AI-supported assistance systems in enterprise learning processes - prospects and limitations

Norbert Gronau, Gergana Vladova

1. Introduction

Artificial intelligence is used today in processes of learning and knowledge transfer – to assess learning outcomes, make recommendations, close learning gaps, or adapt learning to individual needs. It is assumed that the role of artificial intelligence in human learning will increase, that AI will takes over the active tasks of a teacher, and will also be able to support the creative and socio-emotional aspects of learning. This is a promising expectation, in view of the fact that education is a social good of enormous importance in today's world. Learners are increasing in number and diversity - school education is compulsory, colleges and universities are increasingly attended, continuing education and lifelong learning are not the exceptions for organizations, but rather the norm. Educators are faced with new challenges that go beyond imparting knowledge: individualization and personalization of learning as well as differentiation in the classroom; equal education for all; active participation of the learners instead of passive knowledge transfer from teacher to the learner; development of competencies that are crucial in today's world, such as problem solving, critical or creative thinking.

These challenges affect all educational contexts equally. However, this paper focuses specifically on learning processes in companies and the role of AI in them, especially in the context of the use of cognitive assistance systems (AS).

People remain the critical success factor for companies in the factory of the future, but their potential must be developed on the basis of individual dispositions - knowledge, skills and acceptance. When AI is used in production processes - in contrast to classic automation - people are not replaced by technology, but rather supported. The goal is to expand the work capacities of employees or to compensate for missing skills. The increasing degree of digitalization and networking as well as the tasks and responsibilities are becoming more and more complex. Employees perform their tasks in a complex collaborative network environment that is not only connected to people but also to information and communication technologies and assistance systems, which requires new specific knowledge and competences as well as corresponding didactic concepts and learning environments (Gronau et al. 2017).

AS serve the application-oriented, near-real-time provision of information to support employees in decision-making or to guide them in manual tasks. Cognitive

AS are encountered by employees in the form of various artefacts - mobile devices, stationary displays on which the ASs are presented as more or less interactive visualization systems, wearables such as data glasses (Vladova at al. 2020). AS can support employees in learning new tasks by filtering the information relevant to the process and making it available as needed, thus offering potential for faster and work-integrated competence development (Senderek/Geisler 2015). For companies, this not only offers the advantage that employees' work activities and work performance can be directly controlled and optimized from an efficiency perspective. It also enables the flexible adaptation of work processes to new procedures and changing products and makes staff deployment and recruitment much more flexible. This digital employee management offers various advantages for companies, such as direct control and optimization of employees' work activities and work performance (especially low-skilled employees), flexible adaptation of work processes to new procedures and changing products, flexible staff deployment (Kuhlmann et al. 2018). In the enterprise context, AI can also be directly used to create simulated or individualized learning environments.

The major changes in the industrial world have been caused by the concepts of Industry 4.0 and the Smart Factory (Rauch et al. 2020). People, machines and products are networked and together form a new production system in which workers and robots work together and supported by web technology and intelligent assistance systems, and information and knowledge are exchanged more quickly and efficiently. In the manufacturing execution phase of a cyber-physical production system, different approaches of cognitive assistance were identified, with decision support systems, digital information assistance systems, virtual training, augmented and virtual reality assistance, and IT-based knowledge transfer systems directly addressing the importance of assistance technology for learning and knowledge transfer activities. Rauch et al. (2020) points out, among other things, the possibilities for enhancement of cognitive abilities and skill development of technology users as well as for information support through the system (e.g. Corbett 1990; Hirsch et al. 1992; Fan/Gassmann 1995; Fujita et al. 2009; Mital/Pennathur 1999). The worker is mainly seen as an active consumer and provider of information, acting within knowledge brokerage and skill transfer systems (Gorecky at al. 2013). The system can support the user in different ways to meet the challenges of working in new, very flexible and data-rich environments: e.g. with augmented reality (Paelke 2014), head-worn displays (e.g. Rauh et al. 2015), virtual training systems (Gorecky et al.)

