Through the Cognitive Functions Lens - A Socio-Technical Analysis of Predictive Maintenance

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Abstract. The effective use of artificial intelligence promises significant business value. Effective use, however, requires a thorough exploration of its strengths and weaknesses from different perspectives. Information systems research is particularly invested in the management and use of artificial intelligence in organizations. It has proposed the use of cognitive functions to guide this exploration. In this paper, we evaluate the usefulness of such a cognitive functions lens for a relatively mature application of artificial intelligence, predictive maintenance. Our evaluation is informed by the insights we collected from an embedded single-case study. We find that a cognitive functions lens can indeed be a useful tool to explore artificial intelligence. In particular, it can aid the allocation of tasks between human agents and artificial intelligence-based systems and the design of human-AI hybrids. It is particularly helpful for those who investigate the management of artificial intelligence.

Keywords: Artificial Intelligence, Predictive Maintenance, Cognitive Functions, Embedded Single-Case Study.

1 Introduction

The transformative prospect of artificial intelligence (AI) inspires researchers and practitioners in many fields (e.g., transportation, health care, and education) and focus areas (e.g., deep learning, robotics, and collaborative systems) [1]. Since AI reaches many areas of life and might affect a substantial part of our society in the future, the expectations for guidance are substantial. The information systems (IS) community seeks to contribute to this research mainly through the exploration of the socio-technical effects and management of AI, drawing on the community's substantial body of theories and knowledge about the use of conventional IT [2]. Its efforts are directed especially at future workplaces in which human agents and AI-based systems work together [e.g., 3, 4]. In these workplaces, AI-based systems may substitute (*task substitution*) or improve human labor within specific tasks (*task augmentation*), but may as well complement human labor in joint human-AI-teams (*task assemblage*) [5–7].

So far, however, IS research on AI has struggled to find a definition of AI that serves its particular perspectives and needs. While this lack has likely benefitted initial explorations [1], it has also led to a substantial variety in conceptions of AI and a certain vagueness in discussions. To address this issue, Rai et al. [7] propose the use of cognitive functions commonly associated with the human brain, such as reasoning, learning, decision-making, or problem-solving, to describe and characterize AI-based systems. Such a cognitive functions lens could particularly benefit the study of AI-based systems that are designed to perform specific, pre-defined tasks. Exemplary of such task-specific AI-based systems are those for predictive maintenance (PdM) [8].

PdM aims at predicting future maintenance needs by continuously analyzing a machine's operating conditions and predicting when to initiate preventive maintenance activities [9, 10]. PdM offers several benefits and provides organizations with novel opportunities to build knowledge about their products. The implementation of PdM systems, however, requires new maintenance strategies and a new allocation of tasks between the PdM system and human maintenance workers. As such, PdM presents an interesting and relevant case for the application and study of the usefulness of the cognitive functions lens. In this paper, we thus explore the following research question using PdM as our contextual domain:

RQ: How do cognitive functions affect the distribution of tasks in the context of AI-based PdM systems?

To address this question, we conduct an embedded single-case study on a project in which multiple manufacturing organizations and researchers collaboratively developed PdM strategies and implemented prototypes to evaluate their applicability. Based on our case study, we illustrate how the cognitive functions lens can help to better frame human-AI collaboration. In particular, we propose a distinction between cognitive functions that can be performed superbly by a particular AI-based system (core cognitive functions), functions that can be performed either by the system or a human agent (shared cognitive functions), and functions that, so far, human agents excel in. Such a distinction is useful because it allows us to understand Rai et al.'s [7] classification of substitution, augmentation, and assemblage as the result of allocating tasks between human agents and PdM systems based on the (type of) cognitive functions needed to perform the task.

From a theoretical perspective, we contribute to IS research by illustrating how a cognitive functions lens can be a useful tool to explore AI. The cognitive functions lens allows researchers to better understand and frame human-AI collaboration. This is particularly helpful for those who investigate the management and use of information technology. That is, the cognitive functions lens provides researchers with a tool to study the managerial and organizational implications of the implementation of AI-based systems. Moreover, our study has several practical implications. A cognitive functions lens can aid practitioners in better understanding a system's functionalities and support organizations in deciding whether a system fits their needs, which human and organizational capabilities they need, and how to adapt surrounding processes.

