Industry 5.0 and Operations Management—the Importance of Human Factors

Fabian Lindner
Faculty of Business Administration and Engineering
Zittau/Görlitz University of Applied Sciences
Zittau, Germany
0000-0001-8249-534X

Gerald Reiner
Department of Information Systems and Operations Management
Vienna University of Economics and Business
Vienna, Austria
0000-0001-7560-3410

Abstract—**In this position paper, we highlight the importance of human factors, especially cognition, for operations management during the transition from Industry 4.0 to 5.0 and within. We argue that the increasing prevalence of (digital) technology and data for manufacturing operations urges human-centered approaches and solutions, as well—to enable efficient and effective operations that benefit from both humans' and technologies' strengths. To stress our point, we give examples from behavioral operations management where technology may both foster or mitigate deviations from rational decision-making. In addition, we show prospects of human-AI interaction and explainable AI, specifically by using visualizations, to improve operational performance.**

Keywords—human factors, behavioral manufacturing operations management, Industry 5.0, cognitive biases, visualizations

I. Introduction

New communication technologies like 5G or 6G on the industries' shop floors enable further connectivity of machines, materials, information, processes, products and even human workers. These developments further propagate the concept of the Internet of Things (IoT), Big Data Analytics (BDA), and the use of Artificial Intelligence (AI) in complex production systems to achieve higher levels of automation and digitalization and to become more efficient and effective in the manufacturing of products and provision of services.

On the way to digitized and automatically or even autonomously controlled production systems, there are still some challenges ahead. Besides the integration of legacy technologies, trustworthiness and reliability of the digitalization solutions is required to ensure acceptance and accountability for them among the shop floor workers, engineers, and decision-makers, resp. managers. I.e., the human factor is needed in particular in highly automated and digitized production environments as well [1], [2].

The human will not only be necessary for monitoring, maintaining or controlling production processes. For the optimal functioning of such complex systems he or she will also be required to bring in his or her experience, intuition (heuristics), as well as context, expert knowledge and related reasoning. To foster the best possible usage of these human factors, however, the above-mentioned technologies themselves may serve as enablers. In the transition from Industry 4.0 to 5.0 not only products and services may be mass customized [3], but also the digital assistance systems for the employees may be (automatically) individualized according to their personal strengths and needs [4]. Thus, the human will not longer require to adapt (possibly under strain) to some new technology, but the technology may adapt to the employee. This will result in improved ergonomics at the workplace and a better collaboration between each entity in a complex socio-technical system like a production environment [5].

Therefore, in this position paper, we take a socio-technical perspective on the transition from Industry 4.0 to 5.0 and focus especially on the interplay between human decision-makers and digital assistance as provided by decision support systems, visualizations or AI for the management of manufacturing operations. The remaining parts of this paper are organized as follows: In the subsequent section, we summarize the theoretical backgrounds that we base our arguments on. The third section encompasses examples and prospects of human factors for Industry 5.0 operations management, before we conclude our arguments on the importance of human-centered solutions for manufacturing in the last section.

II. Background

A. Industry 5.0 and Manufacturing Operations

While the term of Industry 4.0 (I4.0) was first coined in 2011 as part of the German government's high-tech strategy, it has become a global notion for the next manufacturing evolution by linking machines and processes using information and communication technologies (ICT) to improve performance and competitiveness of the industry [6]. Similar concepts in other countries may also be understood under IoT, Internet of Everything, Smart Factory, Smart Production, Industrial Internet [7], or Second Machine Age [8].

While the digitization of production (I4.0) in most European countries and companies is still ongoing [9], there are already signs of a new phase of industrial revolution: Industry 5.0 (I5.0) [32], [33]. A similar concept of Society 5.0 was already introduced in Japan in 2016 [10]. Other notions might also include Industry 4.h referring to the human [11]. According to Breque et al. [10], I5.0 consists of the three core aspects human-centricity, sustainability, and resilience to *"become a resilient provider of prosperity, by making production respect the boundaries of our planet and placing the wellbeing of the industry worker at the centre of the production process."*

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In the subsequent parts of this work, however, we want to focus especially on human factors and human-centricity in future production systems. With regard to the concepts of I4.0 and I5.0 first attempts have been already made to synthesize the implications and benefits of new assistance systems and technologies for the workers. Romero et al. [12], e.g., propose a typology of the Operator 4.0 including the Super-Strength, Augmented, Virtual, Healthy, Smarter, Collaborative, Social, and Analytical Operator.

By using technologies and assistance systems that support physical (e.g., exoskeletons, health trackers, collaborative robots), cognitive (e.g., Augmented and Virtual Reality, wearables, intelligent personal assistants, BDA), and social (e.g., social networks) tasks and activities on the shop floor, improvements of the workers' physical and mental well-being, as well as quality and lead times of the manufacturing operations can be achieved [12]. The One-of-a-kind Operator even promotes further workplace inclusiveness by adapting to the individual worker's needs and preferences, as already mentioned above [13].

