Prerequisites for Applying Artificial Intelligence for Scheduling in Small- and Medium-sized Enterprises

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Abstract: With the increasing spread of Artificial Intelligence (AI), the prerequisites for a successful implementation in practice are becoming more relevant for large enterprises as well as for small and medium-sized enterprises (SMEs). The latter are usually characterized by flat hierarchies, high flexibility, but also by a lack of AI experts and data organisation. One field of AI application for SMEs is scheduling as part of production planning. Scheduling belongs to the most relevant digital solution areas for SMEs. In this article, we examine the prerequisites for the application of AI methods in scheduling in SMEs. For identifying relevant prerequisites, we conduct a literature review and combine it with the results of three AI adoption and readiness models. Afterwards, we describe the results of an interview study on our research question. The main findings include a list of prerequisites. We connect our list with already existing approaches for AI adoption and AI readiness with a strong focus on SMEs and scheduling. Furthermore, we conclude that the prerequisites are dependent on the application context. However, the effect of the size of a company on the prerequisites remains unclear.

1 INTRODUCTION

The potential and increasing spread of Artificial Intelligence (AI) in companies is undisputed. According to a study by PWC, the effect of AI on the gross domestic product of Germany is to grow by 430 billion euros (PWC, 2021). AI '[…]is a branch of Computer Science, which is mainly concerned with automation of Intelligent behavior.' (Chowdhary, 2020) Intelligent behavior includes perceiving, analysing, and reacting (Chowdhary, 2020).

One application field of AI is scheduling. Scheduling means determining the order sequence in production as part of production planning (Nguyen et al., 2019, Takeda-Berger et al., 2020). At the same time, scheduling belongs to the most relevant digital solution areas for small and medium-sized enterprises (SMEs) (Schönfuß et al., 2021). Combined with the importance of SMEs, as evidenced by the fact that nearly 40% of employees in Germany work in small and medium-sized enterprises, the application of AI for scheduling in SMEs is a highly relevant research topic (IfM, 2021). In addition, various solutions for AI-based scheduling have been developed (Kumar and Dimitrakopoulos, 2021, Ramirez-Asis et al., 2021, Zhang et al., 2021).

SMEs are often associated with attributes in addition to their size. Starting with flat hierarchies with frequently person-centered decision-making structures, through the necessary flexibility to the qualification of their employees (Kukharuk and Gavrysh, 2019, Cus, 1997). It raises the question of what prerequisites are necessary for the effective use of AI in the scheduling of SMEs. To this end, we first examine existing research results with a systematic literature analysis, primarily on the prerequisites for the use of AI in general and on SME-specific and scheduling-specific prerequisites. Subsequently, we describe the design and the outcomes of interview study, which aims to confirm the findings from the literature and reveal aspects not previously considered, particularly about SMEs and scheduling.

2 LITERATURE REVIEW

Our research question clearly refers to AI adoption and AI readiness research. Here, we build on the interview study of Jöhnk et al al., (2021). They developed a list of 18 factors that represents AI readiness. The factors belong to the five categories Strategic alignment, Resources, Knowledge Culture,

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and Data. The model considered the research work of Alsheibani et al., (2018, 2019), which proposed a maturity model with four dimensions (AI functions, data structure, people, organisations). Bettoni et al. (2021) developed a more specific maturity model of companies analysing the five dimensions Digital & Smart Factory, Data strategy, Organisation structure, Human Resources, Organisation culture. They detected a difference in AI maturity between 9 large companies and 30 SMEs. Baabdullah et al., (2021) investigated the relationship between the AI acceptance and several factors. According to the results of their empirical study for SMEs the acceptance of AI practices is dependent on technology roadmapping, attitude, infrastructure awareness, but not on expertise or technicality.