2 Theoretical Background

2.1 Artificial Intelligence

Interest in Artificial intelligence (AI) has been growing over the past few years, not only in practice but also in IS research. AI, however, is not a nascent field. Its roots reach back to the 1950s when researchers began to explore the possibilities to compute and simulate intelligence [11]. The first IS publications on AI date back to 1984 [12]. While the 1990s saw various studies on aspects surrounding AI, interest subsided again in the 2000s. However, in the wake of significant technological advancements in hardware (e.g. processing and storage capabilities) as well as the availability of data and data analysis techniques, such as deep learning, AI has begun to regain its earlier foothold in the IS community [1, 12].

This renewed interest has also given birth to various new research streams, many of which revolve around the exploration of AI's impact on corporate strategy, business processes, as well as the future of work [5]. The essential question that underpins these streams is one of the interactions between human agents and AI-based system, that is, whether AI-based systems will change, replace, or enhance human labor [3, 6, 7]. IS research has begun to explore this question from a task-based perspective and identified three archetypical interactions: *task substitution, task augmentation, and task assemblage.* Task substitution refers to the substitution of human labor through an AI agent. Task augmentation describes contexts in which a human or an AI agent performs support functions that allow the supported to perform a task more effectively or efficiently [7]. For instance, AI-based systems can improve human decision-making through highly accurate predictions and decision proposals [13], or human agents can improve an AI-based system's decision-making by factoring in judgment or moral values [14]. Task assemblage refers to contexts where AI and human agents jointly perform a task [7].

The renewed interest in AI has also created new challenges, such as the establishment of a conception of AI that serves the particular perspectives and needs of the IS community. Whereas IS research has been effective in guiding practitioners in understanding and managing traditional information technology [2, 15], the ability of AI-based systems to perform cognitive functions may require a re-examination of various IS concepts [7]. Cognitive functions refer to the various mental processes of the human brain. They are particularly useful to explore task-specific applications of AI because they enable a discussion of the type of intelligence required for the task [16]. Exemplary of such task-specific applications is predictive maintenance (PdM) [8].

2.2 Predictive Maintenance

Traditionally, organizations minimize machine faults through regular maintenance cycles and preemptive activities based on the experience of seasoned maintenance workers. Once a fault has occurred, they respond based on reactive maintenance strategies [10].

PdM presents a fundamental shift from these premises. Technically speaking, PdM is a maintenance management method that is based on a machine's conditions instead of general statistics on a machine's lifetime [9]. It relies on the continuous monitoring of mechanical conditions and system efficiency in order to predict the occurrence of faults and defects and, by extension, allows the prevention of machine failure. PdM systems commonly use techniques such as tribology, oil analysis, vibration analysis, thermography, or process parameter monitoring to collect various data points [9, 17, 18] that are then fed into models that extract meaningful knowledge from the data [19]. PdM enables companies to forecast a machine's future condition and, thus, enhances human decision-making [20].

PdM can have a range of positive effects, such as increased process availability, reduced maintenance costs, increased quality, productivity, safety, and profitability [21]. Successful implementation of PdM, however, requires the addressing of various challenges [22]. For instance, manufacturers need to be able to collect and process data in real-time, provide a data supply chain for simple data transmission among different business units, build knowledge on PdM intelligence and strategy, and enable machines to collaborate with and better assist humans [23].

2.3 Cognitive Functions

Many unresolved issues in the context of AI result from a limited understanding of natural intelligence [24]. One way of examining natural intelligence is by looking at the finite set of cognitive functions of the human brain. These cognitive functions represent all life functions and mental processes that human brains may perform, ranging from very basic and subconscious functions, such as memory or perception, to highly specific and conscious functions, such as recognition or problem-solving [25]. The concept of cognitive functions is based on the idea that "thinking can best be understood in terms of representational structures in the mind and computational procedures that operate on those structures" [26]. Cognitive functions are being explored in many fields, such as psychology, cognitive science, neuro-philosophy, or cognitive informatics [16].

For the design and exploration of AI cognitive informatics, in particular, provides a useful starting point. The discipline focuses on the discovery of information-processing mechanisms as well as cognitive functions of the brain and their application in what we would refer to as AI-based systems [27]. However, not all of the cognitive functions of the human brain are yet transferable to an AI-based system because they are based on the brain's structure with its inherited and acquired life functions and different kinds of memories [16]. But, many applications of AI do not need to draw from the full set of cognitive functions of the human brain because they are not necessary for the task at hand [16]. Russell and Norvig [28], for instance, make only use of a few cognitive functions in describing different types of (rational) AI agents.

