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IFAC PapersOnLine 55-10 (2022) 854–859

Reciprocal Learning in Production and Logistics

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Abstract: Integration of AI technologies and learnable systems in production and logistics transforms the concepts of work organization and task assignments to human and machine agents. Thus, the question arises of what intelligent machines and human workers may be able to achieve as teammates. One answer may be guiding and training the workforce at the workplace to cope with emerging skill mismatches, emphasized by concepts of work-based learning. The extension of cyber-physical production systems towards becoming human-centered and social systems enabling human-machine interaction, creates opportunities for human-machine symbiosis by complementing each other's strengths. In this way, the concept of "Reciprocal Learning" (RL) between humans and intelligent machines has emerged, which is still rather ambiguous and lacks a profound knowledge base. Especially in production and logistics, literature is fragmented. Hence, the objective of this paper is to conduct a systematic literature review to elicit and cluster the knowledge base in RL represented by adjacent interdisciplinary fields of research, such as social and computer sciences. This work contributes to the literature by developing a comprehensive knowledge base on the concept of RL enabling to pursue future research directions towards the realization of human-machine symbiosis through RL in production and logistics.

Keywords: Human-Machine Symbiosis, Industry 4.0, Reciprocal Learning, Work-Based Learning

1. INTRODUCTION

Darwin's Natural Selection is one of the key mechanisms in the evolution of species. It occurs in all populations alike and explains the adaptive evolution of creatures. While striving for fitness, meaning successful reproduction, to cope with natural selection, creatures have developed social behaviors that influence fitness of individuals (West et al., 2007). As symbiotic partnerships, which are well-known in biology and human behavioral science, defined as relationships that are mutually beneficial to both/all partners (Douglas, 2021). This cooperative interaction between species has been regaining interest by research on human-machine interaction, namely human-automation symbiosis, due to advances in digital technologies (Pacaux-Lemoine and Trentesaux, 2019). From a humanistic perspective "humans should never be subservient to machines" (Tzafestas, 2006). This has been discussed from various angles, inter alia, philosophy, humanities, engineering ethics and specifically in human-machine interaction. Yet, human-centricity has neither been sufficiently discussed in terms of "human gains in interaction with technological agents" (aka human learning) and "mutual benefits for human and machine" (aka reciprocal learning) nor systematized to promote human-centric digitalization in industrial practice. Rather, human and machine agents are utilized to fulfill productivity objectives, which lack human-centricity. This dilemma has been recently addressed under the term Industry 5.0 as coined by European Commission (2021) towards extending Industry 4.0 by focusing on humans and sustainability development goals. However, the concept of Industry 5.0 has not been scientifically well-founded and still requires further investigation. To pursue this line of research on human-centric industrial systems, the authors are interested in investigating (lifelong) Reciprocal Learning (RL) between human and machine in production and logistics to create mutual benefits and foster social behavior of symbiotic human-machine partnerships. RL as a concept itself has already been defined (cf. Ansari et al., 2018b). However, the concept applied to production and logistics lacks a fundamental knowledge base of basic research from adjacent scientific disciplines, inter alia, human learning, machine learning, and its interaction. Further, it remains yet unexplored how and to what extent RL is realizable in industrial practice considering technology readiness of industries and also advancement of Artificial Intelligence (AI) and learnable technologies. Therefore, it is essential to identify potential fields of application for pilot studies toward identification of technological and non-technological RL requirements. In particular, the challenge to analyze requirements of RL and successfully put RL as a means of Work-Based Learning (WBL) into production and logistics practice is not tangible yet. Hence, this paper conducts a systematic literature review to identify relevant scientific disciplines, elicit its contributions, and structure the knowledge base for RL in production and logistics, as well as contribute to the advancement of RL by highlighting future research pathways.

