaining the principle of human centrality.

The interaction between human workers and CPS in factories is addressed by either direct manipulation or with the help of a mediating user interface. Such close interaction between humans and CPS also raises socio-technological [21] issues regarding autonomy and decision-making power. Cybernetics [22] provides an answer on how a system that controls another system can compensate for more errors in the control process by having more operational variety. As the most flexible entity in the cyber–physical structure, the human will assume the role of a higher-level control instance. Through technological support, it is guaranteed that operators can develop their full potential and adopt the role of strategic decision makers and flexible problem solvers, thus managing the increasing technical complexity. In this research work, the inclusion of the human as a central element in the CPS will be presented, leading to the introduction of particular examples of human-centred cyber–physical systems (HCPS).

3. Metacognition in human-centred cyber–physical systems

A human cyber–physical system (HCPS) is defined in [16] as a system consisting of humans and integrated computational and physical components, creating new levels of socio-technical interactions between humans, machines, materials, and objects. However, from a human-centred perspective, a HCPS is redefined in [23] as a work system that improves the capabilities of human operators by dynamic interactions between humans and machines in the cyber and physical worlds through smart human–machine interfaces. The objectives in a HCPS are achieved through interactions between: the physical system (or process) to be controlled, cybernetic elements (i.e. communication links and software modules), and human workers that monitor and influence the functioning of the cyber–physical elements, including those from the AIoT.

3.1. The centre is the human, the focus is cognition

The joint cognitive system (JCS) approach to cognitive systems engineering [11] acknowledges that cognition emerges as goal-oriented interactions of people and artefacts in order to produce work in a specific context, and at the level of the work being conducted [24]. Importantly, it does not produce models of cognition, but models of co-agency that correspond to the required variety of performance and thereby emphasises the functional aspects. The JCS perspective further expands on situated interaction

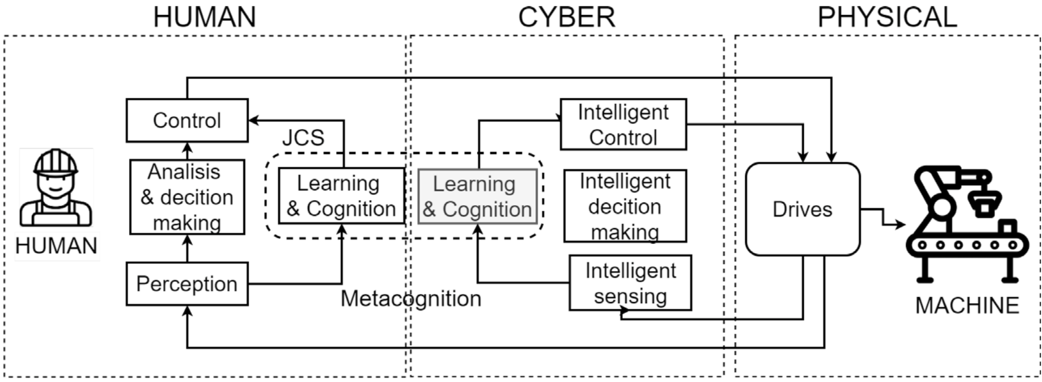


Fig. 1. Model of a human-centred cyber–physical system for a human–robot workspace focused on cognition according to the joint cognitive system approach.

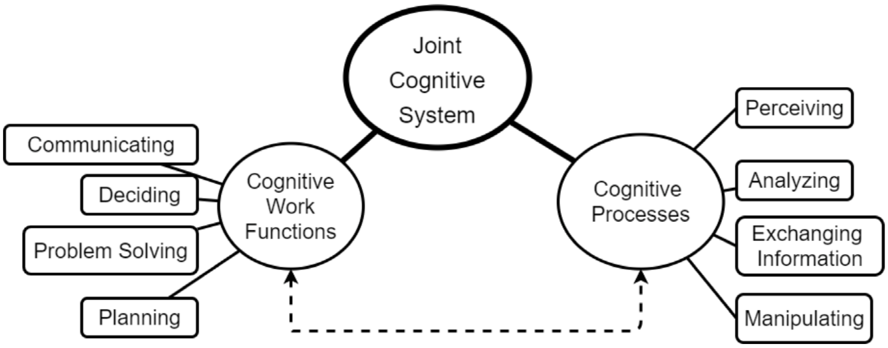


Fig. 2. Supporting functions of the joint cognitive system to emerge a process of metacognition into the model of a human-centred cyber–physical system.

