Artificial Intelligence and Assistance Systems for Technical Vocational Education and Training – Opportunities and Risks

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Abstract. Artificial intelligence and Assistance Systems are having an impact on the economy, society, skilled work and work environment. However, there are often very different assessments of the effects: On the one hand the loss of jobs and even professions have been predicted, on the other hand new support and options for work are emerging.

The actual promotion of these systems will depend on the opportunities of intervention and control by skilled workers. How can problem situations and imponderabilities in virtual environments be handled and solved? Both the opportunities and the risks of Artificial Intelligence and assistance systems for vocational education and training are reflected in this article.

Keywords: Assistance system · Skilled worker · Man-Machine-Interface

1 Introduction

Skilled work and vocational learning are increasingly influenced by digital assistance systems. The actual promotion of learning by applied assistance systems or systems of Artificial Intelligence will depend on the opportunities of intervention and control by skilled workers. How can problem situations and imponderabilities in virtual environments be handled and solved? How can Artificial Intelligence support vocational learning by creating a work environment and supportive learning?

Digitalization in vocational education leads to two objectives for the shaping and thus for the didactics of vocational learning processes: Digitalization for making use of digital media/technologies (vocational media pedagogy) and digitalization as a subject of vocational educational processes (vocational didactics). These two objectives are often intermingling. The article concentrates on the digital technologies for concrete work-oriented learning and on the systemic level of vocational education and training.

2 Changes of the Man-Machine-Interface (M-M-I) in the Age of Digitalization

The promotion of learning in a digital world of work will strongly depend on how future work-processes are shaped along with the possibilities of intervention of skilled

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workers. Three theses on the design of the M-M-I are currently being discussed for the shop-floor-level (Windelband/Spöttl 2012; Schlund/Gerlach 2013; Ahrens/Spöttl 2018):

1. Tools scenario/assistance scenario – Development of expert systems with tool character for skilled work;
2. Automation scenario – Limitation of the design leeways of skilled workers and devaluation of qualifications;
3. Hybrid scenario – New forms of interaction and cooperation in monitoring and control tasks are leading to new requirements for skilled workers.

These three theses date back to first considerations made by Windelband/Spöttl (2012) within the framework of a research project on present and future qualification requirements set by the "Internet of Things" (IoT) in the field of logistics.

The scenarios have been taken up by social sciences, work sciences and vocational-educational sciences in the context of surveys into the development of Industry 4.0 in reference to M-M-I as well as the distribution of control and responsibility between technical and human systems, above all in the field of production, and were advanced by further aspects. The work sciences often mention assistance systems that support users with their respective work tasks. This encompasses for example the use of (lightweight) robots that could take over physically strenuous or monotonous work, the use of smart devices for a context-sensitive support of work (cf. Deuse et al. 2018) or for monitoring and controlling of intelligently networked production resources (cf. Schlund/Gerlach 2013). The Man-Machine-Collaboration is playing a decisive role for fully taking advantage of the potentials of artificial and human intelligence. According to Traumer et al. (2017), it is necessary to analyze tasks in terms of the required abilities necessary for problem solving in order to select the "correct" kind and way of collaboration (Man-Man, Man-Machine, Machine-Man). This decision should consider the development of the most resource-friendly and at the same time socially desirable collaboration that should adhere to existing norms and legal stipulations. This should form the basis for the development of collaborative work practices at the Man-Machine-Interface (e.g. during the development of collaborative robot systems) in order to safeguard human-centered and humane work and to comply with the use of the strengths of both human beings and machines.

The dependence and the interrelationship between technology, organization, and the workforce in the context of assistance systems in Industry 4.0 are manifold and depend on different influence factors such as legal framework conditions, participation rights, or safety requirements/data protection. It becomes apparent that along with the progressive automation and an increasing complexity of the systems only limited controllability of technology remains, accompanied by a highly functional and economic failure potential and incalculable requirements for acting at work (Hirsch-Kreinsen 2016). The research on automation has coined this development the "ironies of automation": Due to their high routine character in case of malfunctions, automated processes often generate work situations that are difficult to cope with (Bainbridge 1983). According to work-sociological surveys, ways of action such as intuition and sense but also experiential knowledge about the operation of complex plans are crucial. This is called "Subjectivating acting at work" (cf. Böhle 2013). Mastering complexity in an increasingly networked world of work will be a great challenge in the future. Due to further networking and thus the opening of the systems within the entire value-added chain, there is a discrepancy between the data-technological compilation and the analysis and use of data for process optimization on the one hand and the complexity and dynamics of what is really happening on-site on the other hand (cf. Böhle 2017). In order to master these conditions and requirements between the real and the virtual world, uncertainties have to be dealt with and skilled workers must act correctly in unplannable situations (cf. Pfeiffer 2014). This can only be achieved with the ability to acquire new experiences and to apply existing experiences in a new way to react to and cope with unpredictable challenges (ibid. 5). However, the M-M-I must be designed in a way that the operator can still intervene into the system. The more decisions are taken over by computer programs, the more the ability to deal with complex situations and to actively shape the world of work will fade away. Thus, the design leeways of skilled workers and their options to make decisions will be restricted.