10.1016/j.ifacol.2022.09.519

Considering the above discussion, the following research questions (RQ1-3) emerge:

- ***RQ1**: Which scientific disciplines contribute to a knowledge base of RL in production and logistics?*
- ***RQ2:** What is the knowledge base of RL in production and logistics?*
- ***RQ3:** Which research pathways can be derived from this knowledge base to ensure a successful application of RL?*

To address these questions, relevant terminologies on RL between human and machine are outlined, and insights from previous relevant literature reviews are discussed in Section 2. Section 3 describes the methodology of the systematic literature review. Section 4 presents the results towards discussing the concept of RL. Promising future research pathways are highlighted followed by a conclusion in Section 5.

2. BACKGROUND AND TERMINOLOGIES

2.1 Terminologies of Human Learning

Human Intelligence has been understood broadly as the general ability for reasoning, problem-solving, and learning of humans (Colom et al., 2010). Human learning has been the subject of various disciplines in humanities, which has led to a wide variation in definitions and learning theories and the absence of universal consensus (Ertmer and Newby, 2013). The authors choose to follow Ertmer and Newby (2013) with "learning is a change in behavior, or in the capacity to behave in a given fashion, which results from practice or other forms of experience". The experience itself is constructed in a social situation (Jarvis and Parker, 2006). In production and logistics, human learning has been a key research theme for many decades due to its relevance for operational performance (Glock et al., 2019). Particularly, WBL aims at tackling emerging skill mismatches in the manufacturing workforce by the integration of learning into productive work systems (Nixdorf et al., 2021).

2.2 Terminologies of Machine Learning

Machine intelligence, mostly referred to as AI, is the exhibition of human-like intelligence, in terms of behavior, reasoning, problem-solving, and learning. Machine Learning (ML) on the other hand is a method for modeling the ability of human learning and reproduction of human skills by artificial models and computational algorithms (Russell and Norvig, 2021). ML algorithms are, e.g., based on (semi-/un-) supervised training data, iteratively maximizing reward functions (Reinforcement Learning), minimizing the size of labeled data sets (Active Learning), or imitating human brains (Deep Learning) (Russell and Norvig, 2021).

2.3 Terminologies of Mutual Human-Machine Learning

Reciprocal Learning (RL) between human and machine in the context of Industry 4.0 has been defined by Ansari et al. (2018b) as «*a bidirectional process involving reciprocal exchange, dependence, action or influence within human and machine collaboration on performing shared tasks, which results in creating new meaning or concept, enriching the existing ones or improving skills and abilities in association with each group of learners*». The concept (Fig. 1) has been inspired by i) Reciprocal Altruism, in which human behavior is beneficial to others (West et al., 2007) and ii) Reciprocal Teaching, in which humans learn from each other by switching between trainee and trainer (Rosenshine and Meister, 1994). Essentially, RL exploits the complementarity and reciprocity of human and machine to achieve benefits. Human and machine may benefit from RL unilaterally or mutually.

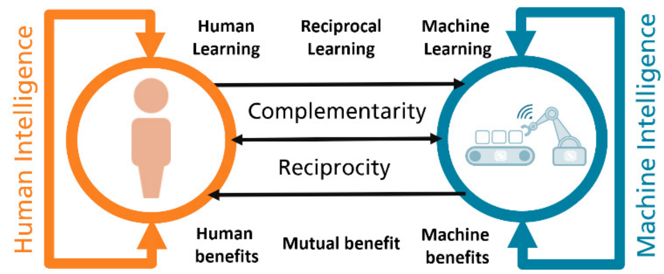

Fig. 1. Conceptual model of RL adapted from Ansari (2019).