with the world, which inevitably involves interactions with other agents and dynamic contexts, and forces the analysis to include a new system in which joint activity is distributed [25].

For cognitive assistants, cognition refers to the mental processes involved in gaining knowledge and comprehension. In automation processes, solutions have mainly focused on the physical activities of the operator, leading to the development of automatic machines and robots. Currently, with the introduction of disruptive technologies in the workplace such as collaborative robots, virtual reality, augmented reality, or smart HMI, the operator must handle systems with a greater amount of data that must be transformed into information and later into knowledge for decision-making.

Fig. 1 shows the model of an HCPS, in this case a human–robot collaborative workspace, focused on cognition according to the JCS approach. The automation system is in charge of sending control commands to the physical system, a collaborative robot, and obtaining feedback from the environment. In the cyber space, an intelligent assistive system analyses the behaviour of the environment, obtaining the required information for the cognitive functions. On the other side, the human receives the processed information and the necessary elements of judgement for learning and taking the required actions that lead to their own decision. These two sides of the information are studied in the JCS in such a way as to gain knowledge of the system and issue final actions towards both the physical system and the human. Hence, a cyclic interaction emerges between the cognition of the system and that of the human, which is understood as metacognition [26]. The concept of augmented cognition or metacognition extends the paradigm in automation by explicitly establishing the symbolic integration of human and machines in a closed-loop system in which the cognitive state of the operator and the operational context must be detected by the system [27].

Focusing on the JCS, the mission that the metacognition shall perform is avoiding vagaries into its human resemblances. It performs cognitive work via cognitive functions such as communicating, deciding, planning, and problem solving. These kind of cognitive functions are supported by cognitive processes such as perceiving, analysing, exchanging information, and manipulating. All these supporting functions are illustrated in Fig. 2.

3.2. Our proposed approach for metacognition

Both, the products and the production environment are becoming increasingly complex. In this situation it is proposed to put emphasis on the principles of human centrality elaborated in [16], as part of the disruptive transformations, plus a paradigm shift of independent human and automated activities towards a human-automation symbiosis as defended in [23,28]. These systems are characterised by the cooperation of machines with humans in work systems and designed not to replace the abilities and skills of humans but rather to coexist with humans and help them to be more efficient and effective. In this symbiosis of human and machine team, research will seek the gain of both parties from a cognitive viewpoint.

A combined view of automation and JCS proposes the need to support employees with available assisted technologies in order to cope with the increasing diversity of work tasks and the complexity of industrial production. A major aim is to increase and support existing capabilities of the workers and/or compensate for shortages or deficits of the operators. There is currently a need for research on:

- Further case study applications of worker assistance systems;
- A methodology for the selection of appropriate worker assistance systems for specific user groups;
- A methodology for a structured evaluation of the suitability of worker assistance systems.

3.3. Some research lines

Only for illustrative purposes, let us mention two research lines following our proposed general approach about new software development methods to be developed in the form of assistants and wizards to help operators to be context-aware and reduce their technical workload regarding coding or computer-oriented skills, focusing on the task/service at hand.

The first research line refers to the principles of human centrality developed in [16,29,30]. Assistants should integrate/communicate with the operator in the workplace when taking decisions from the Enterprise Resource Planning (ERP) and/or Customer Relationship Management (CRM) systems. These informed or agreed decisions should help in a better understanding of the work in hand for the operator in the workplace, as well as changes in the production line in the form of quality, time or task.