Nevertheless, the development and the acquisition of this experiential knowledge can only be successful if skilled workers are adequately qualified and able to make use of this expertise during their work. The solution of problem situations and imponderabilities above all in dealing with virtual environments is in the center of interest and aims at developing vocational experiential knowledge. Life-long vocational learning, the ability and readiness to change, and the handling of imponderabilities can thus be considered the keys to a successful transformation.

3 Challenges for (Vocational) Learning

Thus, the requirement profiles of skilled workers take a different orientation based on the use of Industry 4.0-hardware in plants and a wider networking of work and business processes in companies. Aspects of networking and thinking within networked systems are increasingly playing an important role for skilled workers on the shop-floor-level (Spöttl et al. 2016; Zinke et al. 2017). Increasing automation in production is leading more and more to a change in the vocational tasks of skilled workers: They have to complete their tasks with digitalized tools, operate the production facilities via human-machine interfaces, and develop their professionalism with the help of digitalized media, assistance systems, and cooperative work structures. More and more the ongoing merger of information technological and classical production processes can be observed. The decentralized intelligence within the framework of Industry 4.0 leads to a higher availability of highly process-relevant data, which are analyzed, processed, and worked on by skilled workers for the optimization of work-processes and problem solution (cf. Spöttl et al. 2016; Becker et al. 2022).

The following challenges in the context of developments towards digitalized work can be derived from a study for the M + E (production and mechatronics) sector for skilled work in Germany (Becker et al. 2022, p. 75):

- Overall understanding of production and mechatronics: interface knowledge, interaction of software and production process;
- Process understanding and overview of the complexity of processes: synchronization of processes along product creation;

- Process optimization /ensuring process reliability: variable use of production parameters, problems disruptions;
- Process data, data analysis, and its evaluation: processing order data, recording, and utilizing production parameters;
- Programming (low code) /parameterization tasks: use of application software;
- Data analysis and networking processes: data-supported support of work processes, increasing productivity, networking of production areas;
- Troubleshooting: analysis and elimination of causes of problems (reading live images, evaluating and solving the problem);
- Hybrid task performance: combining traditional tasks and ensuring mechanical, electrical, and information technological functionality.

However, not only production is affected by the development of digitalization. A current study into fourteen different training occupations – from specialists for wastewater technology, industrial managers, up to digital and print media designers– conducted by the German Federal Institute for Vocational Education and Training (BIBB) shows that the “digital” permeation process is taking place at a different pace and indeed differs in terms of depth and rigorousness, also between the surveyed occupations (Zinke 2019). Although digitalization has meanwhile arrived in all of the fourteen surveyed occupations, just “one out of three interviewed skilled workers, trainers, superiors of skilled workers, and persons responsible for in-firm training estimates that the grade of digitalization of the work places in the surveyed occupations is already high.” (BIBB 2018) This varying velocity of permeation of digitalization depends on different factors such as the respective business model, the economic framework conditions, the strategies for the introduction of new technologies, the acceptance of technologies by the employees as well as implemented qualification concepts, and last but not least the shaping demands and objectives connected to the implementation. The shaping of future workplaces combining an interaction of man and machine will become of utmost importance.

4 Which Challenges Can Be Derived for Occupational Learning?

Nevertheless, digitalization cannot only be determined by technological development and its changes. Likewise, it is not enough to embed Industry 4.0 technologies into the context of work processes with a focus on a didactical reflection of the shaping of learning processes of initial and further training. Further to a specialist understanding, an understanding of the entire process chain, the organization, and business processes, and the changes of the Man-Machine-Interface have to be established. Thus, the object of vocational education is considerably widened up as both digitalization itself and the changes it has triggered must be seen in a multidimensional way (see Fig. 1).

So far, initial and further training have mainly concentrated on the so-called Industry 4.0-technology and its comprehension and functioning (as for further training issues cf. Richter 2017, p. 242 ff.). Thus, the didactical understanding is predominantly still focused on functionalities or artifacts of digitalization (objects, products, media) (cf. Becker 2019, p. 2).

