# Human in the AI Loop in Production Environments

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**Abstract.** The integration of Artificial Intelligence (AI) in manufacturing is often pursued as technology push. In contrast, this paper looks upon the AI-human interaction from a viewpoint that considers both to play an important role in reshaping their individual capabilities. It specifically focuses on how humans can play an important role in enhancing AI capabilities. The introduced concepts are tested in an industrial case study of vision-based inspection in production lines. Furthermore, the paper highlights the need to consider relevant implications for work design for AI integration. The contribution can be of practical value for system developers and work designers in how to target at the design stage the human contribution in AI-enabled systems for production environments.

**Keywords:** Human-in-the-loop · AI · Work design · Industry 4.0

## 1 Introduction

Modern manufacturing environments are not simply technical systems but complex sociotechnical ones. In sociotechnical systems, human actors hold a key role with implications for system performance, alongside the physical technical systems. However, while the interaction between human and non-human actors in sociotechnical systems has been broadly explored, there is still a lack of understanding regarding the inclusion of Artificial Intelligence (AI) actors within sociotechnical systems. Aiming at narrowing this gap in the literature, this paper critically assesses human engagement with AI. It then proposes a model of human-AI interaction that goes beyond augmentation, and applies that on an industrial case study to show how selected aspects of these interaction can positively affect outcomes. This can be of practical value for system developers and work designers in how to effectively integrate human-centric AI in production environments at the design stage of such a process. This paper is structured as follows. Section 2 analyses related work and the role of human and AI actors in sociotechnical production environments. Section 3 outlines key aspects of integrating human and non-human actors to enhance AI capabilities. Section 4 applies elements of the proposed concepts on an industrial case study. Section 5 outlines work design implications and concludes outlining next steps for the research.


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## 2 Human and AI Actors in Sociotechnical Systems

The joint consideration of human and technical actors in sociotechnical systems has been studied for long, going back to the early years of Human System Engineering (HSE). HSE refers to the application of principles, models, and techniques to system design, taking into account human capabilities and limitations [1]. Increasingly literature accepts that human actors can be more effective when they act upon a shared context ("situational awareness") of work activities, which is a "collective activity" view of work environments [2]. A collective activity is not merely the sum of individual parts but is shaped up from interacting actors. The nature of these interactions is now deeply influenced by the introduction of AI in production activities [3]. The integration of human and AI actors in manufacturing can be looked upon as a collective activity. It is therefore justified to consider not only how processes can be automated, or how humans can be augmented by AI [4], but also to capitalize on the emergent outcomes of the evolving human-AI interaction. These outcomes become more powerful when the opportunities offered by humans augmenting the AI [5] or by integrating the human cognitive capabilities in the AI loop are designed-in the systems [6]. Human cognitive capabilities have been part of the design of artificial cognitive system architectures [7] but are not often sufficiently integrated in AI deployments in manufacturing. Human-AI interaction can drive radical changes in the affordances of the human and non-human actors in such environments. The term "affordance" is used in different disciplines and broadly "denotes action possibilities provided to the actor by the environment" [8]. The significant expansion of interaction affordances arising from the human-AI integration has not received sufficient attention when dealing with AI in manufacturing. This adds to the growing acceptance that, since the application of Industry 4.0 technologies in production systems changes the role of workers in unprecedented ways [9], there is a need to address challenges to enhance both operational performance and work design and human effects. As a result, human-centricity, which emphasises the need to pay attention to human workers during the design and adoption of sociotechnical systems, is now pointing towards human-centric design approaches, and human-centered principles in the design of AI, within the view point of work design [10]. While the role of humans regarding changes in work and work organization has received ample attention in the literature in the context of today's technological change [11], for many practitioners the human implications of integrating AI within the technology toolset of their operating environments remains a black box. Part of the difficulty lies with the relative lack of understanding regarding the nature of human-AI interaction. This in turn limits both the effectiveness of the integration of humans in the AI loop, as well as the perspectives of work design towards integrating more effective human-AI synergies in production environments. These are looked upon in further detail next.

