Human Operator 4.0 Performance Models in the Smart Factory: a Research Framework

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Abstract: With the advances of new information and production technologies, the smart manufacturing era calls for a perfect symbiosis between workers and machines and for operational excellence towards a cognitive, smart factory. To accomplish this vision, the Operator 4.0 strives for meaningful physical and cognitive interactions with the cyber-physical production system (CPPS). The physical-cognitive interfacing with Industry 4.0 enabling technologies, the greater attention on human factors, an ageing workforce and an increased cognitive task load require the definition of new tools and approaches to model and assess human performance. An upgrade of current human performance models (HPMs) to meet the features of the Operator 4.0 is therefore essential in order to predict their expected performance. This paper investigates the new role assumed by operators in industrial 4.0 systems and points out the main elements to focus on in the development of Human Operator 4.0 Performance Models. The future challenge for researchers and practitioners is to develop a holistic "Operator 4.0 Virtual Entity" that integrates multi-sided aspects of the human performance and can be incorporated into the digital twin of the Smart Factory with the ultimate aim to predict future states of the manufacturing processes where the human component is still crucial.

Keywords: Industry 4.0, Operator 4.0, Human Performance Modelling, Ageing, Cognitive Factory

1. Introduction

The Industry 4.0 paradigm is increasingly emerging as a new organizational-management method based on the integration of digital technologies and industrial automation aimed at optimizing the production cycles and increase productivity. Industry 4.0, however, is not just about technology, it is also a new cultural paradigm with an impact on the workforce at all levels. With the advances of new information and production technologies, the smart manufacturing era calls for a smarter symbiosis between workers and machines and, hence, for operational excellence towards a cognitive, smart industry (Jones et al., 2018). The Industry 4.0 paradigm is changing the roles and job requirements of workers, affecting the operators and the nature of their work and creating new interactions, not only between humans and machines but also between the digital and physical worlds. As a result of this transformation, the Operator 4.0 (also called Smart Operator) evolved from an analogy with the 4th industrial revolution concept. The Operator 4.0 perform the work with the support of the machines, interacting with collaborative robots, advanced systems and sensors, and enriches the real-world with virtual (VR) and augmented reality (AR) (Zolotová et al., 2020). This concept requires "smart interaction" with the machines mainly described as physical and cognitive interactions (Romero et al., 2016a). On one hand, the physical interaction with exoskeletons and collaborative robots reduces efforts and increases operator's strength, endurance, and power (Neumann et al., 2002). On the other hand, VR/AR or wearable technologies potentially increase human's capacity in accomplishing cognitive tasks. However, if the enabling technologies are beneficial, they also profoundly change the work practice and may have negative impacts on human performance due to the adaptation to new technologies or the learning process. Besides the challenging aspects of the Operator 4.0 itself, even the context where the Operator 4.0 is asked to work is facing two different major transformations:

- the 4.0 evolution of current industrial systems cannot be separated anymore from the ageing problem (Calzavara et al., 2020) as the relationship among job demands, human factors, enabling technologies and occupational health & safety change for older workers as reported in many studies (Di Pasquale et al., 2020; 2017);
- the adoption of I4.0 enabling technologies in manufacturing process led the 'new' operators to be employed in more cognitive tasks (Guerin et al., 2019), such as control and supervision performed by means of a constant interaction with machines

and robot through users' interfaces. This implies an increase in the cognitive load of tasks performed, and the risk of negative impact on the production outcome due to the achievement of cognitive limits (Thorvald et al., 2019).

Therefore, it is essential to analyse the impacts on the Operators 4.0 performance of individual factors, such as experience, age and physical-cognitive interfacing with enabling technologies as well as of cognitive load of task to be performed. It also urges researchers to define proper and reliable performance measures and models for differently aged and skilled human workers within a 4.0 Smart Factory.

The aim of this paper is to identify research challenges arising from the new role assumed by operators in industrial 4.0 systems. The analysis addresses, through a systematic literature review, the operator 4.0 concept that is developing in the scientific literature. Then, human-machine interfaces (HMI), collaborative environments and Human Performance Models are investigated. Particular attention is paid to the problems of man-robot-plant interfacing with changes in age, experience, and type of task performed. This preliminary analysis allowed us to define a modelling framework of the worker in the Smart Factory for the development of appropriate Human Operator 4.0 Performance Models.

