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Extension of the CCMS 2.0 maturity model towards Artificial Intelligence

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Abstract: The role of Artificial Intelligence (AI) is becoming more and more important in the area of production and manufacturing. While experiencing the rapid changes in the Industry 4.0 era, companies are striving to remain competitive by exploiting the potential of digitization. In the road towards Industry 4.0, companies have to evaluate their capabilities and determine goals for the future: these are supported by maturity assessment models, such as the Company CoMpaSs (CCMS) model. As technologies evolve, these models have to be improved as well: the aim of the paper is to update the CCMS model with AI aspects that were not detailed enough previously. In the paper, the authors first perform a literature review on the topic of application of AI in the production area, and also interview experts from the industry and academia in order to create a basis for the AI aspect in the CCMS model. Second, the model is extended with one additional dimension called AI applications, based on the above-mentioned results and taking the pathways and development levels determined in the Connected Factories project into consideration.

Keywords: Maturity model, Artificial Intelligence, Digitization

1. INTRODUCTION

The connection between the real and virtual world is becoming more and more important in the area of production, manufacturing and logistics. Digital twin provides a virtual representation of a physical asset in a company facilitating improved decision making, optimization, prediction and monitoring (Rasheed et al., 2020). It plays a key role in the operation of cyber-physical intelligent systems strengthened with the recent hype of AI solutions in the industry. Artificial Intelligence (AI) based systems are human-designed software or hardware systems that perceive their environment through data acquisition, interpret the collected data, argue on the basis of their knowledge or process information derived from this data, and decide on the most effective measures to achieve a given goal. AI systems can use symbolic rules or learn a numerical model and change their behavior by analyzing how previous measures have affected the environment. AI can also help increase the efficiency of companies, thanks to robots in manufacturing, optimizing logistics systems, or maintaining factories and forecasting potential problems (Rathore et al., 2021).

However, the literature of AI solutions and methods in the context of digital twins and production, manufacturing and logistics are in the preliminary stage and started to grow recently. Most of the scientific publications are from 2020 and 2021 according to the Scopus database; their number started to grow from 2018. Surveys are rear, we found only four articles dealing with these topics in Scopus in January of 2022 (Minerva et al., 2020; Yitmen et al., 2021; Bosch-Sijtsema et al., 2021; Rasheed et al., 2020).

Rasheed et al. (2020) discuss the recent status of methodologies and techniques related to the construction of digital twins, mostly from a modelling perspective. Bosch-Sijtsema et al. (2021) focus on opportunities, barriers, use and knowledge of digital technologies for the different actors in the Swedish Architecture, Engineering, and Construction (AEC) industry. Yitmen et al. (2021) perform a survey of industry experts focusing on life cycle applicability, interoperability, and the Cognitive Digital Twins (CDT) model's integration in practice. Minerva et al. (2020) deals with the essential fundamental characteristics of digital twins, its technical and business value from the applicability and opportunities aspects. They present four application scenarios and, as a conclusion, a generic digital twin architectural model.

Nowadays, in the era of Industry 4.0, it is essential for organizations to develop themselves in terms of digitization in order to remain competitive. This means a different thing for each of them, depending on their current situation and the goals they are planning to achieve. This is a complex area where the companies need some guidance, which is the exact role of Industry 4.0 maturity assessment models. Nick et al. (2019a) show the difference between Hungary, Austria and Germany in terms of Industry 4.0 interpretation, strategies and readiness models. According to this comparison, the aims of the countries and the maturity level of the companies are also different: for Germany the main goal is to preserve its leading role, while in Hungary

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the challenge is to catch up with the frontrunners and join the international value chain. This can be observed in the scientific publications in the different countries as well: according to the results of a survey conducted in Hungary Nick et al. (2019b), although data is being collected in manufacturing companies, in most cases its use has not yet become the integral part of the production processes in the country. Meanwhile, in Germany, the question in general is not whether the collected data is used, the digitization level of the companies are higher than in Central Europe. Research institutes are already investigating topics e.g. on what extent do the companies implement AI in production planning and control (Colangelo et al., 2021).

