Human-Centered Work Design for the Internet of Production

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Abstract

Like all preceding transformations of the manufacturing industry, the large-scale usage of production data will reshape the role of humans within the sociotechnical production ecosystem. To ensure that this transformation creates work systems in which employees are empowered, productive, healthy, and motivated, the transformation must be guided by principles of and research on human-centered work design. Specifically, measures must be taken at all levels of work design, ranging from (1) the work tasks to (2) the working conditions to (3) the organizational level and (4) the supra-organizational level. We present selected research across all four levels that showcase the opportunities and requirements that surface when striving for human-centered work design for the Internet of Production (IoP). (1) On the work task level, we illustrate the user-centered design of human-robot collaboration (HRC) and process planning in the composite industry as well as user-centered design factors for cognitive assistance systems. (2) On the working conditions level, we present a newly developed framework for the classification of HRC workplaces. (3) Moving to the organizational level, we show how corporate data can be used to facilitate best practice sharing in production networks, and we discuss the implications of the IoP for new leadership models. Finally, (4) on the supra-organizational level, we examine overarching ethical dimensions, investigating, e.g., how the new work contexts affect our understanding of responsibility and normative values such as autonomy and privacy. Overall, these interdisciplinary research perspectives highlight the importance and necessary scope of considering the human factor in the IoP.

1 Introduction

The goal in developing an Internet of Production (IoP) is to realize distributed networks of cyber-physical production systems (CPPS) by integrating digital manufacturing technologies and the large-scale collection and analysis of corresponding production data. Using this infrastructure, CPPS can effectively connect sensors capturing information about the physical environment and actuators interacting with it, linking the physical and digital worlds (Lee and Seshia 2016). While CPPS will enable further automation of production processes even in dynamic and complex task environments, their introduction is not expected to eliminate the need for human presence in production systems (Neumann et al. 2021). Instead, future production systems will be characterized by the close collaboration between humans and machines, thereby benefiting from the respective strength of both sides (Becker and Stern 2016). This observation highlights that the introduction of the IoP will not only transform the technical side of socio-technical production systems but will also reshape the role of the humans within them (Kaasinen et al. 2020; Rauch et al. 2020; Neumann et al. 2021). Most importantly, humans' tasks will continue to move away from repetitive manual tasks (Kadir et al. 2019) and towards cognitive tasks such as strategic decision making in production planning and control as well as problem solving (Fantini et al. 2016; Kaasinen et al. 2020). This shift in tasks will also change the skills and competencies required of workers, with an emphasis on information technology skills, self-organization, problem-solving, and communication skills for collaboration in interdisciplinary teams (Hecklau et al. 2016).

As the role of humans within production systems changes, it is important to consider how these changes affect both the humans' work performance as well as their physical and mental well-being (Dul and Neumann 2009). On the one hand, introducing CPPS provides unique opportunities for improving human work. Rather than replacing humans with technology, the transformation can be used to extend human capabilities so that their contributions become more effective and efficient (Gorecky et al. 2014). Central opportunities for this involve the flexible adaptation of the work system to the individual worker and the use of advanced assistance systems. Regarding work system adaptation, the analysis of production data can enable the adaptation of machine behavior, user interfaces, and production planning to the physical attributes, skills, experience, preferences, and current state of the human users (Villani et al. 2017; Kaasinen et al. 2020; Mertens et al. 2021). In addition, advanced assistance systems can support humans in dealing with a wider range of task responsibilities (Gorecky et al. 2014). Whereas cobots as a form of physical assistance system have the potential to reduce physical workload to a minimum, aid systems such as decision support systems can improve human task performance in cognitive tasks by providing the user with task-specific information and suggesting alternative actions (Rauch et al. 2020). Based on the aforementioned opportunities, researchers have envisioned the human worker in future production systems as a close collaborator of technical systems, using digital skills in innovative work processes that provide greater work autonomy and opportunities for self-development (Romero et al. 2016a, b; Kaasinen et al. 2020; Taylor et al. 2020).

On the other hand, the upcoming transformation of the production industry is also associated with threats for human job quality and job security. Foremost, while the described opportunities may benefit the human workers in the future, current real-world implementations of such adaptive work systems and advanced assistance systems are limited and may still be considered far-fetched (Kaasinen et al. 2020). In contrast, the replacement of humans by cyber-physical systems for highly standardized tasks will certainly become reality, thus creating fears of unemployment and limited job opportunities in the workforce (Adam et al. 2018). To acquire the necessary capabilities for the newly developing task environments, workers will require skill development programs with a particular focus on continuous learning (Gorecky et al. 2014; Bonekamp and Sure 2015; Longo et al. 2017). While these trainings provide opportunities for self-development, the constant need for learning also places additional demands on workers and can raise concerns about not being able to keep up with new requirements (Kadir and Broberg 2020). Moreover, the integration of humans in CPPS can also have detrimental effects on human job characteristics. While cobots can reduce physical strain by supporting humans in handling heavy objects, the close interaction of humans and machines also evokes new safety concerns (Kadir et al. 2019). Regarding system automation, increasing the automation level of a production system can move the human's role away from active control to passive monitoring, introducing the risk for automation complacency and deskilling (Bainbridge 1982; Parasuraman and Manzey 2010; Wickens et al. 2015). The changing balance between physical and cognitive tasks can also lead to cognitive overload when the required information is not provided to the worker in a suitable manner (Dombrowski and Wagner 2014; Czerniak et al. 2017; Kong 2019). Finally, the omnipresent collection of data in CPPS can threaten the privacy of the employees when personal information is stored and analyzed (Bonekamp and Sure 2015; Mannhardt et al. 2019).