Overall, cognitive functions can help researchers to better grasp the gestalt of intelligence and, thus, enrich research in many different AI disciplines [16]. For instance, we follow Rai et al. [7] that cognitive functions are a useful conception of AI that serves the particular perspectives and needs of the IS community in exploring task-specific AI-based systems, such as PdM. In a simplisitc manner, the cognitive functions lens allows us to parse PdM systems into their individual functions and, thus, to describe more precisely what it is that makes such systems AI-based. Moreover, it can help us to better understand the socio-technical aspects and requirements of the adoption of AI-based systems as demaned by Sarker et al. [2]. That is, a cognitive functions lens allows for considering human, social and organisational factors, as well as technical factors, in analyzing and designing PdM systems [29].

3 Research Method

3.1 Case Setting

To address our research goal of understanding how a cognitive function lens can help to conceptualize AI-based PdM systems, we conducted an embedded single-case study guided by the recommendations of Yin [30]. Specifically, we examine an applied research project in which organizations and applied researchers from different backgrounds collaborated to work on PdM strategies and their prototypical implementation in the respective organizations. Embedded single-case studies allow for the analysis of a single-case (the project) while simultaneously considering the specifics of multiple "embedded" units of analysis (participating organizations). According to Yin [30], a single-case is justifiable if it is either critical, unusual, common, revelatory, or longitudinal. Although PdM as a research topic has already gained traction back in the late 1990s, many organizations are still struggling with the implementation of PdM systems [31]. Therefore, we selected a case that reflects common circumstances and conditions faced by many manufacturers.

The applied research project began in early 2018 and concluded just over a year later. The project was publicly funded and saw four non-competing German medium-sized enterprises from the mechanical engineering sector collaborate with two German research organizations to develop intelligent analytics solutions, increase production transparency, and create data-based services and business models. We, as the authors of this paper, were not actively participating in the project. We chose the project because it provided in-depth insights into the PdM implementation process from many different perspectives.

3.2 Data Collection and Analysis

We decided to conduct semi-structured interviews as our primary method of data collection to elicit stories from the participating organizations [32]. Our interviews lasted between 30 and 60 minutes, were audio-recorded, and fully transcribed afterward. The interviews aimed, inter alia, at eliciting individual viewpoints on either the cognitive functions that experts had already identified in PdM applications or those that they were hoping to make use of for their organization. In several cases, we approached the interviewee again after the interview in order to clarify questions.

We conducted interviews with relevant representatives from all of the involved organizations to take advantage of this unique project setting. We based our selection of interviewees on two aspects. First, we selected only those closely involved in the project and thus able to provide deep insights. Second, we made sure to involve different roles in the interview process, such as managers and engineers, to obtain multiple perspectives. Table 1 provides an anonymized overview of the interviewees.

At the beginning of the interviews, the interviewer introduced himself and the research project followed by an introduction of the interviewee including their background, current organizational position and their experiences within the respective organization. In the further course of the interview, we particularly asked questions related to the cognitive functions of PdM. For instance, we asked the interviewees how they intended to or already used PdM and about the (type of) tasks performed by the PdM system. Moreover, we asked them how their maintenance workers collaborated with the PdM system and how PdM would change their organization's maintenance processes and business models. Lastly, we were also interested in how the organization would need to adapt to implement PdM systems.

Table 1. List of organizations and interviewees

#	Interviewee's Role	Organization	# Employees
1	Data analytics researcher	Research Organization 1	> 100
2	Data analytics researcher		
3	Digital business model researcher		
4	IoT researcher		
5	Data analytics researcher	Research Organization 2	< 10
6	Data scientist	PdM Implementing Organization 1	> 5000
7	Pre-sales management		
8	IT-specialist	PdM Implementing Organization 2	> 1000
9	Manager		
10	Engineer	PdM Implementing Organization 3	> 1000
11	Engineer		
12	IT-specialist		
13	Manager		
14	Manager	PdM Implementing Organization 4	> 1000

To triangulate our results [33], we directly observed workshops that were held as part of the project and analyzed project documentation that the participants provided us with.

In analyzing the collected data, we followed a two-stage process of inductive and deductive coding of data [34]. First, researchers scrutinized and coded the data independently of each other. Subsequently, we discussed our interpretations and constructed categories and subcategories, grouped codes and looked for relationships and patterns. During data analysis, we assigned the codes to higher-level concepts which were either based on our theoretical lens (deductive coding) or emerged during data collection (inductive coding).