The aim of the Company CoMpaSs (CCMS) model (Nick et al., 2020) is an online Industry 4.0 maturity assessment tool, which most important output is a prioritized list of *intervention points* that are the recommended areas to work on for the company (see more details in Section 4. As the different technologies evolve, the tools that are measuring the development of these technologies has to be updated as well, in this case resulting in the fine-tuned CCMS 2.0 (Nick et al., 2021). Based on the results of the literature review and expert interviews, there is a need now to assess the application of AI in the company, also; the CCMS 2.0 model will be extended by adding one more dimension including intervention points in connection with AI. For the development levels assigned to this dimension, the authors are considering the levels determined in the Connected Factories (CF) project (European Factories of the Future Research Association, 2020), which aim is to help and navigate companies in their digital transformation with elaborating pathways and cross-cutting factors between them (see Section 5).

The goals of this paper are the following: First, to conduct a literature review and expert interviews to see the role of AI methods in connection with digital twins and production, manufacturing and logistics. Second, to extend the CCMS 2.0 model with an additional dimension by taking the conclusions drawn from the above results and the development levels of the CF project into consideration.

2. RESEARCH METHODOLOGY

First, a literature review was performed to see the role of AI, the relevant application fields that can be included in the maturity model intervention points and the application levels of AI methods both in research and in industry. As Snyder (2019) states, a review can be applied as the first step of a research method and process for identifying and appraising relevant research, as well as for collecting and analyzing data in order to draw consequences that can be used as a basis of a research study. Second, *interviews with experts* were performed to see the effect of AI in a real industrial environment. In total 36 interviews were made with experts working or doing research in the area of manufacturing, production and supply chains. 24 of them (66%) had a degree in engineering, 12 (33%) in economics, 6 (17%) in both. 10 (28%) of the interview participants had an MSc degree, 26 (72%) had a PhD. Practical recommendations and suggestions made by these experts were also taken into consideration when formulating the new dimension in the CCMS model (see Subsection 4.2)

Teichert (2019) proposes a *six-step development approach* for developing a digital transformation maturity model in service organizations: (1) defining scope (2) design (3) populate (4) test (5) deploy (6) maintain. This approach was applied in the development process of the CCMS 2.0 model (which was already tested by companies and their feedback were collected), and the authors are using the same for the extension of the model, also. As the scope is already defined - the application of AI has to be measured - the design phase of the extension process is introduced in the paper.

3. LITERATURE REVIEW

3.1 Research method

Despite the rapidly growing popularity of digital twin models and artificial intelligence, comprehensive systematic literature reviews related to the above-mentioned methods are rare. Rathore et al. (2021) filled the gap by giving an extensive review and presentation of research currently using state-of-the-art digital twin models and artificial intelligence in the industrial sector. They searched several electronic libraries and covered a wide range of industries, such as manufacturing, power and energy, automotive and transportation, healthcare, network and communication. However, the focus of this section is similar, our aim was to get a comprehensive overview of the latest research topics and results, applications of combining digital twin and artificial intelligence on the field of manufacturing, production and logistics. The search presented here was carried out in October, 2021, using the electronic bibliographic database Scopus. The search strings, which are the crucial part of the literature extraction, is shown in Fig. 1. Digital twin is included in the search strings because it is a must-have in order to use AI capabilities in the most efficient way. The authors further narrowed our search results to journal articles which language is English and was published since 2017: in total, 176 articles have met this criteria. The following main research questions were defined in connection with a reviewed paper that was investigated in the literature review:

- Which topic of the following is the article related to: product design/development, optimization, logistics, production network, or other?
- What method of the following has been applied or proposed in it: deep learning, reinforcement learning, regression, classification, clustering, digital twin, simulation or some other? In this section, we also examined if no specific method is proposed or applied, but only a theoretical approach is presented.
- What are the trends in the number of papers presented in the above areas?

3.2 Results

The findings demonstrate that there has been an increase in the quantity of academic research in the field of AI method applications in digital twin modeling since 2017 (see Fig. 2). This is also in alignment with the work conducted by Rathore et al. (2021).

In order to answer the research questions, several keywords were defined for each topic, and then the articles in

"digital twin"	AND	"artificial intelligence" OR "big data"	AND	"manufacturing" OR "production" OR "logistics"
	AND	"machine learning" OR "deep learning"	AND	
	AND	"predictive analysis" OR "regression" OR "classification"	AND	
	AND	"cluster analysis" OR "cluster"	AND	