As in any other context, the use of AI in learning processes also involves risks and challenges. Goals such as the individualization of learning can only be achieved to a limited extent, and the question of which learner characteristics need to be taken into account and how they can be captured has not yet been answered in research and practice.

DOI: https://doi.org/10.30844/wgab_2021_5

In this paper we address the opportunities and challenges of cognitive AS in the context of workplace learning. In chapter two, we first discuss against the state of the art perspectives of AI-supported assistance systems, especially with regard to process support and the support of specific employee groups. In a next step, we specify the limitations of these systems in chapter three. In the final chapter, we summarize these findings and identify opportunities and necessities for future development as well as essential areas of work for further research on the use of AI in industrial processes.

2. Prospects of AI-supported assistance systems

Gorecky et al. (2014, p. 90) describe employees as the "most flexible part of the production system" that must "constantly adapt to new and changing technology trends". According to the authors, these trends fall into five main categories: demographic change (skills shortages, ageing and changing workforce); globalization (new and changing markets, emerging competition); changing customer demands (product diversity, personalized customer solution, emerging competition); rapid technological developments (adaptation to new technologies, shorter product life cycles); and knowledge economy (knowledge as a productive asset). Therefore, organizations need to learn how to benefit from the positive effects and potential of ICT-based training and knowledge sharing at the individual and organizational level. Required competencies and qualifications can be easily taught, satisfaction and motivation can be increased; for organizations, the full potential of employees can be tapped. The use of assistance systems in the manufacturing context opens up new possibilities for learning approaches such as situational learning. Learning takes place continuously and as part of the work process and the learner interacts actively with the learning environment instead of being a passive recipient (compared to classical VET activities). Training is ad-hoc and on-the-job and uses digital media and educational technologies in imparting knowledge and developing skills. In the future factory, the role and tasks of teachers, mentors and experts are expected to be complemented and supported by smart information technologies (Gorecky et al. 2014). However, these changes influence existing process structures and procedures and are associated with changes and challenges.

2.1. Process-related prospects

Many assistance systems for the enterprise context currently exist and are under development. In general, they can be divided into physical assistance systems (systems that support the worker in physiological work), sensory assistance systems (systems that collect and provide data) and cognitive systems (Romero et al., 2016). The area of cognitive aids for the execution of production systems represents the main research topic in the context of companies. These systems represent new opportunities for virtual training using virtual reality technologies, with dramatic improvements in the learning process and outcomes (Rauch et al. 2020).

Rauch et al. (2020) see the use of assistance systems for learning and information provision as a research focus within Industrie 4.0. Here, the systems can be viewed from two different angles: They support both the human worker in the factory of the future, and they define new challenges for the human worker, requiring new skills and competences to create a collaborative learning environment for both - human and technology. Depending on the adaptivity of the system with regard to the selection of assistance measures, a cognitive assistance system in a can be used both for the induction of new employees into work processes and for quality management and general assistance tasks for professional, experienced employees (Halsgrübler et al. 2018).

According to Gorecky et al. (2014, p. 92), assistance in the work context "aims at high output (...) by guiding a person to imitate a certain behaviour, e.g. in the form of detailed procedural, step-by-step instructions". The focus of learning, on the other hand, is on pedagogical objectives and effective repetition with the long-term goal of broadening the worker's experience and general understanding of a task or related tasks. However, assistance and learning in a manufacturing context are becoming more similar, with both initial peak performance on an unfamiliar task and skill development being important. An assistance system (for training and knowledge sharing) can combine both goals - full assistance can be offered at the beginning and gradually removed. Eiriksdottir/Catrambone 2011 analyze the influence of instruction type on initial performance as well as on learning and transfer and present a structured overview of the factors that help or hurt in both cases. According to this review, procedural instructions can help in the context of initial performance by providing specific step descriptions, supplementing general step descriptions with examples, or providing specific goals. However, the same negatively influence the procedural instruction process in learning and transfer. General step descriptions are counterproductive in the context of procedural instruction for initial implementation. On the other hand, general step descriptions are helpful when learning and transfer are the focus of the instruction. Differences were also found in the use of principles and examples (more similarity to the task in initial performance vs. use of examples without support to guide generalization within learning and training).