## 3 The Role of Human Actors in Enhancing AI

There is barely a single definition of what constitutes AI, but to the extent that intelligence characteristics are associated with thought processes and behaviours, the expectations for an AI agent would be to exhibit at least some of those characteristics. The thought processes viewpoints are typically looked upon from the cognitive systems and logic viewpoints, while the behavioural ones may result from applying concepts, methods, and practice related to machine learning, knowledge representation and reasoning, natural language processing, and agent-based systems [12]. While AI has the potential to take on human tasks [13], there is a growing consensus to design human-centric technologies which integrate rather than eliminate humans and their capabilities [6, 14, 15]. While the majority of such human-in-the-loop scenarios consider how AI augments humans [16], the opposite (humans aiding AI) also holds significant potential for the successful integration of humans and AI in manufacturing [5, 6, 15]. The advances made in the practical application of AI, involving scenarios of automation and augmentation of human work [13], create the need to better understand the interactions between human and AI actors. Human augmentation in manufacturing has benefitted from a range of technology enablers and the established paradigm shift to ubiquitous computing [17]. Contributing enables include multimodal interfaces [18], augmented [19] and virtual [20] reality, context-adaptive computing [21], exoskeletons for physical augmentation [22] and natural interfaces, including speech [23] and brain – computer interfaces [24]. Yet, the potential contribution of humans towards AI agents [5] can be beneficial across the whole process workflow of data-driven machine learning. Considering this from a software-based systems perspective [25], the workflow of activities wherein humans can have a distinct role can be outlined in the waterfall diagram of Fig. 1. The diagram illustrates the five typical phases of such a software engineering process. While the

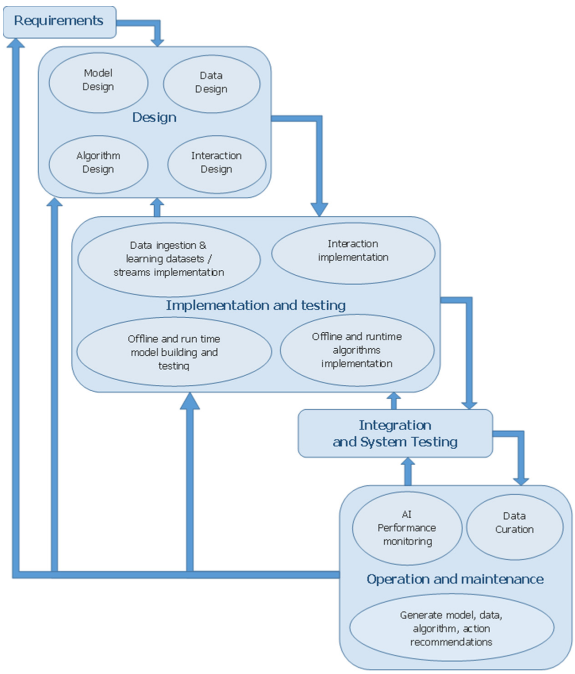


**Fig. 1.** Machine learning waterfall diagram outlining human actions

requirements and integration and system testing phases are certainly relevant to human involvement, the interest is nonetheless placed on the design, implementation and testing, and operation and maintenance, to outline key human involvement with machine learning, rather than the system or software process.

Table 1 shortlists specific human involvement activities for the design stage, while the corresponding activities for the implementation and operation stages are seen in Table 2 and 3 respectively. Both domain and data/AI experts have distinct roles there.

**Table 1.** Humans aiding AI actors - design

| Activities | Application perspective | Machine learning perspective |
|---|---|---|
| Problem definition | Set application targets (e.g. recommend actions, classify states, estimate values) | Translate application to ML targets (ML problem formulation) |
| Data design | Link aims to data collection<br>Ensure data are representative of the problem domain states<br>Explore and assess veracity of data (visual analytics, statistics)<br>Labeling data records<br>Enrich data with domain-relevant contextual information<br>Domain-specific data attributes | Ensure appropriate statistical representation of data in samples<br>Design data types and structures<br>Determine data quality management (for example missing values policy)<br>Produce recommendations for data management activities<br>Design ML-specific data features<br>Feature selection/extraction for ML |
| ML model design | Domain-relevant abstract model of problem (for example, time series, spatial or other; decision or recommender system, etc.)<br>Impose constraints/relations on models (for example "forced" associations in relational models according to application specific knowledge) | Select family of ML models to address problem needs (for example a Time-Delayed network for times series, a Convolutional Neural network for vision, an explainable model for model transparency, etc.)<br>Select method for initialising structure of models (for example, how many layers, how many computational nodes per layer, the type of function that nodes perform) |

