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Assessing human-centricity in AI enabled manufacturing systems: a socio-technical evaluation methodology

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Abstract: The emerging interest in Industry 5.0 is consistent with the growing importance of instilling human-centricity in manufacturing technological innovations. Human-centricity concerns the creation of a human-technology symbiosis that enables the capitalization of respective human and technical capabilities for optimal system performance. While Industry 5.0 advocates the need to consider human aspects already at the design of technical systems, there is currently a lack of insights regarding the relevant performance criteria to consider when evaluating human-centric manufacturing. This paper presents an evaluation methodology for artificial intelligence (AI)-enabled manufacturing in the transition towards Industry 5.0. It adopts a multi-viewpoint assessment via an appropriate set of social, technical and operational factors to be considered when designing or implementing human-centric AI. The methodology can guide designers and decision-makers to evaluate the embedding of AI into industrial work systems, providing clarity on relevant criteria to consider when moving towards human-centricity in AI-enabled manufacturing.

Keywords: manufacturing plant control, human-centric manufacturing; Industry 5.0; intelligent manufacturing systems; socio-technical systems, socio-technical evaluation; artificial intelligence

1. INTRODUCTION

The concept of Industry 4.0 has recently been upgraded to a new version, assigning technological advancements a central role towards the achievement of human-centricity, sustainability and resilience (Dixson-Decleve et al., 2022). While Industry 5.0 may not be very technologically different from its earlier 4.0 version, it provides a different perspective, which places the well-being of the workers at the centre of the manufacturing processes (Leng et al., 2022). With AI-driven systems making headways in production settings, the principles of human-centred designs for software-enabled interactive systems become more relevant. Human-centred designs apply human factors, ergonomics and usability knowledge and techniques throughout the lifecycle of computer and thereby AI-enabled systems (ISO 9241-210, 2019). Applying human-centred design principles leads to putting the humans at the centre of system design, rather than relegating them as an afterthought (Hartley, 2022). In contrast to the overly technology-driven development of Industry 4.0 (Neumann et al., 2021; Waschull et al., 2022), human-centricity is about putting the core human needs, interests and well-being at the heart of the production process. It aims to provide a safe, comfortable, and motivating environment for working, learning and growth (Xu et al., 2021). However, despite being fairly well-formulated for computer-enabled interactive systems, human-centricity to date is an early and contentious concept in manufacturing that urgently needs further discussion and consensus to clarify its differentiation beyond techno-centric manufacturing approaches (Lu et al., 2022). Given the complexity and multifaceted nature of emerging socio-technical, and in particularly AI-driven systems, the boundaries between human and technological capabilities, and as a result the degree to which human or AI-enable actors operate with autonomy and delegate functions to each other, become increasingly blurred (Abbass, 2019). Human work extends to cognitive tasks linked to AI, including collecting and annotating data, interacting with intelligent systems to enrich their knowledge, as well as tuning or maintaining them (Emmanouilidis et al., 2021).

This paper aims to contribute towards the better understanding and thereby assessment of what characterizes a human-centric AI-enabled work system in manufacturing, building on earlier work on ergonomics and human factors, work design, ethics and trust. This is achieved by introducing a methodology for evaluating human-centric work systems in the overall context of AI deployment in manufacturing. A number of steps for the evaluation activities are specified, including important performance criteria necessary to determine the success, and preliminary recommendations for measurements. The research contribution is the conceptualization of relevant design and implementation criteria for human-centric AI-enabled systems, and the development of a hands-on evaluation methodology. It may support and motivate key stakeholders to consider important human aspects early during the design and/or implementation of Industry 5.0 aligned systems. The paper is structured as follows. In the next section, relevant background is provided, followed by the methodology development, including listing the proposed criteria in Section 3. Section 4 concludes with presenting future work.

