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Value Creation in Connectionist Artificial Intelligence – A Research Agenda

Rainer Schmidt
Munich University of Applied Sciences, rainer.schmidt@hm.edu

ALFRED ZIMMERMANN
School of Computer Science, alfred.zimmermann@reutlingen-university.de

Michael Moehring
Munich University of Applied Sciences, moehring@hm.edu

Barbara Keller
Munich University of Applied Sciences, barbara.keller@hm.edu

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Completed Research

Rainer Schmidt
Munich University of Applied Sciences
rainer.schmidt@hm.edu

Alfred Zimmermann
Reutlingen University
Alfred.zimmermann@reutlingen-university.de

Michael Möhring
Munich University of Applied Sciences
michael.moehring@hm.edu

Barbara Keller
Munich University of Applied Sciences
barbara.keller@hm.edu

Abstract

Artificial Intelligence enables innovative applications, and applications based on Artificial Intelligence are increasingly important for all aspects of the Digital Economy. However, the question of how AI resources such as tools and data can be linked to provide an AI-capability and create business value is still open. Therefore, this paper identifies the value-creating mechanisms of connectionist artificial intelligence using a capability-oriented view and points out the connections to different kinds of business value. The analysis supports an agenda that identifies areas that need further research to understand the mechanism of value creation in connectionist artificial intelligence.

Keywords

Artificial intelligence, machine learning, capabilities, value creation.

Introduction

Artificial Intelligence (AI) receives a high degree of attention due to recent progress in several areas such as image detection, translation, and decision support (McAfee and Brynjolfsson 2017). It is a decisive factor for the competitiveness of companies, but the necessary strategy development is very challenging (Davenport and Ronanki 2018). Connectionist Artificial Intelligence is the most important general-purpose technology of our times catalyzing complementary innovations (Brynjolfsson and Mcafee 2017). Artificial Intelligence enables innovative applications such as predictive maintenance, logistics optimization, and improved customer service management (Chui et al. 2018). AI supports decision-making in many business areas (Russell and Norvig 2016), and most companies expect to gain a competitive advantage from Artificial Intelligence (Ransbotham et al. 2017). Therefore, applications based on Artificial Intelligence are increasingly important for all aspects of the Digital Economy, be it business processes or business models (Tapscott 1996).

However, the question of how AI resources such as tools and data can be linked to provide a capability and create business value is still open (Varian 2018). The importance of AI for the competitiveness of companies suggests that one should speak of AI-capability as a specialization of the general capability concept introduced by Teece et al. (1997). Up to now, to the best of our knowledge, there is no framework giving guidance in the acquisition and the leveraging of AI-Capabilities to create value. The connection between AI-capabilities and the creation of business value is largely unexplained. Instead, the development of AI capabilities happens often ad-hoc, which motivates us to ask the following research question:

What is the connection between AI capabilities and the different forms of business value?

The contribution of this paper is to identify the value-creating mechanisms of connectionist artificial intelligence using a capability-oriented view and to point out the connections to different kinds of business value. With this analysis, we create an agenda that identifies areas that need further research to understand the mechanism of value creation in connectionist artificial intelligence.

The structure of this paper follows recommendations for design science research projects (Hevner et al. 2008). We demonstrate the relevance and begin our research project with a systematic literature research (Recker 2013). The core result of our design cycle is a framework for business value as a model artifact (Recker 2013). The business value framework abstracts different types of value created by connectionist artificial intelligence. The framework abstracts fundamental capabilities that enable the creation of three process-related capabilities. We identify areas of research and develop the research agenda based on the previous analysis. In the end, we give a conclusion and outlook on future research.

Background

The endeavor to mimic cognitive and human capabilities on computers has created a number of development streams whose origins date back into the 1940s. The development of artificial intelligence consists of several sub-disciplines based on fundamentally different approaches, where we are setting a focus on symbolic AI, machine learning, and connectionist approaches (McAfee and Brynjolfsson 2017). The latter developed into the now dominant flavor of AI is called deep learning. Most of the progress in digitalization made in the recent years stems from deep learning approaches (McAfee and Brynjolfsson 2017).

