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Empowerment Effects in Human-machine Collaboration - A Systematic Literature Review and Directions on Hybrid Intelligence Behavior Patterns

Elisabeth Akmeikina
University of Kassel, elisabeth.akmeikina@wi-kassel.de

Karen Eilers
University of Kassel, karen.eilers@uni-kassel.de

Mahei Manhai Li
University of Kassel, mahei.li@uni-kassel.de

Christoph Peters
University of St. Gallen, christoph.peters@unisg.ch

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Elisabeth Akmeikina
University of Kassel
e.akmeikina@outlook.de

Karen Eilers
Research Center for Information Systems Design, University of Kassel
karen.eilers@uni-kassel.de

Mahei Manhai Li*
Research Center for Information Systems Design, University of Kassel
mahei.li@uni-kassel.de
&
Institute of Information Management, University St.Gallen
mahei.li@unisg.ch

Christoph Peters
Institute of Information Management, University St.Gallen
christoph.peters@unisg.ch
&
Research Center for Information Systems Design, University of Kassel
christoph.peters@uni-kassel.de

Abstract

The potentials of artificial intelligence (AI) are manifold, and their discussion has gained momentum in research and practice. At the same time, AI also raises fears among employees of being replaced by AI technologies, therefore shying away from using them. Generally, employees want to be empowered to do their job and seek both more responsibility and the ability to make their own decisions. In this paper, we conduct a systematic literature review that investigates the current state of the literature on the potential empowering effects of AI-based human–machine behavior. We thus sorted the literature into three behavioral categories: humans shape machine behavior, machines shape human behavior, and human–machine co-behavior. We crossed them with psychological empowerment dimensions of significance, competence, self-determination, and influence. Our results show corresponding literature streams and provide future research directions in a field that is likely to disrupt the way we work in the future.

Keywords: empowerment, artificial intelligence, effects of AI, hybrid intelligence, employee centricity

Introduction

Artificial intelligence (AI) is a key technology. It has become increasingly clear that AI will affect all areas of life and thus companies in the near future. 73% of surveyed companies in Germany, which has an arguably technology-conservative technology mindset, view that AI is one of the most important future

*Corresponding author

technologies. Even though they recognize the enormous potential of AI, only 6% of all companies currently use AI, and only 22% plan to employ AI in the near future (Bitkom e.V. 2020). There seems to be an underlying, perplexing, AI paradox between recognizing the need for AI and organizations refraining from its use, in part due to fears of job replacement (Frank et al. 2019).

The workforce implications of AI are multifaceted and take time to affect the economy (Brynjolfsson and Mitchell 2017). On the one hand, AI can "make complex calculations, solve problems and improve inefficiencies much faster than the human mind" (Deyo 2020). On the other hand, some people reject fully automated decisions or AI-based systems either due to fear of replacement (Huisman et al. 2021) or other threat-faced emotions (Hornung and Smolnik 2021). Still, AI technology enables people to improve their work by minimizing routine tasks or employing technology-enabled analysis of previously overwhelming amounts of data for more informed decisions (Brynjolfsson and Mitchell 2017; Dellermann et al. 2018). To unleash this potential, it is necessary to decrease anxiety and foster trust by empowering employees in interacting with technologies (Hitron et al. 2019). Psychological empowerment of employees is a well-established field in organizational and vocational psychology, establishing that empowerment leads to higher satisfaction, motivation, work performance, and well-being of employees (Welfare et al. 2019). With work becoming increasingly agile, employee empowerment has been shown to be a key factor to improve employee work effectiveness (Eilers et al. 2020, 2021). While recent studies have shown that employing AI systems could positively affect job satisfaction (Nguyen and Malik 2021), so far, there has been little research on the empowering effects on employees interacting with AI technology explicitly. Thus, our study aims to provide further insights and an overview of the current IS literature on the empowering effects of AI technologies on employees based on the four core constructs of psychological empowerment.

AI technology is currently doing simple tasks in companies, such as personalized advertising (Bitkom e.V. 2020). However, rapid technological progress can lead to AI systems taking on more complex tasks and acting autonomously (Berente et al. 2019; Schmidt et al. 2021; Schmidt et al. 2022). On the one hand, employees are taking on more responsibility and want to make important decisions. On the other hand, an AI system should also act and decide independently. Autonomous AI systems as structural empowerment factors that can lead to benefits but also challenges in terms of AI–employee cooperation (Rahwan et al. 2019). So far, there is no uniform approach to the influence of empowerment in the context of AI systems to mitigate risks during the introduction and to strengthen the potential. With the help of a systematic literature analysis, we want to explore how different AI–employee work constellations support employees, expand their skills, and enable new fields of activity in terms of empowerment.

We investigate the following research questions:

RQ1: What is the current state of research regarding employee empowerment and the use of artificial intelligence technologies?

RQ2: What are directions for future research in relation to the empowerment of employees and interaction with AI?

