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Human-AI Collaboration in Smart Manufacturing: Key Concepts and Framework for Design

Maria HARTIKAINEN[1], Guna SPURAVA, and Kaisa VÄÄNÄNEN
Tampere University, Computing Sciences
ORCiD ID: Maria Hartikainen https://orcid.org/0000-0001-5997-0368
ORCiD ID: Guna Spurava https://orcid.org/0000-0001-5323-9806
ORCiD ID: Kaisa Väänänen https://orcid.org/0000-0002-3565-6021

Abstract. Demographical reasons and the increasing demand for improved production efficiency are steering the transformation within the manufacturing domain towards *smart manufacturing*. This entails introducing artificial intelligence (AI), data analytics, and automation to improve the efficiency, productivity, and flexibility of manufacturing processes. With the integration of AI, there is a shift from humans merely interacting with technology to actively collaborating with it, especially with AI-enabled agents. This shift brings changes in work practices and tasks. Hence, comprehensive understanding of the phenomenon becomes central for the design of human-AI collaboration that genuinely contributes to effective production and supports operators' well-being. This scoping review study aims to shed light to the evolving landscape of human-AI collaboration in smart manufacturing by presenting six key concepts derived from an analysis of 23 academic papers. Based on the findings, we propose a framework that offers an initial basis for the design of human-AI collaborative systems for smart manufacturing.

Keywords. Artificial Intelligence, Human-Centred AI, Human-AI Collaboration, Human-Machine Interaction, Smart Manufacturing, Human-Centric Smart Manufacturing

1. Introduction

The increasing demand for improved production efficiency as well as demands stemming from demographical issues, like aging workforces, are steering the transformation within the manufacturing domain towards *Smart Manufacturing* [13][18]. Smart manufacturing, similarly to Industry 4.0, refers to the use of smart technologies like artificial intelligence (AI), data analytics, and automation to improve the efficiency, productivity, and flexibility of manufacturing processes [9][16][18]. Continuation to smart manufacturing is *Human-Centric Smart* Manufacturing (HSM) that similarly to EU-led Industry 5.0 emphasises individual well-being and addresses social challenges, placing human factors, particularly operator well-being, at its core [2][4][6][13][20][23]. With the integration of AI, there is a shift from humans merely interacting with

[1] Corresponding Author: Maria Hartikainen, maria.hartikainen@tuni.fi.

technology to actively collaborating with it, especially with AI-enabled agents [7][15][24]. Enabled by AI, technology takes proactive role, as machines now perform tasks autonomously, and the roles between the human and machine are becoming more interchangeable [7][17]. Hence, the machine actors, referred as AI agents, are increasingly viewed as colleagues or teammates, signifying a new era of artificial colleague where human and AI collaborate towards common goal - *human-AI collaboration* [7][15][22][24]. This new form of interaction characterised by interdependencies and teamwork means changes to the work tasks and processes, especially for the operators, the workers in the manufacturing domain [2][15][23]. Hence, comprehensive understanding for the design of human-AI collaboration in smart manufacturing that genuinely is effective and supports operator's well-being as the operators are the crucial part of the successful implementation of the collaboration [7][13][19][23]. Because of the collaboration with AI-enabled agents and integration of AI in work life, there is a need for human-centred artificial intelligence (HCAI), aiming to prioritise human needs over technology [3][12]. HCAI seeks to provide efficient solutions and positive outcomes for users and society, augmenting human abilities rather than replacing them [11][20][28]. Ethical development and use of AI are integral to HCAI, ensuring fairness, trustworthiness [10][11][22][27], whereas explainable and transparent interaction between humans and AI enhances trust and user understanding in human-AI collaboration [8][12][26]. Additionally, autonomy and human control must be carefully considered in human-AI collaboration [12][25]. Despite the topicality, the human-centred approach to the collaboration design and the operator's well-being in changing work environments is under-explored. Hence, in this study, we review the related literature to understand, how do support the operator well-being by design and how to acknowledge the human factors in the collaboration design. We approach the study aim with the following research question: *What are the main concepts related to human-AI collaboration that have been suggested by existing literature?*

In this article, we present a scoping literature review that identifies the key concepts to acknowledge and address in the human-AI collaboration design [14]. Building upon these insights, our study proposes an initial human-AI collaboration framework for smart manufacturing, providing a foundation for designing and implementing effective and efficient collaboration strategies that support operator's well-being.

