Generative mechanisms of AI implementation: A critical realist perspective on predictive maintenance

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Abstract

Artificial intelligence (AI) promises various new opportunities to create and appropriate business value. However, many organizations – especially those in more traditional industries – struggle to seize these opportunities. To unpack the underlying reasons, we investigate how more traditional industries implement predictive maintenance, a promising application of AI in manufacturing organizations. For our analysis, we employ a multiple-case design and adopt a critical realist perspective to identify generative mechanisms of AI implementation. Overall, we find five interdependent mechanisms: experimentation; knowledge building and integration; data; anxiety; and inspiration. Using causal loop diagramming, we flesh out the socio-technical dynamics of these mechanisms and explore the organizational requirements of implementing AI. The resulting topology of generative mechanisms contributes to the research on AI management by offering rich insights into the cause-effect relationships that shape the implementation process. Moreover, it demonstrates how causal loop diagraming can improve the modeling and analysis of generative mechanisms.

Keywords: Artificial intelligence, causal loop diagramming, experimentation, generative mechanisms, predictive maintenance, techno-organizational context

1. Introduction

Artificial intelligence (AI) offers various opportunities to challenge established value creation logics and redefine organizational practices (Stone et al., 2016; Vial, 2019; Wessel, Baiyere, Ologeanu-Taddei, Cha, & Jensen, 2021). Some proponents go as far as calling AI the next general-purpose innovation (Agrawal, Gans, & Goldfarb, 2019; Jöhnk, Weißert, & Wyrtki, 2021). However, it is often not self-evident how organizations – especially in more traditional industries – can seize the opportunities presented by AI, nor how its use can improve their competitiveness (Benbya & Leidner, 2018; Yan, Leidner, & Benbya, 2018). As a result, many organizations struggle to realize value from their efforts to develop AI-enabled applications (Shollo, Hopf, Thiess, & Müller, 2022).

What makes the extraction of business value especially challenging is the fluid nature of AI as a moving frontier of computing technologies with the ability to perform cognitive functions associated with the human mind (Anderson, Rainie, & Luchsinger, 2018; Berente, Gu, Recker, & Santhanam, 2021; Rai, Constantinides, & Sarker, 2019). Many organizations struggle to navigate this fluid nature and the resulting shortcomings of AI technologies (M. C. Lee, Scheepers, Lui, & Ngai, 2023; Merhi, 2023; Rai et al., 2019). Some also have a hard time with the organizational capabilities required to successfully employ AI-enabled applications and to revise established value creation logics and organizational practices (Berente et al., 2021; Weber, Engert, Schaffer, Weking, & Krcmar, 2023).

Especially with new AI technologies, it is often not clear how organizations can best navigate the implementation process (Sarker, Chatterjee, Xiao, & Elbanna, 2019; Teodorescu, Morse, Awwad, & Kane, 2021). In this study, we aim to clear some of this uncertainty by identifying and analyzing the cause-effect relationships that define this process. To better account for the perspective of more traditional organizations, we focus our study on AI-enabled predictive maintenance (PdM), a popular application of AI among manufacturing companies. AI-enabled PdM refers to the automated and intelligent scheduling of maintenance activities based on the continuous analysis of a system's operating conditions. We ask:

RQ: *Which socio-technical dynamics shape the implementation of AI-enabled PdM?*

To answer this question, we examine two cases in which organizations in the manufacturing business adopted AI-enabled PdM systems. Throughout our analysis, we identify and unpack five "generative mechanisms" that describe the socio-technical dynamics that can constrain and stimulate the path to effective usability of AI-enabled PdM systems. We use causal loop diagramming (Sterman, 2000) to provide a comprehensive picture of these mechanisms and to identify how certain techno-organizational factors (such as organizational culture and structure as well as the pre-existing technological base) affect the implementation of AI-enabled predictive maintenance. Our analysis offers a deeper understanding of important cause-effect relationships that affect the implementation process and how organizations should approach their AI initiatives and projects.

The remainder of this paper is structured as follows. In section 2, we provide a brief review of the literature on the implementation of AI and AI-enabled PdM and discuss the basics of generative mechanisms. We present our research approach in section 3 and provide a detailed description of our findings in section 4. Lastly, we discuss these findings as well as their implications in section 0, and then share concluding thoughts in section 6.

2. Theoretical background

2.1. AI-enabled predictive maintenance

Over the past ten years, interest in AI has increased steadily. This surge is made possible by the availability of large amounts of training data, a substantial increase in computational power, and the identification of a growing number of use cases in a variety of professional, educational and domestic contexts (Stone et al., 2016). Today's AI-enabled systems can master various cognitive functions, such as perceiving, learning, reasoning, problem-solving, planning, decision-making, natural language processing, and interacting with their environment (Fabri, Häckel, Oberländer, Rieg, & Stohr, 2023; Rai et al., 2019; Russell & Norvig, 2016).

However, realizing actual business value from the implementation of AI-enabled systems remains a challenge for many – especially more traditional - organizations (Shollo et al., 2022). Barriers to successful implementation in these organizations can be manifold, ranging from problems with data quality, quantity, and governance, inert IT infrastructures, security, privacy, ethical and legal constraints as well as the organizational culture (M. C. Lee et al., 2023; Merhi, 2023). Some organizations also struggle with questions of professional identity that may arise when employees feel substituted by AI-enabled systems (Strich, Mayer, & Fiedler, 2021). Others have a hard time adjusting to the loss of unique human knowledge (Fügener, Grahl, Gupta, & Ketter, 2021) and coming to terms with an increasing disconnect between codified knowledge and human expert know-how (Lebovitz, Levina, & Lifshitz-Assa, 2021).