The second research line aligned with our general proposal relates to the idea of "programming without coding" [31]. For instance, current robotic technology in the form of collaborative robots (cobots) is affordable for small and medium enterprises (SMEs), however, its adoption is being delayed mainly due to the associated engineering/coding skills needed to take advantage of this kind of installation. Particular examples in the case of using cobots [32] are tasks such as (i) co-manipulation, with an operator guiding an object's path while the cobot supports the weight of the object; (ii) operators inserting bolts in a plate while a cobot tightens these bolts from the opposite side of the plate; or (iii) assembly actions that are dynamically distributed between operators and cobots according to workload and energy consumption. Such intensified mutual support of tasks will require further advanced perception, human awareness, or decision-making capabilities.

This concern is extendable to general AIoT systems. Assistants and wizards should be developed to reduce operators' technical workload in relation to coding. Learning by demonstration, semantic awareness and ontologies are areas that should be explored.

4. A conceptual framework for the design of a cognitive assistant

Assistance systems are considered intelligent when they support the improvement of production performance in the factory. The necessary predictability of the system must be taken into consideration in human–machine interaction, because it is a key characteristic to minimise the so-called automation surprises [33]. Hence, an important role for a cognitive assistant in a work team is to aid their human counterparts by [34]:

- Maintaining awareness of member actions and status;
- Updating team members regarding important changes in within-team and external information, without diverting their attention from the central tasks;
- Monitoring intra- and inter-team communications;
- Tracking task execution and completion and progress towards achieving the team's goals;
- Providing timely feedback on performance and guidance on correcting team errors.

The conceptual framework proposed for the design of cognitive assistants will follow a comprehensive operational definition of cognition using two iterative loops of three key attributes: anticipate, adapt, learn; and action, perception, autonomy, as it can be seen in Fig. 3. These attributes can explain the variety of skills that the cognitive assistant should possess: goal-oriented behaviour, autonomy, interaction via cooperation and communication, intention reading, interpretation of expected and unexpected events, prediction of the outcome of its own and of others' actions, action selection and evaluation, adaptation to changing circumstances, learning from experience and monitoring and correcting its own performance [35].

This general framework to develop cognition is in line with the systemic coverage of capabilities of robots in cognitive robotics [36], now extrapolated to the Artificial Internet of Things (AIoT) domain. The human operator and the cognitive assistant are part of a team with the ability of adaptation to changes in the human-centred cyber–physical system.

4.1. The iterative cycle of design

In the context of an operator interacting with an assistant and working as a team with the components in the process line, the quality and acceptance of the AI-based system must be assessed [37,38]. Therefore, it should also be within the AIoT domain with the cognitive assistant. To analyse this interaction, it is convenient to start with an iterative cycle in which design, methodology, and qualitative evaluations can be carried out quickly with the aim of acquiring expertise and building future formal systems.

Some examples of steps to follow in the iterative cycle for the cognitive assistant design are:

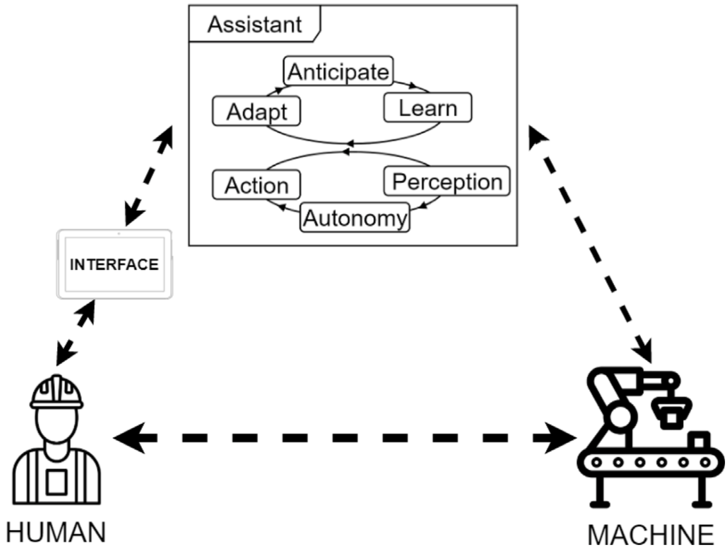


Fig. 3. Cognitive assistant in the interactive cycle when emerging metacognition.