Theoretical background

Defining artificial intelligence

Originating in 1956, artificial intelligence was defined as "the science and engineering of making intelligent machines" (McCarthy 2007). Today, there are many research approaches to defining the term AI. Other computer scientists, such as Marvin Minsky, see AI as a science that makes machines do things for which human intelligence would be needed (Dennis 2020). To understand how artificial intelligence can change the empowerment of people, a comprehensive perspective of AI is required. Russell et al. (2016) provides four AI categories. The first category "human action" aims to create a system that acts analogously to humans. In this way, methods are attempted to be developed so that the computer or the system is attested to do things that can currently only be done by a human or in which humans are superior to the computer. The second approach "human thinking" describes a system that is meant to think like a human, but this approach is at an early stage of research because human thinking has not been adequately researched. The third approach "rational thinking" describes a system that thinks according to logical understanding. An example of such a logical thought process would be "Socrates is a human (major premise), all humans are mortal (Minor premise), so Socrates is also mortal (Conclusion)" (Russell et al. 2016). The fourth approach "acting rationally" uses the agent approach of AI. In this case, an agent is a system that performs an action in reaction (output) to its environment (input) and acts autonomously, can adapt to changes, and pursues a goal. We, define the term AI as an algorithm-based technology that includes all four categories according to Russel et al (2016). This technology has skills that typically require human intelligence. These include, for example, operating autonomously, perceiving its surroundings or its context, being stable over a longer period, adapting to changes, and being able to set and pursue goals. Hybrid intelligence (HI) is an AI concept that stresses the benefits of collective human–AI interactions (Dellermann et al. 2019). In other words, either AI provides input for human decision-making (Agrawal et al. 2018) or humans assist the machine learning process to support AI tasks (Dellermann et al. 2019; Mnih et al. 2015). Thus, to study the interacting effects of AI and employees, we chose HI as a suitable two-pronged concept that captures both elements.

Related work on empowerment

Research and practitioners have been dealing with the term empowerment for many years. There are two approaches concerning the understanding of empowerment: structural empowerment and psychological empowerment. Some researchers use the term empowerment to describe both psychological and structural empowerment and do not distinguish between both perspectives, because of its strong interactive nature (Menon 2001). Nevertheless, other researchers tend to consider these two concepts separately built on two different research streams (Maynard et al. 2012). Structural empowerment focuses on the structures of the IT platform, guidelines, and practices for the targeted transformation and adaptation of organizational structures (Durward et al. 2019; Eilers et al. 2020; Simmert and Peters 2020). In this approach, the power difference between management and employees is to be changed in favor of the employees. Power stands for "the probability that one actor within a social relationship will be in a position to carry out his own will despite resistance" (Weber et al. 1979), p. 53). The structural changes are intended to give employees greater scope for action and decision-making as well as better access to information, resources, and development opportunities (Spreitzer 2008). Based on this, AI technologies can be seen as a structural empowerment measure. A weakness of this approach is that the individual perspective of the employee is not considered so that the individual empowerment of an employee cannot be explained (Schermuly 2015; Spreitzer 2008).

Unlike the structural approach, psychological empowerment takes the individual views, experiences of employees, and their intrinsic motivations into account (Spreitzer 1995). According to (Spreitzer 1995) psychological empowerment is based on self-determination theory and manifests itself from four core dimensions: **significance**, **competence**, **self-determination,** and **influence**. Significance describes the value of a work goal or purpose in relation to the ideals or values of the employee (Thomas and Velthouse 1990). The second dimension, competence, describes the employee's assessment of the extent to which he or she can fulfil a requirement and task with his or her skills and competencies (Gist and Mitchell 1992). Self-determination is about the individual retaining the choice when initiating and regulating actions (Jung et al. 2020). The influence dimension refers to the power that the employee perceives in his work environment. Highly developed employees believe they can influence strategic administrative and operational results of their work (Spreitzer 1995; Spreitzer 2008). All these dimensions are a subjective interpretation of an employee's professional reality. If one dimension of psychological empowerment is not present, it diminishes the overall experience of psychological empowerment, but it does not completely disappear if the other dimensions are sufficiently pronounced (Schermuly 2015).

Changes in structural empowerment, such as "ensuring more influence on decisions in the company" inevitably lead to more psychological empowerment, in which the importance and influence of the employee increases. Structural empowerment always affects psychological empowerment. Artificial intelligence and employee empowerment should be considered together to highlight the greatest potential of both. Enabling people through different technologies is already of great importance in the human–computer interaction (HCI) community. Schneider et al. (2018) found in their study that the turn to empowerment in HCI has the potential to positively influence technology design. Based on the findings regarding structural and psychological empowerment it can be deduced that technology itself can empower or disempower a person. At the moment, there is little research on this subject. It is not clear to what extent and whether AI changes the empowerment of employees at all. If employees are afraid and don´t use AI, the potential of AI cannot be reached. Giving employees control over AI interactions can empower them which has positive effects on the job satisfaction of employees and therefore has an impact on the performance of a company. For this reason, it is urgent to investigate how an AI affects the empowerment of employees and what influence (empowered) employees have on the AI.