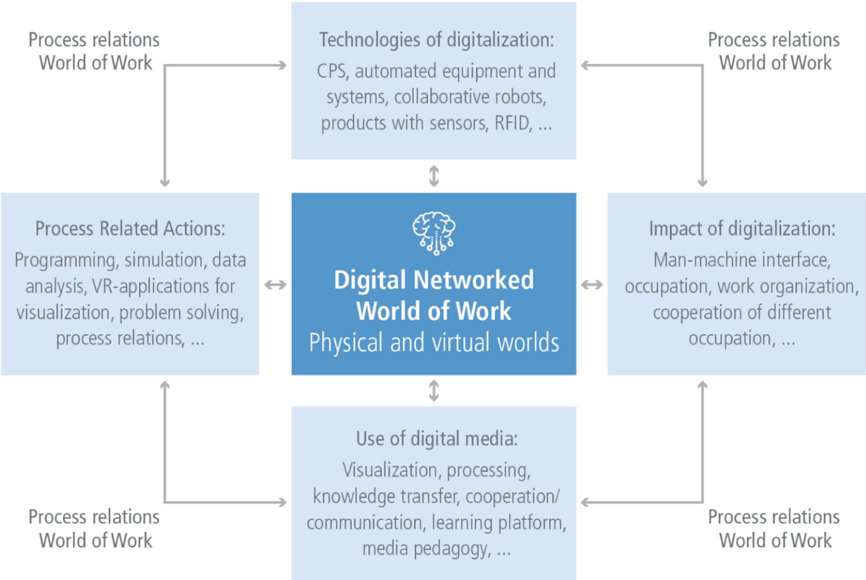

Fig. 1. Digitalization as object of vocational education and training in process related contexts (own illustration)

Above all the process interrelationships, the mastering of interfaces as well as the interaction with specific process data for problem solution are playing an increasingly important role for didactical decisions due to the blending of virtual and physical systems in the world of work (cf. Spöttl et al. 2016, Zinke et al. 2017). This poses central challenges to vocational education, such as (Faßhauer/Windelband 2021, p. 247):

- Working and learning with and within virtual systems (simulations, process visualization, Virtual Reality (VR) applications,
- Work with and at smart plants and processes with Artificial Intelligence (expert systems, diagnostic systems, knowledge management systems, Smart Maintenance),
- Hybrid management of tasks and organization of process structures (hybrid tasks, mixed occupations),
- Work with and handling of data (data compilations, data analyses and transfer, data security),
- Emergence of new Man-Machine interfaces (organization, shaping, control, assistance),
- Interdisciplinary learning and networked cooperation along the value-added chain (occupational didactical concepts across domains, cooperation of different learning environments),
- Learning in real and in virtual environments (digital media, learning management systems, learning tools, learning factories),
- Handling of complexities and unpredictable problem situations as well as thinking in networked systems (system and process understanding, experiential knowledge).

In the sense of a vocational competence to act, this means that concrete learning and work tasks must focus on the presentation of problems in a digitalized world of work rather than on digital tools (e.g. VR glasses or 3-D-printers) or on digital media (e.g. tablets or whiteboards) as such.

5 Changes of Vocational Learning Triggered by New Forms of Learning and New Technologies

Learning in the company is intensifying along with the digitalization of the world of work and enhances the process, the reflection, and learning character of company-based work that has already been practiced in many companies as early as in the 1980s /1990s (Dehnbostel 2019, p. 4). Digital learning can directly link working and learning in the work-process. This is underlined by the growing prevalence of interactive forms of learning and e-learning such as blended learning, webinars, learning platforms, online communities, and mobile and augmented learning as shown in Fig. 2.

Small learning offers such as learning nuggets (94%), learning videos (93%), and blended learning (91%) are seen as digital learning forms in continuing education for the future. In addition to self-determined learning offers, the pure forms of e-learning with Web Based Trainings (WBTs) (71%) or webinars (87%) have shown increased approval since the beginning of the Covid-19 pandemic (Mmb-Trendmonitor 2022, p. 6)[1]. Industry 4.0 is still considered a central driver of corporate further training. The use of simulations such as learning-oriented forms of Augmented Reality (AR)/Virtual Reality (VR) are increasingly gaining importance in vocational education and training, from virtual welding to entire learning factories. Learning in a safe virtual work environment is a great advantage as it is shaped in a flexible, self-regulated and interactive way. Given the fact that the implementation and integration of occupational situations in occupational learning environments are often linked to numerous problems (e.g. high procurement costs, state-of-the-art and complexity of the machine, risk factors due to the work environment), virtual environments can also have methodological advantages (cf. Zinn 2019, p. 22). In virtual learning environments, this experience leeway can be created when the learner interacts with his/her working environment (Haase et al. 2015, p. 193). Learning and working in virtual environments are hazard-free for beginners. There is neither material wear, nor can complex machines/plants be damaged. Practical and process-related learning situations can thus be simulated. At the same time, the learning environment supports collaborative learning and working.

The swift technical progress of VR/AR-technologies opens up more potential fields of application for VR/AR learning applications in vocational education and training. However, these fields of application should always be aiming at the pedagogic and didactical value added rather than focusing on the technological possibilities. With the aid of these new technologies, many new didactical possibilities within vocational education will be generated. However, the aim is to shape completely new teaching and learning processes (Redefinition, Fourth Level) rather than digital media as a substitute

[1] The results are based on an online Delphi survey. A total of 70 experts from the education scene in Germany, Austria and Switzerland were surveyed in 2021.