- Selection of emerging technology: teamwork between the operator and HCPS's workstation with a cognitive assistant;
- Selection of machine learning (ML) methodology: from rule-based learning to deep learning;
- Selection of the level of assistance: the operator's needs must be specified, taking into account variables such as interpretability, accuracy, and explainability;
- Data management and visualisation, with the operator in mind: interface design, interaction design, and human-centred evaluation.

The selected emerging technology should be related to the most convenient AI/ML model [39]. At this point, it should be noted that some models have a high level of accuracy but low interpretability, as is the case with deep learning. Others are on the opposite side, for instance, rule-based learning [40]. For example, [41] shows how the human operator guides the robot's trajectory and, while exerting force on the robot's torque sensor with his hand, data is collected for inspection. In this case, the machine learning model is based on artificial neural networks used with a reinforcement learning algorithm. A similar scenario would be an operator changing speeds and/or frequencies in some work stations of the production line due to unexpected logistics constraints or varying human operator skills.

Since the operator will not always have previous experience in AI, the ML specialist can assess the accuracy of the ML method used and propose guidelines for improving explainability [42]. Methods for explainable AI (XAI) are diverse and a current research hot topic [43–45]. This specialist should decide the level of assistance the operator will need [46] and write an operator requirements list. These requirements must be added into the software functionality [47].

The management of data for its transformation into explainable information with the help of qualitative graphic visualization converges in the interface and in the development of applications. One of the challenges in this aspect is to consider different user profiles: these users can use the interface at their convenience. In [48], an ontology is developed and adapted to different users with an algorithm to generate explanations about cobots' collaborations and plan adaptations. The user wants to know explicitly the risk of damage in a physical contact with the robot: if this risk is high, she/he prefers to work close to the cobot but without physical contact. Similarly, some users could feel more comfortable than others when using either technological visualization tools or when gaining experience in new workstations.

When the interface between human operators and processes is ready, the interaction design approach allows for the design of the communication between the user and the cognitive assistant [49]. Beyond the traditional HCI approach, the interaction between intelligent systems should be investigated. The aim is to obtain a methodology that can be applied in the interaction between humans and AI-based systems.

In the medical field, for instance, there are similar scenarios that can serve as a guide. As it is argued in [50], the employed ML methodology is an intermediate step that allows further causal models. Thus, by combining the aspect of causal models with the users' evaluation in the HCI domain, these authors propose to measure the quality of the explanations using the System Causability Scale (SCS), inspired by the System Usability Scale (SUS). The SCS tool is incorporated with a prediction model into the methodology used by a medical doctor to estimate the risk of coronary artery disease in 10 years for a patient without diabetes mellitus or clinically evident cardiovascular disease. An alternative to SUS or SCS for measuring the user's satisfaction and the output quality of the AI-based system is the traditional technology Acceptance Model (TAM), as used in [38], which offers four relevant factors to be considered: actual system use, perceived usefulness, perceived ease of use, and output quality.

Table 1
Human factors dimensions considered when designing the cognitive assistant in the iterative cycle. In the HCPS column, H stands for human and C stands for H(C)PS.

Resource	Human factor dimension	Assistant output	HCPS
Borg CR-10 scale	HF1 - Physical interaction	Safety	Proximity sensors, force/torque sensors
NASA-TLX	HF2 - MWL	MWL Controller	H-task, C-task, Team-task
Trust scale	HF3 - Trust	Reliability	C Performance
TAM	HF4 - Acceptance	Explainability, Easiness, Usefulness	H Performance, Programming
HCI metrics	HF5 - Usability	Recommender, Task allocation	C Programming, H skills

Again from the medical domain, in [51] it is described how a team of experts in engineering, health informatics and radiology physicians developed an application that assists users in interpreting chest X-rays. It combines four deep learning models that were trained for the detection of four critical findings: pneumothorax, rib fracture, pleural effusion, and lung opacities. This application can be used by several users, each of whom answers a specific questionnaire.