AI initiatives and projects need to identify and address these challenges to realize the potential business value. As with many other change processes, organizational decision-makers need to lead the way and foster strategic alignment, cultural change, and organizational learning (M. C. Lee et al., 2023; Li, Li, Wang, & Thatcher, 2021; Merhi, 2023; Shollo et al., 2022). Organizational learning is especially crucial for the sustainable integration of AI-enabled systems in an organization and should extend across departments and sometimes organizational boundaries to manage the high degree of uncertainty associated with most AI-enabled systems (M. C. Lee et al., 2023; Roy, Stark, Tracht, Takata, & Mori, 2016; Shollo et al., 2022; Weber et al., 2023). Organizational learning can even be facilitated through a proper design of the collaboration between AI-enabled systems and humans (Fabri et al., 2023; Shin, Han, & Rhee, 2021; Sturm et al., 2021). Moreover, organizations need to build technological capabilities, such as mature data infrastructures, user experience, and lifecycle management for AI models (M. C. Lee et al., 2023; Merhi, 2023; Shollo et al., 2022; Weber et al., 2023).

Yet no AI project or initiative will be the same. Implementing AI-enabled systems thus also requires a deep understanding of the underlying cause-effect relationships in the specific context (Raisch & Krakowski, 2021). This need is supported by a growing body of research on guidelines and success factors for implementing AI-enabled systems (M. C. Lee et al., 2023; Merhi, 2023). However, little attention has so far been paid to how these factors interact and the cause-effect relationships that underly these interactions. In this study, we employ a generative-mechanisms lens to identify and unpack these relationships (Bygstad, Munkvold, & Volkoff, 2016).

We focus our analysis on AI-enabled predictive maintenance (PdM). AI-enabled PdM systems continuously collect, monitor, and analyze a machine's condition to predict and preemptively mediate maintenance needs as well as system failures. Based on the intelligent scheduling of maintenance activities, these systems promise to optimize process availability, safety, quality, and productivity (Christer, Wang, & Sharp, 1997; Mobley, 2002; Zarte, Wunder, & Pechmann, 2017). We selected AI-enabled PdM for three reasons: It offers several opportunities to improve organizational performance (Christer et al., 1997; Mobley, 2002; Zarte et al., 2017), it is comparatively mature (LaRiviere, McAfee, Rao, Narayanan, & Sun, 2016), and many more traditional organizations have found its implementation to be challenging (Wagner & Hellingrath, 2019).

2.2. Generative mechanisms

The concept of generative mechanisms has its roots in critical realism. Critical realism is a philosophy of science that has proven useful for the study of various information systems phenomena (Bygstad et al., 2016; Volkoff & Strong, 2013). Critical realists conceptualize the world in three layers (Bhaskar, 1998; Mingers, 2004): the real, the actual, and the empirical. The layer of the "real" consists of physical and social structures associated with mechanisms that generate events or outcomes. These events or outcomes constitute the layer of the "actual". Lastly, the layer of the "empirical" comprises the subset of events or outcomes that can be observed. Based on this conceptualization, we can understand generative mechanisms as the causal structures that trigger events or outcomes (Bhaskar, 1998).

These causal structures can take several forms, be they physical, chemical, biological, psychological, social, or economic, or even, at times, unobservable (Bunge, 2004). They can either enable or constrain action (Volkoff & Strong, 2013). Yet rather than do so in a deterministic manner, generative mechanisms are "characterized by contingent causality"

(Henfridsson & Bygstad, 2013, p. 911). This means that a generative mechanism will not always produce the same events and outcomes but instead be contingent on the events or outcomes previously produced by other generative mechanisms (Elder-Vass, 2010; Sayer, 1992; Smith, 2010). Some mechanisms may also never be actualized, so their potential to cause certain events can remain dormant (Fleetwood, 2011).

These characteristics can make it difficult to identify generative mechanisms without in-depth process of retroduction (Bygstad et al., 2016), a "mode of inference in which events are explained by postulating (and identifying) mechanisms which are capable of producing them" (Sayer, 1992, p. 107). Since events often lend themselves to various generative mechanisms (particularly in technology adoption projects) and since generative mechanisms can affect and alter one another, it is typically impossible to identify all mechanisms at play. Rather, the art of generative mechanisms research is to focus on a topology of foundational mechanisms that best explains the outcomes observed (Gebre-Mariam & Bygstad, 2019).

An understanding of those generative mechanisms can help to better analyze and explain certain phenomena. For instance, Gebre-Mariam and Bygstad (2019) use generative mechanisms to better understand the complex adoption process of health management information systems in developing countries. They identify four important mechanisms: projectification; informatization; embedded inscription; and scaling. Another example is J. Y. H. Lee, Hsu, and Silva (2020) use generative mechanisms to study the construction and evolution of smart technology. They find that the transformation of a smart technology into a real product or system is significantly affected by three mechanisms: a system-environment fit mechanism; a data exploitation mechanism; and a user expansion mechanism that builds on the data exploitation mechanism.