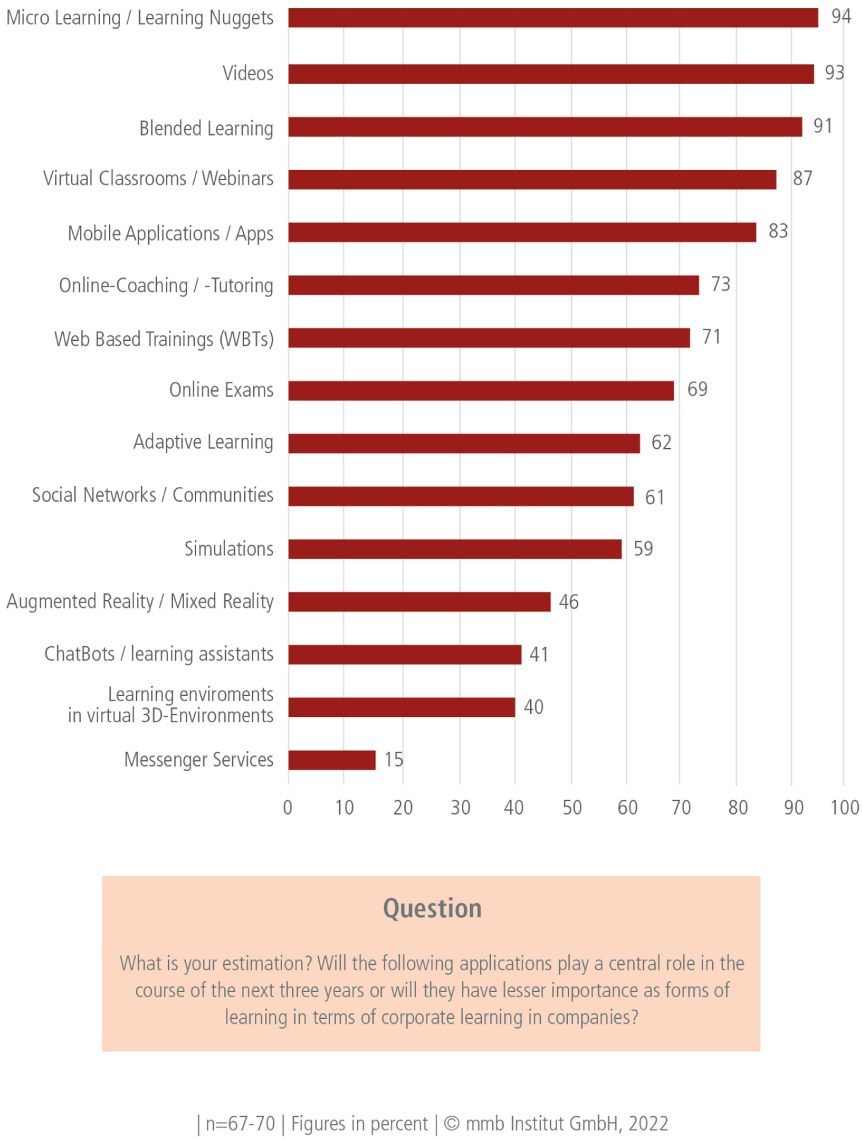

Fig. 2. Importance of applications as forms of learning in companies (own illustration based on mmb-Trendmonitor 2022, p. 6)

for traditional media without functional amendments, such as the e-book substituting the textbook (Substitution, First Level) (cf. SAMR-Model according to Puentedura 2006[2]).

[2] The SAMR model describes how learning has been changing due to the application of technology. The model helps to derive how the shaping and the handling of learning settings with digital media (digital tools) can be improved. With the aid of the model, the educational staff can

An example for the redefinition in the building sector shows the new shaping of learning processes with the aid of an Augmented Reality application. Equipped with AR- glasses, operators of building machines are provided with details on the terrain before them and receive information on the execution of their current work task. During the excavation of a building pit, they are, for example, assisted by graphical information about the depth of the excavation and about the limits of the radius of the excavator arm (Bach 2019, p. 47).

The machine operator of the future not only has all necessary information at hand. He/she can also have all details projected directly to the building terrain in front of him/her with the aid of his/her data glasses – not only in real time but also in 3D" (ABZ 2019). The SAMR-model[3] is based on the presumption that the quality and the pedagogical benefits of the use of digital media will increase with climbing up the various levels (cf. Heinen/Kerres 2015, p. 21). However, this must take into consideration that the effectiveness of media offers depends on various factors, among others on the learners' domain-specific preliminary knowledge and their existing learning strategy, their intelligence as well as their motivation and volition (cf. Helmke 2014, p. 71).

6 Change of Work-Related Learning Triggered by Assistance Systems and Artificial Intelligence

Work-integrated learning – also named learning in the work-process – is increasingly influenced by digital assistance systems. The real functions and the promotion of learning provided by the applied assistance systems or systems of Artificial Intelligence are likely to depend on how the possibilities of support will be used in the respective application case. Adaptive learning and real-time feedback – both based on "Learning Analytics" – will increase the users' acceptance of the assistance systems. Without innovative didactical concepts at the current state-of-the-art research, it will be difficult to implement scientific and workplace-based learning, cooperative and collaborative learning as well as learning motivational approaches for self-reliant, self-regulated learning (cf. Apt et al. 2018, p. 26).