Fig. 1. Search strings

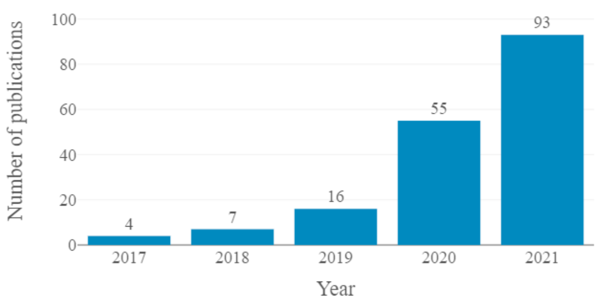

Fig. 2. Number of publications by year

which they appear were counted using a Python script. To decide whether a keyword appears in an article, the Author keywords, the Index keywords and the Abstract fields were checked. Examining different fields, such as manufacturing, production and logistics the authors found that methods combining AI and digital twins have received poor research in the field of logistics, while manufacturing and production appear more frequently. The topic of the articles has been investigated, also: in Fig. 3, the size of each rectangle with a topic name corresponds to the frequency of the keywords, i.e. the multiplicity of articles in which they appear. More specifically the most publications are focusing on production processes, production development and product design, the other categories (logistics, production network, others) were too small to visualize.

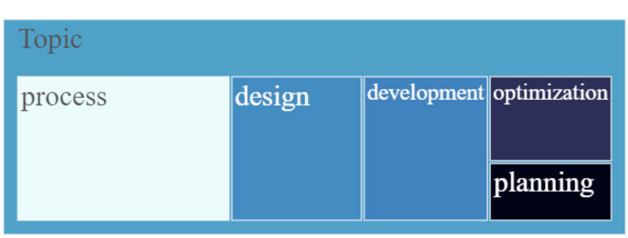

Fig. 3. Frequency of keywords related to the subarea of the articles

The authors also examined the popularity of AI methods in recently published papers. The leading fields are Deep Learning (DL), i.e. neural networks and classification problems. As one can see in Fig. 4, DL is gaining more and more popularity, due to its supremacy in terms of accuracy, when a large amount of data is used in the training phase (Lee et al., 2020).

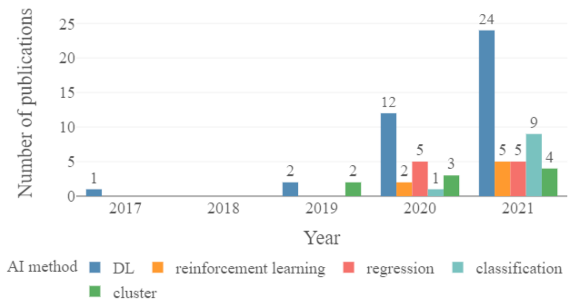

Fig. 4. Frequency of keywords related to the AI methods of the articles

In most of the articles, the leading concept is about proposing a theoretical approach, i.e. digital twin using an artificial intelligence framework or architecture. However, the number of applications in a real industrial environment is still lower than the number of theories. However, the two numbers are getting closer to each other: it can be expected that the number of applications will exceed the number of theoretical approaches in the future. (The applications found during the review were used to define dimensions of the model.) It was also interesting to see that data security and safety issues are rarely (around 12%) discussed in the examined publications. Nevertheless, the authors' opinion is that the importance of this will increase in the future, with the growing number of real applications.

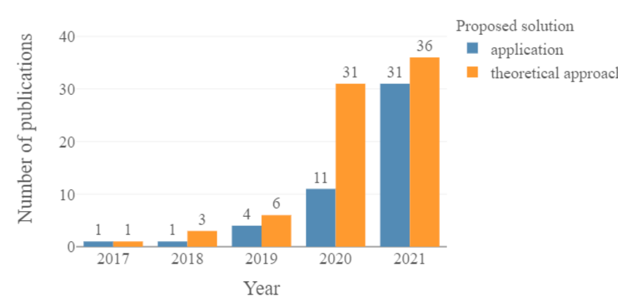

Fig. 5. Number of articles presenting a use case or theoretical approach by year

4. CCMS MODEL

4.1 The existing model

The CCMS model (Nick et al., 2020) is based on an online survey and considers both business and technological views. The answers given by the respondent company are weighted, and intervention points are selected from a predefined set of eight elements per dimension on the basis of analyzing the responses. The output of the model (besides the statistical evaluation of the results like comparisons to averages derived from metadata) is a prioritized list of intervention points that shows the most important fields of action for the respondent on an interactive dashboard.

The applied weightings are determined by the model creators and result from the inherent structure of the model. CCMS provides a quick (meaning that the respondent gets prompt results), low-risk, online maturity assessment for organizations. Tests of the CCMS model revealed that the companies' self-assessment depends heavily on the organizational hierarchy and the organizational approach. The additional problem is that the significant number of intervention points and questions reduced the understandability and applicability of the model. These perceptions led to the development of CCMS 2.0, an updated model Nick et al. (2021).