(*continued*)

**Table 1.** (*continued*)

| Activities | Application perspective | Machine learning perspective |
|---|---|---|
| ML algorithm design | Consider the "physical" source of knowledge about the data and feedback on ML performance (for example penalty / rewards for reinforcement learning, error estimation through real, model-based, or simulation systems) | Performance metrics selection<br>Training [off line, streaming][unsupervised, supervised, reinforcement, semi-supervised]<br>Method to initialise weights/costs for ML<br>Method to set algorithmic hyperparameters<br>Select how outcomes are derived (activation functions, decision thresholds etc.)<br>Select performance assessment data policy (e.g. sampling/training/test/validation data)<br>ML process flow (i.e. data batch sizes, epochs, algorithm termination criteria etc.) |
| Interaction design | Data, features, model and algorithms selection | Integrate human interaction designs into ML designs and enable outcomes validation |

**Table 2.** Humans aiding AI actors - Implementation

| Activities | Application perspective | Machine learning perspective |
|---|---|---|
| Data ingestion | Physical data integration | Link ML models with data sources |
| Model building | Deploy trained models with operational workflows | Develop different ML models<br>Trained model selection |
| Algorithm building | Deploy implemented algorithms | Implement selected algorithms |
| Interaction building | Select recommendations based on domain-specific knowledge | Include interaction interfaces in ML process |

The human role in shaping AI is not static. AI-enabled systems and human operators have their affordances reshaped as a result of their interaction, as they benefit from each other's capabilities. The superiority of human cognitive capabilities over AI in performing cross-domain activities is not a controversial statement and the same applies regarding the superiority of AI in repetitive and data-intensive tasks. Efforts to bridge the deficiency of AI to perform only within narrow contexts have been mostly focused on transfer learning [26] aiming to transfer the learned capabilities from the original

**Table 3.** Humans aiding AI actors – operation and maintenance

| Activities | Application perspective | Machine learning perspective |
|---|---|---|
| Track performance | Monitor if targets are met | Monitor ML performance |
| Data generation, curation | Curate/label new data and assign data to cases | Manage and adjust data distributions for ML (e.g. train/test/validate) |
| Choices and actions | Assess adequacy of assumptions and recommend adjustments<br>Define priorities, utility values<br>Choose 'costs' for outcomes<br>Interpret, select, validate recommendations<br>Select/execute actions | Generate multiple alternative ML models to meet performance targets<br>Evaluation of actions based on defined 'utility values'/predictions<br>Trigger Data, Model, Algorithm revisions |

domain of the learning to a new one. There have been various examples of integrating human knowledge to machine learning [27]. Additionally, there is increased interest in the empowering effect that human and AI-driven non-human actors can have on each other [28]. Additionally, the concept of meta-human learning systems [29] has been proposed to refer to emergent "learning" capabilities of a sociotechnical system and this can be seen also from the prism of collective activity mentioned in Sect. 2. Starting from key concepts about humans-AI interaction proposed in [28] and incorporating ideas about introducing human cognitive capabilities in the AI loop [6], the way the two types of actors interact to maximise outcomes of their collective activity is illustrated in Fig. 2. Human actors, capabilities and interaction affordances are marked in green. AI-driven technical actor capabilities are marked with blue.

