Advances in Reliability, Safety and Security, Part 5 – Kołowrocki, Kosmowski (eds.)
© 2024 Polish Safety and Reliability Association, Gdynia, ISBN 978-83-68136-17-3 (printed), ISBN 978-83-68136-04-3 (electronic)

Advances in Reliability, Safety and Security

ESREL 2024
Monograph Book Series

Human Machine Teaming In Manufacturing Environment: Preliminary Interface Example

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Abstract

The anticipated outcomes of Artificial Intelligence (AI) and Machine Learning (ML), revolve around enhancing efficiency, flexibility, and productivity in industrial and service sectors. However, there exists justified skepticism regarding the implementation of AI. This skepticism arises from the challenge of seamlessly integrating AI into the current workflows of operators in a manner that genuinely supports human involvement. Recent advancements in artificial intelligence, particularly in machine and deep learning, have resulted in unprecedented opportunities for automation, prediction, and problem-solving, significantly influencing operators and their operational dynamics with automation on the shop floor. Hence, it becomes imperative to adopt a user-centric perspective to promote the integration of AI within the human-technology relationship. Within this framework, adopting a human-centered strategy becomes crucial to facilitate a seamless transition and optimize potential benefits. This approach aims to encourage meaningful and effective interaction between operators and AI on the shop floor (Wilson and Daugherty 2018). In the TEAMING.AI project we took into account the fundamental principles of teamwork of Salas et al. (2005) and Endsley (2023) and adapted them such principles to the sphere of AI and human collaboration. The pivotal concepts include: Team leadership, mutual performance monitoring, back-up behaviors, adaptability, and team orientation. In this paper, we acknowledged the important role of planning and designing the Human-Machine Interface to facilitate the quality, timeliness, and clarity of the required continuous communication loop by taking into account the Main phases for improving Human-AI teaming through situation awareness design. We demonstrate this approach by explaining the fundamentals of a human-machine interface and the applications in three different manufacturing environments.

Keywords: human-AI teaming, collaborative intelligence, human-machine collaboration, human-machine interface, human-in-the-loop, human centered AI

1. Introduction

According to the literature (Pérez, A. A., et al, 2022; Estrada-Lugo, H.D., et al, 2022, Hoch, T., et al, 2023, Boardman, Butcher, 2019; Endsley, M. R., 2023), there is a growing attention to developing collaborative intelligence structures that combine autonomous systems and humans rather than full autonomous systems. This perspective underscores the imperative of empower humans from the perspective of augmenting human efficacy and human performance as central objectives in the design of artificial intelligence (AI). This important need arises from the fundamental reality that humans bear ultimate responsibility for outcomes, both legally and ethically, within AI systems. Moreover, human skills such as creativity, empathy, and intuition warrant facilitative support within AI frameworks. Furthermore, empirical evidence, as posited by Endsley and Kiris (1995), highlights that individuals operate at peak efficiency when their engagement levels are elevated, thereby accentuating the necessity of maintaining active involvement within team roles. Consequently, the cultivation of human-centric AI emerges as a foundational starting point, essential for the development of AI systems capable of satisfactory performance across diverse domains.

The paradigm of human-centered artificial intelligence (HCAI) demands that to reorient the emphasis in the advances of AI technology and models from technological aspects to human considerations. Yet, research remains open to discuss the ambiguity regarding the efficacy of prevailing HCAI principles and methodologies in effectively attaining this objective. In the efforts to systematize these advancements, we, as researchers, together with governmental bodies, and institutions, must take directives, to operationalize the principles underlying HCAI (Jobin et al., 2019). Numerous governmental entities have delineated formal guidelines pertaining to HCAI (Zhang et al., 2021). For instance, the European Union has outlined seven essential criteria that AI systems must adhere to in order to engender trustworthiness, encompassing facets such as transparency, accountability, and promoting societal and environmental welfare (European Commission, 2019).

Bingley, W.J., et al, (2023) claimed that the HCAI systems encompass an amalgamation of guidelines, frameworks, and principles; however, a shortage of empirical substantiation exists regarding the adoption of these methodologies by AI developers, and whether the conceptualization and performance of HCAI meet adequately the user requirements. Consequently, the degree to which HCAI authentically embodies a 'human-centered' approach remains ambiguous, specifically in terms of comprehensively apprehending the perceptions and impacts of AI systems on their users. This was one of the purposes of the TEAMING.AI project, to overcome the lack of flexibility in HCAI systems that exist in the Industry 4.0, though a human centered AI collaboration.