The changing role of production workers in the transition to an IoP-based production ecosystem has led many researchers to suggest a stronger consideration of the human factor in this line of research (Romero et al. 2016b; Pacaux-Lemoine et al. 2017; Kadir and Broberg 2021; Nitsch et al. 2022). However, the amount of research that considers the human role in the future of production is still limited (Kadir et al. 2019; Sgarbossa et al. 2020; Sony and Naik 2020; Neumann et al. 2021). This is concerning, as a human-centered work design approach will be crucial to ensure that the upcoming transformation of production systems will in fact enable the improvement of human work characteristics and that threats to human job quality and job security are averted. Thus, only by considering the human early on in the development, the deployment of new technology will benefit human performance and well-being, ensuring organizational profitability (Dul and Neumann 2009) and preventing the erosion of anticipated profits due to poor system design (Rose et al. 2013).

To contribute to the body of research on the human-centered design of work systems shaped by the IoP, we present selected research addressing different levels of work design. To structure the individual research contributions, we follow the model of human-centered work design proposed by Mütze-Niewöhner and Nitsch (2020). The authors differentiate four levels of work design: (1) the work task, (2) the working conditions, (3) the organizational level, and (4) the supra-organizational level (see Fig. 1). Whereas the work task level addresses the interaction between the worker, with her/his individual characteristics, needs, and expectations, and technical systems to fulfill the task goal, the second level encompasses general conditions that influence this interaction. The higher levels leave the focus of individual work systems and concentrate on strategic and cultural changes in work design within organizations, as well as on the discussion of work design principles that takes place in a societal and economic sphere. By presenting research across

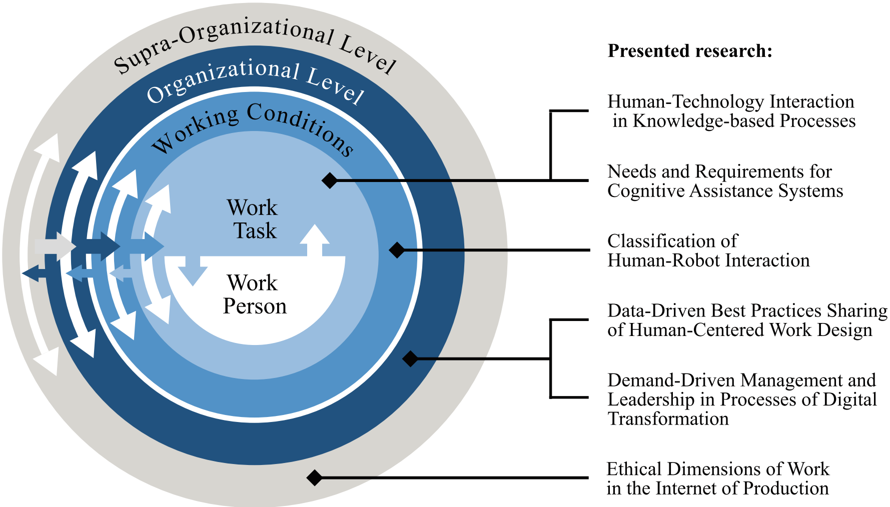

Fig. 1 Levels of human-centered work design, adapted from Mütze-Niewöhner and Nitsch (2020, p. 1198), as the structure for the selected research topics presented in this chapter

the various levels of work design, we seek to motivate researchers and practitioners to consider the transformation of work systems and human work in the course of implementing the IoP and to highlight the range of design dimensions that need to be taken into account.

2 Work Task Level: Human-Technology Interaction in Knowledge-Based Processes

Work tasks incorporating disruptive technologies such as artificial intelligence, collaborative and autonomous robotics, or augmented reality, face two major hurdles: the goal-oriented, successful technical implementation and the acceptance of the worker. In terms of technical implementation, production companies often face challenges with regard to data scarcity, possibilities for data collection, and methods for data exploitation. Additionally, difficulties may occur relating to the material processed, the optimization of production parameters, or logistics. To ensure the acceptance of the workers, it is essential to consider their concerns, wishes, and requirements, such as usefulness, fun, trust, previous experience, and knowledge (Frazzon et al. 2013).

When developing work tasks and the associated work systems, it is thus crucial to take a technology-centered as well as a human-centered perspective. This applies in particular to processes of which the outcome is heavily dependent on humans and their expert knowledge, both in work tasks that require largely manual labor (e.g., assembly, post-processing) and in work tasks with high cognitive demands (e.g., planning, design). However, the knowledge usually remains only with the respective expert, because (especially in SMEs) little to no documentation or knowledge management is implemented (Durst and Runar Edvardsson 2012). This can limit the competitiveness of companies as experts and their knowledge become scarce once senior employees leave the company or retire. Accordingly, it is necessary to extract, store, and transfer expert knowledge, for which both physical and cognitive support can be useful (Lewandowski et al. 2014; Brillowski et al. 2021a).

