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Towards artificial intelligence in production: A competence profile for shop floor managers

Rosemeyer, Jannik[a]*; Bardy, Sebastian[a]; Pinzone, Marta[b]; Bosani, Enrica[c]; Schubert, Tobias[d]; Metternich, Joachim[a]

[a]*Technical University Darmstadt, PTW, Otto-Berndt-Straße 2, 64287 Darmstadt, Germany*
[b]*Politecnico di Milano, Department of Management Engineering, via Lambruschini 4b, 20156 Milan, Italy*
[c]*Whirlpool EMEA S.p.A., Via Aldo Moro, 5, 21024 Biandronno VA, Italy*
[d]*Festo Didactic SE, Rechbergstr. 3, 73770 Denkendorf, Germany*

Abstract

Artificial intelligence (AI) technologies experience an ever-growing interest both in research and industry. Though they offer high potential for manufacturing, recent studies among practitioners reveal that there is a lack of knowledge for implementing AI in production environments and especially for leading an implementation successfully. Therefore, in this paper, a competence profile for shop floor managers has been developed. Shop floor managers are seen as suitable levers in companies for implementing AI technologies. This profile focuses on their practical requirements and encompasses relevant production-oriented use cases, social factors for engaging employees and deeper understanding of the models to interpret the results. The profile has been put into practice by means of learning content and has been tested by shop floor managers. The feedback is promising: About 78% of the testers stated that the content is helpful for them in understanding the benefits, challenges, tasks, and risks when implementing AI based projects. The results serve as a baseline for future development of learning materials with corresponding exercises to be taught in learning factories targeting the hands-on AI implementation.

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Keywords: artificial intelligence; shop floor manager; machine learning; vocational learning; competence

1. Motivation and Background

Artificial intelligence (AI) applications are considered to have high potentials for improving production environments of manufacturing companies [1, 2]. Although the technology is undergoing major changes [3], employees and hereby later users remain a critical success factor who need to be trained [4]. A recent study among German practitioners reveals that only few companies already have competence holders in the form of AI experts – and that the lack is even larger among small and medium-sized enterprises (SME) [5]. To upskill employees, the people interviewed in the study above indicated that practical learning material is required. According to the participants' statements, practitioners require content that they can easily transfer to their every-day problems. Following this gap, the paper at hand focuses on competences tailored to practical needs of shop floor managers to empower them for implementing and work with AI applications in their respective production environment. Therefore, the emphasis of this paper is not on the technical side of implementing AI but rather about selecting use cases in production and managing a team that uses the AI application. In this context shop floor managers are academics, production managers and team leaders with decision-making competence but not necessarily with a data scientist background [6]. Shop floor managers are seen as suitable levers for further dissemination of AI within their company as they bring along broad domain knowledge on the one hand and decision-making competences on the other hand.

* Corresponding author. Tel.: +49 6151 8229658
E-mail address: j.rosemeyer@ptw.tu-darmstadt.de

The remainder of this paper is structured as follows: In chapter 2 relevant background knowledge and terms used throughout the paper are introduced. Chapter 3 explains the procedure for conducting the literature research and the expert interviews. Chapter 4 contains the main part of our work as it outlines the competence profile for shop floor managers. Chapter 5 describes the feedback that was given when introducing the profile in a globally acting company. Finally, chapter 6 summarizes the paper and provides an outlook to future work.

2. State of the art

In the context of this publication, competences are defined in accordance with Erpenbeck and Rosenstiel as "abilities and dispositions that allow meaningful and fruitful action in open, complex, sometimes chaotic situations, i.e., that enable self-organized action under mental and representational uncertainty". [7] According to the authors, competences include actions, knowledge and qualifications [7].

These subcategories are the elements of a so-called competence map, which is used in this paper to systematically record the necessary competences for shop floor managers. In a competence map, main competences are assigned to the respective actions and knowledge elements that are necessary to obtain the respective main competence [7]. Furthermore, the competence map includes a classification for categorizing the educational goal for each competence. It is rated after the six levels of Bloom's Taxonomy to highlight if a competence is in the category remember (1), understand (2), apply (3), analyze (4), evaluate (5) or create (6) [8].

Although numerous researchers dealt with competences in regard of AI in vocational education [9–13], to the best of our knowledge there is no publication directly focusing on shop floor managers and their everyday needs. For example, Rokoss et al. describe learning factory courses for AI implementation in production [14]. Nevertheless, their work is focused on the technical and mathematical details of AI rather than focusing on the management perspective. The authors of [15] develop an exercise for providing a basic understanding of key concepts of AI technologies tailored to decision-makers. The exercise is based on accounting data and once again focuses on technical aspects of AI. Therefore, the learners must transfer the learning content to their own work environment (in our case the production). An AI algorithm used for accounting can only partly be transferred to use cases in production. A more production focused work is done by [10] who developed a competence profile focused on shop floor personnel.

