Facilitating the Adoption of AI Technologies for SMEs Using an Expanded Version of the Periodic Table of AI

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Abstract. In this paper we present the concept of the "KI-Labor Südbaden" to support regional companies in the use of AI technologies. The approach is based on the "Periodic Table of AI" and is extended with both new dimensions for sustainability, and the impact of AI on the working environment. It is illustrated on the basis of three real-world use cases: 1. The detection of humans with low-resolution infrared (IR) images for collaborative robotics; 2. The use of machine data from specifically designed vehicles; 3. State-of-the-art Large Language Models (LLMs) applied to internal company documents. We explain the use cases, thereby demonstrating how to apply the Periodic Table of AI to structure AI applications.

Keywords: AI use cases, Periodic Table of AI, KI-Labor Südbaden

1 Introduction

Recent economic studies suggest that AI and related technologies have enormous potential to add value to the German economy. [1]. It is expected, particularly through advances in new technologies from generative AI, that an increasing number of tasks in a variety of professions can be supported or automated by AI technologies. This will not only lead to significant productivity gains, but also to the transformation of daily work routines for many people.

However, this expected value contribution of AI-based systems, despite their advantages, has not yet been currently seen in implementation. Especially small and medium sized businesses face challenges in integrating AI systems within the current workforce, internal processes, and business strategy. The lack of comprehension and expertise in implementing best practices further complicates and hinders commencement of AI system integration [2, 3]. Publically funded programs, through facilitation services, are striving to support SMEs with digitalization assistance as well as with access to AI expertise.

The "KI-Labor Südbaden"[1] is part of a network of 16 "AI Labs" in the state of Baden-Württemberg and has a strong regional focus to support small and medium companies in the Upper Rhine region. In this paper, we present the concept of the "KI-Labor Südbaden" to support regional companies in the adoption and use of AI technologies. As one part of our activities, we developed a concept based on the "Periodic Table of AI" [4, 5]. The contribution is structured as follows: First we discuss the current state of the concept of the Periodic Table of AI and provide background information on AI within work systems. We then describe three real-world AI use cases from different domains

[1] https://ki-suedbaden.de/

and using different AI technologies that were co-developed with local businesses through the KI-Labor Südbaden project. Next, we demonstrate how the Periodic Table of AI can be applied and illustrate the various challenges companies are facing when they start to use AI technologies. After that, we present the current state of our extended version of the periodic table of AI, and apply it to the three use cases, before concluding with an outlook on future work.

2 Background

2.1 Periodic Table of AI

In 2016, Kristian Hammond [4] published the idea of the "Periodic Table of AI" (PTAI) as a structural and conceptual framework for AI functionalities, independent of specific technologies. An an analogy to the periodic system of elements, the PTAI consists of 28 basic elements that can be combined like LEGO® bricks for assembly into complex AI use cases and applications. Examples of such elements are *Speech Recognition (Sr)*, *Predictive Inference (Pi)*, or *Decision Making (Dm)* (see Fig.1). The elements are organized into three groups: 1) *Assess* – Receiving and recognising information, 2) *Infer* – Processing, inferencing and learning from that information, and 3) *Respond* – Taking actions. Fig. 1 shows the elements of group *Assess* in blue, elements of group *Infer* in green and orange, and elements of group *Respond* in red.

– The group *Assess* is comprised of the following recognition and identification elements: Speech recognition (Sr), Audio recognition (Ar), Face recognition (Fr), Image recognition (Ir), General recognition (Gr), Speech identification (Si), Audio identification (Ai), Face identification (Fi), Image identification (Ii), General identification (Gi), Data analytics (Da), and Text extraction (Te).
– The group *Infer* includes: Predictive inference (Pi), Explanatory inference (Ei), Synthetic reasoning (Sy), Planning (Pl), Problem solving (Ps), Decision making (Dm), Language generation (Lg), Language understanding (Lu), Relationship learning (Lr), Category learning (Lc), and Knowledge refinement (Lt).
– The group *Respond* consists of the elements: Mobility large (Ml), Mobility small (Ms), Manipulation (Ma), Communication (Cm), and Control (Cn).

