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Published in:
IFAC-PapersOnLine

DOI:
10.1016/j.ifacol.2022.04.246

Available online at www.sciencedirect.com
ScienceDirect
IFAC PapersOnLine 55-2 (2022) 516–521

Development and application of a human-centric co-creation design method for AI-enabled systems in manufacturing

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Abstract: The integration of AI-enabled solutions in manufacturing is creating unprecedented challenges to design human-centric, safe and trusted systems. As opposed to designing a system with as little human input as possible, humans will still be expected to continue playing a vital role in the design, operation, and control of AI supported manufacturing systems. Yet, till now, there has been little discussion of what the requirements of human-centric designs might be in an AI environment. To facilitate the consideration of human skills, capabilities and human factors, a human-centric design method was developed and tested through co-creation workshops addressing industrial use cases of AI deployment in manufacturing. The method proved successful in encouraging relevant stakeholders to identify human factors-related issues linked to the different collaboration scenarios of humans with AI systems early in the design process.

Keywords: Human-centric AI, work design & human factors, collaboration scenarios, co-creation

1. INTRODUCTION

Cyber physical production systems (CPPS) have enabled the emergence of smart factories, in which humans and technical systems communicate, collaborate and interact with each other both physically and virtually (Frank et al., 2019; Henning et al., 2013). To achieve these smart factories, the use of Artificial intelligence (AI) is a key driver (Monostori et al., 2016). Its application is therefore receiving increasing attention in a wide range of production activities, including quality-based process control, predictive maintenance, order scheduling/dispatching or human-robot interaction (Burggräf et al., 2018).

While AI systems have the potential to automate many of the tasks traditionally the sphere of humans this applies considerably more to physical and repetitive tasks compared to cognitive, discretionary and decision making ones (Frey & Osborne, 2017). In the latter type of tasks AI is still seen to empower, augment, or supplement, rather than replace humans (Raisch & Krakowski, 2020). The human in the loop of CPPS (HiTLCPS) is already acknowledged to play important roles, for example in supporting data acquisition, in performing state inference, and in executing controls through actuation (Nunes et al., 2017). What is less explored is the human roles in the AI loop in manufacturing. Humans and AI can combine their complementary strengths, enabling mutual learning and extending their affordances and capabilities (C. Emmanouilidis et al., 2021). However, the co-existence of humans and AI to achieve production tasks also creates new challenges, such as reduced employee control (Kellogg et al., 2020), increasing cognitive load (Kong, 2019), creation of new tasks and expertise which both need to be additionally covered (Grønsund & Aanestad, 2020), and safety hazards when working with robots (Fletcher et al., 2020). Therefore, human-centric AI is promoted to mitigate such issues and maximize positive outcomes (Parker & Grote, 2020), which can be better served by integrating, rather than eliminating humans and their capabilities (C. Emmanouilidis et al., 2021; Kadir & Broberg, 2021). Consistent with sociotechnical systems (STS) theory, human-centric design approaches promote considering the workers' physical and cognitive capabilities for delivering system performance (Nääs et al., 2016; Richter et al., 2018).

Although the adoption of human-centric design is increasingly promoted in the literature, there are still limited frameworks and guidelines that can assist practitioners in accommodating human-centricity in the development and deployment of Industry 4.0-enabled systems (Kadir & Broberg, 2021; Sgarbossa et al., 2020). Technology development projects often focus on optimizing the technical system (C. W. Clegg, 2000), and system designers lack the required knowledge and skills to address human factor issues (C. W. Clegg, 2000; Parker et al., 2019; Waschull et al., 2022). Such projects are also characterized by a number of different stakeholders with different types of knowledge and interests that should contribute to shaping the design process (C. Clegg & Shepherd, 2007). In an AI-enabled smart production environment, relevant stakeholders may include system users (including operators), decision-makers, and experts (AI experts, human factor experts, engineers). Yet, in most such a range of stakeholders is not sufficiently involved beyond the requirements or the testing and validation phases of such projects, and thus their input is insufficiently integrated.