One industry that is strongly affected by the growing shortage of skilled workers and the associated loss of expert knowledge is the composite industry. The automation of composite part production is not worthwhile in all cases, for example, when a high amount of flexibility is required or if a part's geometric complexity is too high (Fleischer et al. 2018). Thus, two use cases in the composites industry are investigated regarding human-technology interaction: (a) human-robot collaboration in composite part production and (b) user-centered selection and planning of composite production processes.

To overcome the balancing act between requirements from technology and people in these use cases, we measured acceptance and user factors within usability studies. As a theoretical basis, the Technology Acceptance Model (TAM) is used to investigate perceived usefulness and perceived ease of use as well as attitude towards use, behavioral intention, and the actual use of the technology. Furthermore, the factors hedonic motivation, trust in automation, fun, mental/physical effort, and perceived autonomy when using automated systems are investigated (Davis 1989; Lee and See 2004; Bradshaw et al. 2005).

The two use cases are presented in more detail below.

2.1 Human-Robot Collaboration in Composite Part Production

Automation of composite part production is very complex due to the use of limp textiles and is therefore associated with high investment costs and a loss of flexibility. This applies in particular to composite parts with high complexity and the need for class A surfaces. Therefore, almost every second composite part is manufactured in elaborate manual processes, even though the needed experts are rare and expensive. Up to now, only laser projectors have been used as an assistance system to support these manual work tasks. Using these laser assistance systems in composite part production can result in timesaving of up to 45% and increases in the positioning accuracy of the textile layers. While these effects are especially applicable to the support of inexperienced employees, an increase in efficiency and high acceptance for the system can be noted for all employees, from laymen to professionals (Dammers et al. 2020b).

In order to further support workers and thus retain expert knowledge, we investigate how manual work tasks in composite production can be performed with the help of human-robot collaboration. Thereby, the work task is divided between human and robot based on complexity and experience, so that part quality and worker ergonomics are improved. For this purpose, robot tools for draping and handling were developed so that the efficiency and effectiveness of the process can be increased. During tool development, special attention was paid to work safety and technical limitation (robot payload and range) (Dammers et al. 2021).

Within a usability study ($N = 21$), the tools developed are generally perceived as valuable, so that the robot is regarded as a technical assistant performing the given collaboration task well. No dependence of the worker's satisfaction on the collaboration type, i.e., the degree of autonomy from the human perspective, can be observed. Low mental and physical challenges are indicated for the studied tasks. In general, autonomy and control are perceived as positive as are ease of use, trust, and hedonic motivation. However, usage intention for human-robot collaboration within composite production is rated positive but rather low, which can be attributed to the simplicity and low complexity of the examined tasks. A detailed description of the usability study can be found in the publication (Dammers et al. 2022).

Future research will therefore aim at further optimizing human-robot collaboration with respect to the factors of usage intention and usability. For this purpose, it is necessary to investigate the production of composite parts with a higher degree of complexity and more difficult work tasks. In addition, more suitable interfaces for robot operation will be developed, e.g., voice control or hand/food switches. Furthermore, the aforementioned technologies are to be combined in one workstation to enable more intuitive operation and execution. In order to secure expert knowledge for composite part production, the imitation of human movements by robots is also pursued so that the knowledge is collected, saved, and can be transferred by the supporting systems. For that purpose, artificial intelligence approaches will be investigated, e.g., imitation learning, learning from demonstration, and behavior trees.

2.2 User-Centered Selection and Planning of Composite Production Processes

Planning of production processes for composite parts is responsible for up to 70% of manufacturing costs (Ehrlenspiel et al. 2020). To minimize production costs and to comply with shortening product life cycles, an efficient and systematic planning of production processes is necessary for companies to remain competitive. However, existing planning methods for conventional materials like metals or wood cannot be applied to composites due to changing material properties during the production process (Brillowski et al. 2020). Therefore, the first approaches were developed to foster a systematic process planning. While these approaches increase effectiveness and efficiency, the accompanying methodologies and especially the developed decision supporting tools lack user acceptance (Brillowski et al. 2021b).

As a consequence, we investigate how decision support systems for production planning have to be developed to ensure a high level of acceptance among users. As planning decisions depend on a multitude of influencing factors, we intend to apply artificial intelligence for planning and examine its influences on user acceptance as well (Brillowski et al. 2021a). For this purpose, we developed two decision support systems based on different approaches. One app focuses on user-centered design and makes suggestions that can be rejected by the user. The second app integrates an optimization model, giving the user a mere supporting role. In the course of a user study ($N = 17$) we investigated, how usability, acceptance, trust in automation, performance expectancy, planning efficiency, and objectivity are perceived among domain experts (Brillowski et al. 2022; Zarte et al. 2020). The user-centered approach achieved the highest scores for usability and acceptance as well as performance expectancy, planning efficiency, and objectivity. In regards of trust in automation, users trusted the optimization-app most. However, in some cases, this leads to blind trust, not critically questioning the given results and neglecting crucial tasks, as participants expect the optimization app to relieve them from these tasks. Due to the non-existent transparency of the decision process, the optimization approach achieved an overall insufficient user acceptance. We conclude that automation can help to foster trust and acceptance. However, there is a degree of too much automation, which absolves the user of his responsibility. More detailed information on the user study can be found in the referenced publications. For future work, we want to research the optimal degree of automation to keep the user engaged on the one hand and to support them in the best possible way on the other hand .