In our own study, we draw on Bygstad et al. (2016) to identify a parsimonious topology of interrelated generative mechanisms that either stimulate or constrain the adoption of AI-enabled PdM systems. We are particularly interested in how these mechanisms affect the early stages of adoption, when PdM is still new to the organization. Next, we turn to the two case-studies we used to identify and unpack these mechanisms.

3. Research method

3.1. Case-study setting

Case studies allow for the development of both a deeper understanding of a phenomenon and subsequent rich theoretical insights. They enable the iterative development of constructs, measures, and theoretical arguments based on a constant comparison between theory and data (Eisenhardt, 2021). As the aim of our study is to identify and unpack (or rather "retroduce") foundational generative mechanisms, we chose a multiple-case design (Yin, 2014) with two cases to balance in-depth insights with generalizability (Eisenhardt, 2021; Eisenhardt & Graebner, 2007). We sampled two cases, ProdAI and CarAI, based on the following criteria:

Candidate cases must generate in-depth insights into implementation of AI-enabled PdM systems, including the challenges faced by implementing organizations. To improve cross-case comparability, candidate cases should have the same focus on implementing AI-enabled PdM in a business-to-business context. They should, however, reflect different approaches to implementation. While small and medium-sized companies often join forces to collaborate and cut costs, large (multinational) companies tend to engage with new technologies on their own to secure a competitive advantage.

Our first case, "ProdAI," is a publicly-funded, applied research project in Germany featuring AI-enabled PdM. The goal of the project was to develop intelligent analytics solutions that increase transparency in production processes, and its partners envisioned creating new data-based services and business models. It began in February 2018 and lasted 13 months. The project started with the identification and specification of use cases for AI-enabled solutions within the respective organizational context. Building upon this specification, applied researchers other than the authors of this study collaborated with four medium-sized German companies in the mechanical engineering industry to examine and develop AI-enabled PdM systems for production machines. The participating organizations were particularly interested in using AI-enabled PdM to manage maintenance processes at scale of machines in remote locations. They envisioned establishing AI-enabled PdM as an additional feature when selling the machines. While most of the work was performed in smaller groups with separate weekly coordination meetings, the project's steering committee met every three months to discuss the overall progress and adjust the goals, if required. Upon completion of the project, the participating companies all had working prototypes of AI-enabled PdM systems. Some of the companies then refined these prototypes into production-ready systems.

Our second case, "CarAI," investigates the AI-enabled PdM activities at a production site of one of Germany's premium car manufacturers. The manufacturer developed a data analytics strategy that includes AI-enabled PdM activities that were geared towards reducing the maintenance costs of production tools. In 2018, the car manufacturer began looking for use cases in the pressure casting process and established a new data analytics team that would support the implementation of an AI-enabled PdM system for this process. That is, contrary to the “ProdAI” case, “CarAI” did not intend to sell the feature, but rather to use it in its own processes. By January 2020, the CarAI project had successfully implemented several prototypes that either optimized the use time of tools or supported quality analysis.

3.2. Data collection

Our primary sources of evidence were semi-structured interviews that the first two authors of this work conducted between December 2018 and December 2019. Throughout the interviews, they took comprehensive notes. Furthermore, they made audio recordings and transcribed them for further analysis and reference. The interviews lasted between 45 minutes and two hours. Table 1 presents an overview of the interviewees for both cases and their organizational roles.

The interviews followed a semi-structured protocol to elicit stories about the participating organizations (Myers & Newman, 2007; Rubin & Rubin, 2012). At the beginning of each interview, the interviewers provided the necessary contextual information by introducing themselves along with the research project. Subsequently, the interviewees briefly discussed their relevant backstories, current organizational positions, and pertinent experiences within the respective organizations. Once the introductions were complete, the interviewers took care to minimize social dissonance during the interview by explaining how each interview was to be anonymized and made secure in order to protect the confidentiality of all concerned. Next, we sought to foster a good relationship between the interviewer(s) and the interviewee by encouraging each interviewee to discuss their personal background and involvement in recent AI-enabled PdM projects.

Table 1

Overview of the interview participants in each case.

ProdAI	Organization	Role of the Interviewee
1	Company 1	Manager
2		IT specialist
3	Company 2	Data scientist
4		Pre-sales manager
5	Company 3	Engineer
6		IT specialist
7		Manager
8		Engineer

CarAI	Organization	Role of the Interviewee
15	Company 5	Engineer
16		Data scientist
17		Engineer
18		Engineer
19		Manager
20		IT specialist
21		Data scientist
22		Manager

9	Company 4	Manager
10	Applied research organization 1	Applied researcher
11		Applied researcher
12		Applied researcher
13		Applied researcher
14	Applied research organization 2	Applied researcher
23		IT specialist

At all times, the interviewers were careful to conduct themselves in a way that not only mirrored the tone and vocabulary of the interviewee, but also used terms with which the interviewee was comfortable. Doing so offered the interviewee the flexibility to take the conversation in any direction that they wanted (Orlikowski & Baroudi, 1991). Moreover, we focused our initial questions on recent experiences and projects which were familiar to the interviewees. We asked company employees about how they use or intend to use AI-enabled PdM and how AI-enabled PdM changes the way they work. We also asked the applied researchers working with the ProdAI organization about how to align AI-enabled PdM with business requirements and how to deploy AI-enabled PdM applications. Moreover, we asked about any preconditions that the organizations were required to meet. Example questions included:

- Which fields of application for predictive maintenance are you currently pursuing? Can you think of an AI-enabled PdM project you have recently carried out? Why did you carry out this project? (Request examples)
- How do you use AI-enabled PdM systems, and how did these systems change the way you work? (Request examples)
- How do you think the organizational structure, culture, and leadership affect the implementation of AI-enabled PdM? Why do you think so? (Request examples)

In several instances, we contacted the interviewees a second time to clarify any ambiguities perceived during the analysis of the interviews. We produced a full case write-up for each interview and, wherever necessary, asked for supplementary information to triangulate our results (Yin, 2013). As secondary sources of evidence, we used field observations and project-related documents, such as project reports and documents describing the use of AI-enabled PdM systems among the various organizations. In addition to taking factory tours at both case sites and watching system demonstrations, we spent 10 hours observing three strategic PdM-related workshops at ProdAI.

3.3. Data analysis

We analyzed our case data using the MAXQDA software package. For our analysis, we drew on and adapted Bygstad et al.'s (2016) framework for the retroduction of generative mechanisms. We employed causal loop diagraming to develop a topology of mechanisms and their dependencies in the modelling software Vensim (Sterman, 2000). Table 2 outlines the steps in our adapted framework. Consistent with the principles of building theory from case studies, we iterated between theory and data and employed both within- and cross-case analyses in steps three to six of the retroduction process (Eisenhardt, 2021; Eisenhardt & Graebner, 2007; Yin, 2014).

Table 2

Steps in the retroduction of generative mechanisms (framework adapted from Bygstad et al. (2016)).

Step	Description	Result
1. Description of events and outcomes	The first step concerns the coding of events and outcomes. This step is important because observed events and outcomes are the centerpieces of critical realist research.	We analyzed the collected data to establish a chronology of events and outcomes in the two cases. For this analysis, we applied an initial coding scheme (Saldaña, 2016). Section 3.1 contains a brief description of the two cases. Appendix A includes a chronology of events and outcomes.
2. Identification of key entities	The second step concerns the identification of the "key entities" present in the different cases. The term key entity can refer to individual actors and organizational units but also to technological objects that interact and form causal structures.	We identified the key entities in the two cases as being the individuals (managers, AI specialists, etc.) and the organizational units (departments and divisions) who were either involved in the development of the AI-enabled PdM systems or constituted the target group. The involved individuals included not only employees but also customers and partners (e.g., researchers).
3. Theoretical re-description (abduction)	The third step concerns the exploration of different theoretical perspectives and explanations of key events and outcomes (Bygstad et al., 2016; Danermark, Ekstrom, Jakobsen, & Karlsson, 2002).	We analyzed the collected data and codes repeatedly, while also leaving time for reflection. This led to a broader conceptualization of our analysis. Having initially focused on how organizational knowledge and capabilities affect the implementation of AI-enabled PdM systems, we later also examined the effect of techno-organizational context factors, such as organizational culture. This second round of analysis involved both open and axial coding (Saldaña, 2016; Strauss & Corbin, 1998) to develop conceptual categories and subcategories.

4. Retroduction of mechanisms	The fourth step concerns the identification of the actual mechanisms by means of retroduction, which is the central activity in critical realist research. Retroduction is the “mode of inference in which events are explained by postulating (and identifying) mechanisms which are capable of producing them.” (Sayer, 1992).	From our coded data, we retroduced five generative mechanisms that best explain the observed events and outcomes.
5. Analysis of dependencies and interactions	The fifth step concerns analyzing the interaction and dependencies between the identified mechanisms and the development of a contextual topology.	We established a detailed visual topology of the interaction and dependencies between the identified mechanisms. For this purpose, we turned to the system dynamics literature, which provides useful means for the analysis and modeling of complex systems (Sterman, 2000). More specifically, we used causal loop diagramming to capture variables and the causal links among them (see Fig. 1). As a result, we developed a single model that explains the interaction between the identified mechanisms (see Fig. 5).
6. Assessment of explanatory power	The sixth and final step concerns assessing the explanatory power of the proposed mechanisms and finding the causal structures that best explain the observed events. This requires repeated analysis.	During the development of the model, we regularly returned to the data and evaluated other plausible mechanisms, patterns of interactions, and feedback loops. Moreover, we regularly discussed our results within the research team to identify any needs for additions or clarifications. In this way, we iteratively developed and improved our model until we reached a state of theoretical saturation. In other words, we re-iterated through the modeling process until we were convinced that the model provided the best explanation for our observations. Additionally, we reviewed the causal links between the outcomes against existing literature. This helped ensure that the model is grounded in the case data and is consistent with existing theoretical insights.