This is in line with the results of an experiment that combines both - the transfer of general, process-related information, as well as of specific task knowledge (Vladova at al. 2020). In a learning factory, a highly automated work process was simulated in which human workers are responsible for operating the machines (setting the parameters, starting the work program, inserting the workpieces) and loading and observing the machines. Assistance systems were used to guide the workers/probands, which, similar to a navigation device in a car, inform the workers exactly which activities they have to carry out and when. The focus was on testing whether having a good knowledge of the entire work process has an influence on productivity and quality of work as well as on the motivation and satisfaction of the participants. The results suggest that while digital assistance systems can enable hands-on learning, there is a risk that the holistic knowledge of the work process itself is lost and thus has a negative impact on employees' work performance, motivation and satisfaction. It has been shown that additional knowledge about the production process has a positive impact, especially on high-performing participants.

Gorecky et al. (2011) see personal assistance systems as crucial to strengthening the role of humans in production environments. In this context, technologies for capturing and learning cognitive behaviours and activities of human users in particular will gain importance in order to develop cognitive understanding in user assistance systems.

Assistance systems can be used for process analysis along production chains in Industrie 4.0 environments. Barig/Balzereit (2019) discuss an efficient approach for this with a combination of process-related local and a global assistance system. Local assistants, connected to machine modules, learn and analyze the production processes with artificial intelligence (AI) methods. Their results are used by the global assistance system to obtain a central overview of the entire production chain. In this way, the global system can send information about errors and possible causes to the users and thus avoid long production stoppages due to root cause analyses.

Minhas/Berger (2012) discuss the potential of an ontology-based intelligent assistance system to support the planner in the environmental assessment of custom manufacturing. in decentralized manufacturing networks as well as in production planning decision making. Given the complexity of manufacturing processes and the growing amount of data, workers struggle with the challenge of process monitoring, data analysis and error detection. This leads to delayed problem detection, short maintenance intervals and insufficient use of optimization potential (Windmann et al. 2015). Self-learning assistance systems can observe complex manufacturing processes and automatically detect errors, anomalies and optimization needs (ibid.).

Gorecky et al. (2011) show the potential of a cognitive assistance and training system based on state-of-the-art techniques of motion and object tracking, task analysis, decision making and user-adaptive visualization via augmented reality in an industrial context. The authors use the example of a system that is able to give instructions to workers during the process and to understand and initiate human workflows. The system observes advanced users using high sensory capabilities to automatically analyze and capture assembly sequences. In a next step, an in-system understanding of assembly operations is developed and the system can use the captured knowledge to assist and train inexperienced workers. A similar idea is presented by Bleser et al. (2018). They discuss the development of a concept and demonstrator with the aim of learning workflows by observing multiple experts and transferring the learned workflow models to inexperienced users.

Breitsprecher/Wartzack (2012) report on the development of a self-learning assistance system and show the potential of a knowledge-based assistance system as an extensive area of research in various domains, with the common idea being to map the knowledge of an expert in a computer, store it and use it to emulate problem solving.

Assistance systems can furthermore be used to detect and reduce errors by directly learning what behaviour causes the errors. The main benefits are faster cycle times, reliability, reduced error rate and traceability in assisting the intelligent operator in real time. For example, AR can be used as a digital assistance system to reduce human error and dependence on printed work instructions, computer screens and operator memory as sources of information for a skilled worker (Romero et al. 2016).

2.2. Prospects for specific employees' groups

Aksu et al. (2018) and Drolshagen et al. (2021) describe how technical assistance can help employees with disabilities to work safely and complete their tasks without stress. Mark at al. (2018) discusses assistance as well as the categorization of user groups in the present Production 4.0. As a result of this market and literature review, the authors identify the need to match assistance systems to user groups and show how this is feasible.