To go beyond a techno-centric development of AI systems, in which the social system needs to adapt to the technology rather than being designed concurrently, and to appropriately guide system designers, practical and prescriptive frameworks are required (Kadir & Broberg, 2021; Neumann et al., 2021). Therefore, in this paper a human-centric design method is developed and empirically tested, aiming to contribute towards a more effective human-AI integration. This integration accounts for the human-centricity of the intended solutions at the design stage. To develop the human-centric design method,

10.1016/j.ifacol.2022.04.246

a design science approach was selected as a suitable research method because it seeks to explore new solution alternatives to solve real problems and shaping the phenomenon of interest (Holmström et al., 2009). First, based on litereature analysis, different types of human-AI interaction and their system effects were identified in the solution incubation phase. The method was subsequently tested in three co-creation workshops to shape up human-centric AI-enabled solutions for production settings. This paper outlines the design, execution and synthesis of the outcomes arising from the workshops. The rest of the paper is structured as follows. Section 2 provides an outline of the three pillars of the design approach. Section 3 reports on the design validation, and outcomes of applying the method in co-creation workshops. Section 4is the conclusion.

2. HUMAN-CENTRIC DESIGN APPROACH SYNTHESIS

The development of the proposed human-centric design approach of AI-enabled production systems is based on (i) understanding and mapping the human-AI interaction (ii) work design and human factor effects of the AI-enabled system (iii) defining and targeting performance effects and success criteria. These are presented next.

2.1 Human and AI collaboration scenarios

Human – technical systems cooperation aims to make best use of both human and technical system capabilities. Human factors and their optimization have long been recognised as a key aspect of sociotechnical systems (Haslegrave, 1988) and are explicitly considered as part of Human Computer Interaction (HCI). The introduction of Industry 4.0 technologies in industrial workplaces brings an even higher emphasis on the need to understand the interactions between human and technical actors in production environments (Neumann et al., 2021). While cases of technical actors aiding humans in such workplaces are highlighted by numerous applications, the opposite, i.e., humans aiding technical actors, also holds significant potential enables human cognitive abilities to be integrated in sociotechnical systems (Christos Emmanouilidis et al., 2019). This is increasingly being studied in the case of AI systems included as part of the technical environment in CPPS (Burggräf et al., 2018). Accordingly, there is a need to take explicitly into account the nature of human – AI-enabled systems interaction when determining the architecture of sociotechnical systems (Handley, 2019).

A conceptual model of the human and non human interacting actors and their joint impact on the targeted sociotechnical system is presented in Figure 1. A technical actor can belong to Operational Technology (OT, e.g. machine, device, control), Information Technology (IT, e.g. software component, AI agent) or their fusion in a single entity (software and/or AI-enabled systems and components). Human and technical actors have human and technical capabilities respectively. Both use their capabilities to have an impact on the socio technical system. Additionally, the technical capabilities of technical systems empower humans to perform additional or enhanced activities and provide feedback (data, information, etc) to them. Human actors also augment the technical actor by enhancing, informing controlling or training it in the case of AI-enabled ones. So human capabilities are influenced by technical systems, including learning from the provided data or information. The opositive is also true: algorithms in AI-enabled systems can learn more efficiently or expand their knowledge range through their interaction with humans (C. Emmanouilidis et al., 2021). Based on this model of interaction, four collaboration scenarios can be defined and need to be considered during the design process (Figure 1):

- AI substitutes humans in tsks; for example performing quality control of produced components through artificial vision.
- AI augments humans in tasks; for example providing data and knowle-driven recommendations for human actions, based on AI-driven contextual awareness.
- Human augments AI in tasks; for example performing data labeling or flagging up misclassifications.
- Integrated AI & human task collaboration : for example the interaction of an AI agent enables an emergent system behaviour, such as when a human engages interactively with an AI agent to resolve situation awareness and the AI-agent adjust its behaviour according to it.