When selecting at least one element from each group, this results in an "AI element triple" that might inform an AI-driven use case or application [4]. In that way, the PTAI facilitates the conceptual configuration of such use cases, resulting in a high-level

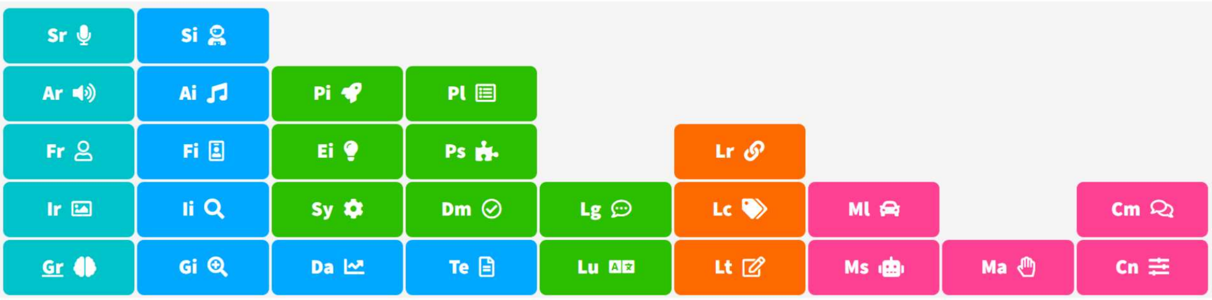

Fig. 1. Periodic Table of AI [5, 4]. *Assess* elements in blue, *Infer* in green and orange, and *Respond* in red

description of the use case or application; this description reflects the complexity and technological requirements [6].

In addition, the PTAI can serve as an educational tool for both digital experts and non-experts, providing fundamental knowledge of AI functionalities and thereby facilitating communication across varying levels of AI proficiency. Consequently, PTAI supports the comprehension of AI by both technical experts and non-experts. For example, Mylo et al. [7], applied the method within a project between machine learning experts and military operators, and demonstrated that it fostered effective communication and collaboration between these two groups [5, 6, 8].

In 2018, Germany's digital association "Bitkom" echoed Hammond's call for further development, and elaborated on the description of the elements and their use in practice [5]. However, as stated by both Hammond and Bitkom, there is still room for improvement in the PTAI. For example, there are missing elements for speech or image generation (while language generation is included) [5]. The user study by Mylo et al. [7] revealed misconceptions arising from either broad element titles or confusion between "recognition" and "identification" in the *Assess* group of elements, suggesting that the PTAI could be improved in terms of its comprehensibility.

Dietzmann and Alt [8] developed PTAI v2. They reduced the PTAI to 25 elements and rearranged them: firstly, along the abilities of perception, processing, action, and learning (based on Russell and Norvig's [9] concept of the intelligent agent), and secondly, by complexity. For this, they extended the PTAI by assigning types of human intelligence defined by Gardner [10] to each element in order to express its complexity. The number of assigned intelligence types gives each element its degree of complexity. Based on the PTAI v2, Dietzmann [6] developed an additional AI application taxonomy, with a focus on the configuration of AI applications detailing functionalities and characteristics while using PTAI v2 for use case analysis. However, the approach by [6, 8] does not include the work system integration and it considers only aspects that affect processes when it comes to organizational impact.

2.2 AI in Work Systems

The successful integration of AI applications within businesses necessitates a comprehensive socio-technical system approach [11–15]. The importance of this is recently demonstrated by the second edition of the DIN/DKE AI standardization roadmap [16, p. 153-176], in which a separate chapter on socio-technical systems has been added. The socio-technical system theory aims to "describe and explain the behavior of organizations and their members while providing critical insights into the relationships among people, technology, and outcomes" [17, p. 66]. The socio-technical perspective suggests that the social and technical subsystems are interdependent and inseparable within a work system and thus determine its effectiveness. In that way, a socio-technical system approach for AI takes into account the development of both social and technical subsystems of work while in relation to a specific context / relevant external environment. The implementation of AI, as a technological change, can have either a positive or negative impact on the overall work system, thereby ultimately affecting individuals [13]. Fig. 2 illustrates the integration of AI technology within a larger socio-technical work system and its impact on the overall system and individual interactions [12]. While some research started to draw attention on the technology, tasks, and people components, the context – specifically the organization and environment components, as well as the interactions among all components – are under-investigated [18, 11].