4.2. Human factors dimensions

The work in [52] determines a conceptual framework to identify the dimensions of human factors related to human–robot collaboration. In our vision, this work can be expanded to the entire human-centred cyber–physical system (HCPS) relationship. These dimensions can be used as input into the design functionality of the cognitive assistant. The assistant then develops a set of outputs directed towards the HCPS and the interface. Table 1 shows these five human factors dimensions when integrated into the HCPS framework, the resources employed for their measurement, the outputs obtained from the assistant for each of the dimensions, and the elements in the HCPS under consideration.

4.2.1. HF1 physical ergonomics

The non-existence or suppression of physical barriers between human operators and HCPS enables physical interaction. The literature in this topic addresses the need to slow down the velocity when the operator approaches the process, the consideration that the movement of the operator can be anticipated and translates this anticipation to the process, the need for physical contact so that the operator can guide the process, and the need to respond to the process in case of unforeseen operator contact. For this dimension, it is necessary to measure the subjective perception of safety of the operator: the Borg CR-10 scale is useful for the assessment of discomfort [53].

HF1 in the cognitive assistant. This dimension, as an input to the assistant, must take into account how to apply machine learning/artificial intelligence algorithms for anticipation. The assistant in this scenario has the role of a safety assistant. It should provide, as output, a set of guidelines for task design and monitor the task deployment. Some elements in the AIoT/HCPS system to consider when assisting the operator are the use of proximity sensors and force/torque sensors.

HCPS input. With the previous recommendations, the process interacts with the operator. The operator needs some haptic/visual feedback of the physical interaction to understand, for instance, how much force to exert, where to be placed and which movements are ergonomically better than others. The particular operator in the workplace could carry out various tuning tests before entering production.

4.2.2. HF2 Mental workload (MWL)

When the operator finishes a task at a particular work station in the production line, during the design phase, they should answer the NASA-TLX questionnaire, which allows subjective evaluation of the mental effort of the proposed task.

HF2 in the cognitive assistant. The assistant in this scenario plays the role of MWL controller. The assistant compares the desired MWL with that obtained with the NASA-TLX questionnaire. It suggests, if it is the case, the development of human tasks with moderate MWL and the division of subtasks between the operator and the automated process.

HCPS input. Tasks under consideration are those that can only be carried out by the human operator or in a semi-automated form with the HCPS, both cases with moderated MWL. If the MWL is high, then the assistant could suggest that the task is suitable only for a fully automated HCPS and/or particularly skilled operators.

4.2.3. HF3 trust

In case the way of working of the operator is modified, for instance, an element is added to the process to work in a team, it is necessary to develop and consolidate trust in the interaction. Using a trust measurement scale, it is possible to capture the perception of how trustworthy the collaboration with the HCPS is and the perception of reliability of the HCPS developing the task [54]. The human operator interacting with the assistant also requires trustworthy communication with the AIoT-based process.

HF3 in the cognitive assistant. For the development of trust, the assistant should give feedback to the operator demonstrating the reliability of the HPCS for each defined task. It takes note of the operator's perception of the process's reliability and notifies the maintenance team to detect, diagnose, and solve anomalous operation of the process.

HCPS input. The task is modified and reliably repeated according to the incorporated performance improvements.

4.2.4. HF4 acceptance

From a first encounter to daily work carried out in a team, the acceptance of technology is based on the perception of ease of use and usefulness, in a cognitive approach. Some authors [55] are studying the relationship between cognition and emotions in the acceptance of artificial intelligence.

HF4 in the cognitive assistant. The assistant should capture the operator's perception of acceptance and adapt the complexity depending on the level of expertise of the operator:

- Improving the explainability of the AI/ML method used;
- Improving the ease of use and useful functionality when working with HCPS.

The cognitive assistant suggests how the cooperation between the operator and process can be improved for those tasks in which the operator's skills are relevant.