Since the literature is fragmented and terms are not used consistently, terminologies related to RL are discussed in the following. As pointed out before, learning and intelligence are directly related, while intelligence refers to several intelligent and cognitive abilities of agents, including learning. Terziyan et al. (2021) refer to collective intelligence, describing the alliance of AI, specifically its analytical skills and human's imaginative intelligence. Collective intelligence, therefore, is a kind of convergence between human's and machine's intelligence (i.e., human plus machine brains) and can be enhanced by RL. Human-in-the-loop (HITL) describes consulting mechanisms of intelligent algorithms that can interact with agents and can optimize their learning behavior through these interactions, where the agents can also be human (Wiethof and Bittner, 2021). For instance, gathering expert (human) feedback in order to correct courses or respond to inquiries (Wenskovitch and North, 2020). Thus, it encourages ML through human involvement and interaction with the algorithm or learning system itself. At the other extreme is machine-in-the-loop (MITL), or computer-in-the-loop (CITL), in which the human is primarily in charge of the task, occasionally consulting the machine for suggestions or assistance in problems that require computational prowess for better task performance (Wenskovitch and North, 2020). Both concepts can be combined into Hybrid Intelligence systems that have the ability to accomplish complex goals by collectively achieving superior results than each of them could have done. Accordingly, Hybrid Intelligence encompasses AI and human intelligence, and encourages the complementary strengths of both (Wiethof and Bittner, 2021).

2.4 Terminologies of Human-Machine Interaction

Human-Machine Interaction (HMI) is a relatively new research area, which has been enabled by advanced technologies like Internet of Things (IoT) or Cyber-Physical Systems (CPS). It is generally described as an interaction and communication between human users and machines in a dynamic environment through several interfaces (Nardo et al., 2020). This development has significant implications on industrial practice where human and machine share a common workplace. Human-machine cooperation is based on this notion, in addition a task is performed at a shared workspace with the machine providing some kind of assistance to the human (Inga et al., 2021). Latest advances in AI technologies and collaborative robotics open new opportunities for new collaborative work forms for humans (Zhang et al., 2021) and machines (Ansari et al., 2020). In this way, human-machine cooperation has been extended toward human-machine collaboration in which human and machine act conjointly and communicate with each other.

In a seminal work, Licklider (1960) had the visionary idea inspired by the biological concept of symbiosis between species, namely human-machine symbiosis, to describe the close union and living together of humans and highly intelligent cybernetical machines in order to benefit mutually. In this vision human and machine operate together to solve problems dynamically and in real time. Human-machine symbiosis has been extended towards Industry 4.0 by which human and machine form intelligent (symbiotic) teams to collectively sense, reason, and act in response to incoming manufacturing tasks and contingencies (Lu et al., 2021), as well as learn from failures and successes (Wang et al., 2019). RL, in this sense, is a feature of human-machine symbiosis systems in which the bidirectional exchange of knowledge underlines the symmetric relationship between both agents, enabling dynamic and flexible switching of tasks and higher performance facilitated by mutual understanding and coordination.

2.5 Insights from published literature reviews

Recently, Wiethof and Bittner (2021) surveyed Information Systems research about developing Hybrid Intelligence integrating HITL and MITL approaches and discussing research gaps. The selection of databases, reviewed literature, and exclusion criteria, which explicitly exclude, inter alia, CPS and robotics, reveal gaps regarding production and logistics. Mark et al. (2021) presented a review about worker assistance systems in manufacturing, with a focus on systems extending the capabilities of workers towards sensorial, physical, and cognitive dimensions. However, learning has not been part of this discussion.

3. METHODOLOGY

A systematic literature review methodology was used in this work in order to ensure systematic and reproducible material collection. The search was performed in three steps. First, the keywords and search string for database search were identified and defined. Second, the search string was searched in Scopus, which is one of the largest scientific databases covering manifold fields of research. Third, several exclusion criteria were iteratively applied, namely screening and refinement, which are explained in the following.

Based on the formulated research questions and the thematic background described in Section 2, the following search string for the Scopus database has been constructed: human AND (machine OR ai OR "artificial intelligence" OR algorithm) AND ((reciprocal* OR mutual* OR collective* OR bilateral* OR bidirectional* OR cooperative* OR collaborative* OR hybrid) PRE/0 (learn* OR train* OR teach*)) OR ((learn* OR train* OR teach*) PRE/0 (reciprocal* OR mutual* OR collective* OR bilateral* OR bidirectional* OR cooperative* OR collaborative* OR hybrid)). The rationale behind this search string is that the authors searched for contributions on RL, consisting of “human” and “machine” (or “AI” and synonyms) agents with RL mechanisms, by combining “reciprocal*” and “learn*”. The core concept of RL was thus paraphrased forward and backward (cf. PRE/0). To widen the scope beyond these wordings, the authors alternatively searched for types of “learn*”, either “teach*” or “train*”, and synonymous alternatives of “reciprocal”, inter alia, “bilateral”, “mutual”, and “collaborative”. The search is applied to titles, keywords, and abstracts, and 667 publications in this first step are identified.