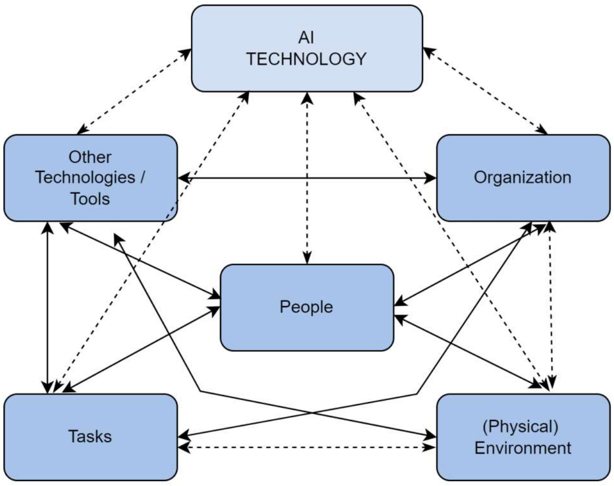

Fig. 2. AI integrated work system adapted from [12].

The DIN/DKE AI standardization roadmap [16, p. 153-176] proposes considering the socio-technical perspective along the complete AI life cycle; especially meeting sustainability criteria would be required. The roadmap sheds a first light on the AI life cycle with respect to the relevant socio-technical issues along the phases *Initiation*, *Design and Development*, *Verification and Validation*, *Transfer to the Operational Environment*, *Operation and Monitoring*, *Reevaluation* as well as *Continuous Validation and Decommissioning*. In addition, the need for standardization with regard to socio-technical aspects in the design of AI systems is identified.

von Garrel et al. [19] extend Hammond's general idea of structuring AI use cases. While the PTAI only focuses on the logical structuring of AI use cases from an AI-centric-perspective, von Garrel et al. focus on structuring AI use cases based on a socio-technical perspective, i.e. that the human perspective is taken into account. With this in consideration, the morphological box includes 14 characteristic features that describe the aspects of the AI use case, as well as how it affects the work system and its employees. Similarly, von Garrel et al. also call for the expansion and further development of the morphological box [19].

3 Use Cases

In this section, we explain the three real-world use cases, thereby demonstrating how to apply the PTAI to structure AI applications.

3.1 The Detection of Humans with Low-resolution IR Images for Collaborative Robotics

The first use case focuses on applying established methods from image processing and object recognition in a new environment. In addition to solving technical issues, this use case also has to address questions of labelled data acquisition, legal issues of data protection and privacy, and employee safety.

In general, this use case is about improving human-machine interaction in the ongoing production process and avoiding accidents between robots and humans in the production environment. To that end, the following tasks are necessary:

– **Step I:** Detecting humans in the working environment of a collaborative robot in a production hall,
– **Step II:** Calculating the probability of when a person is in the vicinity and approaching the robot, and deciding on the appropriate behavior of the robot,
– **Step III:** Initiating slowing down or stopping the robot.

Based on the decomposition into specific task steps and their description, suitable AI elements are mapped and put into context:

– **Step I:** In this specific case, low-resolution infrared images are used for cost-efficiency and data privacy reasons. Having a look at the PTAI, we can find *Assess*-element *Image Recognition (Ir).* The image recognition functionality enables "the detection of certain object types in images or video signals" [5]. In this case, the object type sought is the human being.
– **Step II:** The results of the image recognition process are used to infer whether a detected person will approach the machine, and to determine the appropriate behavior of the robot. The *Infer*-element *Predictive Inference (Pi)* predicts events based on the current state of the environment. The *Decision Making (Dm)* element chooses a particular course of action or solution based on available information, alternative options, and a set of objectives. These courses of action range from avoidance to stop manoeuvres. While ensuring that employees are not put at risk is crucial, it is also important to maintain high productivity, thereby necessitating the avoidance of unnecessary stops or overly complicated evasive actions.
– **Step III:** Depending on the decision made beforehand, the autonomous control of the robot's movement would be enacted. The *Respond*-element deemed suitable for this purpose is referred to as *Mobility Small (Ms)*, and it effectively governs the movement of robots that operate within indoor environments while performing tasks and interacting with individuals.