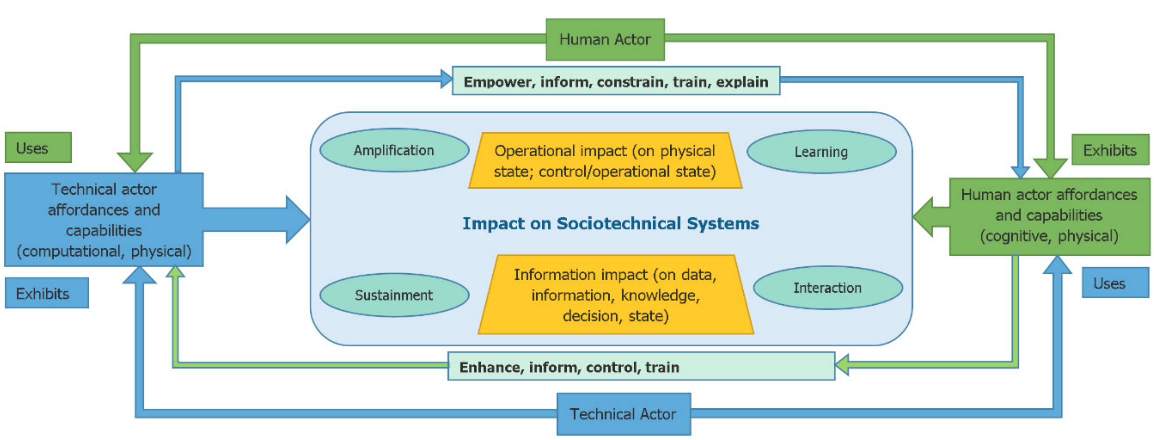

Figure 1. Socio-technical system interaction model.

2.2 Work design and human factor effects

Work design is referring to the content and organization of one's tasks, activities, relationships and responsibilities (Parker & Grote, 2020). Different job characteristics referring to the knowledge, social and task requirements describe the properties of the job, which determine a host of individual and organizational outcomes (Humphrey, Nahrgang and Morgeson, 2007). An enriched work design which leads to such positive outcomes is for example one takes human factors into consideration, for example where humans have job autonomy to make decisions, conduct a variety of tasks, and face appropriate perceptual and cognitive demands (Hackman & Oldham, 1976; Sgarbossa et al., 2020). However, if demands are excessive, then fatigue, discomfort, and eventual injuries can be expected (Sgarbossa et al., 2020). The work design perspective is a suitable theory to better understand and to identify collaboration scenarios of humans and AI systems (Emmanouilidis *et al.*, 2021). Specifically, choices on the collaboration scenarios will have work design effects by changing the job characteristics in terms of task, knowledge and social requirements. During the design process of human-centric AI, it is therefore important to consider these work design effects early on, and design the interaction accordingly. For example, the substitution of human in tasks by AI affects the variety of tasks. On the other hand, an increase in the number of integrated tasks where AI and humans collaborate might increase the mental demands of jobs. Moreover, factors such as trust, engagement, safety, explainability, ease of use are all important factors relevant in the context of human-AI integration (C. Emmanouilidis et al., 2021).

2.3. Production performance effects and success criteria

The primary driver of introducing AI-enabled solutions in production environments is to achieve process improvements, in delivering the right production outcomes. Production outcomes refer to delivering products meeting requirements and process improvements are translated into enhanced production performance. Production performance and production outcomes delivery may present conflicting challenges. For example, it may be straightforward to achieve high production throughput for a certain family of products or components, but such performance may be hardly achievable when product requirements and specifications change. Adding agility requirements, so that a production line can be used for a broader range of products has handled over the years through reconfigurable manufacturing systems (RMS) (Koren et al., 1999; Koren, Gu and Guo, 2018). However, several RMS challenges remain (Khanna and Kumar, 2019) and introducing additional production agility expectations in parallel with achieving targeted levels of production performance for specific customisations of a given production line may benefit from introducing automation and AI but still requires human operator involvement for many tasks (Bortolini et al., 2020). Given that production performance targets can only be defined within the specific context of a given organization, meaningful success criteria should also be context-specific. By identifying human, as well as technical and operational desired effects, success criteria can be identified that ultimately guide the system designers to jointly pay attention to different contributing factors early on in the design process.