2. Method

2.1. The scoping review

We approached our research objectives with a scoping literature review to understand the existing knowledge on the topic, as well as to identify the key concepts associated to the topic in the related literature [14]. First, we developed a review question to reflect the study aim. Second, we defined the inclusion/exclusion criteria. We included articles that are in manufacturing domain and are at least partly concentrating on human-AI collaboration. We included peer-reviewed articles written in English that we had a full access. We excluded articles concentrating solely on human-robot collaboration, as robots normally have specific physical forms and movements that might affect the human's perception and expectations related to them. However, we did include articles that had robots as one example of AI-enabled technologies. Also, we excluded papers that were technical, related to the enabling AI technologies or programming of those, as your aim was in understanding the human factors. Third step was to search literature relevant to our scope. We utilised Google Scholar because it covers all the biggest databases. We searched with different compositions of key words describing humans and AI collaborating or working together like *"human-AI collaboration / cooperation"* and *"human-AI AND manufactur*"*. This search returned 452 articles that we screened based on the title and abstract using our inclusion / exclusion criteria. We included 32 articles to full-text screening. We read these papers and based on our inclusion/exclusion criteria we included 15 papers in our study corpus. After this, we used snowballing method, and based on the full text screening, we included eight more articles. Hence, total 23 articles were included to our study corpus. Figure 1 shows the review process. Detailed list of the reviewed articles is in Appendix 1.

Figure 1. The scoping literature review process

2.2. Analysis

We conducted reflexive thematic analysis to the data withdrawn from the reviewed papers with a purpose of find overarching concepts and their meanings in relation to the studied phenomena in review literature [5]. We began by familiarising ourselves with the data by reading the papers in our study corpus and the first author coded all the data utilising Atlas.ti -tool [1]. Even though our approach was reflexive analysis, we had four predetermined codes related to the key features of HCAI, because we wanted to understand how these are acknowledge in the related literature. These codes were: *transparency, explainability, trust,* and *control*. However, as our study aim is to understand the phenomena and we adapted reflexive analysis method, we left space for additional codes that rise from the analysed literature. Hence, during the first round of coding we combined deductive and inductive coding, and we added codes as they arose from the reviewed literature. After the preliminary coding, the authors discussed about the codes, they refined, combined, and separated them as needed. This led to 23 codes that formed the codebook. Our codebook is presented in table 1. Next, we conducted a second round of coding using the codebook. After the second round of coding, we conducted thematic analysis independently to identify recurrent concepts. We discussed about our individual analysis and combined our findings. Eventually, we defined six key concepts associated to the studied phenomena in the literature.

3. Findings

We identified six key concepts related to the human-AI collaboration from the reviewed literature. Table 1 presents the codes, the concepts and their description, and the literature included to each concept. In the text, we are referring to article with [A#]. Detailed list of referred articles is in Appendix 1.

Table 1. Key concepts and their description of human-AI collaboration identified in our review.

Codes	Concept	Referred articles
motivation, goal, application, benefit	Goal	A2, A3, A5, A11, A16, A18, A19, A20
agent, control, team	Team	A1, A2, A4, A5, A8, A9, A10, A11, A12, A15, A16, A17, A18
skill, learning, training, operator requirement	Skills	A2, A4, A7, A11, A12, A15, A16, A17, A19, A21, A23
AI strengths, human strengths, task	Task	A2, A4, A9, A11, A12, A13, A15, A16, A17, A18, A20, A22, A23
cyber-physical-system, interaction, socio-technical, UI	System	A1, A2, A6, A9, A11, A13, A14, A15, A16, A17, A18, A20
communication, understandability, trust, explainability, transparency	Communi-cation	A1, A3, A4, A7, A9, A11, A12, A14, A18, A19, A20