3 Work Task Level: Needs and Requirements for Cognitive Assistance Systems – Towards Effective and Trusted Interaction

Increased information and automation through the digital transformation of production will significantly influence people's work tasks in CPPS, what their needs are for information, explanation, and decision support, and how future industrial workplaces and user interfaces must be designed (Brauner et al. 2022; Kadir et al. 2019; Neuman et al. 2021; Pinzone et al. 2017).

Despite the increasing possibilities of automation and data-driven optimization technologies in the IoP, humans remain one of the most important factors for the flexibility of production systems. Due to the changing socio-technical work systems, it is necessary to consider the needs and requirements as well as the skills of employees, which they will have to relearn or adapt and expand their knowledge. However, so far there is a lack of knowledge about the optimal trade-off between productivity goals, technical requirements, and the integration of user needs (Zarte et al. 2020). To improve the productivity of production processes and at the same time the acceptance of employees, extensive considerations are necessary for the design of cognitive assistance systems. In this section, we approach this challenge from the perspective of later users. Therefore, we present three studies which demonstrate important challenges as well as acceptance-relevant factors in the context of human-robot collaboration that have to be considered for a successful change of the socio-technical systems.

Cognitive assistance systems are technical systems that process information and support workers in performing their tasks and to improve their skills (Schlick and Trzcieliński 2016). The kind of support they can provide is divided into three different processing steps (Stair and Reynolds 2020), referring to the detection and recognition of tasks (1. task perception), assessing and generating tasks (2. task decision), and exporting the task (3. task execution). When designing new industrial user interfaces, it is important that they support cognitive tasks. However, the affective dimension must also be taken into account. A new system may be technically better, but if employees do not trust it, it will be used reluctantly or not used at all and thus cannot unfold its potential.

To study the affective dimension and task perception of cognitive assistance systems, we investigated moral decision-making in the context of human-robot and human-autonomous vehicle collaboration. A detailed description of the study can be derived from Liehner et al. (2022). In three different scenarios (production logistics, medical, and autonomous driving), participants ($N = 43$) could decide between assigning a task to an automatic agent or performing it manually depending on costs or possibly faulty automation which could result in damage to property or personal injury. The results indicate that both context and risk significantly impact people's decisions. The higher the perceived sensitivity of the context, such as in a medical context, the stronger the tendency to perform the task manually and avoid any personal harm. In addition to ethical and legal perspectives on automation and the interaction with robots (human-robot interaction = HRI), these findings suggest studying individual and contextual factors that influence trust in automated systems.

Considering the above-mentioned study about decision support systems for production planning (Brillowksi et al. 2022), we looked at it from a social accepted instead of a technical perspective. The process of task decision portrays an example for a cognitive assistance system. It supports by assessing and generating tasks. For an effective interaction it turned out that factors such as usability, speed, and functional superiority are relevant. Furthermore, trust was a decisive factor. However, considering that trust is evoked through transparency and comprehensibility of the suggested solutions, it was overshadowed by acceptance relevant features such as performance expectancy. Further information about the study can be extracted from Brillowksi et al. (2022).

For future work, focusing on the needs and requirements for cognitive assistance systems, it is therefore important to develop an understanding for the context of work and, of course, for the prospects of users (Courage and Baxter 2005). Moreover, a participatory design approach is recommended with frequent evaluation cycles as well as the users' involvement from the beginning and taking all stakeholders into account. Thus, the system functionality and interface match with the user and reduce interaction errors and unnecessary frustration.

For a task execution process of a cognitive assistance system, we investigated the collaboration between worker and cobot in textile production concerning different degrees of autonomy (low, middle, high) from the human perspective (Dammers et al. 2022). The technical perspective regarding the tools used in this study was already described in the previous section about human-robot collaboration in composite part production.

The results highlight that the interaction with a cobot generally promotes satisfactory task performance and high perceived control, with low perceived autonomy across all types of collaboration. The study further found ease of use, hedonic motivation, and experience in textile processing as factors relevant to acceptance. More detailed information on the study can be found in the publication of Dammers et al. (2022). Since autonomy and control are related to a higher task performance and job satisfaction (Deci and Ryan 2008), we propose to adapt robot movements and workflows to the workers and to set up intelligent interfaces for better individual robot support. Additionally, the results indicate that participants with little experience in textile processing rate the usability higher. An explanation for this could be that more experienced people already have familiar work processes. Therefore, they consider the cobot as a limitation of their freedom and intervention possibilities. For increasing the usability and acceptance of HRI, the workflows and robot operation should be optimized and the user diversity factors should be examined in more detail.