2. BACKGROUND

Despite the expected performance benefits of the application of AI in manufacturing, their impact on humans must not be underestimated (Soldatos & Kyriazis, 2021). AI has a strong potential to transform the nature of work, ranging from automation to human augmentation (Raisch & Krakowski, 2020) but also to create dynamic human-AI actor synergies (Emmanouilidis et al., 2021). In line with the vision of Industry 5.0, there is an increasing number of studies focusing on developing architectures and mappings of manufacturing and technologies based on a human-centric design approaches for designing industrial work systems (Kadir & Broberg, 2021; Romero et al., 2015, 2016; Vijayakumar et al., 2021; Zarte et al., 2020). However, to facilitate the stronger consideration of humans aspects in practice, these visions must be made much more concrete, including frameworks that focus on the evaluation of the related social criteria alongside necessary technical and other relevant operational performance ones. This direction requires methodologies for evaluating human-centric technologies treating work systems as socio-technical systems, as opposed to solely focusing on system and/or technology performance, including AI performance. Overall, there is a clear lack of such evaluation methods with such joint considerations. For example, while there are a number of different frameworks that facilitate a human-centric approach by outlining different steps, or activities of system designers to pay attention to human aspects during the selection, design or implementation phase (e.g. Fantini et al., 2020; Neumann et al., 2021), they lack specifics on the diverse types of human-centric criteria to consider when evaluating such systems. They also lack insights into the specific evaluation activities to perform. Other studies provide preliminary list of evaluation criteria to consider. For example, Bousdekis et al. (2022) propose a framework for the evaluation of voice-enabled AI solutions in Industry 5.0 addressing a limited number of criteria, including trustworthiness, usability, cognitive workload and overall business needs. Longo et al. (2020) specify a preliminary list of 'values' to uphold during techno-social change in Industry 5.0, such as trustworthiness, privacy, autonomy, the common good, thereby focusing strongly on human aspects. Overall, we lack a holistic list of criteria that allow organisations to evaluate the success of designing and implementing human-centric systems, especially AI-driven systems. In the next section, we therefore develop a holistic methodology for the evaluation of AI-enabled manufacturing systems focused on human-centricity, including specifying relevant criteria and detailed evaluation activities.

3. METHODOLOGY DEVELOPMENT

3.1 Development approach

Regarding the development of the methodology, this paper focuses primarily on the conceptual development phase for developing applied theory building research as proposed by Lynham (2002). The conceptual development of the framework included identifying, naming and integrating the different stages of the evaluation methodology, and specifying the different performance dimensions to be addressed in the actual evaluation of performance. The integration of the different performance dimensions in the framework is based on a synthesis of the literature where we identified and specified different relevant categories and the related criteria. Relevant background regarding these categories and the criteria is provided in the next section. The operationalization phase of the methodology, as proposed by Lynham (2002), links the concept to practice to validate its usability. This research conducted preliminary discussions and validation activities through a number of interviews with and a survey distributed among technology developers and pilot organizations involved in introducing AI-driven solutions in production environments. Moreover, several co-creation workshops were conducted, involving different stakeholders engaged in developing, testing and validating human-centric AI-enabled solutions for different use cases in manufacturing. This enabled further validation of the criteria in general, as well as tailoring the criteria to the specific use cases.

3.2 Development of the evaluation methodology

We propose a systematic methodology for evaluating different performance dimensions of human-centric systems in the context of AI-enabled manufacturing, applicable in the conceptualization, design and implementation phases. The evaluation methodology comprises five steps.

Step 1: Define the unit of analysis and identify use cases

To ensure the validity of the evaluation activities, the unit of analysis needs to be clearly specified. The unit of analysis can relate to different levels of complexity, ranging from the function level of a technology, to the component level, to the overall work system level (which may address different interacting technical components to achieve an objective). The evaluation activities may also involve different (embedded) unit of analysis, for example, the component level and the work system level. In line with the idea that engineered systems are socio-technical systems, different human roles will interact with the technology throughout its lifecycle including design, assembly, installation, operation, maintenance and disassembly (Neumann et al., 2021). For the evaluation activities, it is therefore important to specify which life-cycle phase is addressed and the different types of humans that will interact with the system. The functionality of a technology is usually described in a use-case, specifying how the user will interact with the system, and may be relevant in the context of a specific job. For the evaluation purposes, especially regarding non-technical performance, it is necessary to identify and link use cases to the specified unit of analysis to give meaning to the evaluation outcomes.