In addition to the findings regarding adoption theory, we built our research on the results of a literature review that focuses on research findings from 2015 - 2021. The review considers also search terms regarding success factors, integration, opportunities, etc., which helps us to derive prerequisites for a successful AI implementation in companies. We conducted the literature review according to the recommendations in Webster and Watson (2002). The literature to be analysed includes only scientific peer-reviewed articles and conference papers (Rowley and Slack., 2004). We used the following online platforms for our search: ScienceDirect, IEEE Xplore, Springer Link, EBSCOhost, Google Scholar, and the FHWS database. The literature search aims to obtain an overview of the prerequisites for use of AI in scheduling based on current research and to review the articles to determine the extent to which the company size affects the prerequisites. This leads to the following search terms ("integration of" AND "AI methods" OR "AI techniques"), ("successful integration" OR "integration challenges" AND "AI"), ("opportunities and challenges of AI"), ("opportunities and challenges of use of AI"), ("opportunities and challenges of ai" AND "scheduling" OR "production"), ("requirements for use" AND "artificial intelligence" OR "AI"), ("needs to introduce AI in scheduling"), ("implementation of AI"), ("implementation of AI" AND "in scheduling" OR "in production"), ("requirements of using AI"), ("successful key factors of using AI"), ("success factors of using AI"), ("conditions to use artificial intelligence"). We decided against a more SME and scheduling specific search to ensure a considerable number of results, but we categorized the articles according to their considerations of these two aspects. Furthermore, the publications found were checked for their relevance. Afterwards, we identified further articles from the bibliographies of the received sources. In this way, we ultimately identified 19 relevant sources. None of the sources focuses exclusively on prerequisites. They include, for example, challenges of using AI methods in certain areas, from which we derived prerequisites. The results mainly illustrate that although five sources refer to manufacturing, none focuses on the field of scheduling. They also show that literature sources on the topic have increased in recent years. 15 out of 19 articles were published from 2019 to 2021.

Table 1: Prerequisites.

Prerequisite	Authors
Digital data storage and availability	Iliashenko et al. (2019), Patel et al. (2019), Mansour et al. (2021), Sayyad et al. (2021), Susar and Aquaro (2019), Hildesheim (2020).
Server capacity	Iliashenko et al. (2019).
IT security	Susar and Aquaro (2019), Baviskar et al. (2021), Rathore et al. (2021), Aktolun (2019), Iliashenko et al. (2019).
Network quality	Mansour et al. (2021), Susar and Aquaro (2019), Pizon and Lipski (2015), Aktolun (2019), Iliashenko et al. (2019).
Data management	Susar and Aquaro (2019), Randaliev and De Roure (2021), Patel et al. (2019), Baviskar et al. (2021), Rathore et al. (2021), Mao et al. (2019).
Test environments	Dolgih, 2019, Nguyen et al., 2021.
Cross-disciplinary expertise	Patel et al. (2019), Aktolun (2019), Randaliev and De Roure (2021).
AI expertise	Susar and Aquaro, (2019), Qui and Zhao, (2019), Hildesheim, (2020), Dolgih, (2019), Aktolun, (2019), Luo et al., (2018), Pizoń & Lipski, (2015), Ak'yulov and Skovpen' (2019).
User training/user confidence	Patel et al. (2019), Dolgih (2019), Hildesheim (2020).
Financial resources	Luo et al. (2018), Susar and Aquaro (2019), Qui and Zhao (2019), Iliashenko et al. (2019).

An overview of the detected prerequisites is given in Table 1. In terms of content, we identified several prerequisites. First, the *equipment* and the management of the equipment are addressed by numerous authors. Equipment-related prerequisites are data storage, data availability, data management server capacity, IT security, network quality, and the availability of test environments. Furthermore, *expertise* plays a certain role. Some authors define AI expertise and cross-disciplinary expertise as crucial for success. From the user's perspective, *soft facts* such as trust, and confidence are important for AI success. Finally, a few authors stated that the availability of financial resources is crucial for AI implementation. In summary, general prerequisites are available from the literature. However, the considered publications lack a discussion on prerequisites concerning scheduling and company size. Instead, the results of adoption research and the

differences to other application contexts indicate the relevance of the application context.

An indication for it is, for example, a different relevance for the users, which is significantly higher in the medical field than in scheduling. Unlike in medicine, the factor "interdisciplinary experts" could also be less relevant for scheduling, since production planning, similar to artificial intelligence, originates from the field of mathematics or operations research (based on mathematical calculations or algorithms) (Gelders and Van Wassenhove, 1981, Ilieva et al., 2019). Furthermore, the assumption is apparently that relevant data in the field of scheduling are better available in a structured way than in other fields (Cadavid et al., 2019). Other technical factors, such as external servers, computing power, networks, testing, and cyber protection, are also prerequisites for use in scheduling. At the same time, these factors may be very significant in SMEs. Furthermore, financial resources, especially investments in time, personnel, or hardware, are prerequisites that are related to all application contexts.

