Affordance-Experimentation-Actualization Theory in Artificial Intelligence Research – A Predictive Maintenance Story

Completed Research Paper

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Abstract

Artificial intelligence currently counts among the most prominent digital technologies and promises to generate significant business value in the future. Despite a growing body of knowledge, research could further benefit from incorporating technological features, human actors, and organizational goals into the examination of artificial intelligence-enabled systems. This integrative perspective is crucial for effective implementation. Our study intends to fill this gap by introducing affordance-experimentation-actualization theory to artificial intelligence research. In doing so, we conduct a case study on the implementation of predictive maintenance using affordance-experimentation-actualization theory as our theoretical lens. From our study, we find further evidence for the existence of the experimentation phase during which organizations make new technologies ready for effective use. We propose extending the experimentation phase with the activity of 'conceptual exploration' in order to make affordance-experimentation-actualization theory applicable to a broader range of technologies and the domain of AI-enabled systems in particular.

Keywords: Affordance-Experimentation-Actualization Theory, Artificial Intelligence, Predictive Maintenance, Embedded Single-Case Study

Introduction

Interest in artificial intelligence (AI) is no longer limited to the research community and select software companies. Today, AI plays an important role in public discourse, strategic government agendas, and business considerations (Kantaria 2019). For instance, governments around the world are currently initiating strategic AI research programs to better understand the benefits and risks of the increased penetration of AI applications (Reif 2019). In the short term, Gartner (2017) expects AI to generate $2.9 trillion in business value by 2021. In the longer term, AI may affect the majority of (if not all) industries, potentially contributing $15.7 trillion to the global economy by 2030 (Rao and Verweij 2017). However, these developments rely on organizations making strategic investments in different AI applications.

Inevitably, AI has also attracted the attention of the Information Systems (IS) community, leading to the development of a growing body of knowledge at the intersection of business and technology. Despite this knowledge, IS research lacks a strategic management perspective (Nascimento et al. 2018), yet such a perspective is crucial for organizations attempting to strategically evaluate potential AI investments. In particular, such organizations need the means to assess whether the implementation of AI-enabled systems adds value to their business and aligns with organizational goals. Importantly, research which focuses on the implementation of AI should not only consider its technological features but should also acknowledge human capabilities and goals (Markus 2017; Shmueli and Koppius 2011). The intention of this study is to fill the current gap by providing a strategic management exploration of AI, an exploration which acknowledges technological features, human actors, and organizational goals. Therefore, we chose affordance-experimentation-actualization (A-E-A) theory to guide our research on the implementation of AI (Du et al. 2019). In a technological context, affordances are "the possibility for goal-oriented actions afforded to specific user groups by technical objects" (Markus and Silver 2008). Since affordances are 'possibilities for action', actors must take these actions in order to achieve the relevant outcomes (Strong et al. 2014). The process of taking these actions is called 'affordance actualization'. In other words, we can conceptualize AI implementation as the actualization of a series of affordances. However, organizations can only actualize affordances effectively if a technology is ready for effective use (Du et al. 2019). Since emerging technologies like AI usually lack established use-cases, organizations require an experimentation phase to prepare the technology for effective use. In line with recent research, we understand AI in the sense of AI-enabled systems that are designed for specific tasks (Stone et al. 2016). Predictive maintenance (PdM), for example, can be seen as an AI-enabled system that is designed to improve maintenance activities in the manufacturing sector (Vom Brocke et al. 2018). We will focus on PdM in the remainder of our research and explore the following research questions:

(1) *How do organizations actualize affordances in the context of AI-enabled predictive maintenance?*

(2) *How does the organizational context affect the actualization process?*

To answer these two questions, we conduct an embedded single-case study on a project where different organizations and applied researchers jointly work on PdM implementations. Firstly, we establish the possibilities for action possibilities afforded by PdM systems. Secondly, we study the actualization process of these affordances, focusing on the aforementioned experimentation phase which was recently highlighted by Du et al. (2019). According to Du et al. (2019), this phase includes two activities: 'conceptual adaption' and 'constraint mitigation'. Conceptual adaptation involves adapting a technology to the specific organizational context. Constraint mitigation helps to uncover and mitigate constraints that can arise upon the introduction to this specific context. As PdM is not widely used, we find corroborative evidence for the existence of the experimentation phase and its two activities in our case study. Moreover, we notice that organizations have to gain a basic conceptual understanding of an emerging technology before they can adapt it to their use-case and mitigate constraints. Therefore, we propose 'conceptual exploration' as an antecedent activity to conceptual adaptation and constraint mitigation.

Our study contributes to IS research in the field of AI by illustrating how researchers can integrate technological features, human actors, and organizational goals into their explorations of the implementation of PdM. Generally, we view A-E-A theory as a particularly interesting lens to study the implementation of AI-enabled systems. We contribute to A-E-A research by finding corroborative evidence for the existence of Du et al.'s (2019) experimentation phase in another technological context and by further detailing this experimentation phase. Finally, our study can help practitioners to effectively implement PdM.

Theoretical Background

Artificial Intelligence and Predictive Maintenance

Computer scientists were studying Artificial Intelligence (AI) as long ago as the 1950s. Back then, the focus was on exploring the nature of intelligence and attempting to construct systems which exhibited such intelligence (Simon 1995). Researchers have since developed various AI-enabled systems, but slow progress meant interest in AI decreased over time. However, AI has lately been the subject of renewed public and academic interest thanks to data availability, increased computational power, and the growing number of benefits it offers in a variety of contexts, including the workplace, homes, and schools (Stone et al. 2016). In the definition offered by Stone et al. (2016) AI refers to both "a science and a set of computational technologies that are inspired by—but typically operate quite differently from—the ways people [...] sense, learn, reason, and take action". However, definitions of AI are generally somewhat ambiguous. Russell and Norvig (2016) cluster such definitions into four broad categories: 'Thinking humanly', 'acting humanly', 'thinking rationally', and 'acting rationally'. We can also define AI in a more general way which reflects the historical development of AI research. Most early AI research focused on creating general artificial (i.e., human-like) intelligence, commonly referred to as 'strong AI' (Kurzweil 2005). Yet, more recently, AI researchers have shifted their focus toward AI-enabled systems that master specific tasks. Despite its narrower focus, this so-called 'weak AI' still is highly complex and, thus, requires extensive research efforts (Stone et al. 2016). Popular examples include DeepMind's AlphaGo, which beat a human 'Go' champion (Silver et al. 2016); ImageBiopsy, who use AI to improve the diagnosis of osteoarthritis (Dimai et al. 2018); and chatbots like chatfuel, which automate customer service (Khodl 2015). Moreover, some weak AI projects – for example, predictive maintenance (PdM) – also aim to optimize specific existing business tasks in an industrial environment (Vom Brocke et al. 2018).