HCPS input. The programming must be flexible for semi-automated operation.

4.2.5. HF5 usability

From the perspective of human–computer interaction (HCI) and HRI, task effectiveness, efficiency, and satisfaction metrics are measured after the task is completed. These elements will help to increase the overall usability of the interaction.

HF5 in the cognitive assistant. The assistant plays the role of recommender for task allocation between the operator and HCPS. It suggests how these measured metrics can be improved, giving recommendations to the process management and recommendations for improving the operator's skills.

HCPS input. The process should be reprogrammed for better effectiveness and efficiency.

4.3. Two examples of scenarios

In the design of the interaction between the operator and the cognitive assistant, several paradigms of human–AI interaction can be taken into account [56]: intermittent, proactive, and continuous.

In the intermittent paradigm, the human operator (H) begins the conversation by asking a question and waits for the assistant (A) to respond specifically: *H: What is the task effectiveness of the cobot? A: The task effectiveness of the cobot is 87%*.

In the proactive paradigm, the role of the cognitive assistant is active, as it begins the conversation. This paradigm can be useful when there is a significant change in production, and the assistant warns the operator in time: *A: The task effectiveness has decreased from 87% to 67% in the last 30 min; H: Can you perform a task check? A: I am analysing product delivery speeds and product temperatures, searching to detect irregularities.*

In the continuous paradigm, the assistant works in the background trying to anticipate the operator's decision flow, informing and suggesting proposals. The operator can accept or ignore the help offered by the assistant. The three paradigms can coexist if it is shown that the operator's experience working with the assistant is satisfactory.

From a technological perspective, to endow IoT devices with intelligent services, it is necessary to add an IoT gateway as an intermediate device between the intelligence services provider and the cobot. From data exchange between the IoT gateway to the cobot, it is recommended to use the Open Platform Communications United Architecture (OPC UA). For data exchange between the IoT gateway and the provider of intelligent services, the use of the Message Queuing Telemetry Transport protocol (MQTT) is recommended: programming functionality in the IoT gateway and sending data from the MQTT client (IoT gateway) to the MQTT-Broker (provider). Intelligent services are at the core of Fig. 4, defining the functionality of the cognitive assistant.

For illustrative purposes, two scenarios are sketched using the continuous paradigm in which the assistant makes recommendations and either the supervisor (scenario 1) or operator (scenario 2) decides how to proceed.

4.3.1. Pick and place scenario

This is the most common task in manufacturing. In this scenario, a plant operator picks up objects from a storage and places them in a conveyor. A cobot from the HCPS should pick up objects and, after some manipulations from the automated part, place them in selected stocks. It should be able to deal with the variability of object positioning, so a RGBD camera is available with the aim of obtaining object pose estimation.

Using machine learning methods such as deep reinforcement learning, it is possible to determine robot motion [57] by estimating the probability of grasp success. The role of the cognitive assistant is to select different ML methods and assess their accuracy, explainability, and effectiveness on the robot. Moreover, the interface displays the different options considered to increase the acceptance of the decision (see Fig. 5). The assistant can recommend to the operator supervisor the most effective ML method, but the operator is free to make the final decision. In accordance with Table 1, the operator supervisor and the assistant consider the HF3-Trust, HF-Acceptance, and HF5-Usability factors in their interactions.