In the first screening iteration, publications were included if any of the following criteria was applicable considering title, abstract and keywords: (1) Articles and conference papers to consider peer-reviewed publications only, (2) English contributions only, (3) contributions considering scenarios of systems comprising of both human and machine. As a result, 108 publications remained after this step.

In the second iteration, i.e., the refinement, the remaining publications were sorted by relevance. Publications considering both human learning and machine learning were identified as highly relevant (27). In contrast, publications concerned with unidirectional learning/teaching, e.g., human learns from machine but not vice versa, were clustered as relevant (81). For the results presented in this paper, no forward or backward search was conducted (due to space restrictions).

Table 1: Categories for literature classification

Dimension	Attributes
Symbiosis	Human, machine or mutual benefit
Research domain	Psychology, Education, Engineering, Philosophy, Sociology, Computer Science

The 27 publications classified as highly relevant were thoroughly analyzed and categorized into a set of categories. Only highly relevant papers were analyzed due to space limitations. The underlying paper relies on two of the selected categories (see Table 1) to answer the RQs and to respect space restrictions. In the following, these categories are briefly described: i) symbiosis, inspired by biology (cf. West et al. (2007)), distinct by the beneficiary of partnership, namely “human benefits”, “machine benefits” and “mutual benefit”. As schematically sketched in Fig. 1, RL affects both human and machine. However, the learning effect and benefit are not always balanced. In this way, “human benefits” stands for a symbiotic system in which predominantly the human benefits from RL, and “machine benefits” is defined alike, ii) research domain, which comprises of formal and empirical fields of research that are concerned with RL.

4. STATE OF KNOWLEDGE

To comprehensively outline scientific disciplines (RQ1) and the knowledge base of RL for production and logistics (RQ2), relevant articles are distinct by their types of symbiosis.

4.1 RL for machine benefit

In 7 of 27 relevant publications, the machine is the main beneficiary of the symbiosis. It is to say that many reviewed publications have been excluded because humans just served as supervisors for training data, while the machine learns and benefits from the exchange. For the concept of RL, reciprocal exchange and learning on both sides are required. Scientific disciplines concerned are Computer Science (e.g., Lygerakis et al. (2021), Terziyan et al. (2021)), inter alia, text classification (cf. Zagalsky et al. (2021), Wenskovitch and North (2020)), and Engineering.

Lygerakis et al. (2021) present a training approach for a manual human-robot collaborative game based on Reinforcement Learning. While both agents increase their scoring together, the performance and overall training time could be reduced by optimizing the training algorithm. Optimization of the algorithm is reached by empirically allocating different learning mechanisms. In this way, an acceleration of learning in human-robot task sharing is indicated. In contrast to many excluded papers, in this contribution humans learn as well. They start inexperienced and adapt to the collaboration. However, the machine receives a dedicated training, while the impact and benefit for the human are somehow neglected. The following works deal with human learning as well. Zagalsky et al. (2021) propose a configuration of human and supervised ML mechanisms based on labeled data. The machine learns by generating explanatory feedback and accuracy scoring to the human expert, who revises classification criteria, establishing a RL loop. Another article on collaborative learning of human and AI in text analysis emphasizes challenges in communication between both agents to make interactions explainable and interpretable. The key for AI to learn from human cognition and vice versa is to externalize the cognition and convert it to appropriate inputs for the other agent (Wenskovitch and North, 2020). Both articles propose a machine assistant to a human expert, which significantly improves precision over time. The human expert primarily learns to understand the AI. However, a significant improvement of human's own decisions has not been emphasized. In addition to separated human and machine systems that benefit from one another, Terziyan et al. (2021) propose digital cognitive clones of human's cognitive capabilities for driving digital transformation in manufacturing. In this way, digitalized decision-making behavior of human individuals and groups is automated while keeping the human(s) in the loop. Hence, cognitive agents enable ubiquitous human decision-making services and shared responsibility to enhance the efficiency of human activities. The respected authors claim to form collective intelligence by further training cognitive clones with ML approaches to deal with decision-making in complex manufacturing environments. This notion of collective intelligence is further extended to collaborative decision-making in a group of cognitive clones by providing a recommendation/decision based on a compromise. In conclusion, the proposed agent combines (copied) human and machine intelligence, while necessary feedback loops for RL are missing.