2. Teamwork approach

In the TEAMING.AI project, we considered the fundamental principles of teamwork of Salas et al. (2005) and adapted them such principles to the sphere of AI and human collaboration in the manufacturing industry. The pivotal concepts include:

1) Team Leadership: Within a human-centric AI framework, it is imperative that humans retain leadership roles. This becomes crucial when performing decision-making tasks to maintain the effectiveness and independent actions of the teamwork.
2) Mutual Performance Monitoring: This involves the reciprocal exchange of data between automation and AI-enhanced processes to enhance transparency. Both the automation and AI systems share information pertaining to their respective roles, as well as the inputs and outputs involved.
3) Back-up Behaviors: The human agent critically assesses the accuracy of predictions related to decision support in diagnosing part defects and ergonomic risk assessments. This involves verifying the ground truth in real-world scenarios against the predictions made. Over time, this iterative process aims to furnish an improved dataset for the retraining of algorithms.
4) Adaptability: In the context of work teams, adaptability refers to the capacity of employees to demonstrate flexibility and the ability to reconfigure tasks in response to shifting conditions. Closed-loop communication is integral to this aspect, and careful consideration of behaviors needing adaptability is essential.
5) Team Orientation: This represents the most critical and intricate aspect to address. According to various studies (Endsley 2023, Fan X., et al. 2008, Klein et al. 2014), a two-way flow of information is paramount in AI-Human teaming, with team-like behaviors such as collaboration, coordination, and support for joint planning and replanning deemed essential. Key capabilities for intelligent systems in teams can be succinctly summarized as follows:
    - establishing joint goals and understood roles while communicating when tasks cannot be performed;
    - possessing adequate mental models of team members;
    - being predictable and directable to each other;
    - sharing status and intentions;
    - interpreting the status and intentions of other team members;
    - negotiating goals, particularly in situations requiring adaptations;
    - collaborating in problem-solving, replanning, and re-tasking;
    - guiding teammates' attention to crucial signals, activities, and changes without overwhelming each other;
    - managing coordination costs to maintain acceptable workload levels.

In the TEAMING.AI project, we endeavor to utilize knowledge graph representations to establish a foundation for a shared mental model of the problem space between human and AI agents. Furthermore, we acknowledged the pivotal role of planning and designing the human-machine interface to facilitate the quality, timeliness, and clarity of the required continuous communication loop.

3. Human-machine interface for mutual performance monitoring and transparency

Endsley (2023) sustains that there is a need to develop a systematic approach to discern the specific components of situational awareness (SA) that should be included in displays for a given AI application. The critical aspects of transparency and explainability within AI systems serve unique functions in reinforcing the situational awareness and cognitive models of human operators responsible for interacting with and supervising AI operations (Enrique Munoz-de-Escalona, et al, In press). This recognition underscores the pivotal role of these elements in striking a delicate equilibrium between trust and team performance while collaborating with AI systems. In practical terms, this equilibrium is frequently manifested through the development of interfaces. According to Endsley (2023), a systematic approach is imperative for identifying and integrating the precise components of situational awareness (SA) necessary for displays tailored to specific AI applications.

The process to enhance and improve the human-AI teaming through improving the mutual performance monitoring and transparency involves the analysis of situational awareness (SA) requirements (Endsley, M. R., 2023). Moreover, this process requires the iterative refinement of the user interface utilizing SA design principles, and the assessment of user interface displays using SA metrics alongside evaluations of performance and workload. This procedural framework is applicable to crafting transparent displays aimed at facilitating collaborative human-AI team purposes.

Fig. 1. Main phases for improving Human-AI teaming through situation awareness design (Endsley, 2023).

4. Case studies: industrial applications

The development of the methodology explained in previous sections has been applied in three case studies to demonstrate its usability in real industry-based applications.

4.1. Quality control

The first case study is developed in a plastic injection molding process. Injection molding involves creating molded items by injecting heat-melted plastic materials into a mold, then allowing them to cool and harden. This technique is well-suited for mass-producing items with intricate designs. The technique is being applied in a broad range of manufacturing industries. In our particular case, this technique has been applied for manufacturing plastic-injected parts for the automotive industry. The quality of the resulting products is predominantly influenced by various process conditions, including injection temperatures, pressures, speeds, and ambient temperatures. The specification of optimal process parameters, environmental conditions, and other factors impacting product quality proves challenging through contemporary analytics. Consequently, quality losses and waste occur toward the conclusion of the product cycle.