3.2 The Use of Machine Data from Specifically Designed Vehicles

The second use case aims to make AI methods actionable for a regional manufacturer of specifically designed vehicles. Time series data from the vehicles is currently collected but not really used. The initial focus in this use case is on questions of data quality, data preparation / exploratory data analysis, and predictive maintenance. In the predictive maintenance use case, time series data such as engine speed and fuel consumption is used to predict defects before they occur. This specific use case again can be broken down into three separate steps:

– **Step I:** Analyze the data to extract the information it contains.
– **Step II:** Understand the relationship between the data and the presence of defects based on past states, to be able to predict future defects based on the current state.
– **Step III:** Pass on the information to the responsible personnel.

Mapping the AI elements:

– **Step I:** In this use case, the data must be analyzed in detail in order to extract the information it contains. The corresponding *Assess*-element is *Data Analytics (Da)*, which refers to the analysis of data for the identification of the current facts and events represented by the data.

- **Step II:** The second step uses time series data to build a predictive model. This model learns statistical relationships between the given features and the presence of defects. Therefore, the probability of a defect occurring in the near future could be predicted. The corresponding *Infer*-element is *Prediction Inference (Pi)*, which predicts future events based on known data about the current state.
- **Step III:** Finally, the information has to be communicated to the appropriate personnel (for example, by triggering an alert). This task is described by the *Respond* -element *Communication (CM)*. It is generally defined as a mechanism that supports communication between human and machine.

3.3 Chatting with Internal Company Documents Based on Current LLMs

Finally, the third use case deals with the use of current large language models (LLMs) within companies. The intention is to make internal company knowledge accessible to users via a Q&A chatbot. The main focus here is on reliability and accountability of the answers. As in the previous examples, we explain this use case based on the elements of the PTAI. The use case can be broken down into three separate steps:

- **Step I:** Extract information from the company's documents and the question posed,
- **Step II:** Understand the meaning and the context of the question and the document, and then answer the question in natural language based on the given information.
- **Step III:** Pass on the information to the user in natural language.

Mapping the AI elements:

- **Step I:** In this use case, it is necessary to accurately extract information from the company's documents and to extract the information from the user's question. This task is described by the *Asses*-element *Text Extraction (Te)*, which analyzes and extracts the information of a given text.
- **Step II:** The second step is divided into two separate subtasks. Firstly, it is necessary to understand both the question and the documents in order to be able to map related elements within the documents, and also to match the document information with the question's requested information. The matching *Infer*-element is *Language Understanding (Lu)*, which is responsible for understanding the meaning and the context of the texts by creating semantic representations. Secondly, the matching information of the documents has to be converted into natural language. The responsible *Infer*-element for this task is *Language Generation (Lg)*, which generates natural text from a logical knowledge representation.
- **Step III:** Finally, the information has to be communicated to the user, e.g. visually or acoustically. For this purpose, the *Respond*-element *Communication (CM)* is used. It is generally defined as a mechanism that supports communication between human and machine.

4 Extended Periodic Table of AI

After the original PTAI offered the possibility to logically structure AI use cases, and von Garrel et al. [19] extended the general idea by focusing on the socio-technical aspects of AI use cases, we combine these aspects and further extend the system with a sustainability perspective [16]. For this approach, the standard PTAI serves as a basis and is extended by two additional independent dimensions focusing on the impact on the working environment and on sustainability. To represent the impact on the working environment, the elements of von Garrel et al.'s morphological box are adopted. The sustainability dimension is based on the UN's 17 sustainability goals [20]. The specific integration of the two added dimensions to form a cohesive framework is still a work in progress. Nevertheless, some implications for the working environment and for sustainability are illustrated below by reference to the three use cases previously introduced. For these examples we focus on the features, "nature of work", "level of autonomy", "mode of interaction", "social presence", "explainability/transparency", "change of the working system" and "user" from von Garrel et al.'s morphological box to examine the impact of the use cases on the working environment. To study the impact of these use cases on sustainability, we individually focus on a subset of the UN's 17 sustainability goals.