Symbolic AI

Symbolic AI uses a deductive, expert-based approach (Russell and Norvig 2016). Typically, knowledge engineers collect knowledge from experts and represent this expert knowledge explicitly through rules and other representations. These rules are applied to facts describing the problem to be solved. The solution to a problem results by applying one or more rules consecutively using the mechanisms of an inference machine (Russell and Norvig 2016). An inference path is usually also backward traceable, enabling user transparency about instantiated inference processes by "how" and "why" explanations. Symbolic AI proved to be very effective for formalized problem spaces such as theorem proving. However, it failed to cope with everyday problems, which lead to the formulation of Moravec's paradox (Moravec 1988). After the last vogue of enthusiasm at the end of the 1980s, the focus of research moved to other areas (Russell and Norvig 2016).

Machine Learning

Machine learning uses an inductive approach in which decision rules are identified based on collected data using statistical methods(Provost and Fawcett 2013). There are plenty of approaches used in supporting business processes (Provost and Fawcett 2013). However, an important challenge is selecting the decisive features within a data set. Two basic approaches to machine learning approaches exist supervised and unsupervised ones (Provost and Fawcett 2013). In supervised machine learning approaches, the target value is part of the training data and results from example inputs. For unsupervised learning approaches, there are no given examples for learning algorithms. Typically, unsupervised learning applies for discovering hidden patterns within the analyzed data.

Connectionist Artificial Intelligence

The basic mechanism of connectionist artificial intelligence is the imitation of human neurons in neural networks. The weights representing the strength of the connection between neurons is adapted until the transformation of input signals to output signals shows the required behavior (Chollet 2017). This adaption is called training and is using training data (Chollet 2017). Early approaches to neural networks were inspired by the functioning of the human brain and its neurons (McCulloch and Pitts 1943). In their seminal paper, Rumelhart et al. introduced the backpropagation algorithm that creates substantial progress (Rumelhart et al. 1986). After a slow-down in the 1990s, progress accelerated. Different architectures dependent on a set of application areas were created. Convolutional networks (CNN) combine a multitude of inputs and can thus recognize increasingly abstract objects (LeCun et al. 1998). The long short-term memory approach described in added important concepts to recurrent neural networks (RNN) (Hochreiter and

Schmidhuber 1997). Generative Adversarial Nets (GAN) are an important new development for estimating generative models via an adversarial process (Goodfellow et al. 2014).

Connectionist Artificial Intelligence is already in use for numerous areas of the digital economy (McAfee and Brynjolfsson 2017). Well-known AI applications include virtual personal assistants and chat bots used in diagnostic and recommendation systems (Koetsier 2018). Connectionist approaches unlock business value through automating processes, identifying trends in historical data, and strengthening human decisions by a forward-looking intelligence (Brynjolfsson and Mcafee 2017). Connectionist approaches replace decision-making based on human experts by automated collected and updated knowledge (Brynjolfsson and McAfee 2014). In this way, the decision-making is faster and requires fewer resources. Therefore, decisions can be made more frequently and adapted to changing conditions (McAfee and Brynjolfsson 2017).

AI Capabilities

The importance of AI for the competitiveness of companies suggests that one should speak of AI-capability. Capabilities are integrating, adapting, and reconfiguring of internal and external organizational skills, resources, and functional competencies considering a changing environment (Teece et al. 1997). According to this definition, AI capability is the ability of organizations to use data, methods, processes and people in a way that creates new possibilities for automation, decision making, collaboration, etc. that would not be possible by conventional means.

Our considerations result from the understanding that there is a hierarchy of capabilities (Teece 2010). Capabilities represent for (our) further consideration layered entities (Winter 2003). Starting with capabilities that enable enterprises to survive in the market (Zero-level-capabilities), a hierarchy of even more powerful capabilities can be sketched (Winter 2003). In essence, zero-level capabilities enable companies to collect revenue from its customers. By activating one or several lower-level capabilities, a higher level capability can be created (Teece 2010). The top-level capabilities allow implementing different strategic options (Teece 2010).

Business Value Creation by Artificial Intelligence

To motivate our work and to create awareness, we describe the aspects of predictive maintenance, servitization and, platform creation as three ways of the most important approaches of value creation by artificial intelligence (Ransbotham et al. 2017).