Neumann et al. (2020) investigate the use of AR-enabled assistance systems tailored to the individual needs of workers with different cognitive and physical abilities in an industrial context and point out that the implementation of these assistance devices - in order to be successful - should include user- and value-oriented system design and change management strategies, especially information and participation, which would lead to a better congruence of technology features with those of the workers.

Sahlab /Jazdi (2020) discuss the challenge of developing user-adaptive assistance systems in dynamic environments, especially in the context of demographic change (Teichmann et al. 2019).

Aehnelt/Bader (2015) build on the idea that people do their work faster and better when they use a detailed work plan to orient and structure their tasks (Kokkalis et al. 2013) and describe the positive effect of intelligent systems that autonomously create work plans, make them available to workers and monitor their work. The information on assembly processes provided by the assistance system enables low-skilled workers to produce high-quality products and remain motivated. The authors describe five general types of information support provided by the system: awareness, guidance, monitoring, documentation and guarding.

3. Limitations of AI-supported assistance systems

Cognitive technical systems are equipped with artificial sensors and actuators and differ from other technical systems through cognitive control mechanisms and cognitive abilities. They integrate themselves into physical systems in a real environment (cf. also below Zäh et al. 2007). Cognitive control mechanisms are understood as the ability to exhibit and develop back-referenced and situational behaviours in accordance with long-term intentions. Their cognitive abilities - perceiving, reasoning, learning and planning - make these systems suitable for the following activities:

- drawing conclusions from knowledge;
- learn from its experiences;
- being able to explain oneself and explain to one what its task;
- be aware of one's own abilities and use them in one's the context of one's behaviour;
- reacts robustly to unforeseen situations.

The goal of cognition is to improve the interaction between people and technical systems while making the overall process more robust, flexible and efficient, which is particularly important in the context of production. The fulfilment of these demanding tasks depends to a large extent on the development of technology and the skills and competences of the employees who work together with the technology.

Kokkalis et al. (2013) show the potential of automatic generation of work plans. However, the authors point out that different tasks may be performed by different technical or non-technical units, which should be recognized and indicated by the assistance system.

As a further limitation for the use of AI-based assistance systems, Neumann et al. (2020) emphasize the importance of distinct "self-explanatory" features of (AR-based) assistance systems as well as the quality of the implementation strategy. Users' trust in the system's performance depends, among other things, on their satisfaction with the communication of the features and the system. One way to overcome this problem is to make users aware of such issues during the introduction and coaching phase. The usability of systems (according to TAM (Davis 1989)) has been shown to depend on users' prior experience with technology (AR). Therefore, when designing the systems, special attention should be paid to user-friendly presented instructions and well-coordinated training of future users in the use of the system.

In order to achieve the goals intelligently and successfully, the assistance systems need corresponding information. This can be found, for example, in production data management systems, although the formalization and externalization of procedural and conceptual knowledge remains a major challenge for organizations (Aehnelt/Bader 2015).

Chacón et al. (2020) see humans as generally superior due to their cognitive abilities, but machines as much better at performing repetitive, heavy-load tasks with high precision and reliability. Cognitive systems have the potential to provide the best possible support with minimum necessary interruption. Guidance can be provided as needed and according to the skills of the worker (e.g. trainee versus experienced worker). In addition, newcomers can be trained in on-the-job training scenarios and integrated directly into production.

4. Conclusions

The authors of this paper see three major areas of work for the better study of the use of AI in industrial processes:

First, the mainly used theories of learning and teaching were developed before the digital transformation started and AI technologies emerged. Therefore, there is an urgent need for a holistic theory, or at least a model, that will make it possible to explain the changes that AI brings separately in terms of teachers, learners, content, teaching/learning mode and, last but not least, learning outcomes.