4.1 The Detection of Humans with Low-resolution IR Images for Collaborative Robotics

Working Environment The Infrared human detection is intended for use in collaborative robotics, i.e. the robot's goal is to navigate independently around objects and people, while assisting workers. Independent human avoidance makes the "nature of work" reactive and the "level of autonomy" "automated" or even "fully automated". The "user" is a worker and the "mode of interaction" can be classified as "physical", "collaborative" and "mobile". As the use case is based on object detection, it is possible to mark the object that is recognised as human, leading to at least a low level of "explainability/ transparency". Overall, the "change of the work system" is moderate. This is mainly due to the fact that collaborative robots are designed to be flexible [21, 22]. However, a major challenge might be employee acceptence of AI and collaborative robots as a tool, seen as something that supports them rather than something that replaces them.

Sustainability The Infrared human detection use case mainly relates to four of the 17 sustainability goals:

- Goal 5: Gender Equality
- Goal 8: Decent work and economic growth
- Goal 10: Reduced Inequalities

Gender equality and reduced inequalities: Gender equality concerns creating a level playing field for people regardless of gender, particularly in social, legal, political and economic spheres. The goal of 'reduced inequalities', particularly in sub-goal 10.3, is to ensure equal opportunities for all and to end discrimination. Injustice does not necessarily have to be caused by humans. Artificial intelligence, for example, can also build up prejudices and thus treat people unequally. For example, in the context of the given use case, people of a certain gender, body type, height or skin colour might be better recognised than others. In order to avoid such outcomes,countermeasures are appropriate, such as the use of low-resolution infrared images in combination with optimization methods to improve image quality.

Decent work and economic growth: This Sustainable Development Goal seeks both economic growth, and safe and decent working conditions. For example, Goal 8.8 calls for the protection of labour rights and the promotion of safe working environments. It should be mentioned that very monotonous work can also pose a health risk. For example, findings by Farmer and Sundberg [23] or Sommers and Vodanovich 2000 [24] suggest a link between perceived boredom at work and mental illnesses such as anxiety and depression. Robots along with collaborative robots, as in our use case, can take over monotonous tasks and thus potentially contribute to reducing the perceived boredom of workers. Object recognition is used to recognise and avoid people. Therefore, it also helps to ensure safety in human-robot interaction.

4.2 The Use of Machine Data from Specifically Designed Vehicles

Working Environment In this use case, the data from the vehicles is used to predict impending failures. The relevant personnel are alerted if the current data indicates future failure. To do this, existing information is combined to draw logical conclusions, making the "nature of work" "combinative." The "level of autonomy" can be classified as "decision support," so that the "user," the relevant personnel, would be the final decider. This person is informed by means of displayed output, which makes the "mode of interaction" "conventional software". Especially in this use case, it is pertinent to also display the original data, in order to help the relevant personnel to make the correct decision. This leads to at least a low level of "explainability/ transparency". Overall, the "change of the work system" would be low, because the work in general would not change drastically. The conventional way of communication would also presumably facilitate employee acceptance of AI as a tool for improving their decisions.

Sustainability The sustainability goals that are primarily affected by this use case are:

- Goal 8: Decent work and economic growth
- Goal 12: Responsible consumption and production

Higher Level of productivity: The aim of predictive maintenance is to predict failures before they occur. This can increase productivity by reducing the downtime of the machines, which is in line with sub-goal 8.2. It calls for productivity to be increased through, among other things, the implementation of technological innovation.

Resource efficiency: Predictive maintenance not only increases productivity by reducing downtime, but it can also extend the lifespan of the machine by keeping it consistantly well maintained. This is in line with both sub-goal 8.2 and sub-goal 12.5. While 8.2 calls for greater resource efficiency and more sustainable consumption and production, 12.5 calls for the reduction of waste, including through prevention.