PdM refers to the automated and intelligent scheduling of maintenance activities based on the continuous analysis of a system's operating conditions (Mobley 2002). The general idea is to predict and preemptively mediate maintenance needs and system failures in order to optimize process availability, safety, quality, and productivity, thereby reducing both maintenance and insurance costs (Christer et al. 1997; Mobley 2002; Zarte et al. 2017). PdM also facilitates the generation of additional revenues and profits by enabling the provision of an additional product maintenance service. It supports the transformation of business models within the manufacturing industry from full ownership toward pay-per-use (Meier et al. 2010). However, PdM first requires the collection and processing of large amounts of data in real-time (Roy et al. 2016; Vom Brocke et al. 2018). The Internet of Things (IoT) (Oberländer et al. 2018) – where objects which formerly existed in a merely physical form are increasingly equipped with sensors, actuators, information processing, and networking power (Yoo 2010; Yoo et al. 2010) – provides significant support for this process as the increasing dissemination of IoT technologies means that large amounts of data are available for analysis. In addition to these technical requirements, PdM also poses challenges to organizational actors and to organizations themselves (Roy et al. 2016). For instance:

- Organizations need to strengthen cooperation with customers and suppliers in order to share data across organizational boundaries.
- Designers, data experts, and manufacturing engineers need to exchange feedback regularly.
- Human-machine collaboration has to be improved.

Thus, we need to integrate technological and organizational perspectives when studying PdM implementation. Organizations need to assess whether the implementation of AI-enabled systems such as PdM adds value to their business. Hence, organizations need to evaluate the possibilities for achieving their strategic goals that PdM offers them. While human-computer interaction (HCI) research provides several studies on the interaction between AI-enabled systems and human actors (Rzepka and Berger 2018), IS research, in particular, could further benefit from integrating technological features, human actors, *and* organizational goals into the examination of AI-associated organizational change (Sarker et al. 2019). Our study addresses this issue by introducing A-E-A theory to AI research. In particular, we study the implementation of PdM using A-E-A theory as our theoretical lens.

Affordances, Experimentation, and Actualization

Recent publications in the *AIS senior scholars' basket of eight* suggest that using an affordance lens to study IS phenomena has become quite popular among IS researchers (e.g., Du et al. 2019; Krancher et al. 2018; Leidner et al. 2018; Mettler and Wulf 2019). Introduced by Gibson (1979), the term 'affordances' was originally coined by ecological psychologists as "what [the environment] offers the animal" (Gibson 1979). Affordances are based on the relationship between object and observer, and can either enable or constrain (Gibson 1979). From these descriptions, we can derive properties which make the concept of affordances interesting beyond the field of ecological psychology. Firstly, affordances are action possibilities whose mere existence does not guarantee outcomes (Stoffregen 2003). Secondly, the concept does not treat the object and the observer separately but instead emphasizes the relationship between them.

By establishing Affordance-Actualization (A-A) theory, Strong et al. (2014) made an important contribution to the applicability of affordance theory in IS-research as they integrated an organizational perspective and separated affordances, their actualization, and outcomes. In this context, we can view affordances as possibilities for action that an IT object offers to a goal-oriented actor (Volkoff and Strong 2013). A 'goal-oriented actor' can either be an individual (Leonardi 2011; Majchrzak and Markus 2013), an entire organization, or a specific entity or group of users within an organization (Burton-Jones and Volkoff 2017; Du et al. 2019; Volkoff and Strong 2017). Since we are interested in organizational aspects of AI-enabled systems, we focus our research on organization-level affordances and regard both organizations and organizational entities as goal-oriented actors. Due to affordances being possibilities for action, rather than actions in themselves, goal-oriented actors must actualize these possibilities in order to transform potential into results. Actualization is defined as "the goal-oriented actions taken by actors as they use a technology to achieve an outcome" (Du et al. 2019). We adopt the definition of Du et al. (2019), who propose to refrain from using the term 'immediate concrete' – as originally introduced by Strong et al. (2014) – in defining outcomes of actualization actions. As pointed out by Du et al. (2019), not all (organizational) outcomes occur instantly. This is often the case when certain outcomes are contingent on the actualization of an affordance by multiple individuals. Furthermore, the term "concrete" is rather vague and difficult to grasp (Du et al. 2019). Outcomes, in general, link actualization actions to organizational goals and, thus, enable an organization to assess the contribution the actualization actions make toward achieving these goals. For example, Leidner et al. (2018) analyze an organization that introduced an enterprise social media tool to improve its new hire program. Their study reveals that actualizing a peer interaction affordance enhanced the organization's productivity. Outcomes thus provide important feedback on the existence of affordances (Volkoff and Strong 2013), as do actualization actions. Actualizing basic affordances enhances an actor's capabilities and enables the actor to use a technology in a more sophisticated manner (Bygstad et al. 2016; Strong et al. 2014). Consequently, the actor can recognize and actualize further affordances of this technology.