3 INTERVIEW STUDY

3.1 Research Design

The results of the literature review allow the definition of analysis dimensions as a basis for expert interviews: The general analysis dimensions are "Expertise", "Equipment", and "Soft facts". The former aims to measure the influence of AI experts on the use of AI. Here, we explicitly asked about the effect of experts and their skills on AI deployment within a company. The analysis dimension "Equipment" is intended to identify the technical requirements. The latter dimension relates to the soft facts, i.e., what role the employees' trust in AI plays and why. Moreover, the analysis reveals how trust can be reached in this context. As the financial resources follow the dimension expertise and equipment as well as user training, we do not consider them explicitly. In addition to the dimensions derived from the literature review, we add two dimensions which are explicitly relevant for our research question: Company size and Relevance of the application field, in particular scheduling. Each dimension includes a few questions to get information on the relevance of these dimensions.

We interviewed a total of nine experts. The selection of the experts follows purposive sampling in our professional network. Experts had to fulfil two main criteria, which we derived from the research question. Firstly, the interviewee must be active in the field of artificial intelligence. Secondly, the experts must have experience in AI projects for SMEs. In addition, the context of production planning was relevant for the expert selection process.

The interviews were semi-standardized based on an interview guideline. The mode of communication was face-to-face and online via Zoom (Archibald et al., 2019, Gowda and Ayush, 2020, Hopf, C., 2004, Xu et al., 2019). An expert interview in the context of this work lasts approximately 30 minutes. The evaluation of the expert interviews was computer-assisted using the standard software MAXQDA (VERBI Software, 2021) for qualitative content analyses (Kuckartz, 2019).

3.2 Results

The survey results show that more than three-quarters of the experts surveyed see the involvement of AI experts as a prerequisite for deployment. Only two of the respondents rate this factor as of medium to little importance. They justify this by stating that all users should have fundamental AI expertise. Therefore, no specific AI experts are necessary. The statements of the interviewees indicate that an AI expert typically has AI software knowledge, various programming skills (especially Python), process understanding, and analytical thinking skills. In addition, interdisciplinary openness is another crucial attribute. Six of the nine experts emphasize cross-industry thinking and data understanding in this context. Social skills should also supplement AI expertise, such as communication skills. All experts emphasized the last aspect.

Furthermore, the study examines whether employee trust - as the main *soft fact* - in AI plays a crucial role in the use of AI. All nine respondents confirm this and justify it by ensuring acceptance of AI and avoiding fears of incomprehensible decisions and job loss. Eight out of nine respondents cite communication with those affected as a confidence-building measure. In addition, up to four experts attributed a confidence-building effect to actively picking up employees, user participation, expectation management, and the creation of control options for employees.

Another prerequisite for the use of artificial intelligence is the *equipment*. It includes ERP systems, AI software, programming and visualization programs, and libraries, such as Keras, or PyTorch. In addition, two-thirds of respondents emphasize the importance of hardware for access to powerful computers or cloud solutions. Sensors or data generation are also mentioned. However, the highest importance in terms of equipment seems to have "data

management," which is mentioned by all interview participants. It includes data collection, storage, management, etc.

Three experts mention financial resources, general or change management as further prerequisites. Two experts also list the domain knowledge of the employees, experience with an agile approach to AI introduction, and the openness and willingness of the users (see trust). In addition, one respondent considers the availability of human resources in general as a prerequisite for the use of AI. The findings described so far refer to the application in all contexts and company sizes.

However, our research intends to identify specific requirements for the use of AI in scheduling and SMEs. Here, six of the nine AI experts state that the use of AI is not specific to the company size. These statements are backed by the fact that even in large companies, AI projects of varying scope in different organisational units are taking place. Furthermore, the experts refer to the scalability of today's AI solutions, which make them suitable for both, SMEs and large companies. The remaining 33% of experts are convinced that the prerequisites for using AI also depend on the company size. They suppose that this is primarily caused by the less pronounced digital data management characteristics of SMEs. On the other hand, they recognized greater flexibility concerning the software landscape and IT systems in general within these companies.