Methodology

To be able to answer the research question, a systematic literature review was conducted according to vom Brocke et al. (2018) and Webster and Watson (2002) in mainly four steps (i–iv). To get an overview of the current situation, regarding empowerment of employees and AI, the databases AISeL, IEEE, ACM, and EBSCO were selected for the literature research and included all senior baskets of eight and leading IS conferences (ICIS, ECIS, HICCS). Another important step is to define the search terms for which all proceedings will be examined. After checking some search terms, such as artificial intelligence, employee ability, and organization, the search string **("artificial intelligence" OR AI OR "machine Learning") AND (empowerment OR "self-determination" OR "self-organization") AND (organization)** was chosen. We chose to include self-determination and self-organization since empowerment originates from the closely related self-determination theory (Spreitzer 2008). We searched for all results between (i) the years 2010 to 2021, due to an IS surge in research in AI because researchers have increasingly access and interests to studies on AI in organizations. The starting period also coincides with the resurging interest in artificial intelligence in mainstream media, where an AI system won against human intelligence in the national quiz show "Jeopardy" for the first time. Furthermore, we use the definition of an agent-based view on AI (see chapter 2.1) as a criterion to decide relevancy. This means that the relevant papers must adhere to our **definition** of **artificial intelligence** (ii). The initial search term results were sorted out according to their title and abstract so that 396 papers were selected for further processing. Next, each paper was screened thoroughly for papers that addressed the effects of AI on individuals and papers that do not address **humans** were **sorted out** too (iii). For this reason, proceedings that only dealt with technological or analytical aspects (e. g. predictive models) were also **sorted out** (iv), which made up most of the 369 papers. **30 papers** were classified as relevant. After a forward and backward search according to the screening criteria (i–iv), eight additional papers were also included in the analysis (see Figure 1).

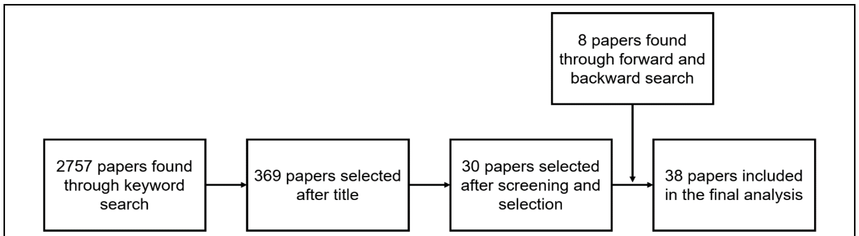

Figure 1. Literature Search Process.

The concept matrix for the literature review on empowerment and artificial intelligence

When analyzing the shortlisted 38 papers, different interaction mechanisms, so-called behavioral patterns, emerged. The importance of behavior patterns between humans and machines has gained popularity in the literature, which is shown in a dedicated science article (Rahwan et al. 2019). There are generally three different behavior patterns between machines and people (Rahwan et al. 2019). These behavioral patterns were adopted to examine the influence of AI on the empowerment of employees (Table 1).

The first area is "**individual machine behavior**". Here the AI algorithm itself is examined. This includes, on the one hand, the study that focuses on creating a profile of the behavior of a specific machine agent and comparing the behavior of a machine. On the other hand, this approach examines how several machine agents behave under the same conditions. In contrast to the individual perspective, the "**collective machine behavior**" describes how individual machines react to the interactive and system-wide behavior of collections of machine agents. In other words, how multiple machine agents interact with each other. Since we are dealing with the influence of AI on employee empowerment, the area of individual and collective machine behavior can be left out, as these only relate to the agent in their investigation and less consider the effects on humans (Rahwan et al. 2019) Another behavior pattern according to Rahwan et al (2019) is the "(hybrid) **human–machine behavior**". A distinction is made between "human shape machine behavior", "machines shape human behavior" and "human–machine co-behavior". With "**human shape machine behavior**", people shape the behavior of machines through the direct engineering of AI systems and the training of these systems. This training can take place through active human input, passive observation, and data. To go into more detail about how an AI system can learn and which areas have already been well investigated, three additional areas were included in the analysis. On the one hand, there is the area of "**mechanical intelligence**", in which the system learns and adapts only to a minimal degree. This type of AI is particularly suitable for automating simple, standardized processes (Huang and Rust 2020). With "**thinking intelligence**", the system learns from the data made available to it. The last area, "**feeling intelligence**", describes learning from observations. The system learns, for example, by observing and analyzing human behavior. Another behavior pattern of "human–machine behavior" is "**machine shape human behavior**". It is assumed here that not only humans can influence the behavior of the machine, but also machines influence the behavior of humans. This includes research on how artificial intelligence can be used as a decision-making aid and thus influence human behavior. The third behavior pattern is "**human–machine co-behavior**". One of the topics is the robot- and software-controlled automation of human work. Machines can improve a person's efficiency. We refer to this type of relationship in this work as "cooperation" between humans and machines. It is particularly important that the system is seen as an equal member of a project team and that i' works cooperatively with people. However, machines can also replace people in their work. Since these approaches are opposite, "**cooperation**" and the "**replacement**" of humans are examined separately from each other (Rahwan et al 2019).