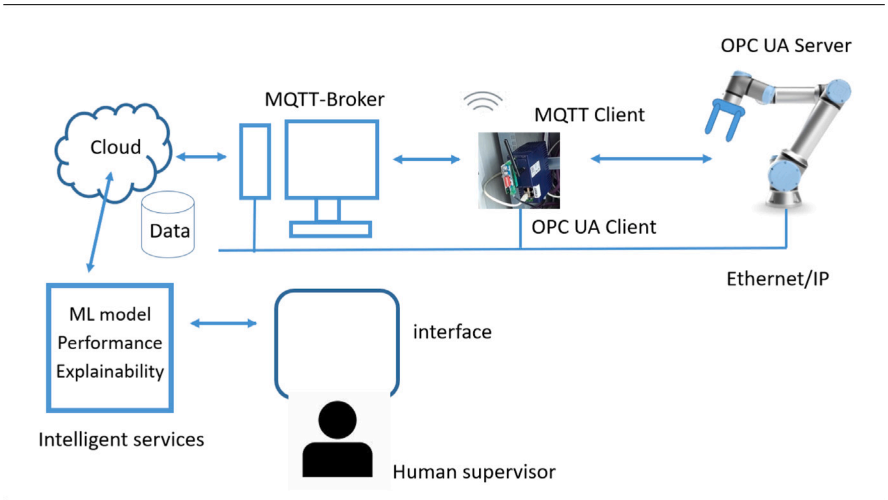
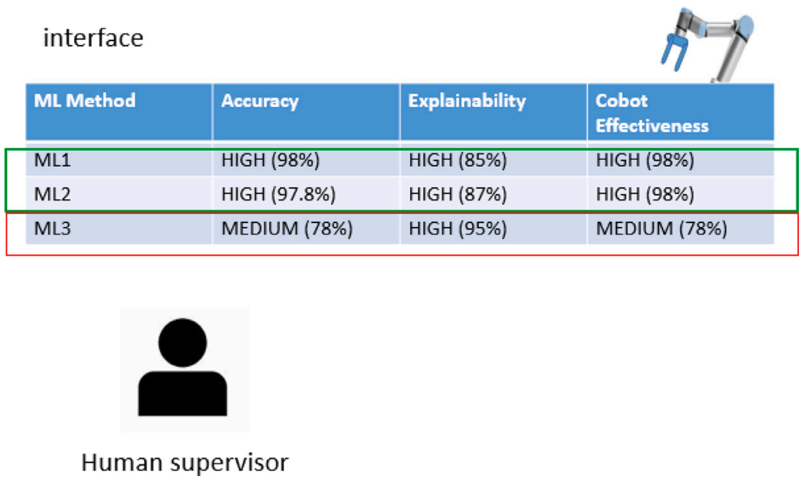


Fig. 4. AIoT and intelligence services.



ML Method	Accuracy	Explainability	Cobot Effectiveness
ML1	HIGH (98%)	HIGH (85%)	HIGH (98%)
ML2	HIGH (97.8%)	HIGH (87%)	HIGH (98%)
ML3	MEDIUM (78%)	HIGH (95%)	MEDIUM (78%)

Fig. 5. The interface of the cognitive assistant offers the human supervisor several choices.

4.3.2. Quality control scenario

The operator is supervising the assembly process carried out by a cobot in the HCPS. The cobot uses a webcam with computer vision software libraries integrated into a low-cost electronic device that detects broken bearings. The role of the cognitive assistant is to inform the operator when the product has a poor level of quality and can recommend an operator intervention activating the blue light (see Fig. 6). According to Table 1, the operator and the assistant are interacting with the HF5-Usability factor in mind, specifically in task allocation.

The operator places a product to be modified and through a control panel interrupts the assembly task. At that moment, it decides that the cobot proceeds to replace the defective bearing with a bearing in good condition, as can be seen in Fig. 7. At the end of this quality control task, the operator can re-establish the initial cobot assembly task.

5. Conclusions and future work

Human–AI systems are expected to play a key role in the future of work as elements involved in Industry 5.0. Changes in the production environment towards more resilient, sustainable, and human-centred industries require a shift to human-intelligent artefact teams.

To obtain high effectiveness in these systems, a full integration of the human into the cyber–physical system must be achieved. This implies knowing the dimensions of the relevant human factors involved in the tasks and establishing an interactive relationship between the human and the AI subsystem. A cognitive assistant with computational capacity, flexibility to use different machine learning methods, and the ability to dialogue with humans can help these human-assistant teams function properly.