2.4 Proposed human-centric design method

To steer AI-based systems development towards meeting stated aims (e.g., human-centric, trusted, safe), it is necessary to jointly consider human, technical, and operational factors as early in the design process as possible, considering the different AI-human collaboration scenarios as discussed in the socio-technical system interaction model. Interaction between human and technology will target positive impact on technical, operational and human effects, and ultimately determine the overall system performance. The design process of human-centric AI therefore needs to consider the impact of design choices in terms of human effects (working environment, work design) and the overall operational effects, all of which contribute towards the performance targets, and the formulation of success criteria. This design method is outlined in Figure 2, where (1) the type of AI-collaboration is first identified, according to the application requirements; (2) the sociotechnical system impact is considered, taking into account both working environment and work design aspects, as well as operational effects targets; and (3) these are distilled into success criteria, which are then examined to re-assess the human-AI collaboration patterns.

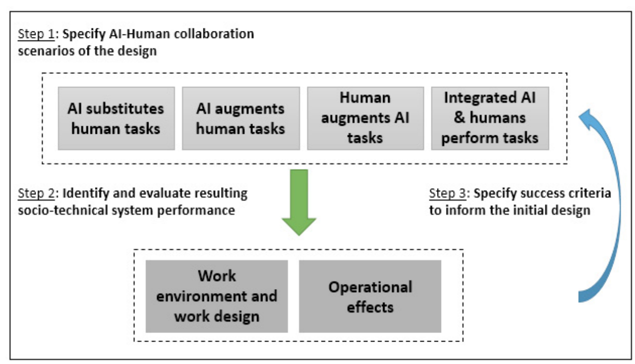

Figure 2. Human-centric design method

3. HUMAN-CENTRIC CO-CREATION WORKSHOPS

We tested and validated the human-centric design method in three co-creation workshops organized as part of a broader interdisciplinary research project. The project is a joint effort of AI and digital manufacturing experts towards enabling the deployment of standards-based, safe, reliable, trustworthy, and human centric AI systems in manufacturing. Development efforts are aimed at three pilot sites, each addressing multiple use cases. Pilot site 1 focuses on the deployment of AI in the context of human robot collaboration for quality inspection. Pilot site 2 focuses on human-centered AI for agile manufacturing of automotive parts. Pilot site 3 focuses on AI in the context of human behavior prediction and safe zone detection for mobile robots. To advance towards the achievement of the projects aim (i.e. human-centric, trusted and safe), each pilot site conducted a first round of co-creation workshops during the definition and design phase of the project's technology, thereby following the human-centric design method proposed in this paper. Due to Covid-19 constraints, the workshops were held online via the MIRO collaboration platform. The workshops took 4.5 h (pilot site 1), 2.5 h (pilot site 2) and 3 h (pilot site 3). 29, 20 and 18 participants joined the workshop for pilot site 1, 2 and 3 respectively. Participants were representative of typical stakeholders needed for the design and delivery of AI-solutions in manufacturing and comprised including AI and technology providers, manufacturers, legal/ethics experts, and research institutions. Table 1 provides an overview of the different use cases developed for the three pilots.

Table 1 Workshop use cases of pilot sites

Use case	Pilot site 1: Human robot collaboration for quality inspection	Pilot site 2: Human-centered AI for agile manufacturing of automotive parts	Pilot site 3: Human behaviour prediction and safe zone detection
1	Easy reconfiguration for automated part handling	Production processes simulations for accelerated decisions and safe processes	Human intention recognition
2	Human - supervised visual quality inspection	Production planning optimization	Robot reconfiguration based in dynamic layout
3	Safe human-cobot collaboration	Employee training for reduction of human errors	

3.1. Co-creation workshops – design stage

A few weeks before the workshops a survey was designed and distributed among participants aiming to identify initial requirements and desired effects for the deployment of human-centric AI systems. Participants were asked to indicate the expected impact of the AI use case on the work design of users, its operational effects and desired success criteria of the design. They were also asked to identify the different AI-human collaboration scenarios. The outcome of the survey provided seeding ideas for the preparation of the co-creation workshops. In addition, manufacturing pilots provided preliminary requirements, such as process workflows for the targeted use cases, as well as draft user stories. Such 'seeding' information was converted into placeholders for (1) user stories, (2) components/functionality that can be used or is required to implement the user requirements, and (3) a structure to host the participants view on the involved AI-human collaboration scenarios, as well as (4) anticipated outcomes (work design, operational) and success criteria. Each workshop collaboration board therefore consisted of multiple sub-boards, with a pre-defined structure to contain the placeholders. These placeholders on the MIRO collaboration board were structured as follows (per use case):