The rest of the paper is structured as follows. Section 2 introduces the novel Operator 4.0 concept and fully explores its state-of-the-art. Section 3 discusses the current trends for human-machine interfaces and collaborative man-man and man-machine environments dedicated to the Smart Operators. Section 4 describes the human performance models adopted in industrial settings and proposes a preliminary design for a human performance model for a Smart Operator. At last, Section 5 describes how Human Operator 4.0 Performance Models may be integrated with cyber-physical production systems (CPPS) and digital twin technology in order to gain deeper insights on the manufacturing processes.

2. The Operator 4.0 concept

In order to understand the current interpretation of the Operator 4.0 in the scientific community, a systematic literature review using the Scopus scientific database was conducted at the end of February 2020 to identify the published, peer-reviewed documents dealing with this subject. For a paper to be included in the sample of identified papers, it was required to have either the keyword "*smart operator*" or "*operator 4.0*" in its title, abstract and keywords. The review was limited to English articles, whose full-text was available and that are related to the industrial context. At last, the screening and selection process resulted into 28 eligible studies, which are categorized by publication year, document type, type of contribution (conceptual, application, review or questionnaire/surveys) and additional focus in Table 1. The term Operator 4.0 came up recently in the works of Romero et al. (2016a, 2016b) where it is defined as "[…] a smart and skilled operator who performs not only cooperative work with robots but also work aided by machines as and if needed by means of human cyber-physical systems, advanced human-machine interaction technologies and adaptive automation". Starting from 2017, researchers started to investigate the enabling technologies the Operator 4.0 interacts with at the workplace (e.g. AR tools and smart assistance systems). The human-robot collaboration in I4.0 environments produced a shift from manual to cognitive labor, even for assembly tasks, which requires to revisit how human performance is intended. Studies started to focus on human factors and knowledge sharing, to assess the acceptance of I4.0 enabling technologies by the operators and their ergonomic implications at the workplace, with the ultimate aim to move towards more cognitive and intelligent spaces and, ultimately, create a human-focused Industry 4.0 context. For this reason, alongside the classic definition of Operator 4.0 by Romero, it emerges a slightly different definition from the literature works that identifies the Operator 4.0 as "an industrial worker whose cognitive, sensorial, physical and interaction capabilities are augmented by the close interplay with Industry 4.0 technologies". Table 1 shows that a large part of the literature is mainly focused on conceptual discussion around the Operator 4.0, while there is still a lack of applications, case studies or experiments with prototypes in real-world industries. There is still an open debate about the practical benefits of I4.0 technologies for the operators and their implications on human work. Due to the close human-machine interplay and the conception of the human as a complement to the robotic and virtual world of the automated production system, investigations of ethics and sustainability of I4.0 technologies are also needed. Given the novelty of the topic and the urgent need to move towards Human CPPSs, researchers and practitioners are today called to investigate further the role of the Operator 4.0 and focus on the multi-sided aspects of the human performance within the Smart Factory with the ultimate aim to predict future states of manufacturing processes where the human component is still crucial.

3. Human-machine interfaces and collaborative environments for the Operator 4.0

Human-machine interaction is recognized in many studies as the key lever between robot productivity and operator's flexibility (Srilakshmi & Kulkarni, 2018). Intelligent smart tooling, VR/AR devices can support workers in decisions, procedures and handling tasks (Simões et al., 2019). Several studies stated that the human factor interacts with process entities (Gilles et al., 2017) while acting on HMI in the form of holistic architecture and/or physical control panel and/or on/off button. Notwithstanding, sociological studies affirm that each worker constructs "mental artifact" to create personal interface, and social interaction, between workers in team (Kozlowski, 2018). Joint cognitive maps overcome the need of awaiting direct actions on interfaces while instituting rule-based control behavior (Jones et al., 2018). In cooperative context, Joint Cognitive Models are used in describing team cooperative working between humans and other "resources" in systems, i.e. machine and robots (Pacaux-Lemoine et al., 2017).