In this case study, machine learning models are used in the quality control process to identify defects in the produced plastic parts. These models are being designed in a human-centered approach to support the operators that currently are in charge of manually inspect the produced parts coming out of the molding machine and separate the faulty parts from those meeting the quality requirements. Common defects such as short shut, sink marks, flow lines, and missing subparts may manifest during the plastic injection process. The escalating diversity of product types further leads to reduced lot sizes, resulting in a diminished dataset for training a customized model to achieve the requisite high accuracy and quality standards, particularly within target segments such as the automotive industry.

To adhere to stringent quality standards, the inclusion of a human quality control step is imperative to preclude the dispatch of defective parts to customers. The proposed human-in-the-loop approach for the mock-up designs take into account two conditions. Firstly, there is a human factor aspect, encompassing elevated mental workload and stress stemming from time pressure and the risk of overlooking features crucial to quality. Secondly, from an economic perspective, the process leads to an extended product cycle time attributed to the bottleneck in manual quality inspection.

The mock-up developed provides a way to integrate process and quality parameters (failures, production speeds, quality issues, etc.) by the operators to feed the knowledge graph in the TEAMING.AI engine. This information is used for quality control, so operators in the shopfloor can adapt the physical parameters in the production line.

4.2. Machine and process diagnostics

This case study emphasizes machine and process diagnostics, rather than solely assessing product quality at the conclusion of the injection molding process. The diagnostic scope extends from pre-processing, encompassing activities such as insert preheating, raw material testing, dyeing, and drying, through the injection process itself, involving variables such as temperature, pressure, and molding cycle time, to post-processing, which includes annealing and humidity considerations. The significance of process diagnostics becomes especially pronounced when transitioning the process to a new product with distinct characteristics and process parameters. In such instances, the consequences of process modifications on product quality and initial waste remain uncertain. Moreover, the characteristics of molds in the injection molding machine undergo alterations during the initial transient phase until attaining a stable state for commencing the production of the new plastic part.

The objective of a Human-Machine Interface embedded in the intelligent system being developed in the TEAMING.AI project is of interfacing with both the injection machine's control unit and the operator's inputs via Human in the Loop (HITL) Dashboards. This system aims to autonomously modify the parameters of the TEAMING.AI platform for quality control in instances where a deviation from the nominal is detected, contingent upon the availability of sufficient trust assurance evidence.

Utilizing the TEAMING.AI engine and knowledge graphs as foundations, a comprehensive system encompassing machine learning, and Human in the Loop (HITL) techniques is being developed. This system is specifically designed to facilitate interaction between operators overseeing production lines and the ML predictive models. Furthermore, the dashboard in the HMI mock-up for data input is being developed to incorporate production state issues (such as failures, production speeds, quality concerns, etc.) as reported by the operators. Additionally, an active learning (AL) system is being formulated to integrate both operator inputs and machine process data with the purpose of predicting purposes for the thermoplastic injection process, i.e., prediction of the next defective part.

4.3. Ergonomics assessment

In this case study, manufacturing machine operators are required to manually manipulate and secure substantial-sized and weighty components in precision manufacturing machinery, specifically for grinding or milling operations characterized by stringent quality standards. This procedural undertaking significantly contributes to the overall duration of a work order, and concurrently exposes workers to occupational hazards.

The execution of the Computer Numerical Control (CNC) program is predominantly carried out through manual intervention. The duration of execution varies significantly, ranging from 3.5 to 5 hours for the identical CNC machining program, contingent upon the proficiency and experience of the machine operator. This wide range contributes to a notable overall variability in execution time. Operators are attentive to the computer screens to know when they are required to execute a manual task or when to approve an automatic action that the machine will perform. Given the inherent work hazards and potential mental stress associated with the process, this circumstance proves unsatisfactory for human operators.

The design of a low fidelity Human-Machine Interface mock-up is proposed to integrate observational data obtained from a visual tracking system with pre-existing scene and process knowledge, incorporating in-process feedback from the human operator through the use of portable devices. Information pertaining to the scene, part geometry, and procedural workflow patterns for handling and processing steps will be encoded within the knowledge graph, along with safety policies. The knowledge graph will undergo real-time updates based on current position specifications during working hours. The integrated self-diagnostics system will assess its level of consistency and completeness, expressing its epistemic self-trust. In instances of ambiguity, the human operator will be prompted for feedback.

In addition, to this mock-up can provide information in the programmed task for the machine. The system should provide with the reaming time before operator intervention so they can plan their actions accordingly. The operator should have access to this screen from different devices.