Step 2: Gather multidisciplinary team of relevant stakeholders

It is well known that all aspects of a system (technical and social) are interdependent, and hence should, but are often not, jointly designed (Clegg, 2000). The interdependencies may not always be apparent during system design due to a lack of awareness, or knowledge provided by the involved stakeholders, risking unintended consequences that may only become apparent once the system is operating (Parker & Grote, 2020). To evaluate interdependencies during the design or implementation phase, it is crucial to provide knowledge about the different parts of a work system (technical and social) and their interactions. This includes the technical system (the functionality and the type of tasks), the social system (the workers and the work design), and the overall organizational context reflecting insights about the strategic directions and goals of the company. It is not possible for a single discipline or profession to have all the answers. Hence, a multi-disciplinary team of stakeholders should be identified for the evaluation to ensure reliable and valid evaluation activities. Dul et al. (2012) specified different groups of stakeholders relevant for system design, including system actors, system experts, system decision-makers and system influencers. In Table 1, we provide examples of stakeholders relevant for the context of AI-enabled manufacturing systems.

Table 1. Relevant stakeholder categories

Stakeholder category	Examples
System actors: front-end staff that will use or work (directly or indirectly) with the AI system	Operators, system engineers, maintenance engineers, quality engineers/control;
System experts: designers of systems with specific and relevant professional backgrounds	AI designers and developers, data scientists, legal/compliance officers, managers, psychology/human factor specialists;
System decision-maker: decision-makers about the requirements for system design, its purchasing and implementation	Managers with specific domain relevant knowledge: e.g., operations, human resources, planning, quality;
System influencers: influencers with general interest in work system and product design	Local community, media and government (national/EU-level), innovation clusters,

Step 3: Identify and validate relevant performance categories

As all work systems are socio-technical systems, the technical and social system should be jointly designed to account for and ensure human well-being and improved systems performance, including operational performance (Cherns, 1987). This human-centric thinking should be taken into consideration during the design, the implementation, and the operational phase of a system through continuous evaluation. The evaluation of the outcomes can further guide (steer, correct, direct) the development efforts into a certain direction. It may also motivate decision-makers to appropriately include human-centric criteria as design requirements. This is because people are often strongly driven in their behaviour and priorities by the metrics used to evaluate success. Thus, the evaluation approach combines elements of human factors and work design theory, operations management, AI, ethics, and safety concepts in an integrated methodology to define evaluation criteria, thereby adopting a system thinking and balanced approach. We specified into three broad categories, namely technical criteria (Table 2), operational criteria (Table 3) and social criteria (Table 4). This is because alongside human-oriented social aspects, human-centric systems also need to ensure adequate technical and operational performance to demonstrate success and provide a suitable justification for implementing the selected technology. It should be acknowledged that not all criteria are relevant for all contexts. Therefore, before the evaluation activities take place, the team selected in step 2 is urged to select which criteria are relevant for their particular use cases and selected unit of analysis. More background on each category is provided next. However, for human-centric AI-driven system, the key concept of trust is of major importance, and is relevant to human factors, technical and operational criteria.

Trust: Trustworthiness is a key quality characteristic for AI-driven systems, and especially human-centric ones. According to ISO/IEC TS 5723, 2022, it is a multi-faceted concept comprising accountability, accuracy, authenticity, availability, controllability, integrity, privacy, quality, reliability, resilience, robustness, safety, security, transparency, and usability. Each one of the above dimensions of trust may comprise multiple specific factors and it would be wrong to see trust from a technical, operational, or human factors and ethics only viewpoint. It attains specific further meaning in the context of AI-driven systems, as discussed next.

Technical dimensions of trust criteria: While technical criteria are largely case-specific, and generic technical systems quality criteria typically include aspects such as reliability, usability, repairability, and security, the shift to AI-enabled systems leads to further specifying them regarding AI-solution quality. Table 2 provides relevant definitions.

Table 2. Technical dimensions of trustworthiness evaluation

Criteria	Definition	Measures
Accuracy	The degree to which a machine learning model generates a correct output	Determined by the nature of problem (for example metrics for classification or regression problems)
Robustness	Ability of AI system to maintain its level of performance in varying circumstances (changes in the datasets, domain shifts, and outliers (Graziani et al., 2022)	Variability in quantitative measures obtained via statistical, formal or empirical methods (for example variability in accuracy)
Latency	The delay in system responsiveness	Measurement of time to process a data unit
Reliability	AI system behaves exactly as its designers intended and adheres to specification	The number of unintended issues where system does not adhere to specification
Security	Ability to identify and withstand external threats and adversarial attacks, maintaining the integrity and privacy of the information, and protecting architecture from modification	For example, risk-based security metrics, penetration testing performance etc.
Scalability	Ability of AI system to maintain its level of performance when problem scales upwards (for example more data, more parameters, more actors, etc.)	Measured in variability of other metrics vs complexity