As opposed to the different behavior patterns between an AI and a human there is the empowerment of people. As mentioned in chapter 2.2, we focus on the psychological empowerment of employees. For this reason, the behavior pattern between AI and humans was compared with psychological empowerment with its four core dimensions (**significance, competence, self-determination,** and **influence**) by Spreitzer (1995) (see Table 1)

		Hybrid Intelligence Behaviour Types					
		Humans shape machine behavior			**Machines shape human behavior**	**Human–machine co-behavior**	
		Mechanical Intelligence	*Thinking Intelligence*	*Feeling Intelligence*		*Cooperation*	*Replacement*
Psychological empowerment	*Significance*	Smirnov and Ponomarev 2019 Wang et al. 2010 Charalambous et al. 2015	vom Brocke et al. 2018		Prilla 2015 Kou et al. 2019 Sun et al. 2010 Rakova et al. 2020	Werkhoven et al. 2018 Seeber et al. 2018	
	Competence	Charalambous et al. 2015			C. I. Chesñevar et al. 2014 P. Mattei 2020 S. Reeves and S. Sherwood 2010 S. Renals et al. 2014	Gunasekaran et al. 2016 Hernández-Orallo and Vold 2019 van den Bosch et al. 2019 Libert et al. 2020 Seeber et al. 2018	Hernández-Orallo and Vold 2019 Welfare et al. 2019 Stock and Merkle 2018 Seeber et al. 2018
	Self-determination		vom Brocke et al. 2018 Bosch 2019 Lai und Tan 2019 Verhulst 2018	Muller and Ulrich 2013	Lee 2014 Wang 2016 Danry et al. 2020 Roussou et al. 2019 Fanni et al. 2020 Sun et al. 2010 Verhulst 2018 Marhraoui und A. El Manouar 2015 Mattei 2020 Kocsis et al. 2019	Benbya et al. 2020 Mioch et al. 2018 Green and Chen 2019 Maitra 2020 Seeber et al. 2018	Werkhoven et al. 2018
	Influence	Madaio et al. 2020 Charalambous et al. 2015	Bosch 2019 Amershi et al. 2015		Kou et al. 2019 Mattei 2020 Reeves and Sherwood 2010	Amershi et al. 2015	Wang et al. 2019

Table 1. Concept matrix – Hybrid intelligence behavioral pattern analysis

Findings

Hybrid Intelligence Behavioral patterns

How humans influence the learning behavior of machines

Organizational communication– Through psychological empowerment, the employees are much more concerned with their task but also with the organization itself. As a result, they understand their task requirements much better and want to make more decisions in the entire organization. The fact that the employees are increasingly empowered and therefore more concerned with the company makes it more important that the company's change management needs to be ideally prepared for the introduction of AI. Effective communication is particularly important for implementation. By involving employees in the change process, decisions are shared between supervisors and employees, which increases the feeling of personal responsibility and control (Charalambous et al. 2015).

Human supervising AI– The role of the employee in mechanical intelligence is typical to perform tasks that are still difficult for the AI (e.g., handling incomplete information). In the meantime, the AI only processes and coordinates data. There are already approaches in which the system is given more freedom, but in these systems the adaptation processes can only be controlled by humans (Smirnov and Ponomarev 2019). It can be said that human supervision will always be necessary for the area of mechanical intelligence because, e.g., changed goals must be communicated (Seeber et al. 2018; Wang et al. 2010). The use of AI increases the importance of people with their tasks.

Human intervention– Employee skills and competencies are crucial company resources. In the area of mechanical intelligence, people continue to be empowered through their skills because an AI system is not mature enough to think exactly like a human. According to this, AI systems, for example, would rather take care of tasks that require a reasonable amount of physical strength and repeat themselves, while workers can concentrate on tasks that require human skills (Libert et al. 2020). It is emphasized again that the users of an AI must be given additional control to promote the acceptance of the system and increase the influence of the employee on the AI (Mnih et al. 2015) (Charalambous et al. 2015). However, the collaboration between humans and AI should be based on an AI fairness checklist. Such checklists enable the team to be empowered even more, as the checklists are supplemented with additional resources and can be adapted by every team (Madaio et al. 2020).

Organizational intervention– In the area of thinking intelligence, an AI system can show possibilities based on the preferences of the user. The AI uses data that is provided by humans and thus supports humans in many areas. "Big Data" is the keyword here to allow AI to learn (Bosch 2019) and to provide decision-making aids. Transparency is particularly important because empowered employees want to understand how the system came to this decision (Lai and Tan 2019). The leadership style must leave room for experiments and mistakes to structurally empower the employees (vom Brocke et al. 2018). Innovative companies are characterized by fluid structures so that the employee has a great influence on the decisions in the company (Bosch 2019; vom Brocke et al. 2018). At the group level, teams can benefit from faster decision-making processes. At the organizational level, a better exchange of information and knowledge can take place on a large scale (vom Brocke et al. 2018). The whole team is empowered in thinking intelligence because a lot of collaboration must take place. The teams have to be aligned in such a way that continuous responsibility for the achievement of goals and customer requirements is guaranteed (vom Brocke et al. 2018).