Secondly, it will be necessary to describe and control the non-linear influence of AI on the whole learning process. When AI is used to teach and help the teacher and the learner at the same time, there can be a non-linear evolution of the teaching and learning process. This is not seen in today's teaching environment as it does not adapt to the teacher or the learner.

Thirdly and most importantly, we need to test new approaches in real-world environments. Learning factories could be a very good start because some of them also have an adaptive environment.

Undoubtedly, the undisputed use of AI in teaching and learning will improve the learning process, sometimes in ways that we cannot clearly see today.

Acknowledgements

This work has been partly funded by the Federal Ministry of Education and Research of Germany (BMBF) under grant no. 16DII127 ("Deutsches Internet-Institut")

References

Aehnelt, M., & Bader, S. (2015, January). Information Assistance for Smart Assembly Stations. In I-CAART (2) (pp. 143-150).

Aksu, V., Jenderny, S., Kroll, B., & Röcker, C. (2018, July). A digital assistance system providing step-by-step support for people with disabilities in production tasks. In International Conference on Applied Human Factors and Ergonomics (pp. 775-785). Springer, Cham.

Barig, B., & Balzereit, K. (2019). Assistance systems for industry 4.0 environments. In 17th embedded world Conference.

Bleser, G., Damen, D., Behera, A., Hendeby, G., Mura, K., Miezal, M., ... & Stricker, D. (2015). Cognitive learning, monitoring and assistance of industrial workflows using egocentric sensor networks. PloS one, 10(6), e0127769.

Breitsprecher, T., & Wartzack, S. (2012). Architecture and realization of a selflearning engineering assistance system for the use within sheetbulk metal forming. In DS 71: Proceedings of NordDesign 2012, the 9th NordDesign conference, Aarlborg University, Denmark. 22-24.08. 2012.

Chacón, A., Angulo, C., & Ponsa, P. (2020). Developing Cognitive Advisor Agents for Operators in Industry 4.0. New Trends in the Use of Artificial Intelligence for the Industry 4.0, 127.

Corbett, J. M. (1990). Human centred advanced manufacturing systems: From rhetoric to reality. International Journal of Industrial Ergonomics, 5(1), 83-90.

Gorecky, D., Worgan, S. F., & Meixner, G. (2011, August). COGNITO: a cognitive assistance and training system for manual tasks in industry. In Proceedings of the 29th annual European conference on cognitive ergonomics (pp. 53-56).

Davis, F. D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13 (3), 319 (1989).

Drolshagen, S., Pfingsthorn, M., Gliesche, P., & Hein, A. (2021). Acceptance of Industrial Collaborative Robots by People With Disabilities in Sheltered Workshops. Frontiers in Robotics and AI, 7, 173.

Eiriksdottir, E., & Catrambone, R. (2011). Procedural instructions, principles, and examples: How to structure instructions for procedural tasks to enhance performance, learning, and transfer. Human factors, 53(6), 749-770.

Gorecky, D., Mura, K., & Arlt, F. (2013). A vision on training and knowledge sharing applications in future factories. IFAC Proceedings Volumes, 46(15), 90-97.

Gronau, N., Ullrich, A., & Teichmann, M. (2017). Development of the industrial IoT competences in the areas of organization, process, and interaction based on the learning factory concept. Procedia Manufacturing, 9, 254-261.

Fan, I. S., & Gassmann, R. (1995). Study of the practicalities of human centred implementation in a British manufacturing company. Computer Integrated Manufacturing Systems, 8(2), 151–154.

Fujita, M., Kato, R., Watanabe, K., Tan, J. T. C., & Arai, T. (2009). Operators' mental strain induced by information support in cell production. Assembly and manufacturing, 2009. ISAM 2009. IEEE international symposium on (pp. 196–201). IEEE.

Haslgrübler, M., Gollan, B., & Ferscha, A. (2018). A cognitive assistance framework for supporting human workers in industrial tasks. IT Professional, 20(5), 48-56.