Generally, the technical assistance systems are classified into information assistants, assistance systems and learning assistance systems (see Fig. 3). Steil/Wrede (2019, p. 14) provide the following definitions:

assign, analyze and evaluate their own training offers. However, the model neglects the shaping of learning processes and thus the didactical implementation. Overall, the SAMR model describes a context-free teaching and learning environment with a focus on the learning product (cf. Hamilton/Rosenberg/Akcaoglu 2016).

[3] The SAMR model (Puentedura 2006) has been developed to analyze the technological integration of digital media in the classroom. This model attempts to measure the degree of technological integration at four levels ranging from enhancement to transformation of learning: substitution, augmentation, modification, redefinition.

Information Assistants: Systems that process and edit digital data and make them available for the users. They draw on databases or internet resources. However, neither physical assistance is involved nor is the environment directly sensorially perceived.

Assistance Systems: All help functions assisted by computers in everyday situations or during work situations are called Assistance Systems. AMan-Machine-Interface is obligatory.

Learning Assistance System: Designates a part of Artificial Intelligence that generates data for models (machine learning) based on existing example data (experiences) with the help of mathematical rules (algorithms). The AI is the generalization, i.e. the application of the models to new entries or situations.

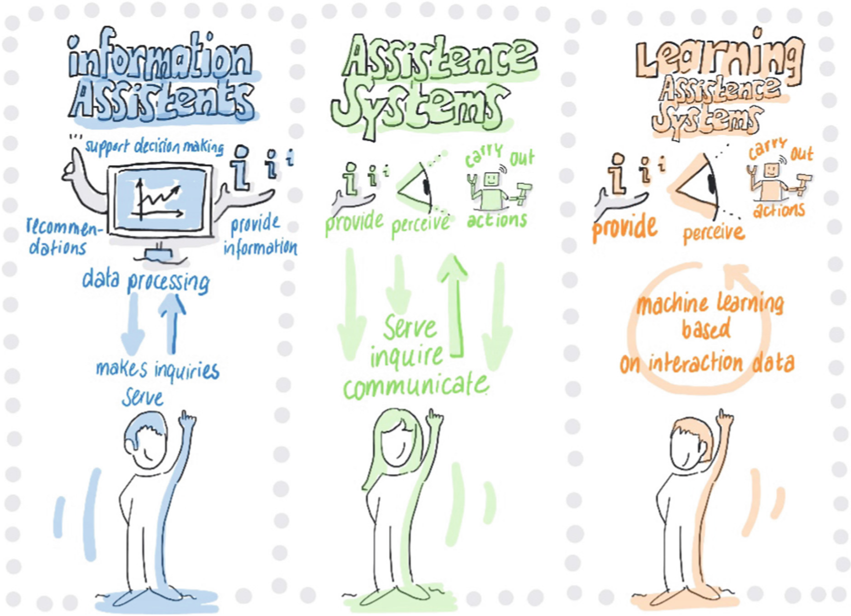

Fig. 3. Interrelationship of assistance systems and machine learning (source: in the style of Steil/Wrede 2019, p. 15)

Based on providing information on work-related information and learning sequences, digital assistance systems are increasingly able to take over tutorial functions and can thus contribute to learning in the work process. Some examples of characteristics supporting learning are mentioned below (cf. Apt et al. 2018, p. 27).

- Functions for providing further information (e.g. on texts, images, videos, and animations that provide a deeper understanding of work tasks and work situations or reveal alternative ways for solutions and acting),
- Providing feedback for one's own actions and decision making (e.g. with regard to effectivity, efficiency, and movement patterns relevant for health as well as so-far not yet considered implications of decisions made in the past),

- Functions on information and knowledge research/documentation (e.g. knowledge databases and knowledge management).

In terms of learning, there will be new possibilities as well as personalized support within the work process, with concrete handling instructions for assembly, putting into operation, the operation as such, or the maintenance of the plants. Information is supplied on demand. According to the context, the assistance system automatically fades in information. A respective control unit helps the users to make use of the information for their acting. However, this only works as long as the actions are predictable, i.e. without new problem situations or imponderabilities. At the same time, the skilled worker can only make limited use of and provide his/her experiential knowledge. The skilled workers' tasks to handle imponderabilities and to act adequately when it comes to unpredictable situations in an increasingly complex and networked world of work will be more difficult than ever. Therefore, assistance systems have to be further developed in order to facilitate this feedback. Skilled workers must remain able to tap into their occupational experiential knowledge to contribute to the solution of the problem (cf. Diagnostic work with expert systems – Becker/Spöttl/Windelband 2021, p. 45).

Based on Stein/Wrede (2019, p. 16) there are currently two trends dominating in practice. Numerous manufacturers of machines and technical systems are equipping their plants with an increasing number of assistance functions: simulations, virtual-reality animations or data displays, and apps for tablets or smartphones. Here, the individual machine or individual work steps are in the foreground rather than the production and the work process as a whole. Second, a lot of applications concentrate on information assistants for the automatization of simple routine decision making, e.g. in terms of customer queries or the processing of orders.