5. Results: mock-up storyboards

In this section the first mockups of the Human-Machine Interfaces are shown to demonstrate the fundamental principles of closed loop-communication within the teamwork that is being developed in the TEAMING.AI project. Based on the requirements assessment previously done, presented in Pérez, A. A. (2022), the mock-ups for each of the cases are presented. Due to space constraints, only the most relevant screenshots are shown in this document.

5.1. Quality control interface

This constitutes part of the storyboard for the HMI developed for plastic-injection machines used in the case study explained in Section 4.1. The following segment contains details of how to navigate the different screens and the usability of the low-fidelity HMI.

In Figure 2, the main screens that should be presented to the operator when initiating production are shown. The following features should be in each screen to increase accessibility and operator situational awareness:

- System configuration screen: This button will show the system configuration screen shown in Figure 2a.
- Image labelling screen: This button shows the data labelling screen, see Figure 2b.
- Quality control screen: This screen is shown when operator needs to manually input the defect found in the produced part, refer to Figure 2c.
- Historical records screen: This button shows the records of all the incidents (defective parts), Figure 2d.

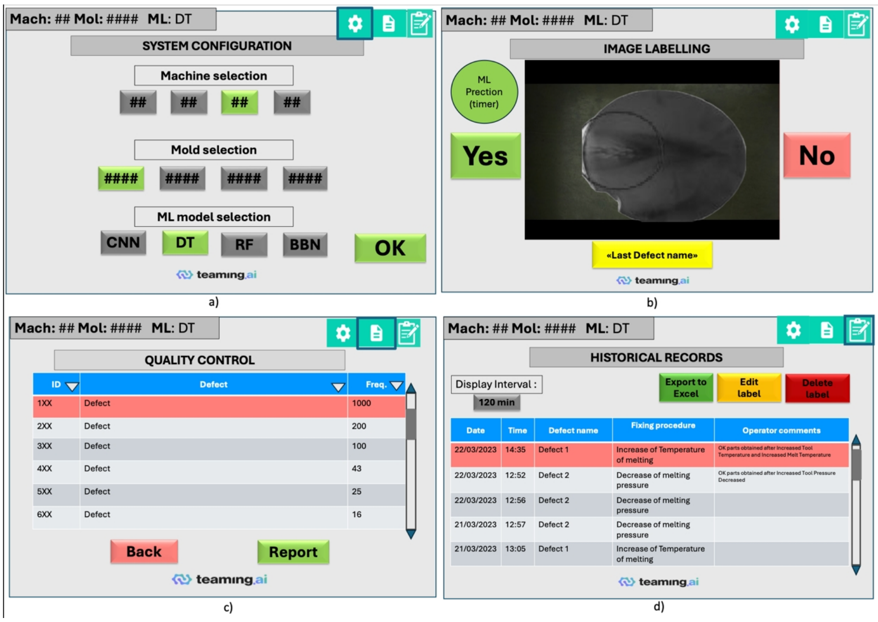

Fig. 2. Mock-up main screens for case study 1: (a) System configuration screen; (b) Image labelling; (c) Quality control screen; (d) Historical records screen.

The features specific for the system configuration screen, in Figure 2a, are explained as follows. The *Machine Selection (Mach)* - this section contains buttons with the numbers of the machines available in the shopfloor. The *Mold selection (Mol)* shows a list of the available machine molds that will be available. The *ML model selection* will show the different Machine Learning (ML) models available for predictions (e.g., CNN: Convolutional Neural Networks, DT: Decision Tree, RF: Random Forest, BBN: Bayesian Belief Network). At the moment, there is no model update mechanism, this situation should change when the data labelling and training process are completed.

The *OK* button is used to proceed to the Selection mode screen once all parameters have been set. The screen in Figure 2b, contains the following items: The picture space is the main part of this screen. It shows a picture (not a video) of the plastic part recently produced. The ***ML Prediction (timer)*** is an colour-coded indicator containing the prediction made by the ML model for operator verification. Such predictions will be:

- Non-defective part presents no production defects.
- Defective part presents imperfections.

The indicator will have a (timer) giving a few seconds for the operator to validate (by clicking the Yes button) or reject (by clicking the No button) the prediction displayed. If operator does not choose either of these options, the prediction produced by the ML model will be recorded for that image. This indicator is colour coded so that the operator has a better situational awareness about the accuracy of the prediction produced by the ML model. The *Yes* this button approves the prediction by the ML model. The *No* button rejects the prediction. The operator should specify the defect found for that part in the Quality Control screen. The *Last Defect name* button changes dynamically the name of the previously recorded defect. The operator should click this button instead of the NO button if the ML prediction is incorrect, or the defect name shown in the Last Defect name button corresponds to the defect found in the current produced part.