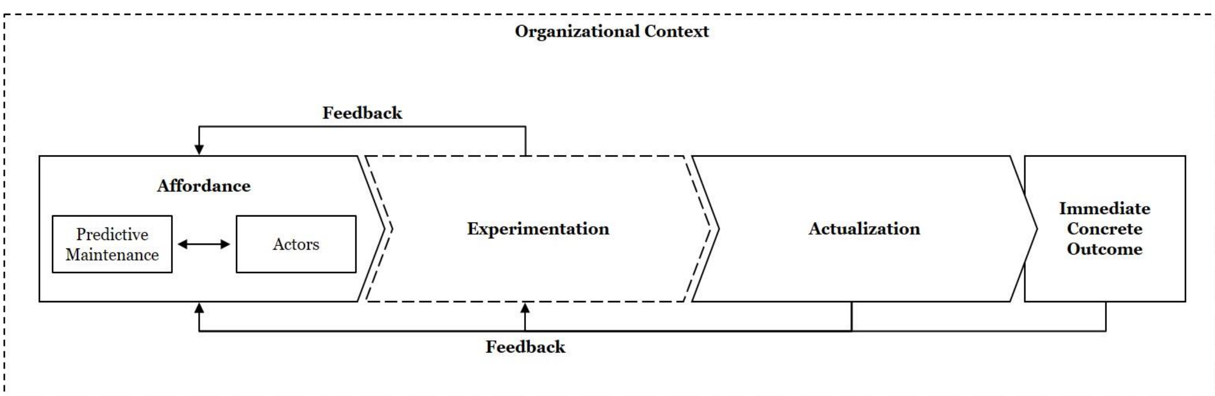

Figure 1. Affordance-actualization process of predictive maintenance (adapted from Du et al. (2019))

As discussed above, we can understand implementation processes as a series of affordances actualizations. However, organizations usually cannot effectively use a technology that lacks established use-cases (Du et al. 2019). Organizations need an experimentation phase, which precedes the actualization of affordances, in order to prepare the technology for effective use. Since PdM lacks a wide variety of established use-cases

(Hermes 2019), we adopt A-E-A theory as our theoretical lens which – as illustrated in Figure 1 –allows us to separately consider affordances, experimentation, and actualization (Du et al. 2019).

Based on a case study involving blockchain technology, Du et al. (2019) find that experimentation includes two main activities: conceptual adaptation and constraint mitigation. Conceptual adaption helps to adapt the original framing of a technology to the specific context of an organization. Blockchain technology, for example, became popular in the context of the cryptocurrency Bitcoin. However, this original framing did not fit the organizational context in Du et al.'s (2019) case study. The organization in question needed conceptual adaptation to establish new use-cases for blockchain technology. Constraint mitigation serves the purpose of uncovering and mitigating constraints that can arise when a technology is introduced in a specific organizational context. Implementing blockchain technology might, for example, entail unknown risk. Experimentation with the technology in demonstrator projects can help to reveal such risks (Du et al. 2019). By experimenting with the technology, actors are not only able to establish new use-cases and to recognize and mitigate constraints but also to recognize affordances themselves (Du et al. 2019). This recurrent interaction with a technology is similar to the aforementioned idea of being able to actualize further affordances based on the actualization of basic affordances. Moreover, it relates to Orlikowski's (2000) enactment view of structuration theory. Structuration theory is based on the work of Giddens (1984), who regards structure and agency as mutually constitutive. He proposes that structures influence human actions, and, at the same time, these actions create and recreate structures. In her attempt to adapt structuration theory to IS research, Orlikowski (2000) proposes the concept of technology-in-practice as "knowledgeable human action and how its recurrent engagement with a given technology constitutes and reconstitutes particular emergent structures of using the technology". A-E-A theory captures this recursive enactment view as feedback to preceding stages in the A-E-A process. While experimentation and actualization are high-level concepts, their concrete manifestations in organizational actions can assume many different forms. For instance, organizations can use methods of agile requirements engineering such as prototyping (Ramesh et al. 2010) or action research (Baskerville and Wood-Harper 1998; Davison et al. 2004) for constraint mitigation and conceptual adaptation.

Another concept that reveals a close link to structuration theory is that of the 'organizational context'. The organizational context plays an important role in A-E-A theory because it can stimulate experimentation (Du et al. 2019) and affordance actualization (Bygstad et al. 2016). For example, Krancher et al. (2018) find that cross-functional teams are better able to actualize affordances in the context of Platform-as-a-Service (PaaS). Moreover, a culture of independent decision making and openness to experimentation positively impacts affordance actualization. Du et al. (2019) identify 'openness to collaboration with startups' as an important cultural factor that influences actualization and experimentation. Bygstad et al.'s (2016) conceptualization of the organizational context influencing affordance actualization and being influenced by actualization relates to Giddens's (1984) view of the mutual constitution of social structures and human agency. Consequently, we recognize this mutual constitution as an important part of A-E-A theory and agree with Jones and Karsten (2008), who propose that structuration theory provides an interesting perspective on the concept of affordances. Vyas et al. (2017), for instance, integrate structuration theory into the concept of affordances as social and cultural aspects that influence technology affordances.

In summary, Strong et al.'s (2014) A-A theory offers several interesting contributions to the investigation of technology implementations. In particular, it treats affordances, their actualization, and outcomes separately. This accounts for the fact that not all affordances necessarily have to be actualized. Likewise, actualizing the same affordance might produce different outcomes depending on factors such as organizational goals and context. Based on their single-case study in the context of blockchain, Du et al. (2019) make an important contribution to A-A theory by introducing an experimentation phase. They reconceptualize A-A theory as A-E-A theory to make the theoretical lens applicable to the context of new technologies that lack established uses-cases. However, A-E-A theory lacks verification beyond the context of its induction. Our study performs a detailed exploration of the experimentation phase and examines the relevance of this phase in the domain of PdM.

Research Method

Our research focuses on a large project wherein different organizations and applied researchers jointly worked on PdM implementations. We conduct an embedded single-case study and regard the different organizations as the embedded units of analysis within the overall case, the project itself. Our research design is guided by the recommendations of Yin (2014), who suggests that conducting a single-case study is appropriate if it is critical, unusual, common, revelatory, or longitudinal. More generally, single-case studies are a prominent approach in IS affordance research (e.g., Du et al. 2019; Leonardi 2013; Seidel et al. 2013) because they enable a deeper examination of IS in their socio-technical context (Klein and Myers 1999; Orlikowski and Iacono 2001). PdM is a phenomenon which researchers began investigating investigate in the 1990s, but whose implementation has since been a challenge for many manufactures (Hermes 2019). Therefore, we selected a case which reflects common circumstances and conditions faced by many manufacturers. Moreover, the case provides access to a significant phenomenon in a complex real-world situation. Using a single-case study to perform explorative research in this instance is consistent with Eisenhardt's (1989) and Eisenhardt and Graebner's (2007) recommendations.