Concerning scheduling, there is an ambiguous result. Thus, four respondents state that the use of AI is scheduling-specific, with four also of the opposite opinion. One expert did not answer about this topic. Four experts explain the dependence on the application context with different data formats. For example, data for scheduling is often available in structured form in relational databases. Real-time data from sensors enhance the production data. In contrast, the statement that the AI use is not context-specific is backed by the fact that it is purely dependent on the use case itself. Use cases in different application contexts can be similar but differ within an application context. Even though only four experts confirm an effect of the application context on AI prerequisites, seven experts stated that introducing AI in scheduling requires more communication skills than for other applications. The reason for it is, that scheduling often bothers more departments and stakeholders than, for example, an AI-optimized production machine.

Nevertheless, according to the experts, artificial neural networks are currently gaining ground as a method in scheduling, for example, and are, therefore, a current and future research topic.

4 DISCUSSION

The discussion of our results will consider mainly three perspectives. Firstly, we compare the results of our interview study with those of our literature review (Table 1). Secondly, we connect our results with the AI readiness and adoption theory. Thirdly, we emphasize again the results regarding the company size and the application field.

Figure 1 shows a comparison between the prerequisites from literature and those from the interview study for each category. The dimensions with an asterisk were addressed by all experts. Starting with the equipment (hardware resources in the literature include the network infrastructure and software) it appears that the results of the empirical study back findings in the literature. AI software and ERP systems affect data management as another crucial prerequisite of the dimension equipment. (Randaliev and De Roure, 2021, Susar and Aquaro, 2019, Aktolun, 2019, Mao et al., 2019, Iliashenko et al., 2019, Patel et al., 2019, Hildesheim, 2020, Poniszewska-Maranda and Kaczmarek, 2015, Luo et al., 2018, Qui and Zhao, 2019, Pizon and Lipski, 2015, Dolgih, 2019).

The results regarding the expertise show that AI experts exert a high effect on the use of AI, as indicated by 80% of the experts, which social competence belongs to. It is mentioned in addition to the prerequisites in literature. The empirical analysis confirms the specification of expertise in the form of technical competencies, specialized knowledge, and interdisciplinary knowledge. It is supplemented by cross-industry knowledge, data understanding, and software and process knowledge. (Patel et al., 2019, Aktolun, 2019, Susar and Aquaro, 2019, Qui and Zhao, 2019, Hildesheim, 2020, Dolgih, 2019, Luo et al., 2018, Ak'yulov and Skovpen', 2019, Pizon and Lipski, 2015).

The results of the empirical study regarding “Soft facts” show that the item "trust" of employees in AI is crucial. Communication and education foster trust. Moreover, the results of our expert interviews confirm the results in the literature. (Patel et al., 2019, Dolgih, 2019, Hildesheim, 2020).

Furthermore, financial and human resources were also empirically confirmed as prerequisites, whereas time resources were not addressed at all. However, change management, internal domain knowledge, and agile approaches to AI implementation were complementary (Luo et al., 2018, Susar and Aquaro, 2019, Qui and Zhao, 2019, Iliashenko et al., 2019). As of the literature review, no effect of company size on AI prerequisites is identified. However, the specific attributes of SMEs suggested that specific

prerequisites exist here. Here, rather negative tendency occurs in the expert interviews.