Agile team intervention – Agility is particularly suitable for being able to work with an AI. When agility is introduced, the teams receive a considerable degree of empowerment, initially within their team boundaries (Bosch 2019). The aim is for everyone to take full responsibility for their role and act in an authoritarian manner (Bosch 2019). Introducing empowerment in an agile team requires carefully defined output metrics so that it is clear what success means for the company and how the team can contribute to it (Bosch 2019). Humans still have to provide the system with data so that they can process the information. The human ability to empathize and innovate remains a competitive advantage over AI (Amershi et al. 2015; vom Brocke et al. 2018). For this reason, the employee retains influence and control over his work.

Emotional and sensory human input– Unfortunately, there is still a large research gap in the area of feeling intelligence. Being able to solve problems by oneself increases psychological empowerment and this has been shown to be especially useful for job satisfaction (Muller and Ulrich 2013). Support systems are less suitable for tasks that require creativity (Muller and Ulrich 2013). So, it can be said that in the area of feeling intelligence, AI can both increase and decrease empowerment. We can say that at feeling intelligence the systems must be self-describing, self-discovering, and self-organizing to achieve a company's goals (Bent et al. 2018). The AI systems observe people closely, for example, to be able to correctly interpret their emotions (Ivanović et al. 2014). This increases the social acceptance of AI systems and auxiliary robots (Schürer et al. 2017). Such a learning behaviour of the AI reduces the time for programming for humans, so that time and costs can be saved here too (Wang et al. 2018). AI can be attached directly to the human being (e.g., with the help of an external device on the forearm) (Wang et al. 2018) or learned through other sensors. The system can also repeat the user’s commands (e.g., via voice commands) to improve his intelligence more effectively (Wang et al. 2018). Feeling intelligence from both an emotional and sensory perspective remains to be a green pasture full of future research potentials.

The influence of machines on human behavior

Changing employee’s job roles– Although humans influence machines, nowadays, machines are increasingly influencing human behavior. Employees with specialized AI-related roles report that they benefit from an organizational structure that enables them to design their own job roles in a very dynamic and context-specific way (Rakova et al. 2020). People are no longer seen merely as supporters of the systems but are given a significant role as shapers of how AI systems and machines learn (Rakova et al. 2020). When using AI, collective intelligence can arise, in which the knowledge of humans and AI collide the significance of humans increases as a result (Sun et al. 2010).

AI augments employee skills– AI can identify collective thought patterns and thus improve the decision-making ability of employees (Chesñevar et al. 2014). AI systems can also be used for supporting the employees beyond their actual tasks. For example, such a system can recognize what training the employee needs or what his state of health is. An employee can also be empowered by the fact that the AI promotes communication between people, for example, by being better structured via social media platforms or meetings (Renals et al. 2014). Both increase the employees' competence because, through the additional training, which the AI recognizes, the employee is constantly expanding his skills. Besides, the employee benefits from ready-made structures in communication so that he can use his skills in more suitable areas. Monitoring the behavior and health of employees leads to fewer absences in the long term and thus to greater productivity (O. Kocsis et al. 2019, p. 436). It is important that employees realize what competencies and abilities they have to effectively and continuously develop AI-related skills to control the AI system (Mattei 2020; Reeves and Sherwood 2010). Controlling and applying technologies creates new jobs, especially in the area of machine learning and data science (Mattei 2020).

AI opens new decision-making paths– In terms of empowerment, the use of AI systems increases the self-determination of employees. They have the opportunity to access a wealth of information and decide for themselves which information is most relevant for them (Mattei 2020). Much more, they can concentrate on essential tasks when an AI takes on less efficient tasks. This saves time and money (Mattei 2020). AI systems give the employee decision-making aids, which on the one hand leads to the maximization of benefits (Verhulst 2018), and on the other hand, the machine "manipulates" human behavior. However, through their decision-making ability, the employee retains influence over his work (power to) and uses the system (consciously) as support (power over) (Kou et al. 2019; Prilla 2015; Wang et al. 2016). It is important that the system can show how a decision was made. If the source is found to be untrustworthy, the suggestions of the AI do not influence the decision of the employee (Danry et al. 2020?). Decision-making aids should not be allowed to get out of hand, because employees can quickly feel bothered, and their importance is diminished (Prilla 2015). For this reason, it is important to keep such requests as inconspicuous as possible (Prilla 2015). Agility increases the empowerment of employees and can be used excellently for cooperation with an AI. AI can, for example, be (Marhraoui and El Manouar 2015) used as a tool for agile work to strengthen teamwork through team mechanisms (Lee 2014). When using agility, the morale of employees concerning their tasks in the company can be increased. This empowers the entire agility team (Marhraoui and El Manouar 2015). A lack of agility in a company inevitably leads to less IT innovation (Marhraoui and El Manouar 2015). Provocative answers from an AI can also be used to encourage employees or the entire team to think more closely about a particular topic or to look at it from a different perspective (Roussou et al. 2019).