3.1. Collaboration goal

Collaboration goals refer to the objectives set for the collaborative actions performed by humans and AI. These goals are aimed at achieving specific outcomes that leverage the strengths of both humans and machines to improve productivity, efficiency, quality, safety, and innovation in the manufacturing process [A3, A19, A20]. In manufacturing, collaboration goals can be short-term goals (e.g. solving a problem) or long-term goals (e.g. enhanced productivity), and these goals may change over time [A11]. Goals should be well defined at the beginning of the collaboration design, so that informed design decisions can be based on these goals. In addition, expected benefits should be defined before the design. In the manufacturing domain, human-AI collaboration offers various benefits, and it seamlessly integrates into every phase of the product construction process, from design to predictive maintenance [A19, A20]. It provides an effective solution for overcoming limitations in real manufacturing environments [A2]. Moreover, it enhances the production process and creates more versatile and engaging job opportunities for employees [A11, A16, A18]. The measurement and metrics for the collaboration success can be planned based on the goals and expected benefits. These measurements can be quantitative (e.g. product efficiency) or qualitative (e.g. operator' well-being). Once the collaboration has been introduced and running, based on the defined measurements, human-AI collaboration performance can be measured, and adjustment can be done to the collaboration design as needed [A5].

3.2. Collaboration team

Collaboration team is formed with two or more agents, human and machine actors, that work together pursuing common goals [A9, A10, A15, A18]. In manufacturing, these agents can be humans, AI-agents, or AI-enabled robots [A17, A18, A23]. All agents have individual capabilities, strengths, and weaknesses [A8, A15]. Agents' strengths and weaknesses should be mapped and understood beforehand, so that collaboration tasks can be planned based on these for effective team performance [A8, A11]. From human-centred perspective, AI strengths should be used to enhance and augment the operator's skills [A4, A11, A12, A15, A20]. In smart manufacturing, the strengths that AI can pose are physical strength, speed, scalability, repeatability, and quantitative capabilities for complex analytical approach or data processing, and this way they can reduce the operator's mental workload [A1, A2, A16, A18, A20]. In addition, AI can help capture the equipment conditions and prevent system failures proactively. However, several manufacturing operations remain manual, as humans can perform these better and cannot be replaced by AI systems [A2]. Humans pose superior skills in unpredictable physical work, teamwork, social interactions, applying expertise, creativity, and managing [A2, A16, A18]. In addition, humans tend to be better to address anomalous situations and provide flexible solutions in case of need as well as evaluate the outcome of decision [A16, A18]. Moreover, in many cases regardless the strengths, humans will still be expected to be in control [A22, A23].

3.3. Skills

All agents possess individual skills, or capabilities, that can be acquired and developed through collaboration, training, and learning. In smart manufacturing, collaborating with AI and the fast-evolving technologies and changes is work processes, demand of new skills is high [A15, A16, A17, A19, A21]. Establishing appropriate skills represent the decisive factor to keep up not only with current but also future technology as the dynamic nature of the system underlines the constant evolution of skills among all actors involved [A7, A23, A17]. Perceptual, cognitive, emotional, and motoric skill demands on the agents are determined in the design [A11]. If these demands are higher that the capacity of an individual, there can be negative impacts on system performance, trust in AI, and worker well-being [A7, A11, A21, A19]. In addition, the current techno-centred design of smart manufacturing systems tends to demand extreme skills from the human operators as they are expected to handle any unexpected situations efficiently [A16]. At the same time, operators need to be able to operate and manage these adaptable AI systems, which requires corresponding skills [A7, A11]. Hence, *training* is a cornerstone of smart industry [A15, A21, A19]. Implementing a new system that heavily involves human-AI collaboration could demand significant training for workers to adapt to the new system, and there might be resistance to change [A21, A17]. Training is important not only because of the well-being of the operator, but also because inexperienced or under-trained personnel are prone to committing human errors [A2, A23]. Especially because in manufacturing, AI is increasingly applied in use cases with potentially severe consequences for humans [A7]. In addition, *learning* is an important part of collaboration, and it is important for the skill development of all agents. In human-AI collaboration in smart manufacturing, all agents possess ability to learn from each other or from the collaboration - this way collaboration team benefits mutually [A4, A12, A15, A19]. The dynamic nature of the overall system brings requirements where the capabilities and skills of all the actors change over time, hence, continuous learning is necessary [A4, A16, A11, A19].