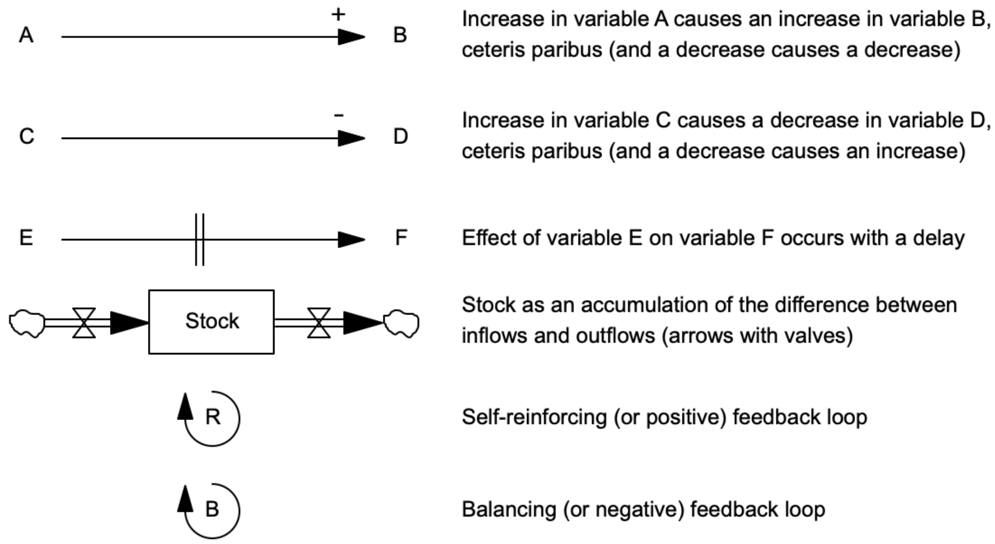

Fig. 1. Notation of the causal loop diagramming method (based on Sterman (2000)).

4. Findings

We now turn to the five mechanisms that emerged from our analysis, and the topology of their interaction and dependencies. We gradually build this topology from a description of the two cases in the next subsections. Our point of departure is the experimental approach that the organizations in the ProdAI and CarAI cases took to the adoption of PdM.

4.1. The experimentation mechanism

Both cases began with a strong focus on experimentation due to the *lack of established use cases* that could serve as a blueprint for the *ability to effectively use* AI-enabled PdM. To support this experimentation, they mobilized substantial financial, personnel, and technical *resources*. Those organizations that made more resources available for experimentation not only made more speedy progress, but they also developed more specific use cases, which in turn strengthened their subsequent, more applied *experiments* with PdM. Interviewee 7 emphasizes how the mobilization of resources in the ProdAI project helped them:

> *"[ProdAI] was extremely helpful for us because without it, we would not have had the time to experiment, to program something, and to examine the data for days."*

Depending on the level of experience of the organization, experimentation included different activities. For instance, some organizations in the ProdAI case only had little prior knowledge of PdM. These organizations first had to develop a conceptual understanding before being able to proceed to more material experimentation activities. In this process, they benefited substantially from the *external input* of other more experienced organizations which were working within the project, as well as the input of the participating applied researchers. Interviewee 5 explains these background differences and the influence of external input:

> "*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." [I5, ProdAI]*

Once the organizations in both projects had established a solid conceptual understanding of PdM and its use cases, they started to adapt it to their specific context in order to progress toward effective usability. They also began to mitigate *constraints* (i.e., restrictions and barriers that stand in the way of effectively using AI-enabled PdM) that arose from *organizational barriers,* such as the pre-existing technological base and organizational culture. Interviewee 1 emphasizes the importance of these constraint mitigation activities and the cultural changes that were required:

> *"Agility, experimenting, lean management, etc. are characteristics that support organizational success, rather than intensive requirements management and strict execution according to plan. These are cultural differences that we fight for every day." [I1, ProdAI]*

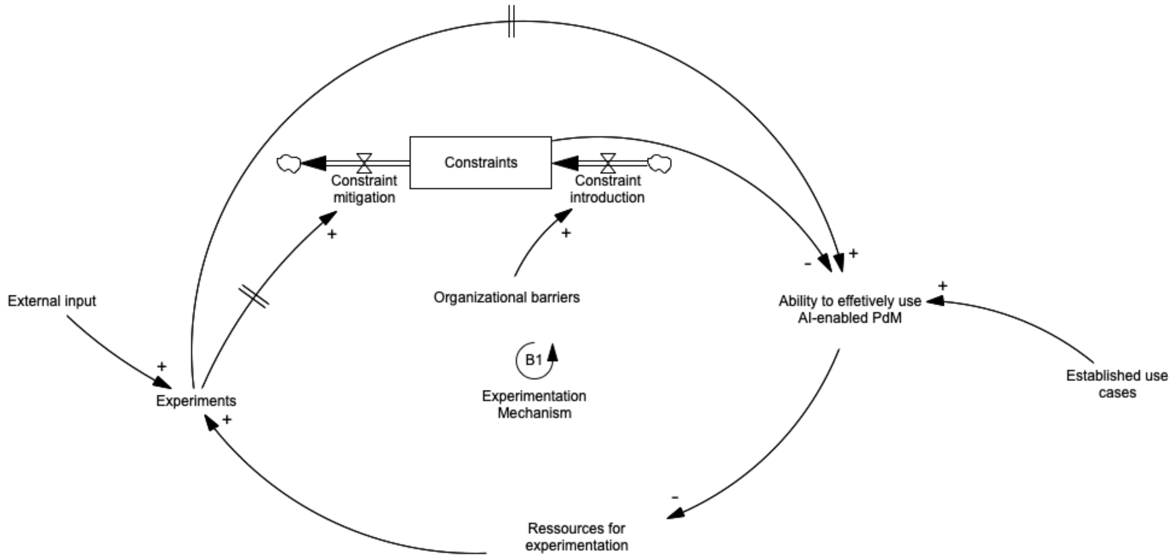

Fig. 2. Experimentation mechanism.