4.3 Chatting with Internal Company Documents Based on Current LLMs

Working Environment In this use case, a chatbot is used to inform clients about complicated contract documents. To gather more reliable information, the clients still need to consult an expert. The text generation from information in the documents can be seen as a "combinative" or even a "creative" "nature of work". Also, the chatbot works completely independently, which makes the "level of autonomy" fully automated. As mentioned above, the "user" is a "client". The chatbot communicates with the user via a user interface, which makes the "mode of interaction" conventional software. To enable the user to check the information in the original document, the referenced sections of the text are provided. This at least leads to a low level of "explainability/ transparency". Overall, the "change of the work system" is minor, because the work in general does not radically change. The expert will still be consulted when necessary. Again, the main challenge might be employee and client acceptance of the chatbot as a useful tool.

Sustainability The sustainability goal that is primarily affected by this use case is:

– Goal 8: Decent work and economic growth

Higher Level of productivity: By implementing the chatbot, many simple questions can be answered without consulting an expert. This allows the experts to focus on the cases where their expertise is actually needed. It is also likely to lower the inhibition threshold for clients to inquire about the document details, as expert consultation becomes required less often. Taken together, these two effects have the potential to increase productivity, which is in line with sub-goal 8.2.

5 Conclusions

The article explains the aforementioned use cases and demonstrates how the Periodic Table of AI can be used to structure AI use cases and applications. It illustrates how simple AI element triples can be created to configure a manageable, yet complex AI use case and application from elusive problem settings such as employee protection from accidents with collaborative robots. It also further facilitates the discussion between domain experts and digital / AI experts [6]. Furthermore, an extension of the PTAI is proposed that includes a dimension based on von Garrel et al.'s morphological box [19] and a dimension based on the 17 UN sustainability goals [20]. This concept helps to represent the whole impact of a specific AI use case, both inside and outside a business use case. The application of the two added dimensions is demonstrated with three real-world examples, providing a holistic view of each of the use cases. Further work focuses on the implementation of the adaptations proposed by Dietzmann et al. [6] for the conception and creation of a coherent extended PTAI framework.

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References

1. IW Consult: Der digitale Faktor. `https://der-digitale-faktor.de` Accessed: 2023-09-26.
2. Chowdhury, S., Budhwar, P., Dey, P.K., Joel-Edgar, S., Abadie, A.: Ai-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. Journal of Business Research **144** (2022) 31–49
3. von Garrel, J., Jahn, C.: Design Framework for the Implementation of AI-based (Service) Business Models for Small and Medium-sized Manufacturing Enterprises. Journal of the Knowledge Economy (March 2022)
4. Hammond, K.: The Periodic Table of AI. `https://www.xprize.org/prizes/artificial-intelligence/articles/the-periodic-table-of-ai` (2016) Accessed: 2023-07-12.
5. Balada, C., Bellanova, A., Brüst, R., Bruss, M., Buchberger, S., Cirullies, J., Corro, L.D., Festag, R., Fuhs, G., Goetze, S., Gressling, T., Hartmann, T., Havemann, M., Hoffart, J., Holtel, S., Hufenstuhl, A., Kraus, W., Pfleger, N., Pikus, Y., Plumbaum, T., Rolletschek, G., Satow, L., Schnakenburg, I., Siepmann, R., Steffner, R., Shozo, M.T., Weber, M., Wieczorek, S., Wittenburg, G.: Digitalisierung gestalten mit dem Periodensystem der Künstlichen Intelligenz. Technical report (2018)
6. Dietzmann, C.: Towards a framework for assessing the business impact of artificial intelligence. PhD thesis, Universität Leipzig (2023)