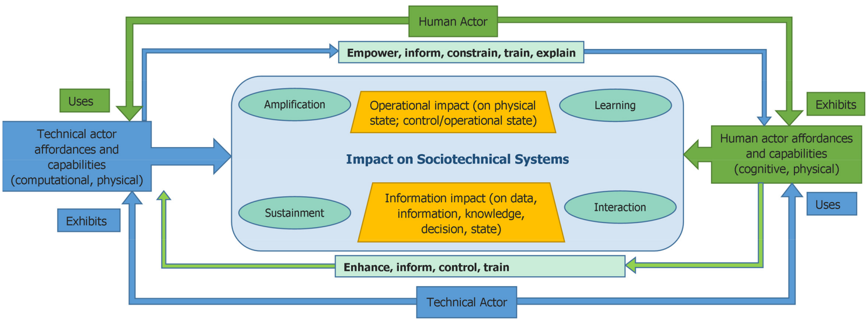


**Fig. 2.** Human and AI-enabled actors benefiting from each other's capabilities

All actors exhibit capabilities which are expressed in interaction affordances in the operating environment. Technical actors empower humans to expand their capabilities, inform them about relevant processes or knowledge, train them on certain tasks, explain outcomes or recommendations, but also bound their affordances within an admissible range of actions. Human actors can exert control over AI and perform a range of actions listed in Tables 1, 2 and 3, such as labelling or enhancing the knowledge range of the machine learning model. Through their interaction both actors' capabilities are enhanced, resulting in higher added value outcomes as part of collective activity.

## 4 Humans and AI in Vision-Based Quality Inspection

To illustrate some of the earlier concepts, an industrial use case of vision based quality inspection in consumer goods manufacturer production lines is selected. The manufacturer aims to automate part of the quality inspection via a human-cobot solution. Quality inspection cobots are equipped with digital cameras. AI capabilities aim to distinguish between good and bad quality components. Thus, the vision is to automate the repetitive task of checking each product by a human and instead introduce different human roles to undertake more cognitive demanding tasks. To explore this, tests were conducted with an image pool of labeled samples. The aim was to explore tasks that can be undertaken by AI and assess possibilities offered by integrating the human in the AI loop. The setup comprised 400 samples, equally divided between good and bad quality products. An example is shown in Fig. 3.

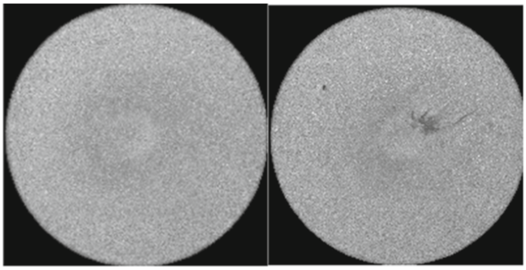

**Fig. 3.** Vision-based quality inspection showing good (left) and bad (right) quality products. Source: courtesy of Philips, through STAR project, ID: 956573, www.star-ai.eu.

The experiments involved training convolutional neural networks (CNN). Their grid-type structure makes them appropriate for image processing [30]. Defining a kernel of influence in the grid, a CNN is able to process image data in ways that are invariant to unimportant changes in the data, for example the exact position of an object in an image, or the exact angle of view when taking the image. There can be several convolutional processing steps in a CNN. Each step includes a convolution stage (image transformation into a different feature space). Defining the number of kernels of influence (neurons) and their spread (size of kernel) are the key user-specified parameters that define the convolution layer, which transforms the original data into an alternative "feature space" and for that reason the next layer of processing is considered the "feature detector" layer. This layer applies a nonlinear function on the features resulting from the convolution layer. It is possible to have multiple feature detector layers at different abstraction layers.

The final layer is the "pooling" when the processed features are combined to produce the final output. Being one of the earliest examples of deep learning, CNNs have witnessed a renaissance as their computational requirements ceased to be a challenge for computers with standard computing power. The experimental setup emulated active learning interaction tasks [31]:

A. standard experiment with training, test and validation sets
B. emulation of data labeling by humans to expand the knowledge pool of the CNN
C. emulation of human-driven data resampling to emphasise hard to learn cases

These scenarios are now brought into the form of part of the Tables 1, 2 and 3: The achieved performance on each scenario is presented in Table 5, where TP, TN, FP, and FN standing for true positives, true negatives, false positive, and false negative cases. These experiments served the purpose of illustrating that even a basic level of human engagement in the AI loop can lead to notable AI performance enhancements. However, assuming that human engagement in the AI loop is bound to be integrated into future jobs, the next section takes a work design viewpoint of the studied problem.