Across all studies, we identified trust, acceptance, and usability as essential factors for a positive attitude toward cognitive assistance systems which facilitate work tasks. Since in all processing steps of a cognitive assistance system data and information are collected, processed, stored, and evaluated, it is necessary to focus on the acceptance of data sharing especially out of a worker perspective. Therefore, there is a need to investigate information in future studies referring to the willingness to disclose personal data in an increasingly interconnected smart factory. Only broad empirical investigations with regard to the design of cognitive assistance systems can improve acceptance, trust, and usability and consequently increase the productivity of production processes.

4 Working Conditions Level: Classification of Human-Robot Interaction

In the production of the future, human-robot interaction (HRI) and collaboration (HRC; commonly viewed as a particular case of HRI) will gain importance (Matheson et al. 2019). For this reason, a deep understanding of this type of work system and a way to synthesize and analyze it is important. In order to achieve this, a suitable HRI framework is among the things required.

Existing HRI frameworks can be grouped according to which aspects they classify: There are classifications (1) by function (e.g., Parasuraman et al. 2000), (2) by degree of robot autonomy (e.g., Parasuraman et al. 2000) and (3) by work- and spatial distribution (e.g., Otto & Zunke 2015). In addition to these main categories, there are other approaches, mostly targeting specific applications, which will not be discussed further here. Onnasch and Roesler (2021) provide a detailed overview of existing HRI frameworks.

To survey HRI-relevant research activities in IoP, a survey was conducted, and from its results, requirements for HRC were elaborated in a workshop. In a subsequent literature search, no framework could be found that fulfills all these requirements of HRI applications of the production of the future, as they are being researched in the IoP. The problem, in particular, is that existing frameworks cannot map the entire range of applications across many disciplines. Moreover, many of them are designed for HRI within a social context and not for the industrial production domain.

Accordingly, it was decided to adapt and extend the framework of Otto and Zunke (2015): In addition to the dimension “HRI level”, the two dimensions “precondition & implication” and “data sources” were added (see Fig. 2; Baier et al. 2022).

The framework uses (shape- and) color-coded dots that indicate strengths and weaknesses and can also be labeled with text to represent information in the grid fields.

Dimension HRI level. For the distinction of the HRI level, the overlap of the workspaces of human and machine is used – from (physically) separated to completely overlapping. In addition to the categories in the original framework, another category has been added that refers to a common platform, as needed for wearables, prostheses, or exoskeletons.

Dimension Precondition and Implication. The preconditions and implications of the HRI application are described here from technical, legal, and social per-

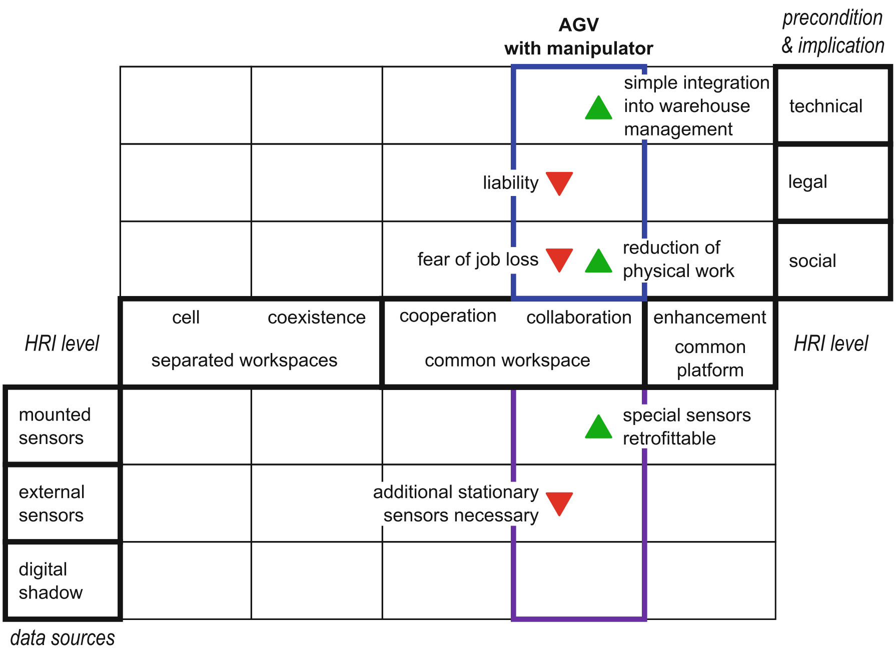

Fig. 2 Extended human-robot interaction (HRI) framework (Baier et al. 2022) – example filled in

spectives. For example, a technically well-engineered solution that is also legally compliant can nevertheless trigger a problem from the social perspective in the form of dissatisfaction due to a feared job loss among employees.

Dimension Data Source. For many HRI applications, the source of the data is relevant. The distinction between mounted and external sensors as well as digital shadow/digital twin reflects the dependence of the HRI application on external infrastructure. For example, mounted sensors as the primary data source allow for more independent operation from data infrastructure, but this can be at the expense of quality.

Figure 2 shows a completed schematic: In this fictitious example, the introduction of an automated guided vehicle (AGV) with manipulator in a warehouse is being planned. The shape- and color-coding allows for a quick overview and simplifies the identification of problematic and unproblematic areas of this solution. The obstacles apparently lie in the legal area as well as in the acceptance of the robots by the employees. Except for the fact that a sensor infrastructure has to be installed, there is no technical reason not to implement the robots.