According to Yin (2014), there are six different sources for case study evidence: documentation, archival records, interviews, direct observations, participant-observations, and physical artifacts. Our primary method of data collection was semi-structured interviews, which we based on an interview guide in order to better secure a comprehensive coverage of the subject area (Rubin and Rubin 2012). Using these interviews, we were able to explore the project participant's interpretations of events that took place or were expected to take place (Walsham 1995). This is vital as affordances and their actualization cannot themselves be directly observed, only the associated outcomes (Volkoff and Strong 2013). Interviews are one way of uncovering such outcomes – or expected outcomes – which we can use to deduce affordances (Volkoff and Strong 2013). Our interviews ranged from 30 to 60 minutes, were audio-recorded, and later fully transcribed. In several cases, we approached the interviewee again after the interview in order to clarify further questions. We also tried to increase construct validity by obtaining interviewee feedback on the drafted case study reports (Yin 2014). In addition to conducting interviews, we studied project documents and participated as external observers in project workshops.

In analyzing the collected data, we followed a two-stage process of inductive and deductive coding. Our analysis was guided by the recommendations of Miles et al. (2014). First, we jointly went through the interview transcripts, our workshop notes, and secondary project documents to assign initial codes to the data. Afterward, we clustered these codes across data sources and assigned them to higher-level concepts which were either based on our theoretical lens (deductive coding) or emerged during data collection (inductive coding). For instance, we took the initial codes "potential to assess future breakdowns" and "potential to increase customers' maintenance plannability" and assigned them to the higher-level concept "potential to plan future maintenance activities", which constitutes an affordance of PdM described in more detail below.

Field Site

We selected a publicly-funded, applied German research project in the context of PdM to conduct our research. The project aimed at developing intelligent analytics solutions in order to increase transparency in production processes, and its partners envisioned creating new data-based services and business models. It began in February 2018 and had a duration of 13 months. In the course of the project, applied researchers other than the authors and four medium-sized German enterprises from the mechanical engineering sector jointly examined and developed PdM solutions to optimize the companies' product portfolio. That is, participating organizations planned to implement PdM in their products rather than their production. We found the selected case to be of interest for several reasons: For instance, we were able to study the complete implementation process of PdM applications including the associated common challenges faced by many small and medium-sized enterprises from the mechanical engineering sector, a type of organization which represents an important part of the German economy. Moreover, the case involves companies joining forces to co-create innovation, which is particularly interesting in the context of PdM. The case also provides us with access to both user organizations and applied researchers.

Inspired by the 'completeness criterion' of good case study research (Yin, 2014), we conducted a total of 14 interviews with relevant project participants from all companies and the applied researchers involved. We specifically selected the participants who were deeply involved in the project and could provide significant insights, rather than employees and applied researchers who only consulted on a few occasions. We also made sure that our selection of interviewees gave a balanced representation of both the technical and managerial perspectives on the project. In several cases, we approached the interviewee again after the interview in order to clarify further questions. Consequently, we are convinced that the interviews, together with workshop observations and secondary project data, provide us with sufficiently deep insights into the project. As the individual companies were at different stages in their development, interviewing various participants allowed us to gain a broader understanding of the PdM implementation process. Table 1 provides an anonymized overview of the interviewees and their roles. To get insights into the A-E-A process, we adapted questions devised by Du et al. (2019) to fit our technological context. We also used questions recommended by Volkoff and Strong (2013) to induce affordances. We asked all interviewees questions about how they collaborated with the other project participants in developing PdM use-cases and applications. We asked company interviewees questions about how they (intend to) use PdM and how PdM changes their working methods. We asked applied researchers questions on how to align PdM with business requirements and how to deploy PdM applications. We also asked about any preconditions that the organizations need to meet.

Company	Employees	ID	Role
Company 1	> 1,000	1	Manager
		2	IT-specialist
Company 2	> 5,000	3	Data scientist
		4	Pre-sales manager
Company 3	> 1,000	5	Engineer
		6	IT-specialist
		7	Manager
		8	Engineer
Company 4	> 1,000	9	Manager
Applied Research Organization 1	> 100	10	Applied researcher digital business models
		11	Applied researcher data analytics
		12	Applied researcher IoT
		13	Applied researcher data analytics
Applied Research Organization 2	< 10	14	Applied researcher data analytics and Industrial IoT

Table 1. Interview participants

Additionally, the project partners provided us with the project proposal, business case descriptions, and workshop documentation. We were also able to participate as external observers in several workshops.

Findings

A-E-A theory allows us to separately analyze affordances, experimentation, and actualization (Du et al. 2019). Experimentation and actualization enable us to recognize affordances. Consequently, we analyzed these phases and the resulting outcomes in order to identify affordances. However, we present our findings in terms of the causal relationships rather than in the order of our analytical process and chose to do so on the basis that affordances must exist before organizations can perform actions of experimentation and actualization. Moreover, organizations can only actualize affordances effectively after selecting and preparing an appropriate new technology, which involves experimentation. Hence, we structure our findings according to the affordance-experimentation-actualization process displayed in Figure 1. Lastly, we describe the organizational context that stimulates experimentation and actualization.

Affordances

In our case study, we identified three affordances which arose from the relationship between PdM systems and the service or condition monitoring department of the respective organization. We find that affordance 3 can only be actualized if affordance 1 and affordance 2 have already been actualized, as actualizing affordances 1 and 2 produces data which enables the actualization of affordance 3. This dependence is consistent with Volkoff and Strong (2013), who find that affordance actualization depends on "appropriate enabling, stimulating, and releasing conditions". These conditions are among those influenced by the actualization of other affordances.