1 User stories
2 Initial components per use case
3 Collaboration scenarios
    a. AI substitutes humans in tasks
    b. AI augments humans in tasks
    c. Humans augment AI in tasks
    d. Integrated AI & humans perform tasks
4 Effects (work design/human factors)
5 List of operational effects
6 List of success criteria

The set-up of the collaboration board was closely developed with pilot partners involvement. This process already increased the awareness of partners regarding the requirements of a human-centric design. The workshop design had the following workflow (Figure 3):

- Introduction
- Description of the as-is and to-be scenarios,
- Presentation of the use cases
- Introduction to the workshop
- Co-creation activities:
    - Phase 1: User stories & initial components per use case (Stage 1 and 2)
    - Phase 2: Collaboration activities to define desired effects (operational/work design – Stage 3a and 3b)
- Evaluation

3.2. Co-creation workshops – execution and synthesis stage

After the design stage, for each workshop important preparatory information was structured as initial 'seeding' for the collaboration as outlined earlier, and the participants worked on the different sub-boards. First, participants evaluated, validated or edited the functional and non-functional requirements through editing the user stories for different stakeholders. To do so, participants were using stickers with different colours, indicating the different categories of users when expressing requirements in the form of user stories. Then they defined components and functionality needed to satisfy the requirements as expressed in the user stories. The next step was to link the components and functionalities with the user stories. The user stories addressed organizational, technical, and operational user concerns, but during the workshops additional user types were also considered, such as technology providers and researchers. After having covered all the use cases, participants worked the aspects of AI-human collaboration, and anticipated outcomes (work design, operational effects) and proposed relevant success criteria. This means that they effectively co-created different collaboration scenarios based on the desired outcomes and success criteria. Scenarios addressed approaches regarding how (1) humans can help/augment the AI, (2) where AI technology can help/augment humans, and

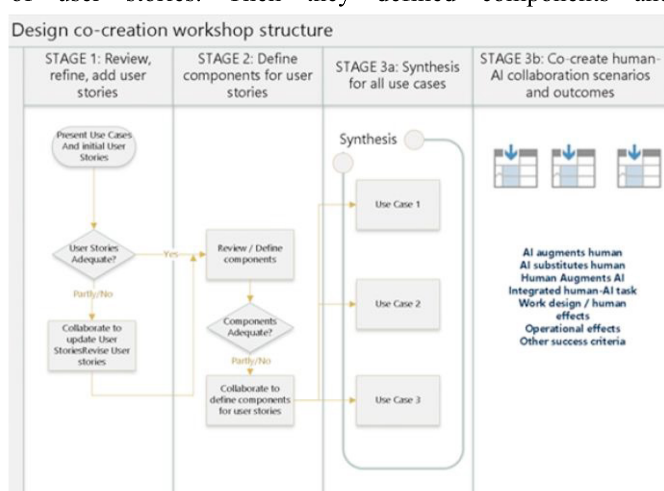

Figure 3. Design co-creation workshop structure

(3) the optimal interaction. Participants were able to propose, represent, interrogate and reflect on the different scenarios, while proposing ideas and visions which are based on the actual use context, and different criteria and anticipated outcomes. Throughout the different activities of the co-creation activities, participants were invited to pose comments to old or newly created content, encouraging short discussions. The workshop structure is illustrated in Figure 3.

3.3. Co-creation workshops – Evaluation of outcomes

The motivating effect of the appropriate preparation and sharing of application-relevant insights from the use cases, as well as the ease of use of the employed collaboration platform, created a highly exciting environment for very effective and engaging collaboration, resulting in updated user stories, components, and newly created ideas about the different collaboration scenarios, their effects and success criteria. Figure 4 shows a screenshot of a MIRO collaboration board for one of the use cases for pilot 1, as a visualization of the collaboration process outcomes.