The table, shown in the Figure 2c, contains all the possible defects a defective part can have. The defects are listed by default by Frequency (Freq. column in the table), the most frequent ones will be shown on top. The user needs to select one defect and then click *Report* to label the current image with the selected defect. User can browse through all the list by using the up and down arrows shown in the right-hand side of the screen shown in Figure 2c. The table contains the following columns: *ID* (Defect identification number; Defect - to select the defect name from a list available), *Freq.* (Frequency of events when such event has occurred).

The screen in Figure 2d contains the following features: The *Interval* functionality allows to enter the time range of events to be shown in the table; the *Export to Excel* button exports data set to a .xlsx, cvs, etc. external file; *Delete label* will delete selected event from the table; the *Modify label* function will modify the label previously recorded in the table. The table has the following sections: *Date, Time, Defect name,* of event recorded; the *Fixing procedure* column contains details on the physical parameter changed to fix the problem producing defective parts are entered, and the *Operator comments* about the conditions of the incidence (machine and process diagnostics screen).

5.2. Machine and process diagnosis mock-up

This is the storyboard for the HMI developed for plastic-injection machines used in the Case Study 4.2. The screens regarding the configuration of the system is very similar to that in Figure 2a. Therefore, here we will focus on the screens that are different to the one mentioned.

The screen in Figure 3a, presents the *Incidence Register* which corresponds to the main screen of the human machine interface (HMI) that allows the operator to register the incidence if the piece has any imperfection. If the produced piece does not meet the quality criteria, the operator should hit the *No* button. Then the operator will be taken to the *Parts quality control* screen shown in Figure 3c. In the screen Figure 3a, the operator is able to see a small summary of the recently produced parts recorded in the bottom left side of the screen, the entries in red correspond to defective parts. If the defect found in the newly produced part is the same as the previous the operator can press the red button labelled *No*.

A reminder like that in Figure 3b, is displayed to remind the operator that all parts produced will be labelled by default as *Yes*, meaning that they do not have defects. This alert message that pops up to engage the operator. The meaning of the message is that if the operator does not give feedback on the defective part, the respective label will follow the label given by the machine learning model. This will avoid the operator from the extra work of clicking the Yes button for each produced part and avoid work overload.

As mentioned before, once the No option is selected in the incidence register screen (Figure 3a), the operator will be taken to the Parts Quality Control screen shown in Figure 3c. In such a screen, the operator can select the defect found in the produced part from the list presented. Once a defect is selected, the operator is taken to another screen where a list of sub-defects specific for the defect selected is displayed for the operator indicate such information according to their observations of the part produced. There is always the *Back* button to back and select another defect in case of error selecting the previous option. Once all the information regarding the defect is input, the user should click on *Report*, so the time-stamped label is saved.

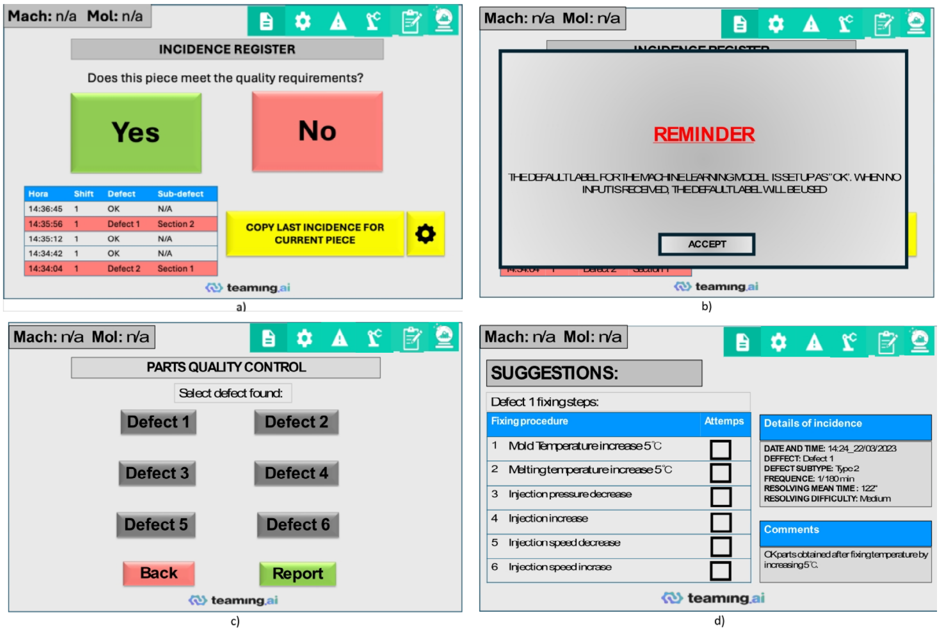

Fig. 3. Mock-up main screens for case study 2: a) Labelling screen INCIDENCIA, b) Reminder screen, c) Quality control screen, d) Defect fix suggestion screen.