Following the goal to close the gap of missing competence descriptions for shop floor managers, this paper aims at preparing them for the implementation and use of AI technologies in their respective production environment. For this, a competence profile is set up encompassing relevant competences that shop floor managers are required to have. These competences e.g., include production-oriented AI use cases, social competences for engaging and convincing employees and the top management or deeper understanding of the models to interpret the results and data used. The competence profile is then translated into digital learning material which can be shared online.

3. Methodology

The research methodology used can be subdivided into two steps. First, a literature research to identify required competences was conducted. In the second step, expert interviews (EI) with 14 industrial experts were held. From both stages relevant competences were extracted that were finally merged into the competence profile. In the following, each of the steps is explained in more detail.

Required competences for shop floor managers as enablers for implementing AI technologies were investigated in the first step. Here, both social-communicative and technical-methodological competences were focused on [7]. Basic knowledge such as the distinction of AI and machine learning (ML) or the functionalities of an artificial neural network was not within the scope of the research. The literature search was finally conducted on the Web of Science (WoS) using the search terms

- ((Artificial Intelligence OR Data Science OR Machine Learning) AND Requirements AND education)
- ((Artificial Intelligence OR Data Science OR Machine Learning) AND competenc#)
- ((Artificial Intelligence OR Data Science OR Machine Learning) AND (competenc# OR Skills) AND production)
- (Industrial IoT competenc#)
- (Managerial competenc# AND Industry 4.0).

Due to the novelty of the subject and the consequently changing competences the search was limited to the last ten years. Papers dealing with the industrial internet of things and Industry 4.0 were included based on their close connection to AI [4, 16].

In addition to the literature review, the findings were supplemented by semi-structured interviews [17] with 14 practitioners working as plant manager, process manager, shop floor manager and employees from human resources tasked with training AI, respectively. At the beginning, the experts were asked to outline their department's vision towards AI and to indicate possibilities for AI technologies in their everyday shop floor management. Furthermore, the experts were asked to name required competences for shop floor managers regarding AI and which of them they would like to develop in the first place.

In the third step, the findings of the two previous steps were merged in a competence profile and extended with corresponding sub-competences, knowledge, and action. Moreover, the competences were classified according to Bloom's taxonomy with the goal to have most of them with a complexity of 3-4, which was considered by the experts to be most suitable for shop floor managers.

In the final step, in order to validate the competence profile, digital learning materials were created to address the competences. The learning material was then tested by manufacturing practitioners. At the end, a survey was distributed among the learners to gather their opinion on the relevance of the competence, the self-assessment of the acquired knowledge and their satisfaction with the learning experience.

4. Results

4.1. Competence profile of shop floor managers

The following explanation presents the results of the first two steps and elucidates each competence in more detail. Table 1 provides an overview over the main competences and respective sources. Table 2 then sub-divides the main competences in sub-competences. Additional information is given in the following paragraphs. The profile is oriented in its sequence to the facets of [18].

Table 1. Main competences with respective source and classification

No.	Main Competence	Source	Level of Bloom's taxonomy
1	Identify possible use cases for production	[5, 19], Expert interviews	3
2	Plan implementation effort for AI	[19–21], Expert interviews	3
3	Predict possible costs of AI implementation	[19], Expert interviews	3
4	Illustrate advantages of AI to top management	[5], Expert interviews	4
5	Engage employees in using AI technology	[4, 22, 23], Expert interviews	4
6	Summarize algorithms in machine learning	Expert interviews	2
7	Interpret results/data of AI	[24, 25]	6

Literature agrees that it is necessary for employees to identify use cases and point out corresponding advantages in production environment [5, 16, 19]. This finding can be underlined by several replies during the expert interviews, in which the importance of use case knowledge was stated. Thus, shop floor managers as levers for AI implementation need to know most frequent used AI use cases which are maintenance, quality, intelligent products and services and robotics, respectively [1, 16, 26]. For each of those use cases, shop floor managers then should be able to indicate how AI applications can enhance existing solutions, e.g., by predicting future failures or to distinguish OK from not-OK parts. Lastly, they are then obliged to transfer the knowledge gained to their respective production environment.

Both research (e.g., [19, 21]) and industrial practitioners highlight the capability to plan, lead and execute many integrated projects as a crucial competence for the successful diffusion of new AI-based solutions in manufacturing. Shop floor managers must be able to define their current organization's maturity with respect to data and AI, the future vision and desired profile as well as identify the prerequisites and actions needed to migrate from the current to the target state. Additional competences have to be gained by considering the links to the business strategy as well as benefits and costs, risks and dependencies, evaluate to what extent investments are justified and what actions should be prioritized to develop and deploy AI [20]

The experts interviewed also point out that shop floor managers need social competences to explain advantages to the top management. This is in line with the results of [5] who reveal that a critical success factor for a profitable implementation of AI projects – especially in SME – is convincing top management of a financial added value. Technical goals like increased Overall Equipment Effectiveness, less maintenance effort or simplified work for employees must be translated in business goals and financial revenue like save of time, save of costs or other suitable key performance indicators. Troublesome is that AI projects can hardly be expressed in return of investment – a mindset that many top managers seem to have [5].