AI control by an empowered employee– The influence of the employee over an AI can be divided into the following two types. Passive employees have no control over the AI and its decision (human-out-the-loop). Active people (human-in-the-loop) have a great influence on the decisions of an AI and constantly monitor them (Fanni et al. 2020). The employee must be aware of his own knowledge, his strengths, and especially his limits before he can work effectively with an AI (Kou et al. 2019). In other words, the employee must be empowered before they can work with the system without fear. AI systems (still) rely on human interaction and judgment. The influence of people who work with an AI increases enormously, since the system has to learn from people, control it and, if necessary, also adapt it (Reeves and Sherwood 2010). By using AI, the empowerment of the employees is strengthened.

Human–machine co-behavior: the new teammate

Employees monitor goals – Cooperation between an AI and a human is about the AI being viewed and treated as an independent member of the team. Psychological empowerment has been very well researched and plays an important role in cooperation. All team members, including AI agents, would need to achieve a common understanding of the goals (Werkhoven et al. 2018). In AI–human cooperation, the employee takes on the role as a "meaningful controller" who integrates the (ethical) goals of the system in the form of target functions "before the loop" (Werkhoven et al. 2018). This increases the perceived significance of employees enormously. An AI which can understand the emotions of the human teammate and react accordingly leads to the fact that the human builds an emotional bond with the AI, which can lead to positive feelings. However, there are also cases where the human feels inferior and less significant through the new nonhuman team member (Seeber et al. 2018).

Employee competence awareness – AI can help people internalize new concepts and ideas (Hernández-Orallo and Vold 2019). When humans and AI work together, a multitude of knowledge arises, which empowers both parties to achieve common goals. As soon as AI enters the team, the employees will have to adapt and change it. For this reason, it is necessary that the organization trains the collaboration skills of employees so that they can work together (Seeber et al. 2018). Employees must be clear about their competencies and bring their knowledge to their team (Gunasekaran et al. 2016; van den Bosch et al. 2019). Otherwise, there is a risk that certain competencies will disappear, and that people will become dependent on AI (Seeber et al. 2018).

Bringing intelligence together – Team members take responsibility not only for their tasks but also for other (Maitra 2020). This requires a certain degree of autonomy. There is a fear that even system developers will at some point no longer be able to control or influence the direction of the autonomous AI or their underlying algorithms (Maitra 2020). This raises questions of the importance of teaching AI human morality as a way of controlling its behavior. In a team, the system could bring its own "machine" intelligence and thus lead to added value at the intersection and interaction of machine and human intelligence (Maitra 2020; Seeber et al. 2018). For better teamwork, working agreements can be established that precisely determine which authorizations, obligations, or prohibitions the respective team members have (Mioch et al. 2018). Initially, this reduces the empowerment of the employee, but the employee can decide completely voluntarily whether to reject or accept such a restriction (Mioch et al. 2018).

Clarify the scope of AI – Employees are afraid of being replaced by machines. According to our analysis, this is indeed the case. Some human tasks are being replaced by AI. In others, humans will play a more dominant role, with different degrees of partial empowerment. When using a humanoid service robot, for example, it is important to find out which properties people appreciate in AI to be able to apply them (Stock and Merkle 2018). Here, it seems that after the learning phase, people become less important. However, even an autonomous AI and stand-alone robots do not have the same capabilities as humans do. AI should be used in areas that harm people or are too strenuous for them. In other words, handing over the negative attributes of work to an AI to protect people should be prioritized (Seeber et al. 2018; Welfare et al. 2019). In this way, employees can devote themselves to other tasks for which their skills are ideally suited. They can take on complex tasks that, for example, require creativity, complex logical and rational thinking, or special skills that are hard to formalize (Seeber et al. 2018). Nevertheless, many applications currently favor replacing humans, for sensory perception, reasoning, decision-making, and other functional uses (Wang et al. 2019). The only touch points with humans would therefore only rise when humans are in a governing position to authorize business-relevant decision that are made by the AI. Ultimately, it can be said that if the goal of AI is to replace a person, this reduces empowerment of the person.

Directions for future research

Based on the systematic literature review we consider several issues that further research should take into investigation. We divided the future research into the previously used patterns: human shape machine behavior, machine shape human behavior and human–machine co-behavior. The directions for future research are summarized in Figure 2. The dimensions were divided into "Influence of AI on psychological empowerment" and "embeddedness of AI". The former shows how great the influence of the AI used can have on the empowerment of employees. *Embeddedness shows the extent to which AI is integrated into an employee's work or life.*

Human shape machine behavior

Some research emphasizes that it is important to develop standards to simplify the introduction of AI systems and robots and to keep people safe (Welfare et al. 2019; Wang et al. 2019). The aim should be to maintain or even increase the job satisfaction and motivation of employees. The overlap of work attributes of humans and AI must be considered more closely (Welfare et al. 2019). Example future research question: According to which standards does an AI have to be structured so that it increases employee motivation, empowerment and offers security?