Operational dimensions of trust*:* Operational evaluation criteria address the performance of the operational processes that the technology or component is implemented at. The performance of an operations systems is primarily measured against the traditional objectives of costs, time, flexibility and quality, which for Manufacturing Operations are defined in established standards (e.g., ISO 2240x), and outlined in Table 3. The ability of an AI-driven system to deliver on operational performance, contributes to its operational trustworthiness. However, operational performance metrics need to be further specified within the contact of each specific enterprise.

Table 3. Operational trustworthiness evaluation criteria

Criteria	Definition	Measures
Productivity (total/labour/machine)	The ratio of what is produced by an operation/process/ machine to what is required to produce it.	Output versus input
Labour productivity		Output of operations versus labor input
Machine productivity		Overall equipment effectiveness
Processing time	Time it takes a process or machine to process one unit	Total processing time/output
Manufacturing lead times		Time between initiation and completion of a process
Order processing time		Time between initiation and completion of an order
Machine set-up/configuration time		Time to set up or configure a machine
Delivery reliability	The degree to which a supplier is able to serve its customers on time	% on time deliveries
Machine flexibility	The degree to which an operation's processes can change what it does, how it is doing it, or when it is doing it	Setup time to pass from one type of process to another
Process flexibility		The volume of a set of part parts that can be processed in a system without major setups
Product flexibility		Changeover time of one part mix to another
Routing flexibility		Average number of ways a part type can be produced
Produced quality	A distinct attribute of a product	% of returned goods or discards
Perceived quality		Customer satisfaction
Quality costs		% of reworks or maintenance cost per product unit

Social dimensions of trust and ethics. The development of human-centric AI solutions implies that the configuration includes interaction between the technical components (AI actor) and a human (human actor). Depending on the desired interaction and outcomes (e.g., automation, augmentation or human-AI symbiosis), and the unit of analysis (e.g. task or overall job), different criteria need to be addressed and in turn evaluated. We identified a number of design criteria to be evaluated across the different units of analysis, namely addressing the interaction between technical and human actors via the concept of trustworthiness (ISO/IEC TS 5723, 2022) earlier. Additionally, adopting a model process for ethically aligned designs (IEEE, 2017), is an important one to follow for aligning human-centric AI systems with organisational, societal, and individual ethical values. and the unit of the work system, addressing work organisation, including the overall work design (i.e., motivational criteria). Regarding the direct interaction of the human actor with the AI, human-centric AI aims to overcome the black-box nature and lack of transparency. Human-centric AI solutions strive for trustworthiness and fairness, and aim to enable higher job satisfaction and well-being. Therefore, criteria such as the degree of explainability, interpretability and fairness of the system are important to include. To ensure high motivation and well-being, work design criteria that relate to the overall work may be relevant to consider including task autonomy, skill variety, task variety or social interaction (Humphrey et al., 2007). Table 4 provides an overview of trust criteria with social dimensions as well as motivational ones.

Table 4. Social trustworthiness evaluation criteria

Criteria	Definition	Measures
Trust criteria with ethical dimensions		
Privacy	Ensure informational privacy; right to determine what data can be communicated to others through informed consent (Longo et al., 2020)	The Assessment list for trustworthy Artificial Intelligence (ALTAI) (AI HLEG, 2019)
Accountability	Mechanisms put in place to ensure responsibility for the development, deployment and use of AI systems	The Assessment list for trustworthy Artificial Intelligence (ALTAI) (AI HLEG, 2019)
Transparency (enabled by e.g. Explainability, Interpretability)	Explainability: the AI's mechanics for producing outcomes can be explained If this can be done in human-understandable terms, this is interpretability	Qualitative user assessment (focus groups) (Linkov et al., 2020); (Graziani et al., 2022)
Controllability (ethics dimensions)	Property of a system that allows a human or another external agent to intervene in the system's functioning	Qualitative, (ISO/IEC TS 5723, 2022)
Fairness and non-discrimination	Data fairness (responsible data acquisition, handling and management), and design/algorithmic/outcome fairness	The Assessment list for trustworthy Artificial Intelligence (ALTAI) (AI HLEG, 2019) (Leslie, 2019)
Inclusivity	Mechanisms put in place to ensure that the AI system caters to a wide range of individual characteristics and capabilities	The Assessment list for trustworthy Artificial Intelligence (ALTAI) (AI HLEG, 2019)
Work design and motivational criteria (Linkov et al., 2020)		
Task variety	The range and variety of tasks to perform	Adapted work design questionnaire