Predictive Maintenance

Predictive maintenance uses the actual operation condition of equipment and systems to optimize the operation (Mobley 2002). The challenge is to reduce unplanned downtime as same as maintenance costs. The ability of AI-based systems to discover and predict events is the key to enhance predictive maintenance (Chui et al. 2018). In this way, it is possible to minimize the sum of the cost for unplanned downtime and maintenance expenditures (Chui et al. 2018). Current research shows that the use of Machine Learning algorithms is essential to implement predictive maintenance information systems. Furthermore, other authors deeply focus on specific Neural Networks to suggest preventive maintenance interventions (Confalonieri et al. 2015). Current research shows that the use of Machine Learning algorithms is important to implement predictive maintenance information systems (Möhring et al. 2020).

Servitization

AI-based decision mechanisms enable the transformation of physical products into the provisioning of service (Dopico et al. 2016). Artificial Intelligence predicts failures more precisely and even give prescriptions on how to cope with this situation. Servitization uses AI capabilities to coordinate the usage of the service with the user. Also, Fleet Analytics is important to improve the reliability of services provided (Winnig 2016).

Platform creation

Platforms, as defined in (Alstyne et al. 2016), are an important example of the extended use of AI in current enterprise systems and digital ecosystems. Platforms inverse the classical structure of enterprises. Instead of owning a considerable amount of resources to achieve scaling effects, they orchestrate resources owned by participants. Two functions of platforms highly profit from the use of AI. The assessment of resources and the matching of demand and supply. On a platform, the assets are not the property of the platform owner. By using AI, it is possible to assess resources by the users of the resources, e.g., the lodgers of an apartment. In this way, discovery and communication capabilities allow to omit the maintenance of detailed sets of evaluation criteria. Employing resource assessment, AI can replace physical resources by acquired ones. The second important function of artificial intelligence in platform creation is the matching of supply and demand. A platform increases its attractiveness to the suppliers and demanders of services by shortening the time to bring together attractive offers and demands.

Framework for Business Value Generation

We demonstrated the relevance of our research in the previous sections, following the recommendations for design science research projects (Hevner et al. 2008). Now we will enter the rigor cycle by investigating the existing research on AI-capabilities (Recker 2013). We did an extensive, structured literature review of research based on widely-accepted recommendations (Okoli and Schabram 2010; Webster and Watson 2002) . We considered a list of publications deemed relevant for the selection of the papers (Willcocks et al. 2008). Our queries addressed leading scientific databases, including ACM Digital Library, AISel, IEEEx-plore, SpringerLink, ScienceDirect, Google Scholar. To increase the number of papers found, we used the search terms Artificial Intelligence, deep learning, connectionist AI, value creation. In this way, we found n=488 paper, while thirty-nine of them we have excluded because of irrelevance to the topic as well as research question. We used forward and backward search to augment the number of sources(Okoli and Schabram 2010). In this way, we could include papers that are highly influential due to their high citation count, but not within the formal scope.

Although there is no comprehensive framework to describe artificial intelligence-based value creation, several research works exist in related areas. A systematic literature review and research agenda on bid data analytics capabilities has been presented (Mikalef et al. 2018). The precursors of the big data analytics capability on business value were analyzed in (Mikalef et al. 2017). A capability-oriented approach for BI is applied to describe the abilities of BI-systems, one of the precursor technologies of today's AI systems (Işık et al. 2013). An investigation of the capabilities introduced by AI into Industry 4.0 is done (Dopico et al. 2016). AI-capabilities are digital capabilities that integrate AI-specific assets, for instance, AI-algorithms, training data, etc. in order to enable value creation (Sandberg 2014).

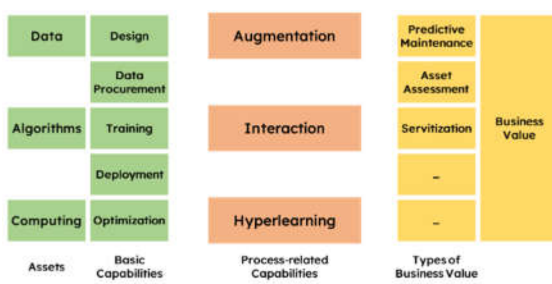

Figure 1. Business Value Framework

According to the recommendations for design science research projects (Hevner et al. 2008), we have derived the business value framework as a model type artifact (Recker 2013), as in Figure 1. The foundation for our framework is the abstract synthesized Information System business value model (Schryen 2013). Following this model, we consider deep learning systems as Informtion System asset, that impacts process performance which in turn drives the organizational performance. We understand business processes as the creation and changing of artifacts in several half-ordered actions that are controlled by decisions (Dumas et al. 2018). There are time or causal dependencies between the actions, and human agents can be assigned to the actions.