The question arises whether the role of the employees during the implementation of assistance functions and systems will move in the direction of control and operation, thus impeding the acquisition of competences. Another option could encourage the employees to contribute their competences to work-processes and thus allow for an interaction between skilled workers and technical systems in both directions (cf. Windelband 2014, p. 20). In case of system failures or other unpredictable problem situations, the skilled workers must have exactly these competences.

The next development step will be learning with AI. The so-called learning systems can automatically spot approaches to problem solving in the range of their defined tasks, among others by observing their environment and by deduction of rules. There is stronger and weaker AI. "Strong Artificial Intelligence" refers to a programmed computer that thinks and acts like a human being and could eventually even develop a conscience. "Weak Artificial Intelligence" is geared to solving specific tasks in a previously defined area – and only in this area (VDI 2018).

Two future options will be shown for vocational education:

- By a collection of data generated during the learning process ("Big Data", "Learning Analytics") and with the aid of complex algorithms, learning needs can be identified and individual learning paths could be created.
- "Machine Learning": When the computer optimizes its functions based on past experiences and impulses from the outside world.

Learning platforms and online courses are currently prevailing in the area of vocational education and training. Teaching material such as documents, webinars, learning videos, etc. is placed at the disposal of the users, and so are exercises,/learning tasks, and test items. Problems are solved collectively within cooperation and communication systems. With the aid of learning analytics, data on the learning process could be evaluated by algorithms in order to increase the learning success and to adapt the learning process to the demands of the students and the teachers. Data on the learning process (learning materials, conducted exercises, necessary time, number of repetitions), indicators for learning success (points acquired with a test or result of problem solving) as well as characteristics of the learners as such (learning type, cooperation type and communication type, demographic characteristics) are analyzed, compared to each other and automatically evaluated (cf. Rubel/Jones 2016). The analysis of these data allows an individualization of learning settings and a more timely identification of learning problems which could e.g. avoid the dropout of participants of a further training measure.

Another option for the use of Artificial Intelligence in vocational education is the further development of adaptive learning systems. With the use of Artificial Intelligence, these systems are gaining further importance, as the evaluation of data and the adaptation of the learning environment and the learning processes are taking place in real time. As a consequence, the learning system can be adapted even more rapidly to the needs and the learners' level of knowledge (cf. Seufert et al. 2020). Meier (2019) describes three models which are central for the function of adaptive learning environments: 1) The domain model with information about learning objects, 2) the learners' model with information about the level of knowledge as well as 3) the tutorial model with information on learning paths.

The widespread various learning management systems can be amended by AI-based functions in order to contribute to a better handling of contents and learning resources by curation[4] (cf. Seufert et al. 2020; Wentworth/Powell 2019):

- Automated key wording,
- Improved classification and organization of learning resources based on algorithms of natural language processing,
- Efficient search (e.g. full-text search in videos),
- Less effort with the reprocessing of learning resources,
- Identification of thematically related learning resources,
- Automatization of administrative tasks, e.g. assignment of learning resources to trainees/learners based on competence profiles and automated context indexation.

In the field of rhetoric and linguistic abilities, first options of Artificial Intelligence allow a reflection of customers and product presentations – also in terms of Virtual Reality applications. These opportunities could also be applied by trainers/coaches as a feedback on the use of fillers, eye contact, speaking rates or body language. At the same time disruptive factors such as interjections or smart phone noises can be added

[4] In the language of IT-experts, curation stands for anything contributing to the processing of knowledge – i.e. researching, selecting, assigning, summarizing, evaluation and networking of information (Source: https://qurator.ai/projekt/).

in order to change the level of difficulties (EasySpeech 2020). The further development for concrete occupational acting situations in the context of customer advisory service (simulation of service conversations) or sales (simulation of sale situations) could offer a lot of potential for initial and further training.

Thus Learning Analytics would offer a variety of opportunities for occupational education although the current data processing methods are still full of risks. Only a few and unbalanced (further training) data are yet available for analyses (cf. Dressel/Farid 2018). At the same time the forecasts are still inaccurate as they are only based on competence-based parameters without taking into consideration the learning process and its framework conditions (cf. Köchling/Riazy 2019). This can quickly result in a discrimination of this learning type or person as soon as he/she deviates from the given learning structure. Various questions of data protection (among others consent to handle personal data, data identification, data processing and data saving) must be clarified prior to making use of the option of algorithmic data processing.

The use of artificial intelligence for further education can also lead to a higher fit between supply and demand as well as reduce the time-consuming process of searching for offers. The first platforms for personnel development and AI-based learning already exist for the metal and electrical industry. Based on the qualifications of the employees, development goals and possible qualification paths are shown. Algorithms then compare the specifications (qualification needs) in a database of different training providers to determine suitable offers and compile individual programs. The accuracy of fit will continue to grow with the amount of data and the integration of as many training providers as possible (Becker/Windelband 2021, p. 38).