An RL approach for collaborative manual tasks, as presented in Lygerakis et al. (2021), has limited transferability to improve production and logistics systems because training collaborative dexterity by trial-and-error is uncommon. RL approaches exemplified in the area of text classification (cf. Zagalsky et al. (2021), Wenskovitch and North (2020)) have high potential in decision-making processes, in which an explainable AI could facilitate maintenance planning and competence management. Implementation of collective intelligence as a recommender system or even for automated decision-making in scheduling and order management has a promising notion in terms of enabling ubiquitous availability of the service. However, questions regarding responsibility pose a substantial (ethical) barrier to implementation.

4.2 RL for human benefit

Among the 8 publications that could be classified into the category "human benefits", three relevant scientific disciplines can be detected, namely, Computer Science (cf. Battistoni et al. (2021)), Engineering (cf. Ansari et al. (2018b), Romero et al. (2019), de Giorgio et al. (2021)), and Education (cf. Bannan et al. (2020), Yin et al. (2015)). Two papers contributed to proposing insights and perspectives for RL. Battistoni et al. (2021) discussed how the human-centered design process should be adapted so that mediation between the human and AI is achieved, which enables mutual learning. Focusing on RL in the industrial domain, Ansari et al. (2018b) presented illustrative insights for mutual learning in a smart factory exemplified by human-robot collaboration, maintenance and assembly. Furthermore, Romero et al. (2019) developed a learning system called "Jidoka". By doing so, humans' interaction with automatic control systems is taken into account. Besides, efforts were also made to realize human benefits through RL in specific industrial processes. For the case of assembly, de Giorgio et al. (2021) studied how industrial assembly times can be reduced by automatically transferring procedural knowledge among human workers using videos. Machines and sensors mediate the autonomous learning transfer. The respected authors found in an experimental study that videos, in general, can support workers learning by transferring procedural knowledge. In the discipline Education and Psychology, Bannan et al. (2020) presented a reciprocal human-machine learning cycle for emergency response training. The computational part of the adaptive socio-technical system autonomously captures and updates behavioral and contextual data using sensors and videos, while AI reveals important aspects of the emergency. With this approach, the computational system adapts and learns to provide enhanced human interpretation and sense-making, from which the human adapts and learns also. Finally, Yin et al. (2015) proposed an analytical model to support a bidirectional learning task between humans and robots for training robots to obtain demonstrated knowledge for human-like handwriting, which they can then use to instruct children for learning handwriting.

To realize benefits for human, the enabling AI should be adequately integrated in the human-centered framework or a socio-technical work system. This would help human to generate a feeling of trust towards the AI system and its decisions (Battistoni et al., 2021), improve their skills to adopt advanced automation solutions (Romero et al., 2019), and, finally, enable human-centered self-learning factories (Ansari et al., 2018b). Although through RL, capabilities of both human and machine can be improved simultaneously, further study is also needed to differentiate RL from learning under human experts' aid (de Giorgio et al., 2021) to identify and emphasize RL's advantages.

4.3 RL for mutual benefit

In 12 of 27 publications, machine and human both benefit from an envisioned learning process. Scientific disciplines concerned are Computer Science (6) and Engineering (6).