4 Findings

We began our analysis of the cognitive functions of PdM by inferring from essential work by Rai et al. [7], Russell and Norvig [28], and Wang et al. [16] eight hypothetical cognitive functions of PdM (creation, decision-making, learning, planning, perceiving problem-solving, reasoning, recognition). Out of these, we find five to be relevant in our case study: Decision-making, learning, perceiving, reasoning, and planning.

Moreover, we find that these functions group into two categories depending on their specific manifestation in a PdM system: Core cognitive functions (CCFs) and symbiotic cognitive functions (SCFs) (see Figure 1). We denote as CCFs those cognitive functions in which a particular AI-based system outperforms human agents. Tasks that require only the CCFs of an AI-based system present substantial opportunity for task substitution. SCFs are those cognitive functions that an AI-based system can provide yet in which it does not necessarily excel human agents. Tasks that require the SCFs of AI-based systems are candidates for task augmentation and task assemblage.

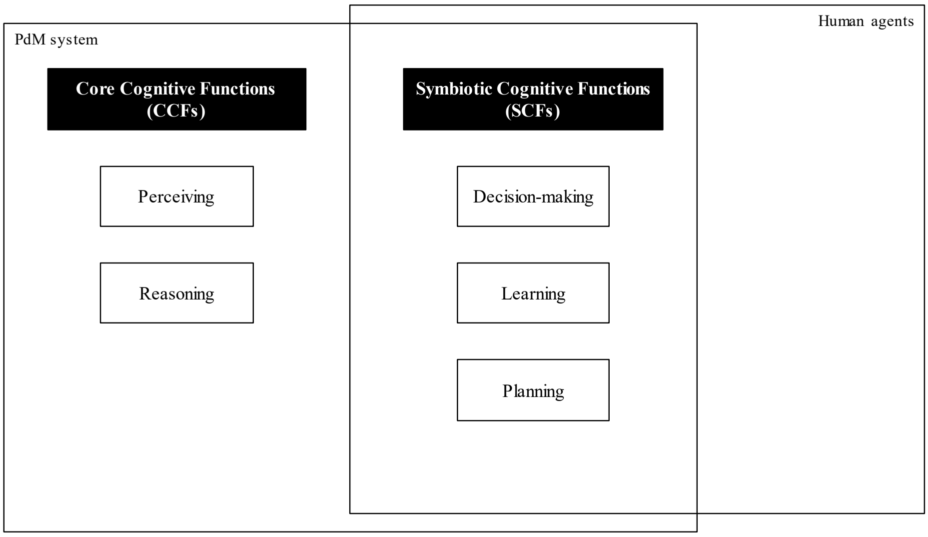

Figure 1. Human-AI hybrids based on a cognitive functions perspective

4.1 Core Cognitive Functions

As described above, CCFs are those cognitive functions in which AI-based systems significantly outperform human agents either because the human brain cannot perform these functions to the desired extent or because the AI-based system is better at performing the function. In our PdM case, we identified two such CCFs: perceiving and reasoning. The workshop participants and interviewees were either hoping or expecting to make use of these two CCFs to replace human agents when implementing a PdM system in their organization.

Core Cognitive Function of PdM 1: Perceiving. Perceiving refers to an agent's ability to gather information about its environment through means such as sensors and cameras [28]. Sensors involved in PdM range from pressure sensors to thermocouples or resistance temperature detectors, which all measure different types of input data [35]. Popular techniques to analyze this input data are, for example, tribology, oil analysis, vibration analysis, or thermography [9, 17, 18]. We categorize "lower-level" cognitive functions such as audition or tactility that also refer to the processing of such sensory responses under the "higher-level" cognitive function of *perceiving* to better account for different types of PdM systems. One of the major advantages of a PdM system's capability to perceive its environment concerns the analyzability of previously unavailable data sources, such as radio, infrared, GPS, or other wireless signals [28].

> *"Well, they [the systems] can already pick up sensor signals today, they can also store these sensor signals for a limited period of time and transmit the data."* (I_{14})

While one researcher reported about maintenance workers who could detect upcoming faults merely by putting their hands on a machine, such workers are the exception, and PdM systems were broadly expected to outperform human agents in perceiving. This is especially the case if a PdM system can perceive a machine's (or any other product's) direct environment that is not directly accessible for human agents. For instance, some of the organizations need to globally maintain products at isolated customer sites, where accessibility is significantly impeded. Moreover, PdM systems are better at continuously perceiving machine conditions as required to predict imminent failures or other maintenance needs.