With the HRI framework developed, it is now possible to analyze (classify) and synthesize (design) HRI as it pertains to production of the future and relevant research. Hence, the framework can also be used for the human-centered design or optimization of an HRI work system. For this purpose, special requirements resulting from the technologies used in a sector or specific legal regulations within it, as well as the demographics of the employees can be taken into account. Solutions can also be compared by filling in multiple schemas. Here, the degree of detail can be freely selected according to the needs. The clear presentation makes it easy to communicate proposals and decisions to superiors or the workforce.

Validation with respect to applications outside the IoP is still pending. In addition, more in-depth research in the Precondition and Implication dimension is planned – especially with regard to the social perspective.

5 Organizational Level: Data-Driven Best Practices Sharing of Human-Centered Work Design

As the intended result of an IoP, CPPS enable the continuous automation of production processes while simultaneously increasing productivity. Nevertheless, human work remains a key factor for productivity due to the specific capabilities of humans and the associated flexibility (Ansari 2019). To realize this productivity, employees are exposed to various forms of work demands during production processes. In addition to enabling cyber-physical collaborations, the increasing digitalization of work processes offers the opportunity to record relevant data and to use this information for the assessment of these work demands (Neumann et al. 2021). The analysis of these data can thus be used to secure competitive advantages by using a data-based comparison of the production processes to identify optimum configurations (Schuh et al. 2021).

In accordance with this optimization principle, the Best Practice Sharing Tool presented in the chapter ► "Long-term Production Management" was developed within the IoP. Despite the relevance of knowledge as one of the most important resources in the industrial context, the transfer of production knowledge for the realization of a continuous learning process between employees presents a challenge for manufacturing companies (Ferdows 2006). The complexity of this transfer is increased by the distribution of knowledge in global production networks, making this field of research particularly relevant (Yang et al. 2008). While the evaluation of production processes in terms of productivity has been elaborated, the necessary consideration of human workload in this data-driven optimization approach for production process design remains a challenge. Accordingly, with the objective of initiating workplace improvement measures across the production network, corporate data are used to identify comparable production processes in terms of human work characteristics and identify best practices by comparing human work demands, extending the current version of the Best Practice Sharing Tool.

For the Best Practice Sharing Tool, two key building blocks were developed to identify knowledge transfer opportunities: First, the data-based identification of comparable production processes, and second, the development of an assessment methodology to identify trigger points for the need of knowledge transfers based on productivity performance indicators. To identify comparable production processes, processes are represented based on a morphological box by linking the constituent product and resource characteristics. Subsequently, the description of the production processes is transferred into a digital shadow, which is used for the data-based formation of clusters of comparable production processes. By means of a cluster analysis, the metric characteristics can be divided into different proficiency categories (Schuh et al. 2020). As a result, performance differences within clusters of comparable production processes can be identified. These clusters are transferred into a dynamic assessment system to identify trigger points for determining knowledge transfer needs in the global production network. The operator can then interact with the tool to initiate the deployment of improvement measures. These are derived from the system-based identification of ideal characteristics. The application thereby serves as a decision support tool for initiating a best practice-sharing approach in the context of production processes in global production networks (Hast 2021).

The transfer of the described method to the human-centered focus requires the capability to compare production processes with each other. Since the criteria used for the elaborated method are only of economic or technological orientation, it is necessary to define the constituting characteristics of production processes from the workers' point of view. Here, the model of human-centered work design by Mütze-Niewöhner and Nitsch is applied to structure the approach (see Fig. 1). The Best Practice Sharing Tool as a decision support system for managers, supporting them in the identification and implementation of measures to reduce the work demands on production workers, is itself located on the organizational level. The individual level subsuming the worker, the work task, and the working conditions serves as a framework for the constituting characteristics of production processes from a human-centered perspective.

Based on a systematic literature review, criteria and description factors of production processes with a human-centered focus are identified (Fettke 2006). The comprehensive database of indicators from this research area is used to compile a long list of criteria in terms of the frequency of occurrence, relevance to the focus of observation, and possible quantification or evaluation for the later identification of trigger points. The indicators can then be classified according to the applied model of human-centered work design.

As the goal of the criteria list is to compare the design of production processes, the worker level is excluded from the analysis as it relates to the individual characteristics of the respective workers. The level of the *work task* includes the execution of the production process and the associated demands on the employee. Thus, the work demands of the process execution by means of intensity, duration, or complexity, but also, for instance, local vibrations and other emissions are included. *Working conditions* represent more general conditions, encompassing job design as a station-specific perspective and the work environment as a macroscopic perspective. The workplace is considered from an ergonomic point of view with regard to working position and accessibility or work equipment. The work environment describes cross-workstation characteristics and thus represents criteria such as noise, air conditions, lighting, or temperature.

Based on the general assignment of the indicators of the long list, a criteria short list is developed via further classification, consolidation, and relevance consideration. Eventually, the short list can be used to compare production processes from a human-centered perspective in order to provide the basis for the identification of best practices through an assessment system of human work demands factors for production processes in global production networks.