Table 1. Operator 4.0 relevant literature analysis (Type: conference paper – C, journal article – J. Contribution: conceptual – C, application – A, review – R, questionnaire/surveys – Q)

Year	Reference	Type		Contribution				Additional Focus
		C	J	C	A	R	Q	
2016	Romero et al. (2016a)	✓		✓				Human-automation symbiosis
	Romero et al. (2016b)	✓		✓				Operator 4.0 typology
2017	Romero et al. (2017)	✓		✓				Social factory environments
	Longo et al. (2017)		✓	✓	✓			Augmented reality, Personal digital assistant
2018	Heikkilä et al. (2018)	✓					✓	Worker well-being
	Papcun et al. (2018)	✓			✓			Human-machine interface
	Rabelo et al. (2018)	✓		✓	✓			Software Robots
	Romero et al. (2018)	✓		✓				Occupational Health & Safety
	Um et al. (2018)	✓			✓			Augmented Reality
	Weichhart et al. (2018)	✓		✓				Human-robot collaboration
	Ruppert et al. (2018)		✓				✓	Technologies
2019	Fast-Berglund and Romero (2019)	✓		✓	✓			Collaborative Robots
	Guerin et al. (2019)	✓		✓				Cognitive Work Analysis
	Kaasinen et al. (2019a)	✓					✓	User acceptance
	Kaasinen et al. (2019b)	✓		✓				Worker well-being
	Mark et al. (2018)	✓		✓		✓		Assistance systems
	Rødseth et al. (2019)	✓		✓				Job qualification criteria
	Wilschut et al. (2019)	✓		✓	✓			Augmented Reality, Learning
	Golan et al. (2019)		✓	✓				Operator-workstation interaction
	Li et al. (2019)		✓		✓		✓	Knowledge sharing, SME
	Stern and Becker (2019)		✓	✓	✓			Human-oriented work design
2020	Kaasinen et al. (2020)		✓		✓		✓	Participatory design
	Mattsson et al. (2020)		✓	✓				Cognitive Automation
	Peruzzini et al. (2020)		✓		✓			Ergonomics, Workplace design
	Rauch et al. (2020)		✓			✓		Anthropocentric production
	Segura et al. (2020)		✓		✓			Visual computing technologies
	Taylor et al. (2020)		✓	✓				Work organization, Safety
	Zolotová et al. (2020)		✓	✓	✓			Cognition, HMI and M2P interaction

Thus, in collaborative man-man and man-machine environments human resource management is applied. In manufacturing systems, human resource assignment is investigated to address optimal performances in gaining (properly checking) process and customer requirements (Bogataj et al., 2019). The overall environment where human workers operate is sketched out in Figure 1. Here, cyber-physical systems, advanced human-machine interaction technologies and adaptive automation system cooperate, while exchanging data, through sensing interfaces. Human typically works in an environment where exogenous stressors act as factors affecting their behavior and the system performances. Human behavior starts with a perceptual state in the form of personal awareness. Those act on states, changing between humans, based on the individual physical state. This can be predicted, based on literature analysis, using features and variables affecting the physical load (may be fatigue) and postural, as well as repetition based, ergonomics. The interference between those states changes dynamically in time (based on operational and behavioral factors reflected on situational variables) and mutually interacts on causal loop. Psycho-social and physical states can affect (black and red dotted lines), with bi-directional actions, the teamwork behavior. Here, prediction, based on cognitive cyber physical model, can be designed using one factor at a time interference analysis. This requires a DoE plan with an IoT based analysis of relevance factors related to desirable systems performances. In the new collaborative smart factory, the behavior of the human operator 4.0 is in the loop with system's resources. Each resource is able to work autonomously. It can cooperatively works exchanging data based on central control interfaces (HMI). They constitute a network of agents that cooperate to perform job and tasks. Such agents (i.e., logistics and warehouses, machine, robots, products, equipment - in the form of software and artificial intelligence tools, humans) are interconnected by sensors and exchange "information data" to enhance human decisions. They move and work inside a modular manufacturing processes characterized by decentralized decision making with real time capability. They can modify tasks based on a service-oriented approach. They make use of virtualization to maintain control and decision (in terms of performances and safety and quality) in processes. The cyber objects reflect the cyber physical conditions we can plan in order to optimize required performances. The experience of the older workers in manufacturing can provide a significant advantage if trained and supported by their organization to the new ergonomic designs and latest-generation equipment. For example, Abubakar and Wang (2019) demonstrated that the decline in physical and mental capabilities can be compensated by the higher skills and knowledge in performing existing or new working tasks. The digitalization and information technologies of the upcoming Industry 4.0 can provide age-friendly workplaces: collaborative robots and lifting/handling equipment allow the companies to automate complex and ergo-quality tasks. Furthermore, usage of smart tools and AR devices will provide older workers with information and procedures cataloguing, thus, improving productivity and lower idle times (Gonzalez & Morer, 2016), thus neglecting the declining mental performance due to age. Elder workers can recovery the gaps thanks to job enlargement and automation (Moraru et al., 2017), more experience-based organizations (Sun et al., 2018) or tools (e.g., exoskeletons) that support the ergonomics of task. In the smart 4.0 context, system is able to adapt requirement for process and tasks according with timely performances. These require collection and analysis in proactive perspective.