Lyytinen et al. (2021) introduce meta-human systems, a hybrid of human and machine that learn to amplify capabilities. It is pointed out that both agents have different cognitive architectures, demanding a common conceptualization of learning irrespective of cognitive architectures. In this concept, learning is defined as "a process of increasing capabilities in a configuration of agents". Moreover, learning between human and machine agents demands improvement to the interface and communication mechanisms. A similar perspective has been emphasized by Azevedo et al. (2017). Trust and mutual understanding of human and machine are the foundation for symbiotic relationships between both agents, possibly enabling shared control responsibilities of systems. In Abdel-Karim et al. (2020), ML based systems classify X-ray images, and in case of contradictions, human experts reconsider their diagnosis, which overall leads to more consistent results. Both agents learn from resolving these contradictions, either by resolving their own errors or by updating supervised training data. The respected authors refer to this as "learning from errors" and point toward the obstructive paradigm of error avoidance in western cultures.

The principle of error-learning (cf. Abdel-Karim et al. (2020)) between human experts and AI expert systems is independent of the contextual setting. Therefore, in cooperative situations where machines may be able to reveal human's wrong decisions, RL enables improving decision-making capabilities of both agents. In production and logistics, decision-making remains a human domain, still AI recommendations may increase precision while reducing failure rates, for instance, in inspection tasks. Further, machine schedulers may be able to flexibly find more efficient production schedules and humans learn from suggestions. Vice-versa machine schedulers could be repeatedly overruled by human schedulers and adjust accordingly (Ansari et al., 2018a). Moreover, machines cannot match human learning yet but could replicate acquired skills to other machines easily (Lyytinen et al., 2021), which portrays scalability of RL systems in general.

5. RESEARCH PATHWAYS AND CONCLUSION

This paper discussed RL for production and logistics, especially by eliciting and assessing a fragmented knowledge base from a collection of literature from past studies of the same or similar topics. An extension towards wider scope of sampled literature to detail the literature review is intended. Further identified research needs, which affect the implementation of RL in production and logistics to complement WBL, are listed below:

i) *Developing frameworks and methods*, inter-alia, data-driven approaches and procedural models, to orchestrate the design and development of use-cases and identify application areas, especially in production and logistics. In particular, it should be investigated how objectives of RL and capabilities of agents are related to dedicated tasks and processes, e.g., task sharing and work distribution.
ii) *Identify technology* capable of bringing RL into practice, as well as advancing technological readiness to enable implementation of use-cases and empirical research on RL.
iii) *Investigate educational opportunities* for RL to complement skill development in production and logistics to close skill mismatches by exploiting learning capabilities of human and machine agents.
iv) Investigate the potentials of RL for enhancing *human-centered production* toward realizing visions of the Industry 5.0 paradigm.
v) *Ethical considerations*, in particular engineering ethics, as machine and human deliberately learning reciprocally, may undoubtedly have severe consequences on their interaction, safety, and individual behavior.

REFERENCES

Abdel-Karim, B.M., Pfeuffer, N., Rohde, G. and Hinz, O. (2020), "How and What Can Humans Learn from Being in the Loop?", *KI - Künstliche Intelligenz*, Vol. 34 No. 2, pp. 199–207.

Ansari, F. (2019), "Knowledge Management 4.0: Theoretical and Practical Considerations in Cyber Physical Production Systems", *IFAC-PapersOnLine*, Vol. 52 No. 13, pp. 1597–1602.

Ansari, F., Erol, S. and Sihn, W. (2018a), "Rethinking Human-Machine Learning in Industry 4.0: How Does the Paradigm Shift Treat the Role of Human Learning?", *Procedia Manufacturing*, Vol. 23, pp. 117–122.

Ansari, F., Hold, P. and Khobreh, M. (2020), "A knowledge-based approach for representing jobholder profile toward optimal human–machine collaboration in cyber physical production systems", *CIRP Journal of Manufacturing Science and Technology*, Vol. 28, pp. 87–106.