Autonomy /human agency	The freedom and discretion to take decisions in scheduling and determined procedures to carry out work	Adapted work design questionnaire taken from Morgeson & Humphrey (2006)
Skill variety	The range and nature of skills needed for the job	Adapted work design questionnaire
Mental demands and fatigue	The mental demands required for tasks, including stimulating workers with challenging and diverse tasks that require continuous learning	Adapted work design questionnaire; quantitative experiments
Problem-solving	The degree to which the task requires unique ideas or solutions	Adapted work design questionnaire
Feedback from job/others	The degree of feedback provided by the task or by others	Adapted work design questionnaire
Information processing needs	The degree if interpreting, gathering and synthesizing information for decision-making purposes	Adapted work design questionnaire
Interdependence	The degree to which employees depend on each other or other system actors	Adapted work design questionnaire
Social support	The overall interaction with colleagues and supervisors	Adapted work design questionnaire
Ergonomics	Ergonomics reflects the degree to which a job allows correct or appropriate posture and movement	Adapted work design questionnaire
Physical demands	Type of physical effort required in a job	Adapted work design questionnaire
Work conditions	The environment where a task is performed including health hazards, noise, temperature and cleanliness	Adapted work design questionnaire

Step 4: Conduct evaluation and feed outcomes back to design/development/implementation/operations teams

As seen in Tables 2 to 4, the evaluation methodology includes both qualitative and quantitative assessment. The qualitative measurements can be collected in an evaluation workshop or focus/stakeholder groups. Quantitative metrics are estimated via experiments with the prototype or the implemented system, or even with focus groups if the system is still in the definition or development phase and a full implementation context is lacking. It is useful to compare the outcomes of the evaluation efforts to a baseline but this might not be feasible depending on the state of the project. The evaluation outcomes must be provided as feedback to stakeholders involved in development. This will includes integrating feedback on social and ethical implications of the design and use of the AI solution.

4. FUTURE WORK

A hands-on proposed workflow for putting the evaluation methodology into practice is seen in Fig. 1. This process has just been put into practice in recent evaluation workshops. Results of this process are currently under processing. A notable but preliminary outcome from such workshops is that the dividing lines between categories of criteria are actually blurred. For example, trust dimensions span across the technical, operational, as well as social and motivational criteria categories. Further inclusion of ethical design criteria will be among future extensions, as recommended in taking into account guidelines for ethically aligned AI system designs, as stated in IEEE P70xx recommendations.

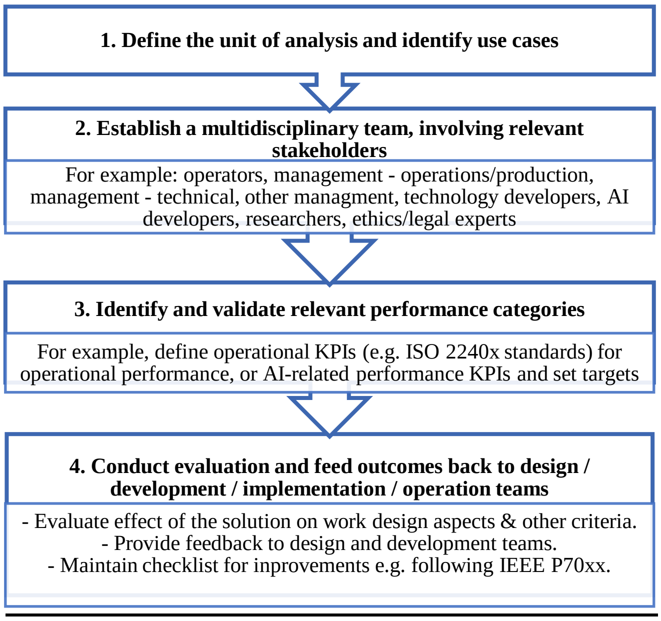

Figure 1. Implementation workflow of the methodology

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