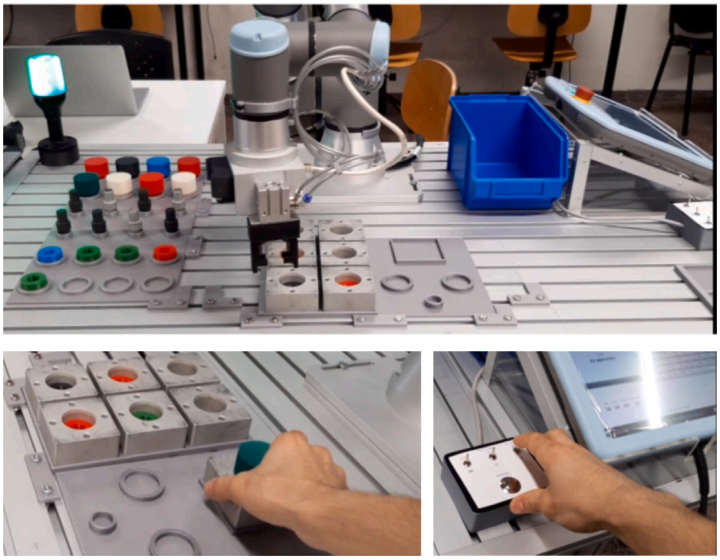


Fig. 6. Quality control scenario. Assembly task of body, bearing, shaft, and cover, with human intervention asking for a quality check.

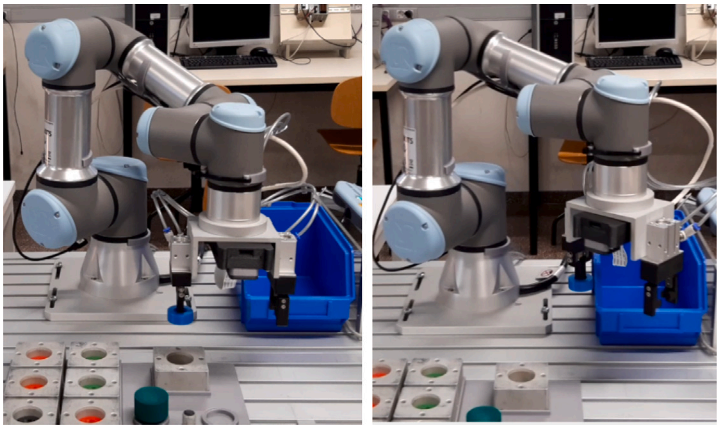


Fig. 7. The cobot moves the broken bearing into the blue box.

Several disruptive technologies are applied in Industry 5.0, such as virtual reality, augmented reality, collaborative robotics, computer vision, and haptic devices. In our research, we focus on human–robot collaboration, mainly because cobots facilitate human interaction with technology and they are excellent examples of artefacts with scalable functionality that can be adapted, together with the operator, to changes in industrial production.

The new approach can be integrated into existing robotic systems by the use of cognitive assistants, allowing the cobot and the human to collaborate into the workspace. The integrated system is supported by machine learning models and dialogues with the operator, balancing the dimensions of human factors at the cognitive level. However, a redefinition of tasks and functions of each team member is required.

The human–AI system must be adaptable in order to facilitate the development of new tasks by the HCPS efficiently and reliably, as well as enabling the human to learn and consolidate skills. The assistant should provide useful help based on various operator/user profiles. In future work, it will be relevant to define performance metrics that are quick and easy to measure, compared to changes in requirements, and that allow for quick and effective redesign adjustments in each of the components of the Human–AI system.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Pedro Ponsa reports financial support was provided by Government of Spain Ministry of Education and Vocational Training. Cecilio Angulo reports financial support was provided by European Regional Development Fund.

Data availability

No data was used for the research described in the article.

Acknowledgements

This work has been partly funded by the European Regional Development Fund of the European Union within the framework of the ERDF Operational Program of Catalonia 2014–2020, grant number 001-P-001643. Prof. Pere Ponsa has been partly supported by the Project EXPLainable Artificial INtelligence systems for health and well-beING (EXPLAINING), Spain (PID2019-104829RA-I00/AEI/10.13039/501100011033).

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