While Learning Analytics have not yet been widely implemented in the field of vocational education, Machine Learning is already emerging in some companies in terms of machines and plants. An example is the proactive maintenance which identifies and monitors the state of wear in components. Sensor data provide information on the condition of machines/processes during their entire lifetime. In the course of time, an exact image of the condition of the machine/plant is building up which can be compared with other machines/plants. Machine Learning algorithms can then be trained with the aid of these data sets on conditions. The Machine Learning algorithms scan this abundance of data for patterns of malfunctions or even a possible breakdown of components (cf. Tidemann 2019). With the aid of the data sets of conditions, Machine Learning algorithms can be trained. They then look for patterns which hint at malfunctions or to a possible breakdown of parts (cf. Tidemann 2019). Predictive Maintenance makes use of data collected by Condition Monitoring in order to forecast future conditions of a machine and to support the planning of maintenance measures. Skilled workers then receive information about the condition of the machine by providing data generated from automated condition monitoring of plant conditions. These data could then support the skilled worker in trouble shooting, by identification of damage symptoms of plants and possible causes for malfunctions (Windelband/Dworschak 2018, p. 77).

Another user scenario is optical quality control which is already applied in a number of companies, e.g. for the identification of spare parts, the differentiation between "good" and "bad" parts, the identification of anomalies or more generally to determine the quality of a manufactured part. The company Festo Didaktik, for example, is working on the integration of Artificial Intelligence in learning companies[5] for further training in the field of vocational education. The image classification has been chosen as an access to the issue. The included software guides the user across the typical production steps, starting with the generation, the saving and preconditioning of relevant data, the choice and the training of an appropriate AI-process up to the use of the application as such (Schubert 2020). According to the user (developer, end user) the case examples must be offered in a didactically reduced way.

Mastering the complexity of these systems is the biggest challenge. This multitude of data must be correctly interpreted and evaluated. The Man-Machine-Interface will play a decisive role. How will decisions be made on which base? In terms of maintenance, skilled workers are trying to base their decision making on their experience and make use of intuition, senses, feel, and certain process data. What remains open is how the support of the skilled workers will look like as soon as Machine Learning will be governing automated machine supervision and which opportunities of intervention will remain at the discretion of human beings. In the light of these increasingly automated systems the question arises: Will it be possible for humans to build up expert knowledge in order to identify malfunctions and possible solutions in decisive situations, above all when Machine Learning cannot find any solutions? At the same time, skilled workers must learn how to analyze, evaluate and process these data according to their occupational training profession (cf. chapter on consequences).

7 Opportunities and Risks of Artificial Intelligence for Vocational Education

It is still very difficult to estimate the exact opportunities and risks for vocational education due to the fact that the development of Artificial Intelligence is still "in its infancy" in the context of vocational learning (Table 1).

The following points illustrate the potentials and risks for vocational education.

[5] The learning company is a learning environment, which resembles an industrial laboratory and is equipped for industrial problem solving in automation. It is meant to offer a practice-oriented preparation for work in complex and networked production processes. Real work pieces are manufactured in learning companies, starting from the first designs up to production along the entire valued-added process (Windelband 2019, p. 34).

Table 1. Overall definition of AI-influenced autonomy-steps in industrial production (Source: Plattform I40 2019, p. 14).

Step 0	*No autonomy:* The human being is in full control without assistance
Step 1	*Assistance with selected functions:* The human being is always responsible and makes all decisions
Step 2	*Part-time autonomy in clearly defined fields of work:* The human being is always responsible and determines (partial) goals
Step 3	*Delimited autonomy in larger partial areas:* System warns in case of problems, human being confirms suggested solution offered by the systems and functions as fallback level
Step 4	*The system works autonomously and adaptively within determined limits of the system:* The human being can supervise or react in case of emergency situations
Step 5	*Autonomous operation in all areas*, also in cooperation and in case of changing system limits. Human beings can be absent

7.1 AI Supports the Handling of Complexity

The handling of complexity is one of the challenges in the age of digitalization. This is where AI can offer support (see step 1 as well as step 2 above[6]) by evaluating all available data and by providing skilled workers with information on current conditions and forecasted developments. Intelligent machines, plants and networked business processes point out the different program options and the respective effects. With the aid of this option, the skilled worker is able to make decisions and to find problem solutions in interaction with technology (Assistance Scenario cf. Windelband/Spöttl 2012).

Step 3 forms the bridge between assistance and automation: Human beings confirm certain strategies for solutions or support them in case of specific problems. This step stands for a delimited autonomy in larger partial areas. The system warns autonomously in case of problems (cf. Plattform I40 2019).

On the highest autonomy step (Step 5) of Artificial Intelligence (ibid., p. 18), the operation of a plant or a comprehensive production process should run completely autonomously. The system works out self-organized solutions. While the human being still has supervising functions in step 4 and can interfere if the need arises, this is no longer intended in step 5. Here, the Artificial Intelligence makes all decisions autonomously (Automatization Scenario, cf. Windelband/Spöttl 2012). Steps 4 and 5 would lead to a serious loss of work places, above all on skilled worker level. If all decisions were taken over by Artificial Intelligence, the ability of skilled workers to handle complex situations would fade away. Thus, the question arises what would happen in case a problem cannot be solved by Artificial Intelligence.