Ansari, F., Hold, P., Mayrhofer, W., Schlund S. and Sihn, W. (2018b), "AUTODIDACT: Introducing the Concept of Mutual Learning into a Smart Factory Industry 4.0", *In Proceedings of 15th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2018)*, pp. 61–68.

Azevedo, C.R.B., Raizer, K. and Souza, R. (2017), "A vision for human-machine mutual understanding, trust establishment, and collaboration", in *2017 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA), Savannah, GA, USA, 27.03.2017 - 31.03.2017*, IEEE, pp. 1–3.

Bannan, B., Torres, E.M., Purohit, H., Pandey, R. and Cockroft, J.L. (2020), "Sensor-Based Adaptive Instructional Systems in Live Simulation Training", in Sottilare, R.A. and Schwarz, J. (Eds.), *Adaptive Instructional Systems*, *Lecture Notes in Computer Science*, Vol. 12214, Springer International Publishing, Cham, pp. 3–14.

Battistoni, P., Romano, M., Sebillo, M. and Vitiello, G. (2021), "A Change in Perspective About Artificial Intelligence Interactive Systems Design: Human Centric, Yes, But Not Limited to", in Stephanidis, C., Kurosu, M., Chen, J.Y.C., Fragomeni, G., Streitz, N., Konomi, S., Degen, H. and Ntoa, S. (Eds.), *HCI International 2021 - Late Breaking Papers: Multimodality, eXtended Reality, and Artificial Intelligence*, *Lecture Notes in Computer Science*, Vol. 13095, Springer International Publishing, Cham, pp. 381–390.

Colom, R., Karama, S., Jung, R.E. and Haier, R.J. (2010), “Human intelligence and brain networks”, *Dialogues in Clinical Neuroscience*, Vol. 12 No. 4, pp. 489–501.

de Giorgio, A., Roci, M., Maffei, A., Jocevski, M., Onori, M. and Wang, L. (2021), “Measuring the effect of automatically authored video aid on assembly time for procedural knowledge transfer among operators in adaptive assembly stations”, *International Journal of Production Research*, pp. 1–16.

Douglas, A.E. (2021), *The Symbiotic Habit*, Princeton University Press.

Ertmer, P.A. and Newby, T.J. (2013), “Behaviorism, Cognitivism, Constructivism: Comparing Critical Features From an Instructional Design Perspective”, *Performance Improvement Quarterly*, Vol. 26 No. 2, pp. 43–71.

European Commission (2021), *Industry 5.0: towards a sustainable, human centric and resilient European industry*, Publications Office.

Glock, C.H., Grosse, E.H., Jaber, M.Y. and Smunt, T.L. (2019), “Applications of learning curves in production and operations management: A systematic literature review”, *Computers & Industrial Engineering*, Vol. 131, pp. 422–441.

Inga, J., Ruess, M., Robens, J.H., Nelius, T., Kille, S., Dahlinger, P., Thomaschke, R., Neumann, G., Matthiesen, S., Hohmann, S. and Kiesel, A. (2021), *Human-machine Symbiosis: A Multivariate Perspective for Physically Coupled Human-machine Systems*.

Jarvis, P. and Parker, S. (Eds.) (2006), *Human Learning,* 0th ed., Routledge.

Licklider, J. (1960), “Man-Computer Symbiosis”, *IRE Transactions on Human Factors in Electronics* HFE-1, pp. 4–11.

Lu, Y., Adrados, J.S., Chand, S.S. and Wang, L. (2021), “Humans Are Not Machines—Anthropocentric Human–Machine Symbiosis for Ultra-Flexible Smart Manufacturing”, *Engineering*, Vol. 7 No. 6, pp. 734–737.

Lygerakis, F., Dagioglou, M. and Karkaletsis, V. (2021), “Accelerating Human-Agent Collaborative Reinforcement Learning”, in *The 14th PErvasive Technologies Related to Assistive Environments Conference, Corfu Greece, 29 06 2021 02 07 2021*, ACM, New York, NY, USA, pp. 90–92.