Core Cognitive Function of PdM 2: Reasoning. Reasoning refers to the inference of causal conclusions from known pairs of cause and effect [16]. Reasoning can assume different forms. For instance, associational reasoning refers to the use of heuristics to associate data with related solutions [36], deductive reasoning refers to the inference of causalities from the general to the particular, and inductive reasoning is exactly the contrary [37]. Case-based reasoning is a method commonly used for computational reasoning. It simulates human reasoning by searching for similar situations that have occurred in the past (cases) and applying insights from these situations to the current one [38]. Systems capable of reasoning are expected to perform tasks for which they have not been explicitly programmed solely based on raw data whilst reacting rapidly to a continuously and unpredictably changing environment [37, 39].

In PdM systems, reasoning is an important function for analyzing historical data to detect previously unexplored causalities on critical pieces of information, such as system faults or plant diseases [40]. Extracting new information on potential or upcoming machine faults is what most of the interviewees expected or hoped to achieve by using a PdM system. Many interviewees emphasized the ability of PdM systems to discover fault patterns through the collection and analysis of process or fault data.

> *"I envisioned that we make progress with the analysis part in a way that our manual effort is reduced and that we are relieved of some tasks. For example, I thought that maybe the alarms can be prefiltered, or that different data types can be combined, such as vibration level, torque, rotation speed, etc. Currently, we have to do a lot of manual work."* (I_{10})

All interviewees agreed that making sense of the collected machine data is one of the key challenges for their respective organizations. Human agents, however, do not possess the necessary capabilities to properly analyze these large amounts of data.

> *"At this point, we entered the project because we had masses of cluttered data that were stored online and to some extent offline. What can we do with it? We have many colleagues who are capable of analyzing data but not those masses. That can't be done by a human."* (I_{12})

An intelligent system's capability to discover causality in large amounts of data is one of its biggest strengths where it clearly outperforms human agents in related tasks. Consequently, PdM systems should *substitute* human agents in these kinds of activities.

4.2 Symbiotic Cognitive Functions

SCFs are those cognitive functions that AI-based systems can perform, in which, however, they are not necessarily better than human agents. Tasks that require the SCFs of an AI-based system present opportunities for task assemblage and task augmentation. We found references to SCFs in various statements related to improving existing tasks that the respective organizations were struggling with. Consequently, we do not regard SCFs as a requirement for every PdM system but rather as components whose integration into PdM systems depends on the context.

Symbiotic Cognitive Function of PdM 1: Decision-making. Decision-making is the process of choosing an alternative under a set of options based on one's preferences, for example, in form of utility. Assuming certainty of outcomes, the preferred decision is the one that maximizes the utility [28]. As the world is usually uncertain, different decision approaches exist. Sometimes, people make decisions based on their "gut-feeling" or by applying judgment. However, many organizations have shifted toward data-driven decisions where human agents make decisions based on data analyses.

AI-based PdM systems can support such an approach by recommending certain actions but leaving the final decision to a human agent and his/her judgment [41]. However, they can also completely take over decision-making from human agents. In our case study, most PdM systems are either supposed to or already make maintenance recommendations, yet leave the decision on whether any actions are necessary to the human system users.

> *"We do now employ a ticket system. That is, we do not need to individually check the data for irregularities, but rather receive a ticket when the system creates an alarm. However, we manually decide on actions."* (I_{10})

Many of the involved organizations employed such a ticket-based system, with some systems creating their alert directly for the technician and others for a centralized maintenance unit that decides about required actions. In other words, human agents make the final decision. Despite the possibility, the organizations involved in the project do not (yet) intend to leave the maintenance decision to the PdM system entirely. However, they share the belief that the insights provided by the systems enable them to make better and more accurate maintenance decisions. In summary, the PdM systems *augment* the decision-making of most of the organizations involved in our case study.

Even if decision-making on maintenance needs was delegated to the PdM systems, human agents still would need to decide upon the appropriate algorithm for the PdM systems to be able to excert decision-making abilities. This yields an entirely new form of the decision-making paradox described by Triantaphyllou and Mann [42].