Following the presented approach, the current research project focuses on the elaboration of the criteria long list through a comprehensive examination of existing research. After the assignment to the three defined domains, the criteria short list can be elaborated in order to present a practicable data-based method for the comparability of production processes with human-centered focus based on the application of corporate data in several iteration and optimization loops.

6 Organizational Level: Demand-Driven Management and Leadership in Processes of Digital Transformation

Krcmar (2018) emphasizes four elements of digital transformation processes that must be considered. From his perspective, transformation processes are (a) inevitable, (b) irreversible, (c) characterized by a high degree of speed, and (d) accompanied by a high degree of uncertainty in their execution (Krcmar 2018). For companies, therefore, the main question should not be how they can decouple themselves from the coming change, but how they can actively shape the transformation process (Krcmar 2018). In this context, the management of digitization processes seems to play a special role. Hoberg et al. (2018) indicate that digital transformation projects are characterized by a high degree of social complexity that needs to be managed actively. They conclude that digitization projects, face the challenge of having to overcome rigid or at least existing and thus mostly established corporate structures (Hoberg et al. 2018). Correspondingly, Hoberg et al. (2018) found in a quantitative study 84% agreement among participants regarding the statement that change management skills are of great importance for the organizational transformation and that management support is required at various management levels (Hoberg et al. 2018). His result is affirmed by research on organizational change projects, showing that support from management is necessary to ensure the targeted allocation of financial and human resources required for the change process (Premkumar and Potter 1995). In addition, unforeseen obstacles that arise during the change process can be overcome more easily if the transformative processes are actively managed (Hwang et al. 2004). Recapped, digitization represents a major challenge for organizations, as it affects the working environment of employees as well as employees' requirement profiles. Moreover, it must overcome organizational structures and processes to be implemented sustainably. Consequently, it results in the need for organization-specific and thus demand-oriented management, to better counter the effects of the change process on the organization and its people. To ensure this, an analysis of the realities on the technical, structural, and personnel sides represents the first step.

The need for a requirement-specific approach becomes even clearer when reflecting industry-specific characteristics. The manufacturing sector is confronted with special requirements that intensify, e.g., element (4), namely a high degree of uncertainty, of Krcmars' (2018) formulated aspects of transformative processes. Production data, which is to be shared if an organization adheres to the idea of an IoP, often represent the core value. As a result, the willingness to share these data is low since sharing such valuable data triggers feelings of uncertainty, which was confirmed by a qualitative study of the Research Group Gender and Diversity in Engineering (GDI) of RWTH Aachen University in 2020/2021. In addition, established and therefore partly old plants and production systems represent the central value of companies in the manufacturing sector. Yet, digitizing these plant systems can only be realized with a corresponding effort. Furthermore, management must consider the people in change processes, diverse target groups, resulting diverse demands and fears that arise. This diversity results on the one hand from the different areas of activity, namely in production itself as well as in the administration and management of the organization. On the other hand, diversity results for example from the individual affinity for digital solutions and age diversity in the workforce. Consequently, diversity must be actively considered when implementing corresponding digitization projects, to increase the acceptance of digital strategies and technologies in the context of change processes (Steuer-Dankert 2020).

To cope with the challenges mentioned, different management methods such as *new and digital leadership* are currently being discussed. Research has shown that success in organizational aspirations toward a productive digital transformation is positively correlate to the enablement, development, and implementation of such a form of managemental leadership (Sprenger 2017; Kane et al. 2018; Abbu et al. 2020; Araujo et al. 2021). Sprenger (2017) sees the future viability of companies in their ability to discuss probable and improbable scenarios and to generate the necessary redundancy through a diversity of opinion. Likewise, he sees companies as well prepared that encourage stubbornness and a spirit of contradiction. For Sprenger (2017), *transformational leadership style*, therefore, represents the ability to create an organization that is willing and able to change, especially in this context of digitalization. So, the active enablement, development as well as implementation of a new and digital style of managemental leadership can be seen as crucial to guarantee the successful satisfaction of transformative demands in digital contexts.

Linking a further management style with digitalization, Araujo et al. (2021) define *digital leadership* in its most fundamental sense as "the use of digital assets of an organization to achieve business goals at both organizational and individual levels" (p. 46), while referring to Dimitrios et al. (2013) and Thomson et al. (2016). What seems to be the most crucial aspect in the light of the addressed challenging demands of digital transformation is the interactive and behavioral cultural change that such a form of leadership brings into the organization and its internal processes; something that is highly needed within such processes of digital transformation (Kane et al. 2018; Abbu et al. 2020; Araujo et al. 2021). What is meant by that is that *digital leadership* or *digital leaders*, as role models, should actively help the organization to detect and evaluate the given demands of the transformation and to change the organization towards these demands of digitalization by showing, guiding, and enabling: flexibility/agility, curiosity, openness, a willingness to learn, an open, egalitarian and non-hierarchal style of communication and decision-making, innovative entrepreneurial tendencies, trust, and credibility as well as transparently laying out a vision and purpose of the ongoing change processes (Kane et al. 2018; Abbu et al. 2020; Araujo et al. 2021). Doing so is not only positively related to the organizations' success in terms of digitalization (Araujo et al. 2021), but also to the psychological well-being of employees, like in this case the leaders/managers themselves, that are involved in these transformative processes (Zeike et al. 2019).