4. Human Operator 4.0 Performance Models: considerations and challenges

In scientific literature the first attempt to model the performance of operators involved in repetitive tasks appeared in 1936 with Wright's Power Model. Starting from the pioneering work of Wright many models have been developed in order to overcome limits of the Power Model and to provide a reliable description of operator's behavior in production contexts. In their research on learning phenomenon, based on evidences from field data collected, (Dar-El et al., 1995) formulated a dual-phase learning model, in which the dual nature of a task, jointly consisting of a cognitive and a motor part, both subjected to the learning phenomenon, was considered. The work of Dar-El was the first in pointing out identifying the variable (depending on the task nature) cognitive content of a task.

Traditionally, HPMs have been developed into two main research areas: production context and safety/control context. In the first research area the main goal is to predict the performance of the operators involved in repetitive tasks by considering both static and dynamic phenomena affecting their performance. In the safety/control research area (Human Reliability Assessment - HRA) models have been proposed in order to predict Human Error Probability (HEP) values. Moreover, in production contexts, ergonomics has been widely investigated, and nowadays many models and tools are available to assess ergonomic risk of operators. Enabling technologies of I4.0 allowed a further development of these models and tools. Examples are real-time monitoring of fatigue and recovery time prediction (Calzavara et al., 2018) or real time ergonomics risk assessment (Manghisi et al., 2017). However, peculiarities of new I4.0 production environments require the development of new models and tools, able to provide a reliable description of operator's behavior.

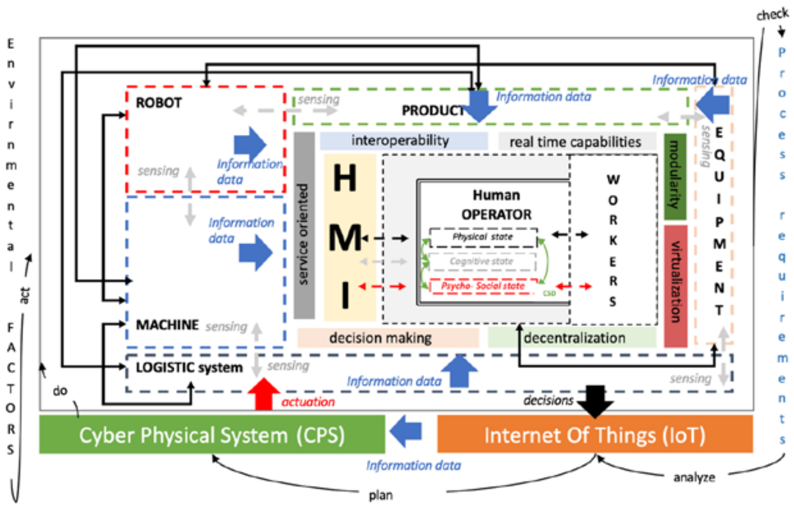

Figure 1. HMI and collaborative environments for the Operator 4.0: a schematic representation

As discussed in the previous section, I4.0 production contexts are characterized by high cognitive content tasks, and often (especially in EU) have to face with the aging phenomenon.