B. Human Factors and Socio-Techncial Systems

Taking on human factors more in detail, several factors like cognitive, social, emotional, and motivational aspects in socio-technical systems and Human-Machine Interaction (HMI) need to be considered. Several authors, e.g., dealt with the assessment, modelling, and simulation of human factors in production systems. Baines and Kay [14] investigated the relationships between human factors of assembly workers like personal traits with the working environment (noise level, temperature, etc.) and their influence on the system's performance like cycle time. Elkosantini and Gien [15] further considered human factors like effort, fatigue, satisfaction, motivation, and stress with the help of a system dynamics model notation.

In addition, and more specifically considering the role of digital assistance technologies in socio-technical systems, Bornewasser et al. [16] researched the effects of cognitive assistance systems like Head-Mounted Displays (HMD) in assembly tasks and how it affects mental strain of the workers. Recently, von der Weth et al. [5] presented a further simulation model to improve the planning of workplaces in the semiconductor industry by reducing mental strain of the workers. Furthermore, von der Weth and Starker [17] stress the relevance of emotional and motivational factors for the successful adoption of new Enterprise Resource Planning (ERP) software.

This leads to the importance of human factors not only in socio-technical systems in general, but also in Human-Computer Interaction (HCI) or even Human-AI/Algorithm Interaction in specific. Therefore, in the light of increasing interconnectivity and volumes of data in production systems, we want not only to consider shop floor workers but also decision-makers, i.e. managers, with respect to the I5.0 concept of human-centricity.

In addition to the concept of the Cognitive Operator 4.0, who works in symbiosis with technology to jointly perform a decision [18], we see the need to consider also cognitive biases from behavioral psychology and economics to optimize the collaboration, interplay, and ultimately decision outcomes (economically) between the individual decision-maker and the decision support systems that he or she uses in I5.0 operations management. In the following section, we will give examples and show prospects of the optimization potentials of further strengthening the rationale of human factors in I5.0 operations management.

III. Prospects of Human Factors in Operations Management

A. Cognitive Biases in Industry 5.0 Operations Management

While the above illustrated research concerning human factors, socio-technical systems, and I5.0 is focusing to a larger extend on the integrated consideration of shop floor workers' individual characteristics, we want to expand this view also to managerial staff and have a look at, e.g., production managers in I5.0 and their reasoning as well as decision-making processes.

In operations management (OM) in general, we can observe different social and cognitive biases, wherever human actors are involved. The field of behavioral operations management (BOM) is specifically concerned with these effects of non-rational behavior and decision-making on operating systems and process performance [19]. Such deviations from (economic) rationality may be due to social and cognitive biases or cultural norms and can be observed in many operational contexts like inventory management (e.g., bullwhip effects), contracting, buyer-supplier relationships, information sharing, procurement and auctions, service operations, project management, forecasting, new product management and risk management to name only few [19]. Focusing on cognitive aspects in the respective operational decision-making processes, non-rational behavior can be accounted to, e.g., individual risk preferences, reference dependency (like anchoring and pull-to-center effects), bounded rationality, overconfidence, mental accounting, and cognitive reflection (System 1/System 2 thinking) [19].

Now, with I4.0 and the transition to I5.0, the usage of digital technologies, digitalization, and data in production will even further increase. Thus, to cope with this sheer amount of data and complexity of highly automated and digitized production networks, the importance of decision support systems (DSS) and tools for the management of manufacturing operations increases as well. However, meant as aid for the human decision-maker to perceive and process required information more easily, we argue that the above-mentioned cognitive biases and behavioral regularities when interacting with DSS are not yet adequately considered in designing such tools, although they are widely adopted in the industry.

Thus, we need to identify whether or not (and why) cognitive biases are enhanced or mitigated by using such DSS that aggregate, pre-select, or automate the presentation of relevant information. Additionally, the influence of the interaction of humans with the DSS on the decision quality, e.g., in terms of economic values and performance of operating systems like production networks is also not sufficiently addressed by now—as it is probably also difficult to measure [20], [21]. Nevertheless, attempts have already been made, e.g., by Arnott [22] or Arnott and Gao [23] to systematically consider behavioral economics in using and designing DSS.

In addition, with the rise of comprehensive, easy-to-use, and scalable visualization software like Tableau [24], the role of visualizations as decision support in industry becomes also more prominent. It is applied to collaborate using visual analytics to foster insights into production processes, derive decisions and actions, as well as to share und communicate them with internal and external stakeholders. As part of DSS, visualization tools are also intended to ease the perception and cognitive processing of large and complex datasets of production systems.