Not only shop floor managers but also their employees need to be able to work with AI applications. Yet, they often bring fears of a new and unknown technology as being overloaded or replacing human activities, resulting in job losses. Thus, shop floor managers should be able to deal with those fears for one thing and then again to engage workers in using the technology with respect to qualifications [4, 22, 23, 27]. Experts from HR in addition indicated that shop floor managers need to be able to strengthen the change management within their department.

Besides, shop floor managers as domain experts need to have deeper knowledge about frequently used algorithms. They do not have to be able to program algorithms themselves but rather understand them. Hence, they are enabled to strengthen the communication with their IT and data science counterparts [23]. This knowledge encompasses most common regression and classification models [24] and the fundamentals of unsupervised models (e.g., k-means algorithm [28]). Additional models like convolutional neural networks [29] or support vector machines [30] should be familiar, without the need to understand them in detail. This knowledge can for example be gained by the courses of [10].

Finally, shop floor managers must be able to assess the performance metrics characterizing an application of AI in manufacturing and interpret the results coming from AI systems during the deployment phase [24]. Unless shop floor managers evaluate the ML performance, the usefulness of the models is difficult for them to determine. They should be able to interpret the performance metrics of different models, decide if they are acceptable or what should be done so that they can be improved [25].

The level of Bloom's Taxonomy for each competence are mainly on level "apply (3)" and "analyze (4)", since for example shop floor managers are not required to teach the content to others. This does not hold true for the interpretation of results of AI, where the shop floor managers must explain and defend results to higher and lower ranked employees which justifies the highest taxonomy level. On the other hand, shop floor managers only need to "understand (2)" statistical methods in competence 6. The taxonomy levels have been evaluated by the experts and are an important aspect in the creation of the learning content described in the next chapter.

In addition, the main competences were further detailed by 26 sub-competences. Those sub-competences were extracted from explanations of the experts and the authors of the publications listed in Table 1.

Table 2. Main competences and sub-competences

No.	Main competence	Sub competence
1	Identify possible use cases for production	Differentiate the main use cases of AI in production Find examples for frequently used AI implementations within the respective production. Distinguish AI implementation fields from not-implementation fields
2	Plan implementation effort for AI	Predict realistic time horizons from development to productive stage Identify the main steps for the implementation Identify possibilities to gain help during implementation
3	Predict possible costs of AI implementation	Predict realistic time horizons with respect to amortization / ROI Identify costs of implementation Identify necessary prerequisites Identify required data Relate problems with AI / possible failures (risk management)
4	Illustrate advantages of AI to top management	Illustrate financial possibilities of AI Illustrate increase in productivity/efficiency through AI Demonstrate how prejudices of employees can be reduced Describe missed opportunities are in case AI in production is not implemented
5	Engage employees in using AI technology	Advantages of AI for the employees Estimate fears and insecurities that go along with the implementation of AI Address fears and insecurities of employees Organize the team with respect to tasks and required qualifications regarding AI use cases Prepare employees for the usage of AI technologies Explain in what way SF workers are required for successful implementation
6	Summarize algorithms in machine learning	Describe advantages/disadvantages of classification and regression models Describe advantages/disadvantages of unsupervised models (e.g., k-means) Name further frequently used algorithms and their most common application field
7	Interpret results/data of AI	Contrast the results with respect to statistical/mathematical background Justify the results to higher and lower ranked employees

4.2. Validation of the profile

In the next step, the dissemination in manufacturing environment is focused. Various approaches are conceivable for this [31]. In order to identify the practical feasibility of the competence profile, digital learning materials were created to address the competences. Seven modules of 30 minutes reflecting the seven main competences based on the systematics of [32] were realized. In those modules, theoretical content addressing the sub-competences and if applicable production-oriented use cases for deeper understanding is provided, which is rounded off by reflection questions. Additionally, two exercises were set up for competences 1 and 7 deepening the respective content. The learning material lastly ends with a test summarizing the entire course.

The learning material was then validated from September to December 2021 with 18 practitioners. The learners had the possibility to consume the learning materials through an online platform in an asynchronous way. They could access the platform as many times as needed. At the end of the period, a survey was distributed among the

learners to gather their self-assessment of the acquired knowledge, their satisfaction with the learning experience and their assessment of the importance of the competences. The survey was based on a Likert-scale with answers ranging from "strongly disagree" (translated with 1) to "strongly agree" (translated as 5). The following paragraph displays an excerpt of the results.