The user can access the *Suggestions* screen (Figure 3d) by clicking on the third button from the left located in the top-right corner. In this screen in which the injection technician can report the procedure followed to fix the parameters of the machine, *Fixing procedure*. A list of pre-loaded process indicated the parameters to be changed to fix the problem causing the defective parts is shown in this table. The technician should tick in order the steps followed to fix the problem. The box in the top right (*Details of incidence*) shows a quick summary of the incidence selected from the historical records. The technician can see the type of defect being addressed and the date and the sub defect. In the box labelled as *Comments* relevant details about the incident and information are given. In the last box the technician can leave a comment about the resolution of the issue.

5.3. Ergonomics assessment

The shown mock-up screens in Figure 4 are a result of having a continuous communication with the use case providers and the end users, i.e., the operators at the shop floor. The first visit to the use case provider was done in March 2022 to verify the user requirements and enhance the needs by directly observing the activities that the operators carry out in a day-to-day journey. A second visit was done in June 2023 when a first version of the mock ups was shown to the operators to obtain their feedback regarding the usability and user satisfaction with the models provided. This HMI has two main modes: *Live* and *Historical*, this mode is shown in the top-left corner of each screen.

Once the user has logged in, the configuration of the system must be done to start the video recording that will be used for the ergonomic assessment. To complete this action, the user should input the information requested in the screen shown in Figure 4a. The user must input the information regarding the production order before starting the recording. The information requested from the user is: the *Product code* that refers to the internal product ID of the metal part being machined; the *Type of activity* that the operator will carry out during the recording time with a drop-down menu is displayed with a list of all the activities an operator normally performs; *Comments*, this space is reserved for user to input comments regarding the production, e.g., anomalies observed, conditions of production, etc. This display gives the option to program a recording time in the *Schedule recording* section. A start and end time and date are selected. Once, the production details and recording time are set, the *start recording* gets activated and user can click on it to start the recording. Once the recording has started the screen below is shown. This is called the live screen which shows an overview of the ergonomic assessment in close to real time.

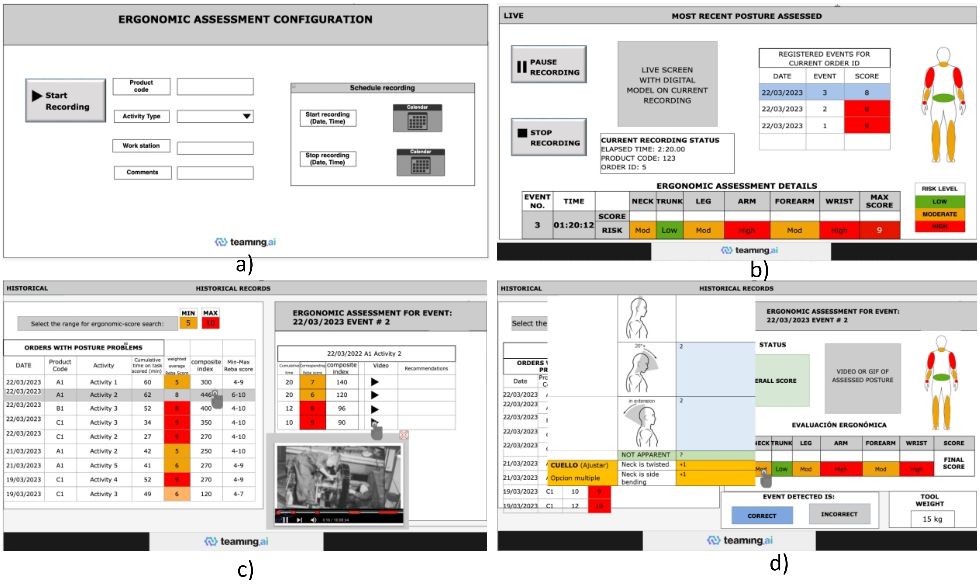

Fig. 4. Mock-up main screens for case study 3: (a) Configuration screen; (b) Live screen: current postures assessed; (c) Historical records screen; (d) Historical records screen with score explanation per posture.