The new digital contexts in which operators are asked to operate are characterized by a high information flow, and there is the need to avoid negative impacts on the production environment caused by (unintended) excessive cognitive load. Traditional models developed to evaluate or predict fatigue are effective in case of physical fatigue, but they are not suitable for measuring or assess mental fatigue. It urges researchers to define models and tools allowing to evaluate cognitive load of a task and the related mental fatigue experienced by the worker in accomplish it. Models should be developed for both production and safety/control context. They will be based on a preliminary evaluation of the information content of the task to be performed, and will relate it with the expected performance of the operator. The assessment of the cognitive load will be based on information theory models (Park, 1987). Performance will be measured in terms of time to accomplish the task in production context as well as in terms of HEP in safety/control context. The model to be developed should quantify, for each task, the associated cognitive load in terms of amount of information to be processed in order to correctly accomplish the task. Based on the results of previous studies which followed the work of Dar-El (Dar-El et al., 1995), a preliminary decomposition of the task in elementary parts will be carried out, by identifying the high cognitive and the low cognitive (motor) parts of the task as well as that parts of the task with a negligible cognitive content. This will allow to estimate, for both high and low cognitive content parts of the task, the amount of information to be processed. This will be possible by applying appropriate information theory models, already investigated in scientific literature in order to assess cognitive capability of subjects of different gender and differently aged. The defined models will be of general application. The effectiveness of the model in assessing the mental workload and predicting operator performance in I4.0 production environment will be tested by means of experiments based on indirect measures of cognitive load (hearth rate variability – HRV, and Electroencephalography – EEG). Preliminary experiments based on HRV measurements of operators involved in NASA-TLX standard test (Hart & Staveland, 1988) in normal and VR mode (Figure 2) with different complexity gave promising results.

Figure 2. Test performed in VR mode at Polytechnic University of Bari laboratories

Once models will be validated, they will be further improved in order to consider dynamic phenomena affecting operator's performance (both cognitive and motor one), such as learning, forgetting, and fatigue.

4.1. Human Operator 4.0 Performance Models: a Modelling Framework

Following the modelling approach proposed by (Tao & Zhang, 2017) and the preliminary analysis conducted in this study, a four-step modeling framework of the Human Operator 4.0 Performance has been developed. HPMs can be built in 4 levels, i.e. personal data, physical/cognitive factors, behavior and rule (Figure 3). Firstly, personal data can be modeled to describe the basic characteristics of an industrial worker, e.g. age, gender, education level, that influence how the worker operates. Secondly, physical characteristics (e.g. fatigue, mobility, speed) and cognitive factors (e.g. stress, attention, memory) are given to the personal data to form the human models, which analyze physical and cognitive actions. Then the behavior models are built to describe the worker responsive mechanism under driving factors, such as the cognitive task load, or disturbing factors, such as unexpected events. At last, rules of association, constraints and deductions are modeled to describe the domain knowledge (e.g. safety or ergonomics rules) and make the above three kinds of models be capable of evaluating, reasoning and predicting. After modeling, the models in the four levels are integrated in both function and structure to form a complete virtual representation of the Operator 4.0. Proper verification, validation and accreditation (VV&A) tests must be developed to ensure the accuracy of these models and represents another challenge to be considered. This framework provides some initial guidelines towards the development of a holistic "Operator 4.0 Virtual Entity" that integrates the multi-sided aspects of the human performance and that can be eventually incorporated into the digital twin of the Smart Factory.