3.4. Collaboration task

Collaboration goals are met with one or more *collaborating tasks* that are conducted by the collaborating team. Tasks are formed with activities that are conducted by the agents individually or collaboratively [A15, A18]. Starting from the analysis of team and task structure, the skills of the team actors are identified and linked to the different teaming activities [A9, A12, A15]. Tasks are carried out via interactions with agents and collaborative systems [A11, A13, A17]. Tasks have well-defined structure, and they have allocations [A12, A13]. An important design decision is the distribution of tasks between the agents [A11]. Each agents' capabilities should be key divider of the tasks, so that the task allocation supports operator's improved ergonomics, safety, and well-being by eliminating or reducing monotonous, hazardous, and physically demanding tasks traditionally performed by humans [A2, A16, A20, A22]. Tasks should be formed so that AI compensates operator's shortcomings or limitations in cognitive (e.g. complex data analysis), physical (heavy or dangerous jobs), or even sensorial capabilities (e.g. operator's state-of-mind) to deliver the best of both worlds, and to explore human augmentation to create manufacturing work that is more productive [A4, A11, A12, A15, A18, A20]. By handling physically and mentally demanding tasks, AI agents ease the burden on workers and that way promote the operator's well-being, safety, and ergonomics [A11, A20, A22, A23]. From the human-centred perspective, there is a need to develop task allocation and teamwork in human-AI collaboration teams so that human workers feel they are in the loop and that human remain meaningful and manageable [A11]. Task allocation must be revised resiliently to adapt to the changes in the dynamic manufacturing environment [A11, A13].

3.5. Collaboration system

Collaboration tasks and most of the interactions between the agents are carried out via *collaboration system*. Hence, a key element for successful human-AI collaboration is a careful design of the coordinating system involved [A9]. In smart manufacturing, these systems are usually socio-technical systems called Cyber-Physical-Systems (CPS) [A6, A11, A13, A16, A17]. CPSs comprises of humans, AI and the physical system that are in connection with the surrounding physical world and its processes [A11, A16, A17]. These systems should promote communication and understanding between the agents, as well as situational awareness, by offering possibility and interface to share knowledge about each other and their roles in the current task or in the collaboration process, or by showing the location of the other team member or predicting their next action in the collaboration process [A1, A6, A11, A14, A18]. In addition, collaborating system should aim to improve and promote learning of the agents and they should be dynamic and resilient, so that they can answer changing needs and dynamic environments in manufacturing, and the design should support this [A1, A11, A15, A16, A17]. In smart manufacturing, human-AI collaboration is moving beyond traditional interaction mechanisms, as smart technologies can allow humans to convey information with AI systems through multiple channels by integrating advanced human-machine interfaces that offer information related to the context and the situation that is relevant to the interaction [A6, A14, A18, A20]. With AI's help, there are more possibilities for the interaction, so the preferred interaction ways should be defined based on the skills and preferences of the human, as well as to fit to the context they are going to be used [A18, A20]. In addition, integrating multiple modalities is an effective approach to overcoming limitations in a real manufacturing environment [A2].

3.6. Communication

Communication is a central element of human-centeredness within human-AI collaboration [A7, A19]. Human-AI communication is dynamic, contingent upon the messages being exchanged at a specific moment within a particular context [A12, A14]. Communication between the agents serves two important purposes: (i) to convey essential procedural information for progressing the manufacturing operations, and (ii) to provide feedback that rewards or encourages good collaborations between humans and AI-agents, leading to mutually positive human-AI relationships [A3, A12, A19]. Human-AI collaboration team can rely on a mixture of verbal-based and nonverbal signs for natural and intuitive communication to coordinate team behaviours and learn from each other [A4, A20]. Important part of communication is *understanding*. Understanding between the collaborating agents promotes safety and efficiency in the collaboration [A7, A12, A18]. In human-centric smart manufacturing, human intent understanding is important, as well as appropriate level of expectations [A18], hence the machines need to possess some level of "empathy" as they need to actively collaborate with humans based on dynamic human intent and align with human's aspirations and motivations [A12]. This promotes understanding between the two agents [A11, A18]. From human-centred perspective, to confirm and reinforce the role of the human, explainability is required to human to understand the usage and results of AI and AI systems should provide easy-to-understand explanations of its actions and recommendations [A3, A20]. Transparency is needed in order the human to trust machine decisions - people need to know how an AI system derives its conclusions and makes its actions [A20]. Also, transparency is important to set appropriate expectations for both sides. From the human-centred perspective, it is important to define what information to convey, via what channel, and in what level, as communication and mutual understanding is important part of successful human-AI communication and trust building [A1, A3, A9, A12, A18].