Symbiotic Cognitive Function of PdM 2: Learning. In reference to Schunk [43], learning can refer to a lasting change in behavior or in the capacity to behave as a result of practice or other experiences. The result of learning is improved performance on future tasks compared to the status before the learning process [28]. While shortcomings in data processing capabilities limited machine learning techniques for a long time, these techniques are well established today. Machine learning can generally assume different forms, such as supervised or unsupervised learning [44]. For instance, a system can learn by identifying certain regularities or patterns in (large) data sets, something humans are often not capable of.

Our interviews revealed that PdM systems give organizations the opportunity to learn more about their products, their behavior in an environment outside the organizations' premises, and the actual usage patterns of their customers. A fundamental difference between the cognitive functions of learning and reasoning is that organizations do not intend to leave learning to the systems solely but rather plan to expand their product and customer knowledge by applying PdM. Therefore, PdM systems can enable human agents to perform their tasks better.

> *"Additionally, we can benefit from knowing how our products are operated. We usually don't receive field data. This is of course very interesting."* (I_{10})

However, human learning processes can also benefit the PdM systems by, for instance, updating the system's knowledge base with new information. Consequently, sharing learning capabilities enables *task augmentation* of the human-AI hybrid in both directions.

Symbiotic Cognitive Function of PdM 3: Planning. Simply put, planning is the creation of an action plan with a given set of information to fulfill a certain goal. The action plan is usually limited by constraints, such as the availability of involved actors [16, 28]. Goals related to maintenance planning are maximizing maintenance resource use and maximizing capacity use of the plant or machine. Especially in the context of large organizations with different customers, maintenance workers and machines, the planning as well as scheduling of maintenance processes can be very challenging and need to be addressed carefully [9]. However, in reactive maintenance settings, organizations do not anticipate and, thus, cannot plan their response to faults and maintenance needs. PdM provides organizations and customers with increased flexibility and corresponding efficiency.

> *"For me, it [predictive maintenance] has only positive aspects. On the one hand, it increases plannability for the customer because he is notified about maintenance needs in advance. On the other hand, we can eliminate quality problems because we can use the analyses to detect regularities in the process of breakdowns."* (I_8)

Moreover, the interviewees pointed out several benefits of this enhanced plannability, such as a reduction of waiting times for spare parts, a reduction of downtimes during business hours and an increase of acceptance on behalf of the customer. Some organizations even intend to take a step further by leaving the planning and scheduling of maintenance activities to the PdM system.

> *"In markets like Germany, where we can reach our facilities within 30 minutes and have a lot of technicians, we probably would not really need this kind of plannability. However, there are certain markets where it will provide huge benefits."* (I_9)

However, automatic and intelligent planning requires decision-making to be left to the system as well. In summary, the allocation of roles can assume different forms depending on the system's design when it comes to planning activities. Task allocation can range from *task augmentation* where the PdM systems support planning activities of the human agents by, for instance, providing flexibility, to *task substitution*, where the system develops a schedule for the maintenance worker.

5 Discussion

Our paper illustrates how a cognitive functions lens can help to better understand and frame human-AI hybrids. Based on an embedded single-case study, we identify both CCFs and SCFs of PdM systems and demonstrate how this differentiation can help to determine the allocation of tasks between human agents and AI-based systems. That is, depending on the (type of) cognitive function needed for a specific task, AI-based systems could, consistent with Rai et al. [7], either replace human agents in performing this task, they could augment each other, or even collaborate on performing the same task. Consequently, we believe that the cognitive function lens is an interesting tool that allows IS researchers to explore the socio-technical effects and management of AI.

Our research contributes to both theory and practice. While research in the field of AI covers many different topics, such as the influence of AI on the workplace of the future [e.g., 4] or specific AI applications such as robotics [e.g., 5], the IS community is mainly interested in the exploration of the socio-technical effects and management of AI [2, 7]. However, so far only very few studies investigate AI-based systems from a managerial perspective. Tarafdar et al. [45], for instance, outline how companies can create value by using AI. The authors focus on the introduction of high-level organizational capabilities, such as data science competence, but lack precise recommendations on a procedural level. Our study contributes to IS research in the field of AI by illustrating how researchers can use cognitive functions as a tool to help conceptualize human-AI hybrids. That is, the cognitive functions lens supports researchers in studying the managerial and organizational implications of the implementation of AI-based systems. Hence, the lens is particularly helpful for those who investigate the management and use of AI in organizations.