7. Mylo, M., Dykta, P., Schoepe, D.: A Periodic System of Artificial Intelligence as an Effective Means of Communication between Machine Learning Experts and Military Operators. In: Proceedings of the STO Information Systems and Technology (IST) Panel Symposium (RSM) on Artificial Intelligence, Machine Learning and Big Data for Hybrid Military Operations (AI4HMO) – STO-MP-IST-190, STO/NATO 2021 (October 2021)
8. Dietzmann, C., Alt, R.: Assessing the Business Impact of Artificial Intelligence. In: Proceedings of the Annual Hawaii International Conference on System Sciences, Hawaii International Conference on System Sciences (2020)
9. Russell, S., Norvig, P.: Artificial intelligence: A modern approach, global edition. 4 edn. Pearson Education, London, England (May 2021)
10. Gardner, H.: Intelligence reframed: Multiple intelligences for the 21st century. Basic Books, New York, NY, US (1999)
11. Niehaus, F., Wiesche, M.: A Socio-Technical Perspective on Organizational Interaction with AI: A Literature Review. In: Proceedings of the Twenty-Ninth European Conference on Information Systems (ECIS 2021). (2021)
12. Salwei, M.E., Carayon, P.: A Sociotechnical Systems Framework for the Application of Artificial Intelligence in Health Care Delivery. Journal of Cognitive Engineering and Decision Making **16**(4) (2022) 194–206 PMID: 36704421.
13. Holdsworth, M., Zaghloul, F.: The Impact of AI in the UK Healthcare Industry: A Socio-Technical System Theory Perspective. In: Proceedings of the 8th International Workshop on Socio-Technical Perspective in Information Systems Development. (2022) 19–20
14. Enholm, I.M., Papagiannidis, E., Mikalef, P., Krogstie, J.: Artificial Intelligence and Business Value: a Literature Review. Information Systems Frontiers **24**(5) (August 2021) 1709–1734
15. Latniak, E., Tisch, A., Kauffeld, S.: Zur Aktualität soziotechnischer Arbeits- und Systemgestaltungsansätze in Zeiten von Digitalisierung und KI. Gruppe. Interaktion. Organisation. Zeitschrift für Angewandte Organisationspsychologie (GIO) **54**(1) (March 2023) 1–8
16. DIN/DKE: Deutsche Normungsroadmap Künstliche Intelligenz. `https://www.dke.de/resource/blob/2008010/776dd87a4b9ec18d4ab295025ccbb722/nr-ki-deutsch---download-data.pdf` (2022) Accessed: 2023-09-22.
17. Kull, T.J., Ellis, S.C., Narasimhan, R.: Reducing Behavioral Constraints to Supplier Integration: A Socio-Technical Systems Perspective. Journal of Supply Chain Management **49**(1) (2013) 64–86
18. Safaei, D., Haki, K., Morin, J.H.: Artificial Intelligence in Information Systems Research: A Socio-technical Perspective. In: Proceedings of the 19th Conference of the Italian chapter of AIS & the 14th Mediterranean conference on information systems. (2022)
19. von Garrel, J., Jahn, C., Schröter, D.: Der Einsatz Künstlicher Intelligenz in produzierenden Unternehmen. Eine Morphologie industrieller, KI-basierter Arbeitssysteme. Zeitschrift für wirtschaftlichen Fabrikbetrieb **117**(5) (2022) 338–343
20. United Nations: THE 17 GOALS. `https://sdgs.un.org/goals` Accessed: 2023-10-09.
21. Sherwani, F., Asad, M.M., Ibrahim, B.: Collaborative Robots and Industrial Revolution 4.0 (IR 4.0). In: 2020 International Conference on Emerging Trends in Smart Technologies (ICETST). (2020) 1–5
22. Mihelj, M., Bajd, T., Ude, A., Lenarčič, J., Stanovnik, A., Munih, M., Rejc, J., Šlajpah, S. In: Collaborative Robots. Springer International Publishing, Cham (2019) 173–187
23. Farmer, R., Sundberg, N.D.: Boredom Proneness–The Development and Correlates of a New Scale. Journal of Personality Assessment **50**(1) (1986) 4–17 PMID: 3723312.
24. Sommers, J., Vodanovich, S.J.: Boredom proneness: Its relationship to psychological-and physical-health symptoms. Journal of clinical psychology **56**(1) (2000) 149–155