Fig. 2 summarizes the observed relationship between the lack of established use cases, resources for experimentation, experiments, and effective usability of AI-enabled PdM. As it took both cases a considerable amount of time before they were able to complete the first experiments, Fig. 2 features a delay in the effects of experimentation. Moreover, it features a balancing (or negative) feedback loop (B1) because organizations (ceteris paribus) reduce the investment of resources for experimentation when they can use PdM effectively.

4.2. The knowledge building and integration mechanism

Organizations can approach experimentation in different ways. They can do so exclusively with internal resources or decide to obtain external support. The premium car manufacturer behind the CarAI case opted for an internal approach because it felt that maintenance should be one of its core competencies. ProdAI – by its very nature – relied heavily on external support. However, both cases agreed on the need for heavy investments into internal capability building, that is, the building of organizational knowledge. Generally, organizational knowledge can be understood as the collective organizational memory and beliefs stored in "forms, rules, procedures, conventions, strategies, and technologies" (Levitt & March, 1988, p. 320). Organizations in both cases recognized that the implementation of AI-enabled PdM required organizational knowledge that the organizations did not have at the time (*knowledge gap*). As interviewee 18 points out:

“[PdM] definitely requires new capabilities and new expertise which […] are not available in a normal maintenance company. Let's put it this way: we must recruit, of course.” [I18, CarAI]

In both cases, the employees involved were mostly mechanics and engineers with no prior skills in data science. To address this skills shortage, their organizations *invested in training and hiring*. Interviewee 4 emphasizes the success their organization had in this regard:

“We now have highly trained developers in all areas […]. Since we work in the field of e-mobility, we have specialists in this field as well. The same applies to the field of additive manufacturing, and so on.” [I4, ProdAI]

The training and hiring measures also provided them with additional possibilities to create interdisciplinary or interdepartmental teams to improve experiments with AI-enabled PdM. These teams were typically better at solving the multifaceted challenges of the early implementation stages. However, the process of building and integrating organizational knowledge through *training and hiring* proved to be tedious. Interviewee 20 nevertheless emphasizes the importance of knowledge integration for experimentation as part of CarAI:

“It is not without reason that we have set up this overarching project so that the topics are not driven out of the individual departments, but interdepartmental, […].” [I20, CarAI]

Knowledge integration and the experiments with AI-enabled PdM in interdisciplinary and interdepartmental teams also produced new insights that helped the organizations improve their conceptual understanding and, thus, contributed to building organizational knowledge. Interviewee 11 emphasizes this knowledge creation aspect of experimentation in ProdAI:

“Learning from each other was a central point of the project. The organizations always had an interest in what the other participants were doing.” [I11, ProdAI]

We refer to this self-reinforcing (or positive) feedback loop as the *knowledge building and integration mechanism* because it fosters the creation of organizational knowledge (R1) and can stimulate experimentation (see Fig. 3). However, the investments in training and hiring will decrease as the gap in knowledge required for AI-enabled PdM narrows. We refer to this balancing (or negative) feedback loop as *knowledge need reduction* (B2).