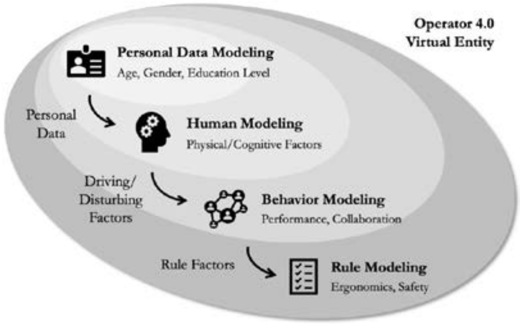

Figure 3. Four-step modeling framework of the Human Operator 4.0 Performance

5. Conclusions

The smart manufacturing era calls for a perfect symbiosis between workers and machines. The use of enabling technologies, the role of human factors, the phenomena of an ageing workforce and an increased cognitive task load demand the definition of new tools and approaches to model and assess human performance in the Smart Factory. An upgrade of current human performance models (HPMs) to meet the features of the Operator 4.0 is therefore essential in order to predict their performance. This paper investigates the new role assumed by operators in industrial 4.0 systems and points out the main elements to focus on in the development of Human Operator 4.0 Performance Models that can be later embedded into the digital twin of the Smart Factory with the ultimate aim to predict future states of the manufacturing processes where the human component is still crucial.

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References

Abubakar, M. I., & Wang, Q. (2019). Key human factors and their effects on human centered assembly performance. *International Journal of Industrial Ergonomics*, 69, 48–57.

Bogataj, D., Battini, D., Calzavara, M., & Persona, A. (2019). The ageing workforce challenge:

Investments in collaborative robots or contribution to pension schemes, from the multi-echelon perspective. *International Journal of Production Economics*, 210, 97–106.

Calzavara, M., Battini, D., Bogataj, D., Sgarbossa, F., & Zennaro, I. (2020). Ageing workforce management in manufacturing systems: state of the art and future research agenda. *International Journal of Production Research*, 58(3), 729–747.

Calzavara, M., Persona, A., Sgarbossa, F., & Visentin, V. (2018). A device to monitor fatigue level in order-picking. *Industrial Management and Data Systems*, 118(4), 714–727.

Dar-El, E. M., Ayas, K., & Gilad, I. (1995). A dual-phase model for the individual learning process in industrial tasks. *IIE Transactions*, 27(3), 265–271.

Di Pasquale, V., Miranda, S., & Neumann, W. P. (2017). The impact of aging on human error in manufacturing systems: a systematic review. Proceedings of the 48th Annual Conference of the Association of Canadian Ergonomists, 386–391.

Di Pasquale, V., Miranda, S., & Neumann, W. P. (2020). Ageing and human-system errors in manufacturing: a scoping review. International Journal of Production Research. https://doi.org/10.1080/00207543.2020.1773561

Fast-Berglund, Å., & Romero, D. (2019). Strategies for Implementing Collaborative Robot Applications for the Operator 4.0. In IFIP Advances in Information and Communication Technology, Vol. 566.

Gilles, M. A., Guélin, J. C., Desbrosses, K., & Wild, P. (2017). Motor adaptation capacity as a function of age in carrying out a repetitive assembly task at imposed work paces. *Applied Ergonomics*, 64, 47–55.

Golan, M., Cohen, Y., & Singer, G. (2019). A framework for operator– workstation interaction in Industry 4.0. *International Journal of Production Research*, 58 (8), 2421-2432.

Gonzalez, I., & Morer, P. (2016). Ergonomics for the inclusion of older workers in the knowledge workforce and a guidance tool for designers. *Applied Ergonomics*, 53, 131–142.

Guerin, C., Rauffet, P., Chauvin, C., & Martin, E. (2019). Toward production operator 4.0: Modelling Human-Machine Cooperation in Industry 4.0 with Cognitive Work Analysis. *IFAC-PapersOnLine*, 52(19), 73–78.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. *Advances in Psychology*, 52, 139–183.

Heikkilä, P., Honka, A., & Kaasinen, E. (2018). Quantified factory worker: Designing a worker feedback dashboard. ACM International Conference Proceeding Series, 515–523.

Jones, A. T., Romero, D., & Wuest, T. (2018). Modeling agents as joint cognitive systems in smart manufacturing systems. *Manufacturing Letters*, 17(6–8).

Kaasinen, E., Aromaa, S., Heikkilä, P., & Liinasuo, M. (2019a). Empowering and Engaging Solutions for Operator 4.0 – Acceptance and Foreseen Impacts by Factory Workers. In IFIP Advances in Information and Communication Technology, Vol. 566).