Our study makes some practical contributions as well. The implementation of AI-based systems surely is one of the future (if not today's) key challenges for the manufacturing sector [22, 46]. However, many practitioners and decision-makers lack a deep understanding of AI [47]. Therefore, they will likely struggle to identify the appropriate functionalities of individual systems that fit their organization's needs. Instead, many organizations take competitive actions based on external pressure that questions the organization's AI competency [48]. As a result, many AI-related actions are poorly aligned with the organization's needs and competencies. Here, cognitive functions are a helpful tool that decision-makers can easily understand regardless of their background. Decomposing an AI-based system into its cognitive functions can facilitate the communication of features and requirements between system engineers and business decision-makers. Moreover, practitioners often struggle with creating the appropriate conditions in their organizations to successfully implement AI-based systems [47]. Although AI-related issues can affect the entire organization on a strategic level, problems often arise at a much smaller scale, such as an adequate adaptation of specific processes or appropriate team designs [8]. Organizational decision-makers need to address these challenges by, for instance, creating an appropriate fit between users, systems, and tasks [49]. The cognitive functions lens can aid practitioners in creating this fit. By analyzing a particular AI-based system's CCFs as well as SCFs, practitioners can better design human-AI hybrids and identify associated requirements on process adaptations. In summary, the cognitive functions lens can assist practitioners in getting even more out of their AI endeavors.

PdM systems possess certain capabilities (or cognitive functions) in which they excel, but so do human agents. Tasks addressed by the CCFs of an AI-based system are usually those tasks for which the system substitutes human agents. Consequently, organizations can redirect their human capacities to other tasks improving their resource efficiency. SCFs, on the other hand, support task augmentation and task assemblage. To benefit from these tasks, organizations should adapt their processes, teams, and cultures in a way that supports human-AI collaboration. For instance, organizations should make sure that at least one team member is capable of training the AI-based system with input from the rest of the team, such as contextualized knowledge or error corrections [50]. In particular, skilled workers who, as mentioned in the previous section, can assess a machine's status based on the noise or vibration could be moved along the line to be part of the team that trains the algorithms. Lastly, organizations might develop entirely new tasks where human agents and AI systems perform tasks as an integrated unit.

In line with existing literature, we find that organizations still rely on human capabilities, such as judgment and explanations to make sense of certain irregularities and machine disruptions as well as human creativity [7, 16, 50]. Possessing certain cognitive functions, such as perceiving and reasoning, PdM systems can provide insights on opportunities for the improvement or development of products and services. However, organizations (still) need human input to develop these products or services. In summary, we regard cognitive functions as an interesting concept to better understand human-AI hybrids. In this way, cognitive functions are a valuable tool to further analyze how the implementation of AI-based systems affects the management of organizations. In line with Raisch and Krakowski [51], we further emphasize the inclusiveness of automation and augmentation when using AI-based systems.

6 Limitations and Further Research

Our paper is but a first step toward making effective use of the cognitive functions lens. As such, it has limitations and offers various opportunities for further research. While we consider a single-case study design to be appropriate for our research objective, single-case studies commonly face criticism concerning their generalizability [52]. While we believe that the embedded setting of the project with multiple participating organizations mediates such concerns to some degree, our research would benefit from further validation. Second, we drew our findings from a specific setting, that of a publicly funded, applied research project with medium-sized enterprises from the mechanical engineering sector. While this particular setting provided us with rich, in-depth insights into PdM implementations, future research should investigate the cognitive functions lens also for other applications of AI, different project settings and different types of companies. Third, our case study focuses on organizations that have merely started implementing PdM. Consequently, we cannot – nor do we intend to – provide a conclusive list of cognitive functions of PdM systems or of design options for human-AI hybrids. Rather, we identify cognitive functions as an interesting lens for researchers interested in the intersection of human agents and AI-based systems in organizations. Future research could further benefit from integrating ideas from collective intelligence literature into the design of human-AI hybrids. While Human-Computer Interaction literature, which we do not cover in this paper, provides several studies on the interaction between human agents and AI-based systems on an individual level [49], we argue that the cognitive functions lens will be particularly useful at the organizational level. Moreover, researchers and practitioners could draw from a better understanding of human-AI hybrids to improve the design of AI-based systems in the future.

In conclusion, we believe that our research, despite its limitations, is an initial step toward exploring the management and use of AI-based systems within organizations. We hope it provides fellow IS researchers with a foundation for continued work in this important domain.

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