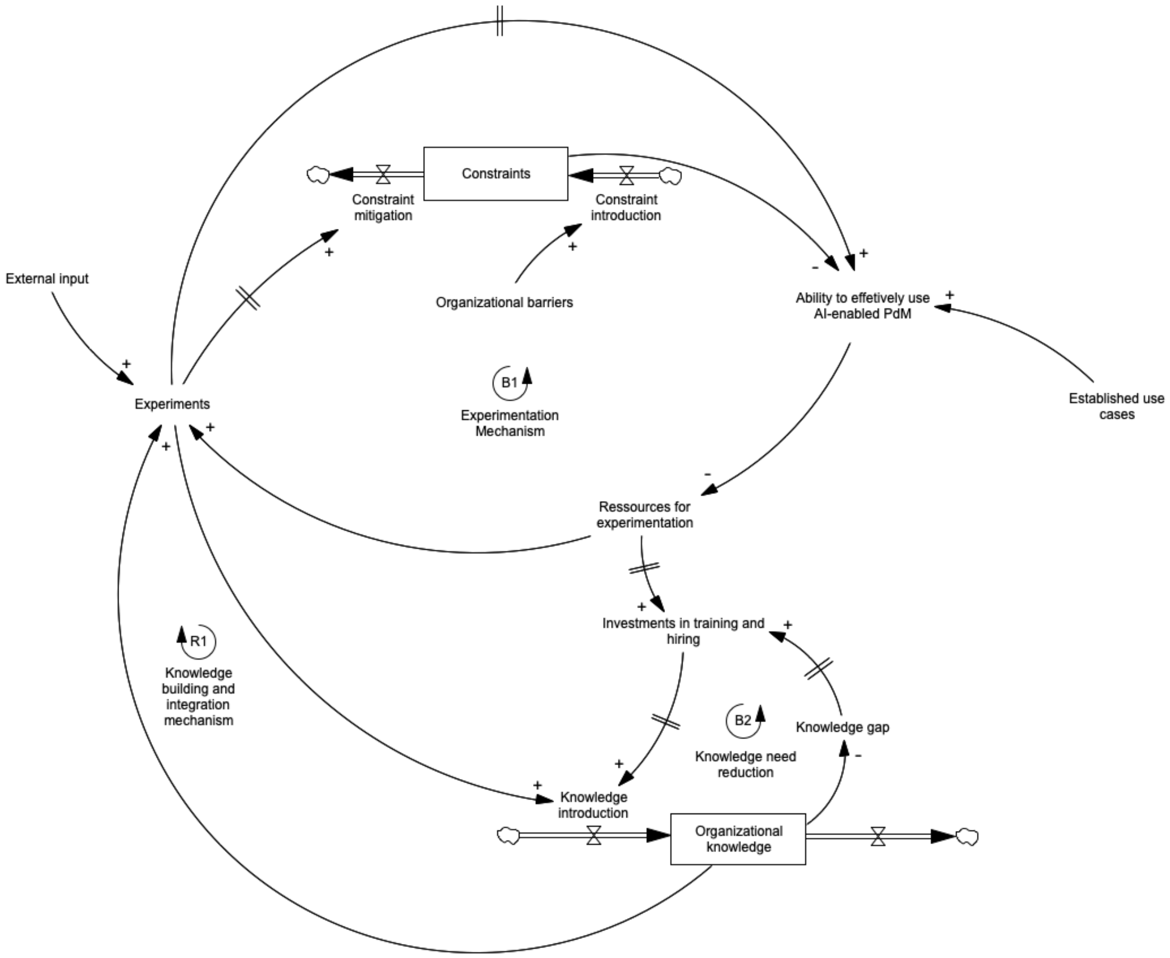

Fig. 3. Knowledge building and integration mechanism.

4.3. The data mechanism

In addition to positively influencing experimentation activities, the *knowledge building and integration mechanism* also contributes to a third mechanism which we refer to as the *data mechanism* (see Fig. 4). More specifically, an increase in organizational knowledge helped the organizations in the two cases to increase the number and quality of *insights* that can be generated from *data analyses*. First, the organizations in both cases were generally able to *collect data* from their machines to provide a basis for AI-enabled PdM as they equipped their machines with different *sensors*. As interviewee 9 describes:

“Well, [the machines] can already pick up sensor signals today; they can also store these sensor signals for a limited time period and transmit the data.” [I9, ProdAI]

However, for all organizations involved, it was not enough to simply possess the data required for PdM, but also to understand and evaluate it. Expanding their organizational knowledge-base helped organizations in both cases address these issues. While interviewee 22 describes the difficulties their organization had initially in this regard, interviewee 3 emphasizes how ProdAI helped their organization progress:

“We often have a lot of data, but our department generally is not able to assess whether the data has the right quality or quantity.” [I22, CarAI]

“With the project, we wanted to intensify reviewing our data and to better understand it. The researchers helped us especially also with knowledge about the formalities, the algorithms, but also with general thought impulses and ideas.” [I3, ProdAI]

Gaining more insights into the data eventually also led to the *identification of additional data requirements*. For instance, the organizations found gaps in their data and needs new data that their sensors were not yet picking up (e.g., gearbox vibrations). Interviewees 1 and 6 describe how ProdAI supported their organization in this regard:

“This is one of the main findings. We must think explicitly about our error patterns to figure out which data are needed for predictive maintenance.” [I1, ProdAI]

“We already had databases with all our data, but we have never studied them that closely. With the start of the project, however, we began to deeply engage with the data and recognized limitations to be addressed. […] There is a significant difference between telling people that we need more data for artificial intelligence and giving them the chance to do something and discuss the results. That was very important.” [I6, ProdAI]