7.2 AI Supports Corporate Learning and Creates a Learning-Supporting Work Environment

In the future, data on vocational learning could be evaluated with the aid of learning analytics and algorithms in order to enhance the learning success. The projected evaluations could thus be enhanced with learning information or simulated in virtual environments as training scenarios (cf. Peissner et al. 2019, p. 11). At the same time, the data could be

[6] Overall Definition of AI-influenced autonomy-steps in Industrial Production (Plattform I40 2019, p. 14).

used to identify early terminations. Learning offers could be better tailored to the needs of the target groups who could then learn more individually[7]. However, this can only be successful when AI systems are shaped in a learning supportive way. Sensitive data must not be used to the detriment of the individual learners.

A learning-supportive work environment is the basic prerequisite for a sustainable development of competence and consequently for the creation of continuous improvement processes. Skilled workers in working environments using AI must be granted a leeway to participate in decision-making or to make their choice between alternative decisions. Competences for the analysis, the processing and the interpretation of data will become increasingly important for skilled workers. A learning-supportive work environment needs room for problematic and thus learning-supportive tasks.

With the aid of AI-based assistance systems, it is possible to train low-skilled persons in the handling of more complex work tasks. They are supported during their processing of work tasks. The quality of the work results can thus be increased. New target groups (semi-skilled and unskilled, refugees without vocational training) could be qualified for vocational training. A decreasing number of more complex tasks in the companies due to their use of AI systems (steps 3 to 5) could result in a predatory competition among semi-skilled personnel on skilled worker level.

7.3 AI Creates and Destroys Work Places

With the introduction of AI-systems on steps 4 and 5, it is most likely that work places on the skilled worker level will disappear. On the other hand, the implementation of AI assistance systems in all branches will create new workplaces, above all during the development and the implementation of AI-systems. At the same time, these AI-systems must be implemented, operated, and maintained.

Concrete forecasts are currently scarce. A study by the German Institute for Employment Research (IAB) and the German Federal Institute for Vocational Education and Training (BIBB) shows the impact of digitalization in a differentiated way. According to the study, the manufacturing industry will probably witness the heaviest loss in employment due to digitalization. Around 130,000 workplaces are likely to be lost. On the other hand, the study expects that the sector "information and communication" could probably be the winner in terms of employment with a forecasted 120,000 additional workplaces (Zika et al. 2018). The current study "Automation, Skills Use and Training" conducted by the Organization for Economic Cooperation and Development (OECD) fears that 14% of all jobs could be lost in the future due to the fact that robots or algorithms are taking over the tasks. Another 32% of occupational profiles in the OECD Member States would witness a radical change (Pouliakas 2018). The highest substitutability potentials are still found in manufacturing occupations (almost 84% of jobs could be automated); the lowest in social and cultural service occupations. 34% of employees paying social insurance contributions are carrying out tasks that could someday be replaced by robots or algorithms. In 2018, this figure was at 25%. This is the result of a study by Dengler/Matthes, published in 2021.

[7] As early as in the 1980s, Bloom (1984) has already shown that learners who were individually supervised 1:1 with tutors showed better results in exams than learners in conventional learning arrangements (frontal-oriented learning settings).

8 Consequences for Vocational Education

The already existing qualification structures and – in the long term – also (almost) all occupational profiles are considerably influenced by changes in the world of work due to digitalization and Artificial Intelligence. At present, the direction of development and a forecast on the necessary competence profiles cannot always be further described.

Digitalization partly creates brand new training occupations such as commercial clerks for e-commerce, a training occupation across all sectors dealing especially with online trade. At the same time, more and more vocational occupations with hybrid structures will probably be needed (cf. Becker et al. 2022). Forecasts are currently very difficult to formulate. A lot will depend on the future shaping of work- and business processes. Interrelationships between the increasing technization of work with assistance and AI-systems, the changed organization processes, the workload as well as the self- or other-directed possibilities for action will be decisive.

Most of the current occupations on skilled-worker level are currently not in danger to be lost – on the contrary: Some occupations are even experiencing an upgrade because routine and heavily stressing tasks are supported by assistance systems. In addition, more qualified tasks in terms of diagnosis, analysis and evaluation of (process) data have been added to the occupational profile. This may lead to an increase of attraction of skilled work, of the "blue collar workers", as soon as the work places are shaped in a way that all competences and above all experiential knowledge can be brought along. Target groups of young people who are currently aiming to start an academic career could be won for skilled work as workplaces are becoming more and more interesting due to the integration of new media/tools such as tablets, augmented-reality glasses or robots. However, the requirements on the skilled worker level are increasing and include interdisciplinary thinking and acting in networked systems. The implementation of digitalization could be supported by assistance systems and AI-systems. These auxiliary systems must be shaped human-oriented in order to leave the better part of decision making within a company to the employees. This would be an important prerequisite for securing work places in a digitalized world of work.

Occupational learning is increasingly influenced by digital assistance systems. The actual learning support of applied assistance systems or AI-systems will depend on whether and how the skilled workers will still be given the option of intervention and control.

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