Lyytinen, K., Nickerson, J.V. and King, J.L. (2021), “Metahuman systems = humans + machines that learn”, *Journal of Information Technology*, Vol. 36 No. 4, pp. 427–445.

Mark, B.G., Rauch, E. and Matt, D.T. (2021), “Worker assistance systems in manufacturing: A review of the state of the art and future directions”, *Journal of Manufacturing Systems*, Vol. 59, pp. 228–250.

Nardo, M., Forino, D. and Murino, T. (2020), “The evolution of man–machine interaction: the role of human in Industry 4.0 paradigm”, *Production & Manufacturing Research*, Vol. 8 No. 1, pp. 20–34.

Pacaux-Lemoine, M.-P. and Trentesaux, D. (2019), “ETHICAL RISKS OF HUMAN-MACHINE SYMBIOSIS IN INDUSTRY 4.0: INSIGHTS FROM THE HUMAN-MACHINE COOPERATION APPROACH”, *IFAC-PapersOnLine*, Vol. 52 No. 19, pp. 19–24.

Romero, D., Gaiardelli, P., Powell, D., Wuest, T. and Thürer, M. (2019), “Rethinking Jidoka Systems under Automation & Learning Perspectives in the Digital Lean Manufacturing World”, *IFAC-PapersOnLine*, Vol. 52 No. 13, pp. 899–903.

Rosenshine, B. and Meister, C. (1994), “Reciprocal Teaching: A Review of the Research”, *Review of Educational Research*, Vol. 64 No. 4, pp. 479–530.

Russell, S.J. and Norvig, P. (2021), *Artificial Intelligence: A Modern Approach, Pearson series in artificial intelligence*, Pearson.

Terziyan, V., Gavriushenko, M., Girka, A., Gontarenko, A. and Kaikova, O. (2021), “Cloning and training collective intelligence with generative adversarial networks”, *IET Collaborative Intelligent Manufacturing*, Vol. 3 No. 1, pp. 64–74.

Tzafestas, S. (2006), “Concerning human-automation symbiosis in the society and the nature”, *Int. J. Fact. Autom. Robot. Soft Comput* 1 (3), pp. 6–24.

Wang, L., Gao, R., Váncza, J., Krüger, J., Wang, X.V., Makris, S. and Chryssolouris, G. (2019), “Symbiotic human-robot collaborative assembly”, *CIRP Annals*, Vol. 68 No. 2, pp. 701–726.

Wenskovitch, J. and North, C. (2020), “Interactive Artificial Intelligence: Designing for the "Two Black Boxes" Problem”, *Computer*, Vol. 53 No. 8, pp. 29–39.

West, S.A., Griffin, A.S. and Gardner, A. (2007), “Social semantics: altruism, cooperation, mutualism, strong reciprocity and group selection”, *Journal of Evolutionary Biology*, Vol. 20 No. 2, pp. 415–432.

Wiethof, C. and Bittner, E.A.C. (2021), “Hybrid Intelligence-Combining the Human in the Loop with the Computer in the Loop: A Systematic Literature Review”, *ICIS 2021 Proceedings No.* 11.

Yin, H., Billard, A. and Paiva, A. (2015), “Bidirectional Learning of Handwriting Skill in Human-Robot Interaction”, in Adams, J.A., Smart, W., Mutlu, B. and Takayama, L. (Eds.), *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction Extended Abstracts, Portland Oregon USA, 02 03 2015 05 03 2015*, ACM, New York, NY, USA, pp. 243–244.

Zagalsky, A., Te'eni, D., Yahav, I., Schwartz, D.G., Silverman, G., Cohen, D., Mann, Y. and Lewinsky, D. (2021), “The Design of Reciprocal Learning Between Human and Artificial Intelligence”, *Proceedings of the ACM on Human-Computer Interaction*, Vol. 5 CSCW2, pp. 1–36.

Zhang, M., Winkelhaus, S. and Grosse, E.H. (2021), “Evaluation of human workload in a hybrid order picking system”, *IFAC-PapersOnLine*, Vol. 54 No. 1, pp. 458–463.