Three assets: data, algorithms, and computing, are the starting point for value creation. The five basic capabilities design, procure data, train, deploy, and optimization use the three assets. In the design phase, the architecture and parameters of the neural network are defined. The data procurement phase contains the description of the data sources, especially the external ones. The training phase describes the procedures for training the neural network. The trained network can be deployed by different means into operational practice. Optimization and retraining are necessary to ensure long-term viability. Each phase is described by several parameters that differ from phase to phase. For instance, in the training phase depending on the specific capability, so-called hyperparameters have to be chosen that significantly influence the training performance (Chollet 2017). Furthermore, the amount of training evaluation and test data is defined. There are process-related capabilities with the types of augmentation, interaction, and hyper learning. The type of AI-capability influences the architecture of the neural network to be created significantly. For instance, convolutional networks (CNN) and deep feedforward neural networks are often used in augmentation capabilities (Glorot and Bengio 2010; LeCun et al. 1998). Recurrent neural networks (RNN) are frequently used to support interaction capabilities.

Basic Capabilities

Capability theories emphasize integrating, adapting, and reconfiguring of internal and external organizational skills, resources, and functional competencies (Teece 2010). However, there are important differences in how connectionist AI-capabilities are acquired and leveraged. These differences are due to the underlying technologies, especially deep learning (Chollet 2017). For instance, instead of applying a deductive approach when acquiring capabilities, an inductive approach of capability acquisition is used. AI-capabilities are not based on expert knowledge but built up from large training data sets. Knowledge is collected by analyzing data from a multitude of sources, also from external ones. The knowledge obtained in this way is mostly represented in the training data of neural networks and can be used for decision-making. Therefore, external data for training and evaluation services play an important role in the acquisition of AI-based capabilities. On the contrary, the development of traditional information technology capabilities starts with knowledge from domain experts. They codify their knowledge into rules and ontologies that are transformed into software (Chollet 2017). Thus, access to domain expert knowledge is decisive for competitive advantage.

Design

In the design phase, the architecture of the neural network is defined. According to the capability to be acquired, different network architectures have to be chosen. For example, deep feedforward neural networks (DFNN) have multiple layers of neurons that are fully connected (Glorot and Bengio 2010). Learning is much more automated than classical machine learning because no feature engineering is necessary (LeCun et al. 1998). DFNN are well-suited for discovering the impact of a multitude of input factors on one or several output factors. However, the complete interconnection of the two following layers creates a huge computing effort necessary. For the processing of images and videos with an extremely high number of inputs, convolutional networks (CNN) are used. They mimic the convolutional processing of images in the visual apparatus. They map a larger set of inputs to a smaller set of outputs. Recurrent neural networks (RNN) can process time-series information and thus are often used to support interaction capabilities that require to understand texts and speech (Connor et al. 1994).

Data Procurement

The availability of training data or labeled data that means of data describing previous cases and the correct solution is a critical success factor in the use of deep learning and machine learning (Chui et al. 2018). It is also necessary to have access to training data sets of sufficient size (Chui et al. 2018). It is essential to gain a competitive advantage to maximize the volume and quality of data used for training. Thus, it is necessary to ensure access to external data sources as much as possible.

Training

During training, the weights representing the strengths of the connections between input and output neurons are adapted until the network achieves an acceptable performance. The training relies heavily on two

IT resources: computing and data (Chollet 2017). The computing resources may be on-site, but increasingly cloud-based resources are used for creating AI-based capabilities ("Cloud AutoML" 2018). An important reason for this is the very high peak demands for computing power during the training phase (Chollet 2017). Contrary to this, the computing requirements during operation are modest. For instance, the training of neural networks for language translation is done in datacenters of large corporations. The resulting trained network, however, can be deployed on smartphones (Liao 2018).

Deployment

After training the neural network, the knowledge acquired is contained in the weights of the trained neural network. Contrary to symbolic AI, knowledge is not localizable but distributed in the weights of the network (Russell and Norvig 2016). The weights data that describe the trained network can be transferred to other information systems where they are applied to a network with the same architecture. In this way, the knowledge is duplicated into one or a multitude of receiving networks (Chollet 2017). For instance, Google provides trained networks to provide offline translation capabilities to smartphones (Liao 2018).