Kaasinen, E., Liinasuo, M., Schmalfuß, F., Koskinen, H., Aromaa, S., Heikkilä, P., Honka, A., Mach, S., & Malm, T. (2019b). A worker-centric design and evaluation framework for operator 4.0 solutions that support work well-being. In IFIP Advances in Information and Communication Technology, 544.

Kaasinen, E., Schmalfuß, F., Özturk, C., Aromaa, S., Boubekeur, M., Heilala, J., Heikkilä, P., Kuula, T., Liinasuo, M., Mach, S., Petäjä, E., & Walter, T. (2020). Empowering and engaging industrial workers with Operator 4.0 solutions. *Computers and Industrial Engineering,* 139.

Kozlowski, S. W. J. (2018). Enhancing the Effectiveness of Work Groups and Teams: A Reflection. *Perspectives on Psychological Science*, 13(2), 205–212.

Li, D., Fast-Berglund, Å., & Paulin, D. (2019). Current and future Industry 4.0 capabilities for information and knowledge sharing: Case of two Swedish SMEs. *International Journal of Advanced Manufacturing Technology*, 105(9), 3951–3963.

Longo, F., Nicoletti, L., & Padovano, A. (2017). Smart operators in industry 4.0: A human-centered approach to enhance operators' capabilities and competencies within the new smart factory context. *Computers and Industrial Engineering*, 113, 144–159.

Manghisi, V. M., Uva, A. E., Fiorentino, M., Bevilacqua, V., Trotta, G. F., & Monno, G. (2017). Real time RULA assessment using Kinect v2 sensor. *Applied Ergonomics*, 65, 481–491.

Mark, B. G. G., Gualtieri, L., Rauch, E., Rojas, R., Buakum, D., & Matt, D. T. T. (2018). Analysis of User Groups for Assistance Systems in Production 4.0. IEEE International Conference on Industrial Engineering and Engineering Management, 1260–1264.

Mattsson, S., Fast-Berglund, Å., Li, D., & Thorvald, P. (2020). Forming a cognitive automation strategy for Operator 4.0 in complex assembly. *Computers and Industrial Engineering*, 139.

Moraru, R. I., Cioca, L. I., & Babut, G. B. (2017). Workforce active ageing case study in a Romanian manufacturing company. MATEC Web of Conferences, 121, 11014.

Neumann, W. P., Kihlberg, S., Medbo, P., Mathiassen, S. E., & Winkel, J. (2002). A case study evaluating the ergonomic and productivity impacts of partial automation strategies in the electronics industry. *International Journal of Production Research*, 40(16), 4059–4075.

Pacaux-Lemoine, M. P., Trentesaux, D., Zambrano Rey, G., & Millot, P. (2017). Designing intelligent manufacturing systems through Human-Machine

Cooperation principles: A human-centered approach. *Computers and Industrial Engineering*, 111, 581–595.

Papcun, P., Kajati, E., & Koziorek, J. (2018). Human machine interface in concept of industry 4.0. DISA 2018 - IEEE World Symposium on Digital Intelligence for Systems and Machines, Proceedings, 289–296.

Park, K. S. (1987). Psychology of Human Error. In G. Salvendy (Ed.), Human Reliability: Analysis, Prediction, and Prevention of Human Errors. Elsevier Science Publishers B.V.

Peruzzini, M., Grandi, F., & Pellicciari, M. (2020). Exploring the potential of Operator 4.0 interface and monitoring. *Computers and Industrial Engineering*, 139.

Rabelo, R. J. R. J., Romero, D., & Zambiasi, S. P. S. P. (2018). Softbots supporting the operator 4.0 at smart factory environments. IFIP Advances in Information and Communication Technology, 536, 456–464.

Rauch, E., Linder, C., & Dallasega, P. (2020). Anthropocentric perspective of production before and within Industry 4.0. *Computers and Industrial Engineering*, 139.

Rødseth, H., Eleftheriadis, R., Lodgaard, E., & Fordal, J. M. (2019). Operator 4.0 – Emerging job categories in manufacturing. In Lecture Notes in Electrical Engineering (Vol. 484).