The live screen, shown in Figure 4b, consists of several sections dedicated to provide a general overview of the ergonomic risks related to the tasks performed by the operator in the shopfloor. On the very left, the *pause recording* and *stop recording* buttons are located. The first section to the right is the live video of the shop floor, shown in the section labelled as *live screen with digital model of current recording*. Below this video, the *Current recording status* shows details about the recording, such as: time elapsed, product code, order ID.

Furthermore, the table labelled as *events registered for current order*, contains the date event number and the ergonomic score (that is based on the REBA tool, Hignett and McAtamney, 2000) for events with scores above the set threshold. The human body diagram is dived in the different limbs that the REBA tool assesses and is colour coded with red representing a high ergonomic risk level and green a low risk level as detailed in the table underneath labelled as *Risk Level*. A breakdown of the ergonomic score is presented in the table in the bottom of the screen labelled as *details of ergonomic assessment*. The table contains information about the number of events (this counter increases one unit every time the operator takes an ergonomic position with risk above the threshold), recording time and the individual score per each limb together with the risk colour (below the score). This table allows for a better understanding of the body parts that are in more risk. This information can be used during periodic meetings with the operators to revise and correct such events.

By clicking on the *Historical* button at the top of the screen, the user will have access to the database of the events when the operator was in an ergonomic risk level higher than the defined threshold. Figure 4.c. shows the historical display of the Ergonomic Risk Assessment Tool. It is composed of two different sections. In the upper part of the left section labelled as *Select a range for ergonomic*-**score search**, the user can choose the range of score they want to search for among the large number of damaging events. Then, thanks to the date and time filter, pressing on the button *Date* they can select start date, end date, start time, end time. In the right-hand side of screen shown in Figure 4c, it is possible to access more details on the event that was labelled as ergonomically-risky together with the option to open the piece of recording showing the moment the operator had a risky position. This can help to identify different ways to perform the same activity in a safer way.

If no event has been selected, the right side will show the overview of the risk assessment as shown in Figure 4.d. This screen also gives the option to the operator or the reviewer to correct or approve the label assigned by the AI to the event being analysed. This is done by clicking on the buttons *Correct* to approve, or *Incorrect* to discard. Moreover, information about the tool weight can be entered in the *Tool weight* box. To make the user more aware of the level of damage and the ergonomic assessment, by clicking on any part of the body of the human figure or on the last row of the table in the right window, a recommendation window appears to explain, thanks to the image in the second column, why the current posture is harmful and what the optimal posture is. The information displayed is based on the REBA tool (Hignett and McAtamney, 2000).

6. Conclusions

In this paper, we have provided some preliminary results of the low fidelity mock-ups designed under the Human-AI teaming through situation awareness approach. To understand such an approach a review of the increasing attention that Human-AI collaborative (or teaming) systems has been done followed by the general concept of teaming and its importance in the human-machine interface. The case studies presented are focused in manufacturing industries resolving, however, different problems. Subsequently, the AI modifies its behaviours to positively influence ongoing collaboration.

In the mock ups presented in Section 5.1 and 5.2, the AI teammate demonstrates adaptability by initially acquiring knowledge about various facets of the human's decision-making process, codified through a knowledge graph. Conversely, the human adapts by incorporating the support provided by the AI team member and offering feedback to refine suggestions when proven correct or incorrect. For instance, in the phase of data labelling in case studies in Sections 4.1 and 4.2. As AI adapts through progressive learning algorithms, the provision of updates by humans becomes pivotal in instigating the process of allowing verified data to reprogram the algorithm itself. It is imperative to recognize that excessive reliance on decision support might lead the human to diminish their capability over time to independently verify suggestions. Thus, assigning tasks to keep the human in the loop and maintain competency is crucial.

In the results shown in Section 5.3, the human agents are expected to reciprocate by sharing data on their performance, as exemplified in the use case concerning the ergonomic assessment of a turning table setup and clamping (please refer to case study in Section 4.3). The operator's tasks are systematically recorded and analyzed via video, providing feedback to the operators regarding the potential risk of exposure to Musculo-Skeletal Disorders (MSDs).

The way forward

As mentioned earlier, the development of such HMIs has been a result of assessing the requirements of the users as presented in Pérez, et al. (2022). The authors hope that the presented interface mock-ups can contribute to the empirical evidence such that a human-centric AI can be capable of perform satisfactorily across diverse domains. However, further studies are needed to measure how the interfaces help the Human-AI teaming according to Endsley (2023).