Affordances 1: Monitoring conditions in real-time

Firstly, PdM affords both the service or condition monitoring department and the customer the opportunity to monitor machine conditions in real-time. In our case study, the organizations equip machines with several sensors by default. Based on a continuous analysis of the machine sensor data, a user interface enables the service department to monitor the condition of all connected machines. This condition-displaying feature is also beneficial for customers who have to supervise several machines. With an appropriate user interface, they can easily monitor the conditions of the machines. Condition monitoring thus constitutes a possibility for goal-directed action for both the service department and the customer, and can be seen as an affordance of the PdM system. Interviewee 3 describes the result of the project as follows:

> *"Now, we are able to see and better understand the current condition."*

The condition analysis feature that enables this affordance is consistent with PdM research, which illustrates that the continuous analysis and recording of machine conditions is an essential prerequisite for subsequent predictions (Zarte et al. 2017). Consequently, an organization can also access this information for monitoring purposes.

Affordance 2: Diagnosing states

Secondly, PdM affords technicians the potential to remotely diagnose current machine states. Traditionally, technicians have to visit the client site in order to examine machines. In the best case, they will be able to identify an error and will already be carrying the required replacement parts with them. In some cases, however, they either have to re-visit the client site with the corresponding replacement parts or find that the machine is not broken at all. Machine learning algorithms within the PdM system enable the identification of patterns of machine operating conditions. If machines are connected to the internet, technicians can use the developed pattern recognition feature to remotely identify machine errors. As interviewee 5 explains:

> *"We can diagnose it remotely. We see an upward trend and can then look into the spectrum. Based on the frequency, we can diagnose the probable cause of the error."*

The pattern recognition feature that enables this affordance is consistent with previous research on PdM modeling which illustrates that the selection of appropriate diagnosing techniques is an essential step in setting up a PdM system (Carnero 2005).

Affordance 3: Planning future maintenance activities

Thirdly, PdM affords the service department the potential to plan future maintenance activities. Traditionally, most organizations either engage in some form of reactive or preventive maintenance. That is, they either only react to machine disruption or, more commonly, perform maintenance activities within pre-specified time intervals in order to prevent such machine disruption. Machine learning enables the PdM system to forecast machine disruptions and maintenance needs. As a result, the organizations can use these forecasts to better plan and schedule future maintenance activities. However, actualizing the monitoring and the diagnosis affordance is a prerequisite for prediction because actualization produces important data. As interviewee 10 explains:

> *"Based on detected error patterns, we currently train neural networks for forecasting purposes. That is, we want to be able to assess how long it will take until the machine breaks down based on the recognized state patterns."*

The prediction feature enabling this affordance is consistent with PdM research which identifies prognostics as the differentiating factor of PdM and builds the foundation for maintenance and mission planning (Roy et al. 2016). However, prediction techniques are very heterogeneous, and their selection strongly depends on the particularities of the organizational use-case (Mobley 2002).

Experimentation

As noted above, Du et al. (2019) introduced an experimentation phase to A-A theory based on a single-case study in the context of blockchain. This experimentation phase precedes the actualization of affordances so as to prepare a technology for effective use. Unlike blockchain technology, PdM is not an entirely new phenomenon. For example, Christer et al. (1997) had already introduced the idea of using prediction techniques as a foundation for replacement decisions. However, organizations and manufacturers, in particular, have not yet widely adopted PdM (Hermes 2019). Cheap new AI-technologies now enable the creation of AI-enabled systems (Agrawal et al. 2018), but PdM still lacks established use-cases that can guide the implementation process. Due to the lack of established use cases, we find corroborative evidence for the existence of the experimentation phase in our case study. In this regard, we can confirm the findings of Du et al. (2019). As mentioned in the theoretical background, Du et al. (2019) hold that experimentation involves two activities; constraint mitigation and conceptual adaptation (see Figure 2).

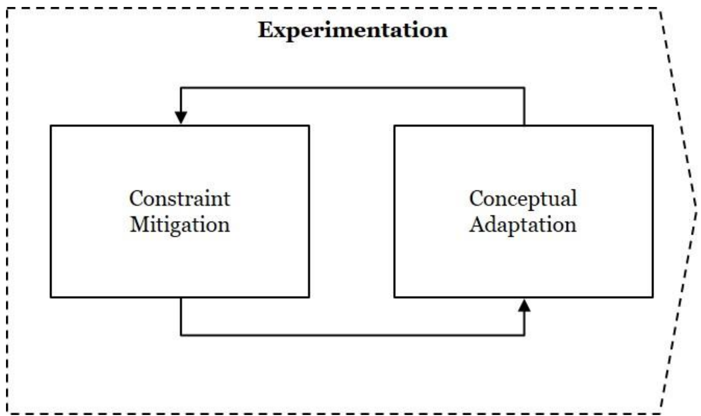

Figure 2. Experimentation phase (see Du et al. (2019))

Constraint Mitigation

Since PdM has not been widely adopted, its introduction in a specific organizational context can impose unexpected constraints (Kendall 1997; Leonardi 2011). Similar to the blockchain case of Du et al. (2019), the constraint mitigation activity played an important role in the PdM project. PdM solutions were implemented only for selected machine parts to test their feasibility and to uncover potential constraining factors. In this regard, we can again confirm the findings of Du et al. (2019). One of the applied researchers, interviewee 11, explains the project activities:

> *"We took a look at their progress and their problems. We simply wanted to gain some first experiences together."*

This approach to identifying constraints is similar to the 'sandbox' approach which Du et al. (2019) describe in the context of uncovering unknown risks of the blockchain technology. A sandbox is a controlled environment, which allows organizations to test their solutions without interrupting regular business operations (O'Reilly and Tushman 2008).

In the following, we elaborate on the constraints we identified in our study of the project. Our analysis reveals that constraint mitigation was one of the activities where the participating organizations collaborated and exchanged information with each other. As Interviewee 6 describes:

> *"We exchanged ideas and consulted each other. It was very interesting to see that many of the participating companies face the same problems."*

Constraint 1: Lack of an actionable data strategy

This first constraint concerns the data strategy. All organizations had already equipped their machines with sensors and, thus, were able to collect data. However, they did so without considering which data is useful for PdM. Moreover, data recordings were not always continuous. For example, machines were sometimes disconnected unintentionally leading to significant gaps in the data. In addition to data collection, data quality and data security were found to be important factors which should be covered by the data strategy. As interviewee 3 explains:

> *"Well, we have clearly seen that the technology itself or the algorithms which are available for predictive maintenance are not the main problem, but rather data quality or the whole data mire that we have."*

This finding is in line with Agrawal et al. (2018), who describe prediction itself as rather easy, and data quality and data strategy as the main constraining factors.