Hirsch, B. E., Hamacher, B., & Thoben, K. D. (1992). Human aspects in production management. Computers in Industry, 19(1), 65–77.

Kokkalis, N., Köhn, T., Huebner, J., Lee, M., Schulze, F., & Klemmer, S. R. (2013). Taskgenies: Automatically providing action plans helps people complete tasks. ACM Transactions on Computer-Human Interaction (TOCHI), 20(5), 1-25.

Kuhlmann, M., Splett, B., & Wiegrefe, S. (2018). Montagearbeit 4.0? Eine Fallstudie zu Arbeitswirkungen und Gestaltungsperspektiven digitaler Werkerführung. WSI-Mitteilungen, 71(3), 182-188.

Livingston, M. A. (2005). Evaluating human factors in augmented reality systems. IEEE Computer Graphics and Applications, 25(6), 6-9.

Mark, B. G., Gualtieri, L., Rauch, E., Rojas, R., Buakum, D., & Matt, D. T. (2019, December). Analysis of User Groups for Assistance Systems in Production 4.0. In 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM) (pp. 1260-1264). IEEE.

Minhas, S. U. H., & Berger, U. (2012). Development of Intelligent Assistance System to Support Eco-efficient Planning. In KEOD(pp. 331-334).

Mital, A., & Pennathur, A. (1999). Human centered manufacturing: A necessity for en- hancing productivity and competitiveness. SAE technical paper, no. 1999-01-1605.

Neumann, A., Strenge, B., Uhlich, J. C., Schlicher, K. D., Maier, G. W., Schalkwijk, L., ... & Schack, T. (2020, June). AVIKOM: towards a mobile audiovisual cognitive assistance system for modern manufacturing and logistics. In Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments (pp. 1-8).

Paelke, V. (2014). Augmented reality in the smart factory: Supporting workers in an in- dustry 4.0 environment. Emerging technology and factory automation (ETFA), annual conference of the IEEE (pp. 1–4).

Rauch, E., Linder, C., & Dallasega, P. (2020). Anthropocentric perspective of production before and within Industry 4.0. Computers & Industrial Engineering, 139, 105644.

Rauh, S., Zsebedits, D., Tamplon, E., Bolch, S., & Meixner, G. (2015). Using Google Glass for mobile maintenance and calibration tasks in the AUDI A8 production line. In Emerging technologies & factory automation (ETFA), 2015 IEEE 20th conference (pp. 1–4).

Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å., & Gorecky, D. (2016, October). Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies. In proceedings of the international conference on computers and industrial engineering (CIE46), Tianjin, China (pp. 29-31).

Senderek, R., & Geisler, K. (2015). Assistenzsysteme zur Lernunterstützung in der Industrie 4.0. In Proceedings of DeLFI Workshops.

Teichmann, M., Ullrich, A., Kotarski, D., Gronau N. (2019). Herausforderung Altersgerechte Weiterbildung: Potenziale arbeitsgebundenen Lernens und mobiler IIoT-Technologien für eine zielgruppenorientierte Bildungsarbeit. Industrie 4.0 Management 35 (2), S. 23-26

Vladova, G., Wotschack, P., de Paiva Lareiro, P., Gronau, N., & Thim, C. (2020). Lernen mit Assistenzsystemen-Vor lauter Aufgaben den Prozess nicht sehen?. Industrie 4.0 Management, 36(3), 16-20.

Windmann, S., Maier, A., Niggemann, O., Frey, C., Bernardi, A., Gu, Y., ... & Kraus, R. (2015, November). Big data analysis of manufacturing processes. In Journal of Physics: Conference Series (Vol. 659, No. 1, p. 012055). IOP Publishing.

Zäh, M., Wiesbeck, M., Engstler, F., Friesdorf, F., Schubö, A., Stork, S., ... & Wallhoff, F. (2007). Kognitive Assistenzsysteme in der manuellen Montage. In wt Werkstattstechnik online (Vol. 97, No. 9, pp. 644-650).