Another direction is about finding out how the burden on people can be reduced with AI. For this purpose, tutorials for models of machine learning and their explanations could be developed (Lai and Tan 2019). Interactions between humans and AI could be supported by semantic overlays (Sun et al. 2010), but more research is needed. Example future research question: *How can the use of AI be simplified for employees?*

Machine shape human behavior

It is often assumed that people can distinguish which information and decisions of an AI are correct and relevant for them. Green and Chen (2019) found that this is not always the case, as humans are unable to detect errors in this information. For this reason, we believe that research should be done on how to keep an AI's information and decisions fair and understandable, so that a human can spot errors when they arise. Example future research question: How does the design of an AI have to be to provide fair and understandable support for the employee? Our results show that AI has the potential to go beyond human capabilities. This raises the question of what such an AI extender should look like so that it fully takes into account the capabilities and autonomy of the extended human being together with an objective function of what the resulting symbiosis can achieve and all the effects of this coupling (Hernández -Orallo and Vold 2019). Example future research question: *How does an AI have to be structured so that it takes into account human empowerment?*

People's empowerment is (indirectly) influenced by the decision-making aids provided by AI. The question here is how ethical this influence is. Mattei (2020) states that ethical bodies already exist, but they significantly slow the pace of AI development. For this reason, we believe that ethics must be considered more closely, and which decisions should be left to humans (Mattei 2020; Berente et al. 2019). Example future research question: How can an AI be taught ethics and which decisions should remain with humans? It must be examined how the human ability to act changes or will change. It is particularly important to find out where there are areas in which the human ability to act is undermined when introducing AI (Fanni et al. 2020). These areas, which undermined the human ability to act, would also reduce the empowerment of an employee. In addition, it must be examined to what extent the introduction of AI brings (new) prejudices or increases the risk of making decisions based on poor data. To this end, it is also necessary to research how a broad spectrum of collective intelligence can be used (Verhulst 2018; Gunasekaran et al. 2016). Example future research question: *Where does AI reduce and manipulate employee empowerment?*

Human–machine co-behavior

The aim is to examine how AI can promote the creativity of employees (Muller and Ulrich 2013). Now, creativity is still a unique selling point for humans, as described in chapter 5.1.1. It may be relevant here to examine to what extent AI can promote the creativity of the employee without the employee feeling inferior or even being replaced. Example future research question: *How can AI be used for human creativity without reducing their empowerment?*

Danny et al. (2020) found that it is possible to make AI transparent by using explainable feedback. As a result, people understand and accept AI better. On the other hand, the question remains open as to whether an AI must also understand the human understanding of intelligence (morality, human values, etc.) or whether an AI should continue to retain rational intelligence (see chapter 5.1.3) (Maitra 2020; Kou et al. 2019). Example future research question: Which intelligence should the AI be taught so that it is transparent and can give feedback at the same time?

It must be examined how interactions arise when empowered humans and machines work together. In addition, it is necessary to research what information an agent has to disclose to elicit adaptive responses from his partner or partners and what effects different explanations of others have on the learning of a team member (Libert et al. 2020). We claim that transparent AI leads to employees becoming more empowered because they have increased access to more information. To be able to work effectively with people, AI must be able to understand people so that a partnership-based interaction arises (Werkhoven et al. 2018). However, more control and more transparent systems do not guarantee successful cooperation. Here it must be examined when which interactions between the user and the AI are desired and when they even disturb (Amershi et al. 2015). AI fairness also needs further research. An AI fairness checklist was drawn up, but no best practices have yet emerged (Madaio et al. 2020). Example future research question: Which interactions are particularly suitable for human–AI collaboration?

Future research must examine the effects of AI–human teams on the effectiveness of the team's performance (Mioch et al. 2018) and also how satisfaction changes among people through the use of AI systems (Stock and Merkle 2018). In our opinion, in addition to the research results to date, it is necessary to examine what the ideal interplay of performance and job satisfaction looks like. Example future research question: *How does cooperation between humans and AI affect the work performance and job satisfaction of employees?*