Romero, David, Bernus, P., Noran, O., Stahre, J., & Berglund, Å. F. Å. F. (2016a). The operator 4.0: Human cyber-physical systems & adaptive automation towards human-automation symbiosis work systems. In Advances in Production Management Systems. Initiatives for a Sustainable World, 488, 677–686.

Romero, David, Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å., & Gorecky, D. (2016b). Towards an Operator 4.0 Typology: A Human-Centric Perspective on the Fourth Industrial Revolution Technologies. CIE 2016: 46th International Conferences on Computers and Industrial Engineering.

Romero, David, Wuest, T., Stahre, J., & Gorecky, D. (2017). Social factory architecture: Social networking services and production scenarios through the social internet of things, services and people for the social operator 4.0. IFIP Advances in Information and Communication Technology, 513, 265–273.

Romero, D., Mattsson, S., Fast-Berglund, Å., Wuest, T., Gorecky, D., & Stahre, J. (2018). Digitalizing occupational health, safety and productivity for the operator 4.0. In IFIP Advances in Information and Communication Technology (Vol. 536).

Ruppert, T., Jaskó, S., Holczinger, T., & Abonyi, J. (2018). Enabling Technologies for Operator 4.0: A Survey. *Applied Sciences*, 8(9), 1650.

Segura, Á., Diez, H. V., Barandiaran, I., Arbelaiz, A., Álvarez, H., Simões, B., Posada, J., García-Alonso, A., & Ugarte, R. (2020). Visual computing technologies to support the Operator 4.0. *Computers and Industrial Engineering*, 139.

Simões, B., De Amicis, R., Barandiaran, I., & Posada, J. (2019). Cross reality to enhance worker cognition in industrial assembly operations. *International Journal of Advanced Manufacturing Technology*, 105, 3965–3978.

Srilakshmi, K., & Kulkarni, R. (2018). Productivity of senior employees - A case study with reference to selected pharmaceutical industries. *International Journal of Mechanical Engineering and Technology*, 9(1), 680–686.

Stern, H., & Becker, T. (2019). Concept and evaluation of a method for the integration of human factors into human-oriented work design in cyber-physical production systems. *Sustainability (Switzerland)*, 11(16), 4508.

Sun, X., Houssin, R., Renaud, J., & Gardoni, M. (2018). A review of methodologies for integrating human factors and ergonomics in engineering design. *International Journal of Production Research*, 57(15–16), 4961–4976.

Tao, F., & Zhang, M. (2017). Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing. *IEEE Access*, 5, 20418–20427.

Taylor, M. P., Boxall, P., Chen, J. J. J., Xu, X., Liew, A., & Adeniji, A. (2020). Operator 4.0 or Maker 1.0? Exploring the implications of Industrie 4.0 for innovation, safety and quality of work in small economies and enterprises. *Computers and Industrial Engineering*, 139.

Thorvald, P., Lindblom, J., & Andreasson, R. (2019). On the development of a method for cognitive load assessment in manufacturing. Robotics and Computer-Integrated Manufacturing, 59, 252–266.

Um, J., Popper, J., & Ruskowski, M. (2018). Modular augmented reality platform for smart operator in production environment. Proceedings - 2018 IEEE Industrial Cyber-Physical Systems, ICPS 2018, 720–725.

Weichhart, G., Fast-Berglund, A., Romero, D., & Pichler, A. (2018). An Agent- and Role-based Planning Approach for Flexible Automation of Advanced Production Systems. In Proceedings of 9th International Conference on Intelligent Systems 2018: Theory, Research and Innovation in Applications, 391–399.

Wilschut, E. S. E. S., Van Rhijn, G. J. W. G. J. W., Könemann, R., Bosch, T., & Murphy, M. S. M. S. (2019). Evaluating learning approaches for product assembly Using chunking of instructions, spatial augmented reality and display based work instructions. ACM International Conference Proceeding Series, 376–381.

Zolotová, I., Papcun, P., Kajáti, E., Miškuf, M., & Mocnej, J. (2020). Smart and cognitive solutions for Operator 4.0: Laboratory H-CPPS case studies. *Computers and Industrial Engineering*, 139.