By using and altering different visual means concerning elements like text, images, lines, shapes, size, or color, the layout structure, and interaction possibilities [25], [26], information and data may be presented in various ways serving different purposes. Visualization tasks like exploration, overview, zooming, filtering, clustering, comparison, or monitoring may be addressed. But again, the investigation of the relationships between single visual means or visualizations and the above-mentioned cognitive biases in specific operational contexts, as well as their effects on economic decision-making in production management, have not yet been fully addressed [27]. Yet, such endeavors seem to be promising and the possibilities of investigations are various.

E.g., purposefully visualizing reference points may influence individuals' mental anchors, when managing inventory levels or forecasting, and result in more rational decisions [28]. Also, the use of associative color coding and data representation can have an influence on decision-making when presenting framed information, e.g., in the newsvendor problem [29]. That visualizations may be well intended but misrepresenting the underlying information is e.g. described by Bendoly [39] and Basole et al. [40]. Thus, in the worst case, visualizations might even result in counterproductive and costly decisions in practice [39].

B. Explainable AI and Human-AI Interaction Using Visualizations

Another aspect that will become relevant in I5.0 is the human-AI interaction and the role of Explainable Artificial Intelligence (XAI) and visualizations. To overcome such cognitive biases of humans like bounded rationality or overconfidence, when making decisions in complex situations with large data as described above, AI is not directly affected by such biases—unless they are knowingly or unknowingly imposed by its human creators or the underlying data. However, when applying AI in engineering or management, the human decision-maker will probably still have the final saying due to unsolved issues concerning the accountability of AI in cases, where undesired or possibly harmful decisions or actions may result. Therefore, also in the interaction with AI, human factors will again play an important role for I5.0. These are aspects like trust in the data and AI algorithms, as well as acceptance of resulting decisions and outcomes.

Hoberg and Imdahl [34], e.g., are concerned with the change of supply chain (SC) planners' role in the future in the light of increased automated decision-making and usage of AI. They propose an outline for successful human-machine interaction (HMI) in SC planning by considering *"hindering factors like human biases, change resistance, or accountability [...] to raise the confidence of the planner in the system"* [34]. Besides a cultural change, Hoberg and Imdahl [34] identify trust and explainability as a main aspect to overcome planners' algorithm aversion, overconfidence in their own decisions, and general discount of advice.

AI techniques like Machine Learning (ML), Deep Learning (DL), or Deep Neural Networks (DNN)s are considered opaque decision systems, encompassing huge amounts of parameters. Due to their learning algorithms and lack of transparency they are also considered complex black-box models [30]. To increase transparency, interpretability, or explainability—and ultimately acceptance and trust—ML techniques are on the rise that provide further information on model mechanisms and outcomes [30], [37]. Although XAI techniques are less efficient or effective, the increase in interpretability may help to detect and correct biases inherent to training datasets, increase robustness by providing counterfactual explanations, or ensure true causality in the data [30].

Senoner et al. [35], e.g., show how the transparency of feature importance and attribution of the XAI technique SHAP (Shapley additive explanations) [36] helped engineers to increase the yield by identifying and optimizing critical relationships between production processes that were previously hidden.

In XAI, again, visualizations provide further possibilities to foster trust and acceptance as an interface between the decision-maker and the ML model. Visualization methods like model, parameter space, data, or prediction uncertainties visualizations can help to improve the understanding of the underlying AI mechanisms [31]. First efforts were made, e.g., by Karran et al. [38] to experimentally investigate how different visualization design choices influence users' confidence in AI systems for image classification. By considering especially sociological and psychological factors like values and attitudes or knowledge and experience, visualizations will enable smarter and individualized visualizations of AI processes [31]. Thus, it will be promising to investigate, what specific kinds of ML-visualization and human-AI interactions will be beneficial in which specific operational contexts of complex I5.0 production systems.

IV. CONCLUSIONS

The goal of this position paper was to demonstrate the importance and prospects of considering human factors in the further evolution of the industry and for manufacturing operations management. Human factors and technological advancements need to go hand in hand. This joint consideration in the design of future socio-technical systems like complex I5.0 production systems, where humans, machines, robots, computers, software, and algorithms work together will lead to considerable improvements for the industry and society. We made a point by elaborating on the relevance of human factors in BOM and XAI and the specific role of visualizations. As an interface between the human, the algorithm, and the data [31], targeted and individualized visualizations may mitigate behavioral biases and improve the joint decision-making processes between AI and human. Thus, fostering human-centricity in I5.0 is of great importance for competitive and resilient industrial processes.

We also provided an outlook on promising research and development opportunities concerning human factors and visualizations in BOM and XAI, and attempted to shed light on the potential benefits of addressing these topics. We are looking forward to the way that lies ahead towards I5.0 and hope to encourage further discussion of its concepts and methods. The classification, mapping, and prioritization of respective cognitive biases in manufacturing and production management with XAI and visualization techniques to improve HCI in I5.0 will be promising further contributions to the field.

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