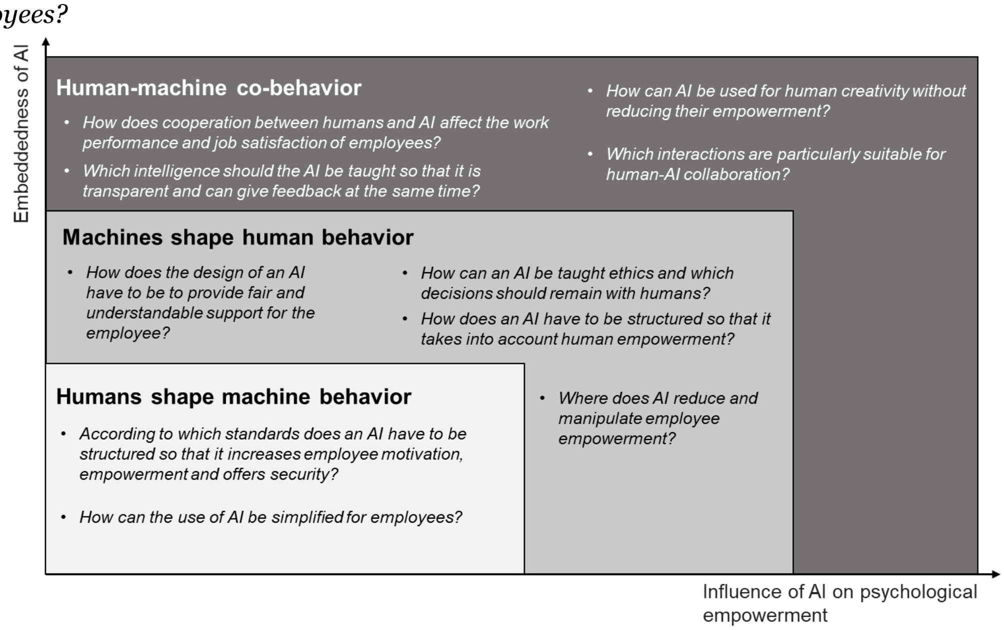

Figure 2. Future Research Directions of Hybrid Intelligence Behavior

Conclusion

The use and effects of AI have major implications for our lives and the work processes in our organizations. Real collaboration between humans and machines in hybrid intelligence settings is and will be an important field in research and industry. To provide a solid base for the design and management of such hybrid intelligence settings (Dellermann et al. 2019), we want to shed light on the behavioral patterns that exist in this context. The corresponding results of our systematic literature review provide a more detailed understanding of how the empowerment of employees is influenced by AI systems and demonstrate the potential of AI systems for employees. Two research questions guided our study. We first examined the current state of research regarding the influence of AI systems on the psychological empowerment of employees (RQ1) and identified instructions for future research (RQ2). Our analysis shows that the use of AI systems affects employee empowerment on different levels. Empowered employees are more willing to work with AI if they have a sense of control over it. The influence of AI systems on employees is also increased (positively or negatively), through decisions and decision-making aids from AI. Here an interrelation arises which could be examined more closely (RQ2). On the one hand, the behavior of AI systems should be further explored to guarantee that they act ethically and fairly. On the other hand, how the cooperation between AI systems and employees can be designed in an equivalent team so that the advantages of both actors can be best used.

We also contribute to how human–machine behavior patterns look like and what effect they have on employee empowerment. As far as we know this was not yet subject to any previous research and we offer insights on how AI can be used to empower employees. Regarding the AI paradox (Bitkom e.V. 2020), AI empowers employees and opens new ways to work. Empowerment is a cornerstone for being able to work effectively with an AI (organization strengthens empowerment). The employee must be able to control and adapt the AI, which also leads to an increased sense of empowerment (human supervising AI). Since AI cannot completely replace humans, human skills are still required (human intervention). However, not only the employee can contribute to the successful use of AI in the company. The organization must strengthen managers, leave room for decisions and mistakes, and give employees freedom in the decision-making process (organizational intervention). Agile working methods are particularly suitable for this so that the employee can strengthen their empowerment (agile team intervention). The area of feeling intelligence has not yet been adequately researched. The AI can observe people (emotions, facial expressions, etc.) or generate data with the help of external sensors that are attached directly to the employee (emotional and sensory human input).

The use of AI gives the employee a decisive role, i.e., that of the "learner" (Changing employee's job roles). When dealing with AI, employees must first be clear about their skills so that they can be used effectively (AI augments employee skills). These competencies can be used to understand the decisions of the AI or to accept the right decision aids from the AI. Here, the AI can also have a positive influence on the empowerment of employees if the employee allows himself to be manipulated by the decisions and becomes dependent (AI opens new decision-making paths). The AI still has to be controlled at the moment, as it cannot work completely autonomously. This also increases the empowerment of employees (AI control by an empowered employee). When AI and employees work together, additional behavior patterns arise. The employee must keep an eye on the common goals of the entire team (employees monitor goals). When working together, human intelligence meets artificial intelligence. The employee must be aware of his intelligence (his competencies, skills, etc.) in order not to be deterred from the AI (employee competence awareness). It is important to use both types of intelligence to be able to extract the best possible benefit (bringing intelligence together). In order not to replace humans, it should be clear which tasks the AI should take over before the introduction of an AI in a company and what the aim of this AI should be (clarify the scope of AI). Future work will particularly focus on improving and exploring the collaboration between humans and AI. The behavior of AI should also be further examined.

Additionally, this research makes a practical contribution toward the need for empowerment by using AI technologies. Companies must ensure that employees can expand their skills and are aware of their skills. This means that they are empowered and can see AI as supportive. AI systems should not simply be imposed on employees. They have to understand what AI is for and how it makes decisions. To increase employee acceptance of an AI, change management must include employees as early as possible in the change process.

In conclusion, this work offers a representative and comprehensive overview of the existing literature on empowerment and the use of AI systems. The structured scientific knowledge can be used to accelerate the introduction of AI in companies and to stimulate further future research to take a closer look at empowerment in this area. The status quo of research shows that there are already many approaches to how employees can be empowered by AI and that this empowerment is important to work successfully with it. The identified future research questions of the identified studies all suggest that there are still some things to investigate in this area, all of which encourage collaboration and empowerment.

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