Optimization

Deep learning-based AI needs to be retrained regularly to avoid the so-called concept drift (Talby 2018). New training data has to be gathered and fed into the training system, which is in case of supervised learning primarily based on observed decisions from similar decision cases. Therefore, continuously new data have to be acquired to provide the training data. Enterprise Architecture has to provide the data to do the retraining and to deploy the retrained models.

Process-related Capabilities

Aiming to identify process-related capabilities, we use the differentiation of AI-capabilities types as a foundation (Gerbert 2018). Each of the types defined is further differentiated into sub-types, as shown in Figure 2. The selection of neural network architectures and parameters results from these sub-types (Chollet 2017). Augmentation describes the use of Artificial Intelligence for augmenting decisions and optimizing actions. Human-machine interaction introduces artificial intelligence as a counterpart. Hyperlearning accelerates improvement processes for physical products by creating digital twins and applying advanced learning methods.

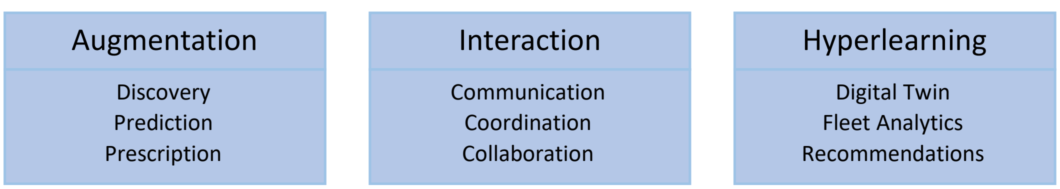

Figure 2. Process-Related Capabilities

Augmentation

The augmentation of decisions has a big impact on business capabilities in several areas, such as decision making (Gerbert 2018). Human decisions are influenced by two factors: Bias and Noise (Kahneman and Brynjolfsson 2018). Noise is the variability of judgments costing enterprises a lot of money due to inappropriate decisions (Kahneman et al. 2016). Although there are also organizational tools for reducing noise, the use of AI is more helpful (Kahneman and Brynjolfsson 2018): AI-based decision mechanisms avoid the noise of human-made decisions. By avoiding noise, AI-based decisions are standardized to some extent. This is helpful for collecting data for further analysis and optimization of decision mechanisms and thus are better suited for backpropagation mechanisms to improve decision making.

A further effect of Artificial Intelligence is the automation of decision tasks. AI-based decision support improves the efficiency and the speed of decisions. AI also improves the quality of decisions. AI-capabilities can be classified into at least three classes: discovery, prediction, and prescription. The discovery capability embraces the detection of hitherto hidden facts and knowledge. Social media are analyzed to find data representing brands, for example (Zimbra et al. 2016). In this way, correlations between users and brands and between brands can be discovered (Gao et al. 2014). AI-enabled prediction provides the value of a variable not known so far. Examples are the detection of fraud (Wang and Xu 2018).

Interaction

The advantages of using AI in the interaction with customers are described by rethinking typical AI objectives(Ransbotham et al. 2017). Customer satisfaction can increase because customers get better informed and thus find better-customized solutions. The interaction can be faster because the interaction is sober. Furthermore, the use of AI avoids social desirability response bias.

An important AI capability is to improve the ability of IT systems to collaborate with human users. The most prominent examples are digital assistants such as Alexa, Google, or Siri that show an excessive growth (Bonnington 2018). Also, their abilities are impressive (Koetsier 2018). They allow extending the reach of information systems significantly. These capabilities can be differentiated into communication, coordination, and collaboration. Communication is the transfer of information from one partner to another without the need for a common task (Malone and Crowston 1994). Information may be exchanged bi-directionally. Digital assistants can deliver information on the human user's request. During coordination, not data or resources, but rather the operations to achieve a given goal are in the center of interest. Thus coordination is defined as the management of dependencies between activities (Malone and Crowston 1994). Cooperation is based on communication and coordination. Cooperation is the joint solution of a problem at the basis of a common set of data or resources (Malone and Crowston 1994).