## 5 Discussion on Work Design Consequences and Conclusion

The collective activity of human and AI-driven actors may pose certain physical, cognitive and mental demands on humans that may affect the overall performance of the operations [32]. Therefore, it is important to design the interaction in a way that the resulting work characteristics lead to positive outcomes. This requires an analysis based on work design theory. Various streams of work design theory came together in [33] and overview is given in [10], including integrative perspectives that provide links between the earlier streams. Work design theory provides a set of work characteristics that should be considered when (re)designing jobs in response to technological and social changes to achieve different individual and organizational purposes. As such, the design of the human-AI interaction needs to pay attention to these characteristics. The focus is on work characteristics related to the task environment (task and knowledge characteristics) and the social environment (social characteristics), as these are affected when the interaction is redesigned. The work characteristics related to the physical and organizational environment (contextual characteristics) are excluded. Adopting the terminology from [34], key task characteristics to be considered are outlined next. *Autonomy* refers to the amount of freedom that a human has during the work in terms of timing of the work, choice of methods, and the ability to make decisions. Jobs that lack autonomy are considered poorly designed. AI may impact autonomy in positive and negative ways [10]. *Task variety* considers the range of tasks that humans need to perform in their job, while *skill variety* relates to the required skills to perform the job. AI may replace routine cognitive tasks, but also create new tasks, requiring new skills from humans who are interacting with the system. The task and skills variety should match the abilities and needs of individuals. The same holds for *job complexity*: too little and the job lacks challenges; too much creates fatigue and stress. AI may impact job complexity by altering the cognitive demands. *Feedback from the job* i.e. being able to evaluate the quality of work while it

**Table 4.** Humans aiding AI actors – operation and maintenance

| Activities | Application perspective | Machine learning perspective |
|---|---|---|
| Problem definition | Classify products quality | Classification machine learning setting |
| Data design | Image data samples (good/bad)<br>Labeled data available in sample | Sufficient quantities of bad/good images<br>jpg image files (1024 × 1024 pixels)<br>Standard image preprocessing (RGB)<br>200 images in training; 100 in test; 100 in validation data sets (scenario A) |
| ML model design | N/A | CNN initialised structure; sigmoid activation in final layer and relu in other layers |
| ML algorithm design | Data ground truth available | Confusion matric performance assessment<br>Standard gradient-based CNN training<br>Kernel sizes of 3 and 5 employed<br>Learning rate: 0.0005<br>Fixed choices for number of epochs (100), batch sizes (20), regularisation (holdout: 0.5) |
| Interaction design | N/A | Manual choices for ML Model and Algorithm |
| Interaction implementation | Selection of A; B; C scenarios | Implementation of data policies: (B: labeling of 10 additional data images per class); (C: including 20 worst performing images in training - sampling) |

**Table 5.** Performance without and with Human in the AI Loop

| Scenario A | | Scenario B | | Scenario C | |
|---|---|---|---|---|---|
| TP: 93.94% | FP: 6.06% | TP: 100% | FP: 0% | TP: 97.06% | FP: 2.94% |
| FN: 20.41% | TN: 79.59% | FN: 2.38% | TN: 97.62% | FN: 0% | TN: 100% |

is being performed, is another task characteristic. AI may contribute by providing more insightful feedback. Poor tasks division between AI and humans may lead to weakened opportunities for learning and impaired situational awareness. *Specialization* refers to extent to which a job involves the performance of tasks requiring specific knowledge and skill, and AI may empower humans to take on a variety of tasks by supplementing knowledge and enhancing capabilities, but it may also shift human work to focus on a narrow set of specialized tasks. *Problem solving* in the job is a task characteristic which should be challenging, but not too challenging for the individual employee. AI can execute routine problems allowing humans to focus on more complex ones. *Information processing* is a task characteristic which should match the worker's cognitive capabilities and is enhanced by digitization. There are also characteristics related to the social environment that may be impacted by AI. These characteristics reflect relations among workers. However, they may also relate to interactions between humans and AI. *Interdependence* refers to the extent that humans connect to each other, but may also reflect the connection between humans and AI. Integrating humans in the AI-loop implies dependency between both actors. Similarly, AI may facilitate *social support* by providing valuable connections between team members and enhancing their communication. Similar effects may be expected for the enhancement of the amount of *feedback from other humans*. Overall, designing the AI-human collaboration in production environments requires further research to establish methodologies for human-centric designs. The added value of integrating the human in the AI loop was outlined conceptually, as well as through an exploratory industrial case, arguing that to unleash the human-AI interaction benefits, design approaches for the effective integration of human and AI actors in manufacturing are needed (Table 4).

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