4.2 New dimension: Application of AI

Hizam-Hanafiah et al. (2020) did an extensive review on papers about Industry 4.0 readiness models by analyzing 30 models from academia and industry and identifying 158 unique dimensions. Their observation is that 70 (44%) of the dimensions pertain to the assessment of a specific technology, concluding that organizations need to focus on their technology readiness to improve their Industry 4.0 maturity level. The results of the expert interviews showed the same: decision-makers are mainly focusing on developing technologies, such as AI in order to "be Industry 4.0". The interviews have also strengthened the consequence drawn from the literature review, namely that the extensive application of AI methods in practice is still missing, but the number of pilot projects, test use cases is increasing. On the basis of the results of the literature review and expert interviews, another dimension was added to the CCMS 2.0 model, called *Application of AI*. As all the other dimensions, this also includes five intervention points. These points were formed taking three aspects that influence the operation of an organization into consideration: Ecosystem, Value Creation and Value.

In the *Ecosystem* aspect, management and statistical data characterizing the strategy of the company are included, and financial resources used to support the R&D&I activities and the extent to which these are applied is taken into account. It is also essential to have an accepted and documented strategy, measure the implementation of it with indicators. Organizational issues, including the availability of the necessary expert base, are also examined. Regarding *Value Creation*, the physical resources that the company creates value with and the processes in the virtual world's sphere are investigated. The existing equipment, future development directions, application of new and digital trends are examined. Internal production and logistics processes are also included in this aspect. The characteristics of smart products and services and the customers, suppliers, and business partners closely associated with them are taken into consideration in the *Value* aspect. Smart products are collecting and transmitting data about themselves during their use phase: the question is how the manufacturer uses this data? How well are services based on usage data built into the company's knowledge base?

The intervention points were assigned to the above-mentioned three main categories, and for each of them an example is provided after their description for the easier understanding. The contents of these five points were formulated based on the literature review: one could see the relevant articles for each point in Table 1.

Aspect	**Intervention points**	**Relevant scientific references**
Ecosystem	Awareness of the company	Fei et al. (2018), Tao and Zhang (2017), Cunbo et al. (2018) Barykin et al. (2021)
	Value chain	Barykin et al. (2021), Greif et al. (2020), Cozmiuc and Petrisor (2018), Rymarczyk (2020), Kuehn (2018), Moyne and Iskandar (2017)
Value creation	Equipment	Qi and Tao (2018), Moyne and Iskandar (2017), Talkhestani et al. (2019), Longo et al. (2019), Tao and Zhang (2017)
	Virtual processes	Rathore et al. (2021), Fei et al. (2018), Qi and Tao (2018)
Value	Products and services	Fei et al. (2018), Qi and Tao (2018), Lee et al. (2020), Liu et al. (2020), Zhang et al. (2020)

Table 1. Intervention points connections to the three main aspects and relevant articles

AI **awareness of the company**: the company operates a separate organizational unit to ensure the continuous operation, updating and development of the AI technologies based on Responsible AI (RAI) approach, taking ethical aspects into consideration as well, and continuously monitors the range of new areas that can be supported with AI within the company (according to expert interviews, a separate organizational unit highly facilitates the development of AI in the company). In addition, special financial resources are allocated for the development of the AI area, for the application of new, cutting-edge technologies in the areas already supported by AI or to be supported in the future. Importance and role of AI is also communicated for the employees. For example, a specific amount of budget is allocated on AI development each year, and responsible persons are assigned to each organizational unit whose job is to look for processes that can be supported with AI, start pilot projects and maintain AI solutions already in practice.

AI in the **value chain**: reaching and communicating with customers and supply chain partners through digital platforms, communicating data and assessing and analyzing customer needs are driven by AI technologies. For example, using social media platforms to reach customers and analyze the target groups and the best intervals to advertise based on the collected data.

AI in the **equipment**: the operation, maintenance and optimization of value-creating (e.g., manufacturing and logistics) processes are supported by AI technologies; no continuous physical presence of the human is required. For example, material flow on the shop floor is modelled with a digital twin, and movement coordinates are analyzed with AI in order to increase the efficiency of material handling workers.

AI in **products and services**: data generated during manufacturing and use of products is processed and evaluated using AI technologies. The results of these are used in the design, development, production and testing processes of the product, as well as in troubleshooting and maintenance. For example, data generated by CNC machines in operation at the customer to optimize maintenance time intervals.