Constraint 2: Absence of formalized expert knowledge

A second constraint concerns the formalization of knowledge. Prediction is based on some form of supervised learning. Therefore, analytics researchers and data scientists needed response variables, based on which they could train their models. However, the documentation of error events was incomplete, and domain experts still possessed much of the knowledge within the respective organization. Thus, the applied researchers spent much of the initial project time in discussions with domain experts, such as technicians, in order to develop adequate documentation. Interviewee 14 describes the formalization problem as follows:

> *"That is just the big issue: How do I formalize certain knowledge? This is a requirement of being able to automate something. That is, to what extent am I able to formalize knowledge about the processes, the data as well as the physical objects that are involved so that a certain automatism can be realized?"*

Constraint 3: Emotionalization of algorithms

A third constraint concerns the emotionalization of algorithms. Emotionalization can take two directions. Firstly, many employees mistrust algorithmic solutions. In order to mitigate this mistrust, project participants developed demonstrators to showcase the potential of PdM. They developed PdM solutions for certain parts within the machines in order to demonstrate PdM's usefulness. As interviewee 1 explains:

> *"Trust in the predictive maintenance solution has to be given [...] That's what the research aimed for that was conducted on the error sensitivity issue. This research showed that there is no single solution. You rather have to adjust the solutions specifically with respect to the market size and the service network. This also represents a certain preoccupation with the trust issue and helps us to sell the algorithmic solution internally."*

Furthermore, the idolization of algorithms constituted a problem, and participants had to develop a certain pragmatism when it came to the potential of analytics solutions. No single algorithm applies to all use-cases, but adaptation instead requires a significant amount of individual effort.

Conceptual Adaptation

In their study of blockchain implementation at a Chinese business conglomerate, Du et al. (2019) found that re-contextualization was needed as the original framing of the blockchain technology did not fit the organization's objectives. While the blockchain technology was initially associated with the cryptocurrency Bitcoin (Nakamoto 2008), the organization's objectives called for a different application (Du et al. 2019).

Unlike the example of Bitcoin raising the profile of blockchain, there is no prominent example of the application of PdM, which meant there was no need for a prior re-contextualization of the concept. Therefore, one would not necessarily expect to find the activity of conceptual adaptation in the context of PdM. Nevertheless, we discovered that conceptual adaption represented an integral activity within the project. However, the idea behind the activity differs from Du et al.'s (2019) idea of re-contextualization. In our case study, project participants were working on the identification of PdM use-cases which met the specific need of their organization. This was necessary for two reasons. Firstly, the concept of PdM is rather abstract and, thus, must be made concrete in relation to the specific business context. Secondly, the organizations' machines are highly complex. Therefore, they could not adopt one of the few existing PdM use-cases. The following statement from interviewee 3 illustrates the complexity issue:

> *"However, you have to take a step back in practice because you just got the problem that the machines, or rather our machines, are, first of all, very different from each other and, second, are very complex due to the many subsystems."*

Adapting the concept of PdM to the particular business context was the key to developing organization-specific use-cases. Therefore, applied researchers worked together with the individual organizations to inspect the organization's circumstances, objectives, and the data that would be available for analysis. Furthermore, the applied researchers shared insights and learnings from the individual cases with the other participants during project workshops. However, collaboration and knowledge-sharing in this activity were limited because the individual use cases were very different. As interviewee 11 explains:

> *"Our first learning concerns the transferability of individual results, which is extremely complex because the companies are very different."*

In summary, the participants adapted PdM to their organizational context in the course of the project and, thus, performed the activity of conceptual adaptation.

Conceptual Exploration

We discovered a third activity of experimentation in our case study: conceptual exploration. Some of the organizations lacked conceptual knowledge conceptual knowledge, such as the fundamental functionality, general use scenarios, and scientific foundations, which they needed to establish organization-specific PdM use-cases and identify potential constraints. Interviewee 3 describes the organization's expectations of the project in the following statement:

> *"Generally, our expectations of the overall project originally were that […] we get those formalities, algorithms, thought-provoking impulses and maybe new ideas from the university, from the scientific perspective, and of course that we discuss this with the project partners."*

Constraint mitigation and conceptual adaptation presuppose a basic conceptual understanding of a technology. Otherwise, organizations can neither identify constraints that arise at the intersection of technology and the business context nor can they adapt the concept to their organizational specifics. Therefore, organizations involved in the project had to develop a basic conceptual understanding of PdM before they could experiment with it in a more advanced form. After developing an initial understanding of the concept, organizations could proceed with further experimentation activities. Conceptual exploration assumed different forms in our case study. Firstly, the applied researchers organized workshops with all participants during which they explained the foundations of PdM to the organizations. During those workshops, organizations also had the chance to share their experience with one another. In this regard, collaboration between different project organizations played an important role. Secondly, applied researchers organized workshops with the individual organizations during which they could work on the specifics of PdM at its intersection with the respective business context. However, some of the organizations already possessed a basic conceptual understanding of PdM that they had acquired elsewhere. For example, interviewee 9 tells that company 4 has already acquired some knowledge of PdM outside the project:

> *"How did we come up with this? Well, that's a gradual process. On the one hand, the topic has already been present at all the conferences for some time. In fact, there are certain congresses and associations where those topics are discussed. Now and then, you can also meet pioneers there who are already pursuing the topics. Well, based on those pioneers, we established the knowledge in our company as well."*

In summary, organizations had different levels of conceptual understanding of PdM. Therefore, not all organizations had to conceptually explore PdM as part of the project. Consequently, some were immediately able to pursue the more advanced experimentation activities of constraint mitigation and conceptual adaptation. Interviewee 5 emphasizes these different levels of understanding in the following statement:

> *"The companies had different backgrounds in this area. Some only had little to no experience, and others already had been able to gain some initial experience. Here, we just tried to share this knowledge with all companies."*

Transferred to the A-E-A process, we infer that organizations can enter into the experimentation phase at different points, that is, they can start with different activities. Either they can begin by conceptually exploring a technology (*Entry Point w/o Basic Conceptual Understanding*) or they can start with constraint mitigation and conceptual adaptation (*Entry Point with Basic Conceptual Understanding*). Experimentation is an iterative process with constraint mitigation and conceptual adaptation being mutually constitutive (Du et al. 2019). That is, conceptual adaptation might reveal constraints that require mitigation and, at the same time, mitigation activities might involve further conceptual adaptation. These experimentation activities help organizations to recognize affordances, which, in turn, helps them to further refine experimentation. In addition, conceptual exploration can help organizations to recognize affordances. The idea is similar to Gaver's (1996) concept of perceptual information, which supports the recognition of technology affordances. Moreover, constraint mitigation and conceptual adaptation provide organizations with information that helps them to improve their conceptual understanding of a technology. In conclusion, we propose extending the experimentation phase of Du et al. (2019) as shown in Figure 3.