Acknowledgements

The authors gratefully acknowledge the funding from the European Union’s Horizon 2020 research and innovation program under grant agreement No. 957402.

References

Bingley, W. J., Curtis, C., Lockey, S., Bialkowski, A., Gillespie, N., Haslam, S. A. & Worthy, P. 2023. Where is the human in human-centered AI? Insights from developer priorities and user experiences. Computers in Human Behavior, 141, 107617.

Boardman, M. & Butcher, F. 2019. An Exploration of maintaining human Control in AI enabled Systems and the Challenges of Achieving it. Workshop on Big Data ChallengeSituation Awareness and Decision Support. DSTL Porton Down: NATO Science and Technology Organization.

Endsley, M.R. 2023. Supporting Human-AI Teams: Transparency, explainability, and situation awareness. Computers in Human Behavior, 140, 107574.

Endsley, M.R. & Kiris, E.O. 1995. The out-of-the-loop performance problem and level of control in automation. Human Factors, 37(2), 381–394.

Estrada-Lugo, H.D., Alonso-Perez, A., Leva, M.C., & Pönitz, T. 2022. Video analysis for ergonomics assessment in the manufacturing industry: initial feed-back on a case study. In Proceedings of the 32nd European Safety and Reliability Conference (ESREL2022), Dublin, Ireland.

Fan, X., Oh, S., McNeese, M., Yen, J., Cuevas, H., Strater, L. & Endsley, M. R. 2008. The influence of agent reliability on trust in human-agent collaboration. In Proceedings of the 15th European conference on Cognitive ergonomics: the ergonomics of cool interaction (pp. 1-8).

Hignett, S., & McAtamney, L. 2000. Rapid entire body assessment (REBA). Applied ergonomics, 31(2), 201-205.

Hoch, T., Martinez-Gil, J., Pichler, M., Silvina, A., Heinzl, B., Moser, B. & Leva, M. C. 2023. Multi-Stakeholder Perspective on Human-AI Collaboration in Industry 5.0. In Artificial Intelligence in Manufacturing: Enabling Intelligent, Flexible and Cost-Effective Production Through AI (pp. 407-421). Cham: Springer Nature Switzerland.

Jobin, A., Ienca, M., & Vayena, E. 2019. The global landscape of AI ethics guidelines. Nature machine intelligence, 1(9), 389-399.

Klein, J. T. 2014. Interdisciplinary teamwork: The dynamics of collaboration and integration. Interdisciplinary collaboration, 23-50.

Lemonne, E. 2021. Ethics Guidelines for Trustworthy AI-FUTURIUM-European Commission.

Leva, M.C., Estrada-Lugo, H.D. 2023. Collaborative intelligence, and human-ai teaming in safety critical applications key challenges and opportunities. In Proceedings of the 33rd European Safety and Reliability Conference (ESREL2023), pp. 2798-2805.

McIntyre, R.M. and Salas, E. 1995. Measuring and managing for team performance: lessons from complex environments. In Guzzo, R.A. and Salas, E. (eds), Team Effectiveness and Decision Making in Organizations. San Francisco, CA: Jossey-Bass, pp. 9–45.

Munoz-de-Escalona, E., Estrada-Lugo, H.D., Perez, A.A.& Leva, M.C. 2024. Situational Awareness and HMI design in collaborative human-machine (AI) teamwork: a case study. Intelligent Systems in the Workplace. In Press.

Pérez, A.A., Estrada-Lugo, H.D., Fernández, E.M.D.E., Leva, M. C., Aperribai, J. & Aranburu, A. 2022. Modifying a manufacturing task for Teamwork between humans and AI: initial data collection to guide requirements specifications. In Proceedings of the 32nd European Safety and Reliability Conference (ESREL2022), Dublin, Ireland.

Salas, E., Sims, D. E., & Burke, C. S. 2005. Is there a “big five” in teamwork?. Small group research, 36(5), 555-599.

Salas, E., Cooke, N. J., & Rosen, M. A. (2008). On teams, teamwork, and team performance: Discoveries and developments. Human factors, 50(3), 540-547.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. Harvard Business Review, 96(4), 114-123.

Zhang, D., Mishra, S., Brynjolfsson, E., Etchemendy, J, Ganguli, D., Grosz, B, Lyons, T., Manyika, J., Niebles, J.C., Sellitto, M., Shoham, Y., Clark, J. & Perrault, R. 2021. The AI Index 2021 Annual Report, AI Index Steering Committee, Human-Centered AI Institute, Stanford University, Stanford, CA.