From an overall perspective the training carried out was successful. The developed training content has been much appreciated by the industrial stakeholders involved in the validation phase. This is supported by the fact that the learners indicate their satisfaction with an average of $\mu = 3{,}83$. The results also clearly show that the profile helped the participants in gaining necessary AI knowledge. Indeed, the average self-assessment increased strongly: $\mu_{previously} = 2{,}39, \mu_{afterwards} = 3{,}50$. The training is addressing a business need that is new for manufacturing people and is considered a crucial enabler for the digital transformation.

The right combination of theoretical parts and practical exercises has been appreciated as well as the simplification at the right level of detail of some complex technical content. Indeed, most of the shop floor managers would even recommend the content to a colleague ($\mu = 4{,}06$).

Finally, learners were asked to assess the importance for each of the main competences (Fig. 1). It is apparent that an overall relevance of the competences is seen. This is especially true for competences 1, 2, 3 and 5, which are attributed to be very important, whereas the competences 4, 6, 7 are slightly less important. Negative feedback has been highlighted on the general duration of the whole profile, even with the possibility to interrupt and restart on demand. Nevertheless, the duration has been justified by the overall logical order and necessity and no content has been identified for a drop.

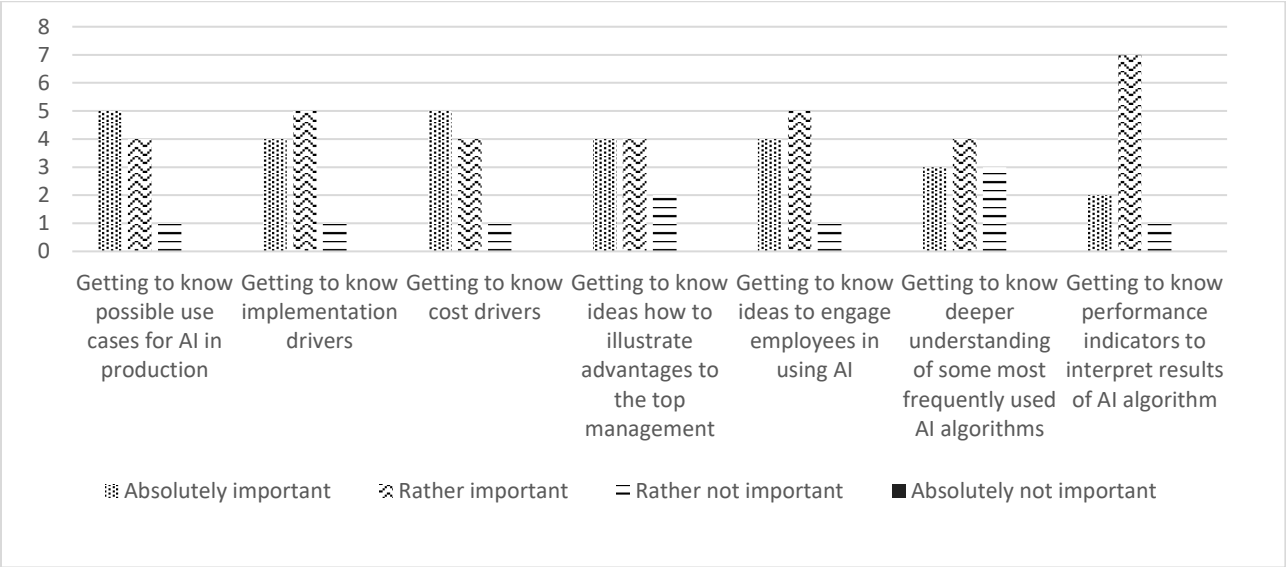

Fig. 1. Participant's opinion regarding the importance of the competences (n=10)

5. Summary and Outlook

The paper at hand provides required competences for shop floor managers when implementing and using AI systems in production environment. Based on a literature research and semi-structured interviews, a competence profile consisting of seven main competences and 26 sub-competences was developed. The profile was then validated by means of digital learning material with practitioners yielding promising results. The feedback clearly shows that the shop floor managers see the competence profile with its competences as relevant and would recommend it to their colleagues.

The research results support companies in preparing shopfloor managers and decision makers in production environment for the implementation of AI technologies. For example, it is possible for interested companies to gain access to the digital profile via the platform of the EIT Manufacturing. It is intended to use the profile as a foundation for the development of training materials in the learning factories of the authors' facilities such that more shop floor managers interested can profit of the works' results.

For future research, the teaching of the content not only in theory but also in other learning settings such as learning factories should be targeted. The conceptualization of related exercises therein should be at the forefront of this process. If applicable, necessary adjustments to the profile should be made based on new insights. An open question is whether proven approaches are also relevant for the competence transfer of AI or whether new approaches should be developed.

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