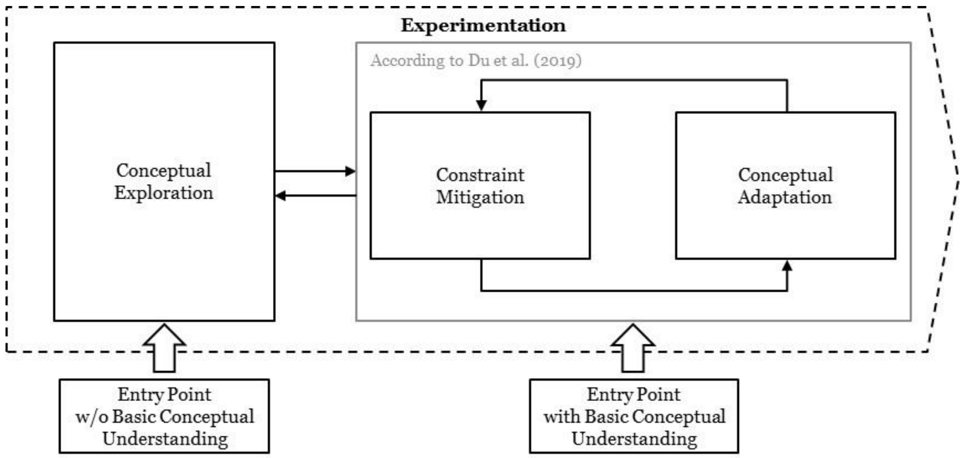

Figure 3. Extended experimentation phase

Actualization

Publicly funded, applied research projects are not supposed to yield ready-made solutions. Therefore, participants generally focused on experimentation within the scope of the project. Nevertheless, some organizations have already actualized affordances outside of the project. Actualization began when use-cases were feasible and organizations could use the PdM system to achieve outcomes in support of their organizational goals (Burton-Jones and Volkoff 2017; Strong et al. 2014).

Most of the organizations are now able to use the PdM system to monitor machine conditions in real-time. For instance, company 3 actualized this first affordance by monitoring specific machines at the customer's site, which they did by connecting the machines to the internet and implementing a feature that performs condition analysis. Given the customer's approval, the condition monitoring department also used the customer's process data to further refine the analysis of machine conditions. Moreover, the system automatically generates alerts if measured values of machine conditions exceed certain thresholds. As a result, the condition monitoring department can respond to machine disruption more quickly. Interviewee 8 explains condition monitoring as follows:

> *"Real-time condition monitoring is enabled by integrating the hardware – the sensors – and the customer's control data into the analysis feature that is made available online."*

Furthermore, companies 1 and 3 use pattern recognition to remotely diagnose machine errors and, thus, have already actualized the diagnosing affordance. Actualization led to the outcome of technicians knowing the parts that require replacement. Interviewee 1 explains the actualized diagnosis affordance as follows:

> *"We also have a remote interface to the facility. That is, we can already support remote error diagnosis as long as the facility is connected – not all of them are connected."*

The participating organizations have not yet fully actualized the planning affordance because they only use the prediction feature in prototypical instantiations.

Organizational Context

Lastly, the organizational context plays an important role in A-E-A theory because it can stimulate experimentation (Du et al. 2019) and affordance actualization (Bygstad et al. 2016). Our analysis reveals four elements of the organizational context that stimulated experimentation and actualization. Therefore, we can deduce that the organizational context also contributed to PdM implementation.

Firstly, an open-innovation culture that supports cooperation with external partners contributed to experimentation in general and conceptual exploration in particular. As described above, organizations need to develop a basic conceptual understanding of new technologies before they can mitigate constraints and adapt the concepts to their specific needs. Cooperation with external partners who already possess the respective knowledge can facilitate the exploration process. As our case study demonstrates, cooperation with applied researchers or universities is one option for acquiring new knowledge.

Secondly, data awareness among employees in different fields supported the mitigation of the data strategy constraint. Data awareness refers to a general awareness of the importance of data and a basic understanding of data management and governance. Interviewee 13 emphasizes the importance:

> *"In any case, you have to create the whole infrastructure concerning data analysis, data quality, etc. so that the people are aware of its importance."*

Establishing data awareness in an organization's culture can help to reduce data preparation efforts as data is consequently more likely to be available in actionable form and quality.

Thirdly, a sub-team structure that supports interdisciplinary collaboration stimulated experimentation and actualization. Both required capabilities from different disciplines and different organizational departments. For instance, data analytic skills are necessary to train the respective algorithms. However, data scientist needed input from technicians and machine experts to formalize the knowledge that is necessary for training. Interviewee 1 points out the importance of interdisciplinary collaboration:

> *"Above all, it is the corporate structure that is important […] because those topics are currently only handled within the individual specialist departments. I assume that it's necessary to join forces somewhere. However, as I said, we are right in the middle of this corporate restructuring phase to support digital solutions."*

Similar to most digital solutions, organizational agility also contributed to experimentation and actualization in the context of PdM. Agility facilitated experimentation and helped organizations to enter the actualization phase more quickly. This stimulating factor shows some parallels to the findings of Du et al. (2019) in the context of blockchain, who assert that "a culture that supports intrapreneurship" stimulated the actualization of the loan affordance. Both agility and entrepreneurship within established organizations support the recognition of new opportunities. As interviewee 1 explains:

> *"Agility, experimenting, lean start-up, etc. are characteristics that support organizational success and not intensive requirements management and execution according to a plan. These are the cultural differences that we fight for every day."*

This is consistent with the literature on organizational agility (e.g., Sambamurthy et al. 2003), which argues that agility helps organizations to explore and exploit new opportunities. Thereby, organizational agility refers to organizations being able to quickly sense and respond to new opportunities.