4. Discussion

We identified six key concepts associated to the human-AI collaboration from the reviewed literature. All the concepts need careful considerations, and they should be acknowledged in the human-AI collaboration design for the collaboration to be genuinely effective. Based on the study findings, we propose an initial framework for human-AI collaboration in smart manufacturing. It presents the key concepts to acknowledge in the human-AI collaboration design, their relationships, and dependencies.

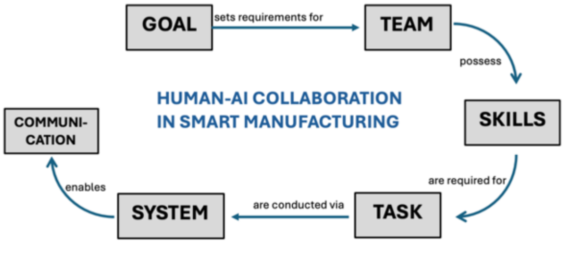

Figure 2. Proposed framework to present the key concepts of human-AI collaboration in smart manufacturing.

The integration of AI into manufacturing is a socio-technical process, influenced by not only technological possibilities but also by social factors such as operators' well-being, trust building, and human interpretation of AI systems that should be acknowledged in the collaboration design. Utilisation of AI makes AI-related factors, like explainability and transparency, relevant in this paradigm. There is a need to investigate how should they be acknowledged in the collaboration design. In the reviewed literature it is clear, that implementing AI to the work practises and processes may radically change the traditional work tasks and practises, and this of course requires very different skills than the more traditional manufacturing tasks. The current techno-centred design of smart manufacturing systems tends to demand extreme skills from the human operators as they are expected to handle any unexpected situations efficiently. As the mismatch between the skills and skills requirements strongly affects to the operator's well-being, it is crucial to ensure the appropriate skills of operator with training and learning to promotes the well-being of the operator. Hence, instructions for mapping the operator's skill requirements or training needs are currently lacking. Existing studies are mostly literature reviews, and empirical user studies are needed to understand the human side in the collaboration. In addition, the operators' point of view is under-explored in current literature, even though operators are the crucial part of the successful implementation of the collaboration [13][23]. Hence, for future research, we suggest the following topics:

- Human-AI collaboration design guidelines should be developed, to support the design of effective human-AI collaboration in manufacturing companies. The concepts identified in this paper, and the proposed framework, can serve as a basis for these guidelines
- Methods to map operator skills and skills demand, and appropriate training schemes should be developed
- HCAI related factors such as transparency, ethics, explainability, should be studied in relation to the human-AI collaboration in smart manufacturing
- Design approaches and methods are needed for the dynamic nature of the overall system where the skills of all the actors change over time

Limitations of our study are that even though we covered several different terms related to human-AI collaboration, in the snowballing phase we comprehended that this topic is covered in papers related industry 4.0 and industry 5.0. In addition, we used ´manufacturing´ as a keyword, however, we later learned that ´production´ is often used as a synonym for it. Hence, we might not have covered all the articles related to the topic in our review. However, we were not aiming to systematic review, and in our opinion, the key concepts and their meaning we clear in the articles we reviewed. In addition, in the future research we can add to this knowledge by including data from more articles, if needed.

5. Conclusion

Human-AI collaboration in smart manufacturing fosters intuitive interaction between humans and AI, leveraging strengths for better system performance. Human-centeredness is crucial, with AI technologies promoting collaboration, augmenting human skills, and adapting to individual skills. By improving production processes and offering varied job opportunities, this collaboration enhances productivity and flexibility. This article contributes to the emerging field of human-AI collaboration in smart manufacturing by presenting key concepts associated to the topic. Based on the identified concepts we propose an initial human-AI collaboration for smart manufacturing framework that serves as a basis for researchers and industry professionals looking to delve into designing effective human-AI collaborations in smart manufacturing.

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