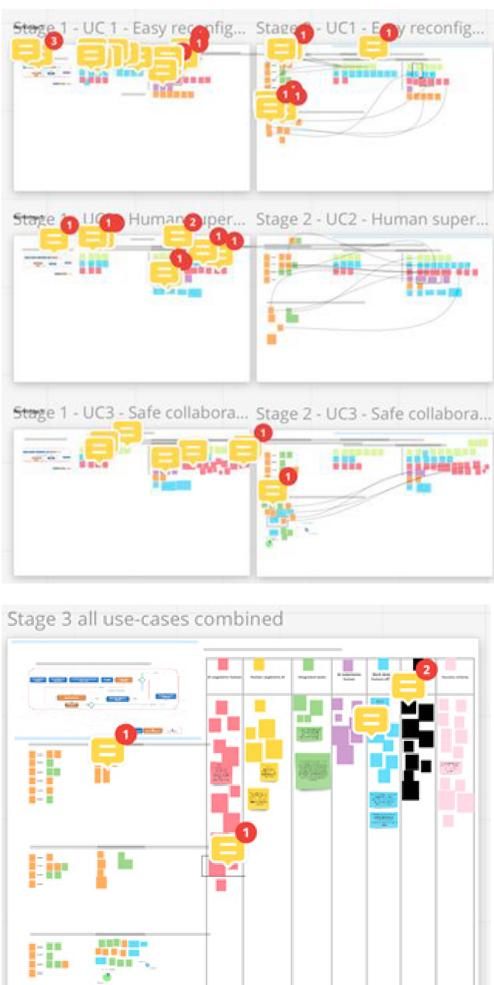

Figure 4. Co-creation collaboration boards

Proposed human-AI collaboration scenarios were:
AI augments humans
- AI supports in planning & scheduling
- AI offers insight from data (non-conformity explanation)

Human augments AI
- Human provides active learning feedback (labeling cases)
- Human supervision (flagging out cases)

AI substitutes humans
- Non-conformity detection

Integrated AI and humans
- Quality inspection for different product

While it was of particular interest to analyze the outcomes in qualitative terms, even a quantitative analysis produced impressive results. For example, just for the user stories and components alone, the following quantitative results were produced (Table 2), as a result of the use cases for 'human robot collaboration for quality inspection' at one of the pilots. After the co-creation activities, the workshop outcomes were summarized, synthesized and fed into the further design and development activities. The aim is to host follow-up co-creation workshops during the testing and evaluation phased for the human-centric AI solutions.

Table 2 Co-creation activity outcomes of user stories and components at pilot site 1

	Use Case 1	Use Case 2	Use Case 3
User stories			
Old	14	8	11
Total (incl. new/modified)	36	40	45
Components			
Old	14	10	10
Total (incl. new/modified)	24	17	26

4. CONCLUSION

This paper developed and demonstrated a human-centric co-creation design approach for delivering AI-enabled solutions in manufacturing. The approach distinguishes 3 co-creation phases in collaborative settings, starting from mapping the human-AI interaction, moving on to consider work design and human factor effects, and then feeding these into defining targeting performance effects and success criteria. System components and desired functionalities are thus linked to concrete outcomes for sociotechnical systems. The approach was applied in co-creation workshops, organized as part of the 'STAR' project which aimed at developing safe, trusted and human-centric AI solutions in manufacturing (John Soldatos & Dimosthenis Kyriazis, 2021). The paper contributes to the current literature on human factors in Industry 4.0 through a simple design method that proved suitable and effective in guiding and motivating technology developers, practitioners and researchers to consider both operational and human effects during the design process of AI systems in which humans play a vital role. While the focus was primarily on describing the adopted method in this paper, further analysis and presentation of the survey and workshops data to analyse in more detail the suitability of the method is planned to be included in a forthcoming paper. While the present paper focused on the collaboration process itself, further work in the project is focusing on feeding the workshop outcomes into the detailed requirements specification for the project components and overall solutions. Developments will be further assessed in the next stage co—creation workshops, where system live components and their functionality will be tested.

ACKNOWLEDGMENTS

Research supported through grant ID 956573. Pilot 1 workshop held by Philips Consumer Lifestyle (PCL) B.V., (credit to Jelle Keizer at PCL for co-organisation), pilot 2 and 3 held by DFKI, IBER-OLEFF. All STAR partners took part.

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