Hyperlearning

New ways of learning are supported by AI-technologies, such as Generative Adversarial Nets (GAN) (Goodfellow et al. 2014). They estimate generative models via an adversarial process (Goodfellow et al. 2014). Contrary to CNN and RNN they perform well on unsupervised learning tasks (Goodfellow et al. 2014). The use of digital twins (Datta 2016) significantly increases the amount of data available, which in turn is very advantageous for the development of optimizations. New forecasting and optimization methods are to be applied to the significantly expanded data pool of digital twins. AI-based analytical methods, especially deep learning profit from the availability of large datasets. Therefore, applying them to the complete fleet of products may significantly improve the insights obtained (Winnig 2016).

Research Agenda

Business value has both quantifiable and less quantifiable measures such as satisfaction or retention of the employees or organizational learning that must be considered. It could also be derived, taking into consideration "unquantifiable human factors such as values meaning and experiences" (Muller et al. 2009, p. 41). Therefore, the following research questions remain still open and are part of a future research agenda:

The currently identified value-creating capabilities do not influence all identified aspects of business value. What can additional drivers of business value creation support?

Are there associated methodologies that help to improve productivity in AI-based applications and align them with the strategic aims of the company?

Which kind of interventions could be used to foster capabilities if a certain dimension of the business value should be strengthened?

How can organizations leverage AI-based capabilities and redesign current work processes to focus on increasing the business value (e.g., in productivity or cost efficiencies) and define new work processes that extend beyond business value to include value, meaning, and engagement for their users (or stakeholders)?

How can users AI-based applications be motivated and retained to participate?

How does the use of a specific AI-based applications will influence next organizations?

How can we measure the value quantitatively created by AI-based capabilities? Are there also interactions providing no or negative value? How can they be detected and mitigated?

Conclusion

Previous research showed that connectionist Artificial Intelligence provides value to corporations and also differentiated forms of value creation. However, only a few investigations of the mechanisms exist that lead to accomplishing value creation. Therefore, we developed a framework that describes the creation of business value based on different layers of AI-capabilities. The identified AI-capabilities can be leveraged to create business value and, thus, the strategic goals of enterprises and organizations. The acquisition of AI-Capabilities, especially those based on connectionist deep learning technologies, differs significantly from that of traditional information technology resources. AI-based capabilities are acquired by collecting training data, training a network or algorithm, and detecting rules, and thus new knowledge is attained (Chollet 2017).

Our research helps practitioners to make better decisions regarding the architecture of information systems. Understanding the business value of artificial intelligence can help to overcome skepticism and help to align its strategic use with the company's goals and use them more efficiently. Furthermore, our research framework improves the requirements elicitation for designing AI-based systems by identifying possible options in the form of emergent interactions.

During the development of the framework, we could further enhance the description of AI-capabilities. Already known is that AI-Capabilities are regenerative capabilities that have to be continuously refreshed (Ambrosini et al. 2009). Furthermore, AI-capabilities are highly idiosyncratic. As a limitation, training data containing knowledge is only usable for certain network architecture and only difficult to transferrable to other architecture due to the implicit knowledge representation. AI-capabilities often lack the generalizability of the acquired knowledge (Chui et al. 2018). On the other hand, AI-capabilities are highly mobile within a certain environment. Knowledge acquired can be easily replicated to millions of other systems, as shown be smartphone-based translations apps using neural networks trained in large data centers.

The developed Framework has long-term effects on the acquisition of AI-capabilities. It standardizes the acquisition of AI-capabilities by providing templates. In this way, it also fosters the reuse of knowledge and best practices on the acquisition of AI-capabilities. A further effect of the framework is easier integration between different capabilities. Research, as well as practice benefits from our research. Current literature on AI, EAM can be extended by a capability-oriented view of it. Our framework combines results from past research to create new usable insights through the creation of an artifact. The artifact can be used for a basic understanding of AI capabilities in the area. Practical experts can, e.g., use it for evaluation and internal development of AI-capabilities.

As no research is without certain limitations, our findings have some limitations as well, which are also tasks for further research. First, future research will have to investigate which of the AI-capabilities can also be dynamic capabilities (Teece et al. 1997), which means they enable to integrate, build, and reconfigure resources. Further (empirical) evaluations of the framework are needed and should be done. Also, the question of whether AI-capabilities are meta-capabilities because they impact capabilities should be investigated more deeply. Another area is the possible bias in data and algorithms (Chui et al. 2018). Furthermore, empirical verification of our findings is an additional task for future work. It will embrace a prototype and its evaluation.

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