Discussion

The present paper examines the implementation of PdM and is based on an embedded single-case study. We use A-E-A theory to guide our research and to analyze how organizations actualize affordances in the context of PdM. In addition, we analyze how the organizational context affects affordance actualization. In particular, we focus on the experimentation phase as recently proposed in A-E-A theory (Du et al. 2019).

Our study makes two interesting theoretical contributions. Firstly, we contribute to IS research in the field of AI-enabled systems by illustrating how technological features, human actors, and organizational goals can be incorporated into the exploration of PdM. We believe that A-E-A theory can benefit AI research because it abstracts from a mere feature perspective and emphasizes the importance of the relationship between human actors, organizational goals, and IT artifacts. In this regard, A-E-A theory allows for a critical evaluation of the value added by the implementation of AI-enabled systems. Although the PdM systems in our case study need further development before they can be fully regarded as AI-enabled systems, we want to introduce a few thoughts about the relevance of some of our findings to the implementation of AI-enabled systems in general. Since many AI-enabled systems lack established use-cases, organizations are likely to require an experimentation phase to prepare such systems for effective use. Moreover, we see some parallels in the constraints that require mitigation. Consistent with Agrawal et al. (2018), an actionable data strategy is a crucial prerequisite for a successful implementation of AI-enabled systems. Organizations are also likely to encounter emotionalization issues upon the implementation of AI-enabled systems. AI entails uncertainties concerning its operating principles, as well as ethical issues that require mitigation. Likewise, organizations must develop a certain pragmatism about the potential of AI-enabled systems, which will not benefit the organization per se. By focusing on the relationship between human actors, organizational goals, and IT artifact, A-E-A theory, in particular, provides a means to address this issue. Advanced AI-enabled systems are characterized by their ability to independently learn representations or features from raw data (Bengio et al. 2013). Therefore, we do not expect the lack of formalized knowledge to constrain the implementation of such systems.

Secondly, we contribute to A-E-A theory by finding further evidence for the existence of an experimentation phase in the context of technologies that lack established use-cases. A-A theory originally covered affordances and their actualization (Strong et al. 2014) because organizations potentially have access to a multitude of established use-cases for technologies such as electronic health records (Du et al. 2019). As a means to overcome the lack of established use-cases in the context of emerging technologies, Du et al. (2019) have recently extended A-A theory with an experimentation phase based on a single blockchain case. We find that constraint mitigation and conceptual adaptation are also essential activities in experimentation outside the context of blockchain. Moreover, we propose that A-E-A theory should be extended further, namely by adding further detail to the experimentation phase. We find conceptual exploration to be an important activity of experimentation that precedes constraint mitigation and conceptual adaptation. We believe that our extension makes A-E-A theory applicable to other emerging digital technologies in general and the domain of AI-enabled systems in particular. Generally speaking, experimentation can assume different forms. In our case study, for instance, organizations collaborated with applied researchers in a publicly funded, applied research project in order to test the feasibility of PdM solutions. However, we can also think of other ways of experimenting and acquiring knowledge. For example, organizations might collaborate with startups who specialize in the respective technology (Du et al. 2019). Alternatively, they might hire IT consultants, or form a specialized internal unit which possesses the necessary capabilities. We believe that there is no single way of experimenting. Therefore, we introduce the concept of different entry points into the experimentation phase. Depending on their existing knowledge and capabilities, organizations can implement new technologies in different ways. As described above, conceptual exploration can help organizations to effectively experiment with and use a technology if they lack a basic understanding of a certain technological concept. Otherwise, they can begin with more advanced experimentation (i.e., constraint mitigation and conceptual adaptation). We believe that introducing different entry points makes A-E-A theory adaptable to a broader range of technologies.

Additionally, our study may help practitioners to effectively implement PdM, since A-E-A theory provides organizations with the means to consider technological features, human actors, and organizational goals in their strategic assessment.

Limitations and Further Research

Our work is subject to some limitations that offer opportunities for further research. Firstly, although we believe the single-case study design to be appropriate for our research endeavor, single-case studies commonly face criticism regarding their generalizability (Walsham 2006). We achieved some generalizability on an analytical level by evaluating our results with respect to existing literature. However, our research could benefit from further validation in the future. Secondly, we draw 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 (Eisenhardt 1989; Eisenhardt and Graebner 2007), future research could investigate the implementation of PdM and other AI-enabled systems in different projects settings and different types of companies like, for example, startups or large multinational corporations. Thirdly, the organizations have not yet fully implemented the PdM systems. Therefore, they have not yet actualized all of the affordances identified. Since we were particularly interested in the experimentation phase, further research could examine fully implemented PdM systems. Finally, PdM systems only constitute a small part of the field of

AI-enabled systems, which is very heterogeneous. The possibilities for the application of AI-enabled systems are manifold, as are the systems themselves. Although we can derive a few thought-provoking ideas on the implications for the implementation of AI-enabled systems in general from our study, AI research in the IS-community could further benefit from studies using A-E-A theory to examine the implementation of other AI-enabled systems. In this context, analyzing how the self-learning ability of AI-enabled systems fits into the concept of A-E-A theory could be particularly interesting. Moreover, affordance actualization depends on an organization's capabilities and knowledge (Bygstad et al. 2016). Therefore, future research could explore the relationship between capability and A-E-A theory and, thus, further complement what we believe is an interesting theoretical lens for IS research. In the theoretical background, we also briefly discussed aspects of structuration theory and their relation to A-E-A theory. Future research could benefit from a deeper investigation of how the concepts of structuration and A-E-A theory complement one another. In conclusion, we believe that our research, despite its limitations, is an initial step toward a strategic examination of AI-enabled systems. We hope it provides fellow researchers with a foundation for continued work in this important domain.

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