Taken together, all of this highlights that if organizations want to satisfy the demand of an increasingly digitizing industry and, thereby, be successful in terms of implementing digital innovations or strategies as, e.g., needed in the context of the IoP, there is also the need to actively implement a demand-driven, evaluative, and reflective management that is able to deal with the arising diverse needs and challenges on a human as well as on a technical level.

7 Supra-Organizational Level: Ethical Dimensions of Work in the Internet of Production

Work takes up a large amount of time in people's lives as their main occupation and activity, and is often a source of their identity, stability, and safety. Changes in the conditions of someone's work thus reflect not only their immediate daily activities, but also often their orientation in life, their sense of identity and social status, and consequently their overall happiness and other ethical values, such as dignity, autonomy, and freedom (European Group on Ethics in Science and New Technologies 2018). The main source of the changes of work conditions are technologically mediated changes, namely via automation and digitization. These necessitate ethical reflection on the impact of those changes on human flourishing in their everyday life (Danaher 2019). It is vital to consider those ethical dimensions early on, together with engineers and social scientists to be able to assess, evaluate, and guide the design and implementation challenges of such technology.

In the IoP, we closely cooperate across disciplines to achieve these aims through exchange of perspectives and ideas. This way, ethical reflection and research is informed of the latest technological developments, while also being able to offer assistance and guidance for engineers and scientists in their work. Next to the more fundamental changes in people's understanding of their own work in light of automation and digitization, there emerge more practical challenges to the way people work. Increased digital capabilities of surveilling workers in their actions and overall performance poses the question of privacy at work (European Group on Ethics in Science and New Technologies 2018; Königs 2022). How much is an employer entitled to control and supervise their employees' actions? With both new tools of surveillance and a more digitized workplace, the work performance of an employee can be measured and supervised to a previously unseen, intrusive degree.

Another issue of changing work environments in the IoP are the ever more distributed and thus shared decision-making processes between humans and machines. Our previous understanding of technology placed agency exclusively in the hands of human agents. Technology thus far has been seen as a mere range of tools to achieve self-set aims. However, the increased and further increasing sophistication of automated and autonomous processes of technological systems in workplaces not only makes it difficult to determine where human decisions played into an automated decision-making process, but also may make these decision-making processes necessarily cooperative in the first place. For the IoP, this was identified as a key challenge for the future of work (Nitsch et al. 2022).

It is important to consider that some decisions may not be made by sole human decision-making but are predicated on decision-support systems that preselect evidence and with that recommend certain paths of decision-making the human decider has little to no control or knowledge of. If, for example, automated systems seek out, evaluate, and on this basis recommend certain paths of action, it will increase the burden of proof of humans when disagreeing with those recommendations. The question arises of just how much autonomous machines can support human decisions without influencing them to the degree it affects our autonomy.

From this development, distributing responsibility in human-technology interactions emerges as an ethical challenge. With more sophisticated and autonomously behaving machines, the bearers of responsibility become less clear. When doubts emerge of how much meaningful human control can be exerted in these processes, just how much should a person be held responsible for the outcome of such a process (Königs 2022)?

These considerations pose genuinely new and hard questions regarding the future of ever more automated work environments and the social sustainability of these developments. Ethical considerations are needed at every step of these developments, as they change the meaning of work as a source of identity, stability, and human flourishing. In the coming steps, we aim to contribute to these developments through analyses of concepts of autonomy, freedom, and manipulation in those more automated work environments. Notably, we aim to incorporate the normative dimensions of the concept of sustainability in both its environmental and social dimension into these analyses and assessments.

8 Conclusion

Realizing the IoP will lead to fundamental changes of how humans work in future socio-technical production systems. To ensure that this digital transformation enables the anticipated improvements in both overall productivity as well as workers' physical and psychological well-being, it is of most importance to consider the human factor as early as possible, implementing a human-centered work design process. The selected research from the IoP presented here highlights the multitude of factors and levels in the design of work systems that needs to be taken into account. For example, the development and deployment of advanced human-machine interfaces such as human-robot collaboration or AI-based cognitive assistance systems require the context-specific analysis of human factors such as trust, acceptance, and usability. Furthermore, the consideration of such interfaces needs to incorporate influences from the present working conditions, including characteristics of the workplace and the work environment. These work system design processes must, in turn, be guided by human-centered approaches on the organizational level. For example, processes should be implemented that enable a large-scale human-centered analysis of work system design. Moreover, the associated transformation poses new and diverse requirements on leadership, raising the need for demand-driven, evaluative, and reflective management. Finally, all these developments must also be considered from an ethical perspective, evaluating how technological changes affect central human needs such as privacy and autonomy. It is important to note that, while these aspects have been discussed in separate sections here, companies that strive towards an IoP will have to consider all these factors and levels of work design at the same time in order to remain competitive for an increasingly mobile workforce in a global market. This emphasizes the challenge that companies face and that must be overcome to ensure the desired outcomes of this digital transformation. To support the companies in this transformation, further and continuing research efforts on the human-centered work design of future socio-technical production systems are required.

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