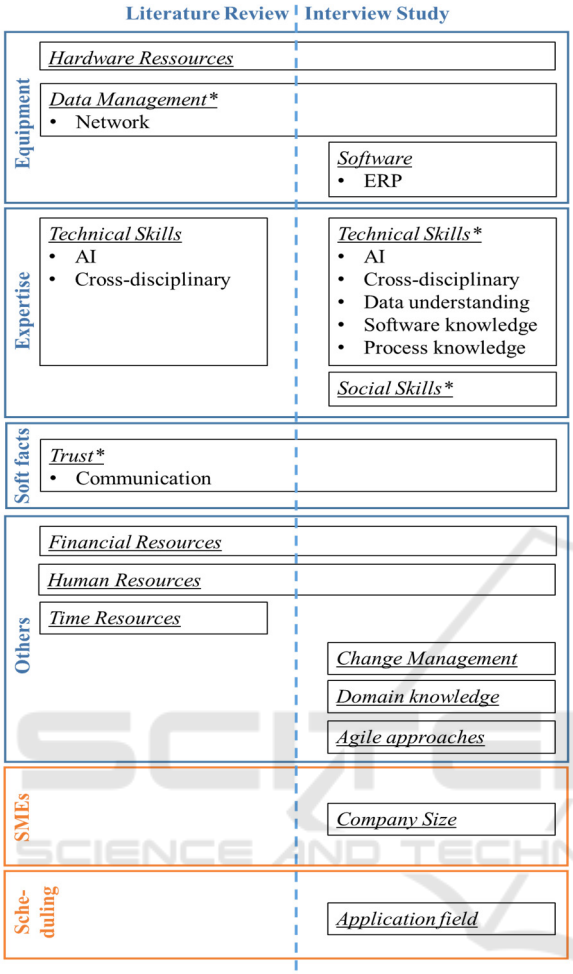

Figure 1: Matching interview study results with literature review outcome.

The literature analysis on AI prerequisites covered various fields, such as medicine or the public sector. For this reason, one objective of the empirical expert survey was to investigate the influence of the application context. Concerning this aspect, we achieved ambiguous results. But it should be noted that the prerequisites depend on the specific application either in the application context or the use case itself.

Our interview study complements and confirms existing research on AI adoption. Thus, we connect our prerequisites with the factors of Alsheibani et al. (2018, 2019), Jöhnk et al. (2021), and Bettoni et al. (2021). It becomes clear, that our findings regarding Expertise, Equipment, Soft facts, and Others confirm the importance of the categories in literature.

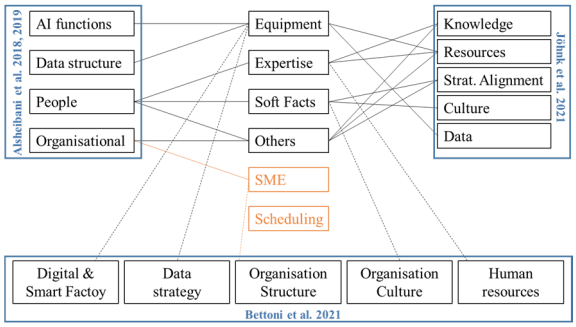

Figure 2: Research findings and adoption models.

Additionally, the organisational factor of Alsheibani et al. (2018, 2019) includes the company size. Bettoni et al. (2021) explicitly show that SMEs have a different maturity level than large companies. According to their results, in particular, the Digitalisation (Digital & Smart Factory) and the Organisational structure are on a more mature level at large enterprises. Our results seem to contradict that. One reason might be that our interviews were strongly project-related. The experts answered considering their project experience. Within large companies, there might be departments on a high digitalisation level and those with a low one. The reason for the statement could be also that the prerequisites are use-case specific, but not application-field specific. That was one argument of the four experts that denied scheduling-specific prerequisites. Figure 2 shows that none of the three approaches considers the application context. However, four of nine experts consider the application field (scheduling) as relevant for the prerequisite. And one reason for the denial of the others was that they believe that the prerequisites are use-case specific, which means that even the application field is too aggregated. Furthermore, the literature review shows, that we have several fields of application. Five of our sources in table 1 analyse AI in the context of medicine, five in the context of manufacturing, and the others in other fields. It seems very clear that patients as users may act differently and are different than experienced production planners. The personal involvement of patients is usually higher than the one of the production planners. This may affect the prerequisites in the categories soft facts and Expertise. This is just one example for the effect of the application use-case on the perquisites.

5 CONCLUSION

In this article, we described the results of both a literature review and an interview study on AI prerequisites for scheduling in SMEs. With our results, we gave an overview of current research work of AI prerequisites from the perspectives of SMEs and scheduling. Our overview shows that there is no research work in the field of AI adoption so far, which covers both concepts (SME and scheduling), or at least scheduling. Furthermore, we figured out indications for the relevance of the application field for defining AI prerequisites. Regarding the scientific discussion on the company size, we contributed some arguments for both sides (against in our interview study and for in our literature review). Finally, we confirmed most of the factors of Alsheibani et al. (2018, 2019), Jöhnk et al. (2021), and Bettoni et al. (2021).

Future research should clarify the results on SMEs and shed light on the question of how the application field and the use case itself affect the prerequisites. Thereupon further research is required on how to make an SME AI ready for specific AI application fields and use cases. At the same time, measures to become AI ready must be examined for their effectiveness and, in particular, their effect on the application goals (e.g., the acceptance of the models, the accuracy of the models, the number of model users, etc.).

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