AI in the **virtual processes**: with the help of the digital twin of the whole value chain, the management decisions are always supported by AI solutions. The applied AI solutions provide the basis for the statistical analysis of the data, the forecasts and the optimization. For example, classification of shipment locations is performed automatically based on several features, such as order frequency, volume per order, and the results are embedded in the logistics network optimization and shipment generation mechanism.

5. READINESS LEVELS ACCORDING TO THE CONNECTED FACTORIES PROJECT

The main objective of the Connected Factories (European Factories of the Future Research Association, 2020) project is to help factories to transform into smart and connected factories of the future. Together with experts and stakeholders across Europe *pathways* are developed that help factories navigate through the digital opportunities and challenges. For example, the *Autonomous & Smart Factories* pathway focuses on the digital transformation of processes that happen within the factory (see Fig. 6).

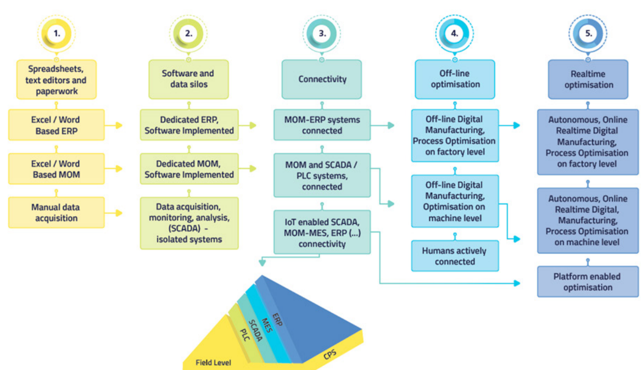

Fig. 6. Autonomous & Smart Factories pathway

Other pathways also show important milestones on the way to realize a *Hyper-connected* or a *Collaborative product-service* factory. There are many factors or enablers such as skills, business models, standards, interoperability and cyber-security, which are pivotal for long-term success in the transformation process. These cross-cutting factors are relevant for many milestones within the pathways, and despite the very individual pathway of each factory, they play an important role along with many specific use-cases. More pathways are being developed in the next step of the project, covering, for instance, *Circular economy, Data spaces, AI* and *Cyber-security*. According to these pathways and the Platform Industrie 4.0 (Plattform Industrie 4.0, 2021), the following levels can be defined for autonomy in terms of AI in industrial production. The intervention points for the Application of AI dimension in the CCMS 2.0 model had been synchronized to the development levels.

Level 0 - No autonomy: humans have full control without any assistance. **Level 1** - Assistance with respect to select functions: humans have full responsibility and make all decisions. **Level 2** - Partial autonomy in clearly defined areas, humans have full responsibility and define (some) goals. **Level 3** - Delimited autonomy in larger sub-areas, the system warns if problems occur, humans confirm solutions recommended by the system or function at a fall-back level. **Level 4** - System functions autonomously and adaptively; humans can supervise or intervene in emergency situations. **Level 5** - Autonomous operations in all areas, including in cooperation and in fluctuating system boundaries, humans need not be present.

6. CONCLUSION

In the paper, the CCMS 2.0 maturity assessment model was updated to include the aspects of AI applications, as the results of the literature review and expert interviews showed that this is a constantly developing area that should be considered when determining the digitization level of a company. A literature review was introduced in order to investigate the newest trends in the application of AI methods in the topic of digital twins, production, manufacturing and logistics. As a result, it can be concluded that the number of papers on this topic has constantly been growing since 2017, as the application of AI becomes more and more important in the manufacturing area. It can also be seen that the number of presented case studies is also growing; consequently, the application of AI methods is becoming more widespread. These presented theoretic models and use cases deal with mainly the area of manufacturing and production, and only a small part of them is investigating logistics issues. The papers are distributed between the topics of investigating processes, design and development, but there are also several examples for optimization and planning. Results of expert interviews were in alignment with the consequences drawn from the literature: application of AI methods in practice is not yet widespread, but the number of use cases, tests and studies are growing. Based on these results, the CCMS 2.0 model was updated by adding one dimension called *Application of AI* including five intervention points (AI awareness of the company, AI in the Value Chain, AI in the Equipment, AI in the Virtual Processes and AI in the Products and Services), categorized into three main aspects (Ecosystem, Value Creation and Value). The maturity levels in the intervention points were synchronized with the development levels defined in the Connected Factories pathways, which aim is to help companies on their road towards digitization.

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