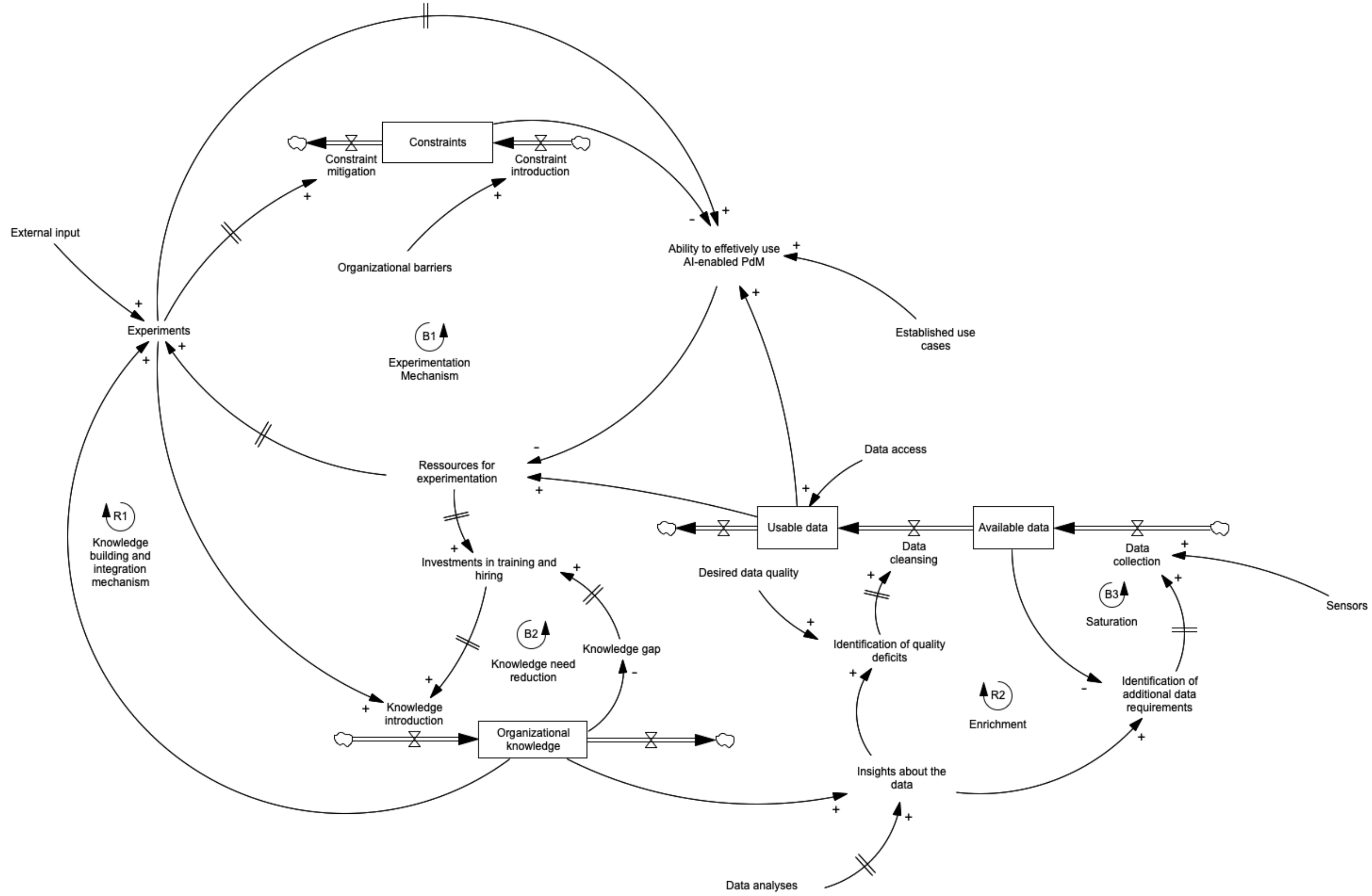

Fig. 4. Data mechanism

However, gaining insights about the data not only contributed to the identification of additional data requirements, but also to the *identification of quality deficits* (i.e., deviations from the *desired data quality*). Interviewee 21 describes how it took their organization some time to translate these findings into *data cleansing* efforts:

> *“We have done a lot of analysis projects where we looked at the process, and we simply noticed that the data quality did not suffice. And then [a group of employees] tried to work on elaborate models instead of doing their homework and improving the data quality.” [I21, CarAI]*

Together, data collection and data cleansing efforts allowed the involved organizations to create *usable data* (*enrichment*, R2). However, both cases also demonstrate that it can take considerable time to build such a usable database. Some organizations also struggled with *data access*. For instance, one company in the ProdAI case used a third-party software provider whose data encryption techniques proved troublesome. As interviewee 5 describes:

> *“That is, data is to some extent encrypted. At the beginning of the project, we thus had problems to get the data. […] We had to approach the provider to find out how they encrypt the data.” [I5, ProdAI]*

Collectively, the links displayed in Fig. 4 between insights, requirements, and usable data form a mechanism that we refer to as the *data mechanism*. The data mechanism increases the set of usable data provides additional resources for both experimentation and effectively using AI-enabled PdM (e.g., training data). However, the *data mechanism* is not a self-reinforcing process. On the contrary, the need for collecting additional data becomes smaller as the set of usable data grows. We refer to this balancing (or negative) feedback loop as *saturation* (B3).

4.4. The anxiety mechanism

In both cases, many mechanics and business-side employees had initial reservations about the introduction of AI-enabled PdM. These employees lacked knowledge about the technology, particularly concerning the ways in which AI-enabled PdM and its underlying algorithms work and draw conclusions. Interviewee 7 describes the issues that they had with *inscrutability*:

> *"We have a large conservative group that doesn't understand those new solutions." [I7, ProdAI]*

This inscrutability of AI-enabled PdM led to general *insecurity* with how it was used and *resistance* in both case studies. Interviewee 19 explains this process in the CarAI project:

> *"I think that the fear of being replaceable still prevails here. That is, the fear that my professional know-how is replaced by a data model and I'm no longer useful. Therefore, there is a lot of resentment." [I19, CarAI]*

At the same time, however, the data scientists depended on the knowledge of mechanics and business-side employees to interpret the results of their data analyses, especially during the training of the PdM models. The lack of willingness to support this training and to work with AI-enabled PdM led to organizational barriers and the introduction of constraints that limited the quality of the results. In due course, the lack of willingness to participate posed a significant obstacle to the progress of experimentation. Interviewee 7 emphasizes these challenges:

> *"As I said, we are a traditional machine manufacturer. [Our company] has an incredibly hard time with change." [I7, ProdAI]*

We refer to this balancing (or negative) feedback loop as the *anxiety mechanism* (B4). This sees the inscrutability of AI-enabled PdM, coupled with a fear among users of being replaced, gradually nourishing feelings of insecurity. These feelings contribute to conscious or unconscious desires by staff to obstruct AI-enabled PdM projects (see Fig. 5).

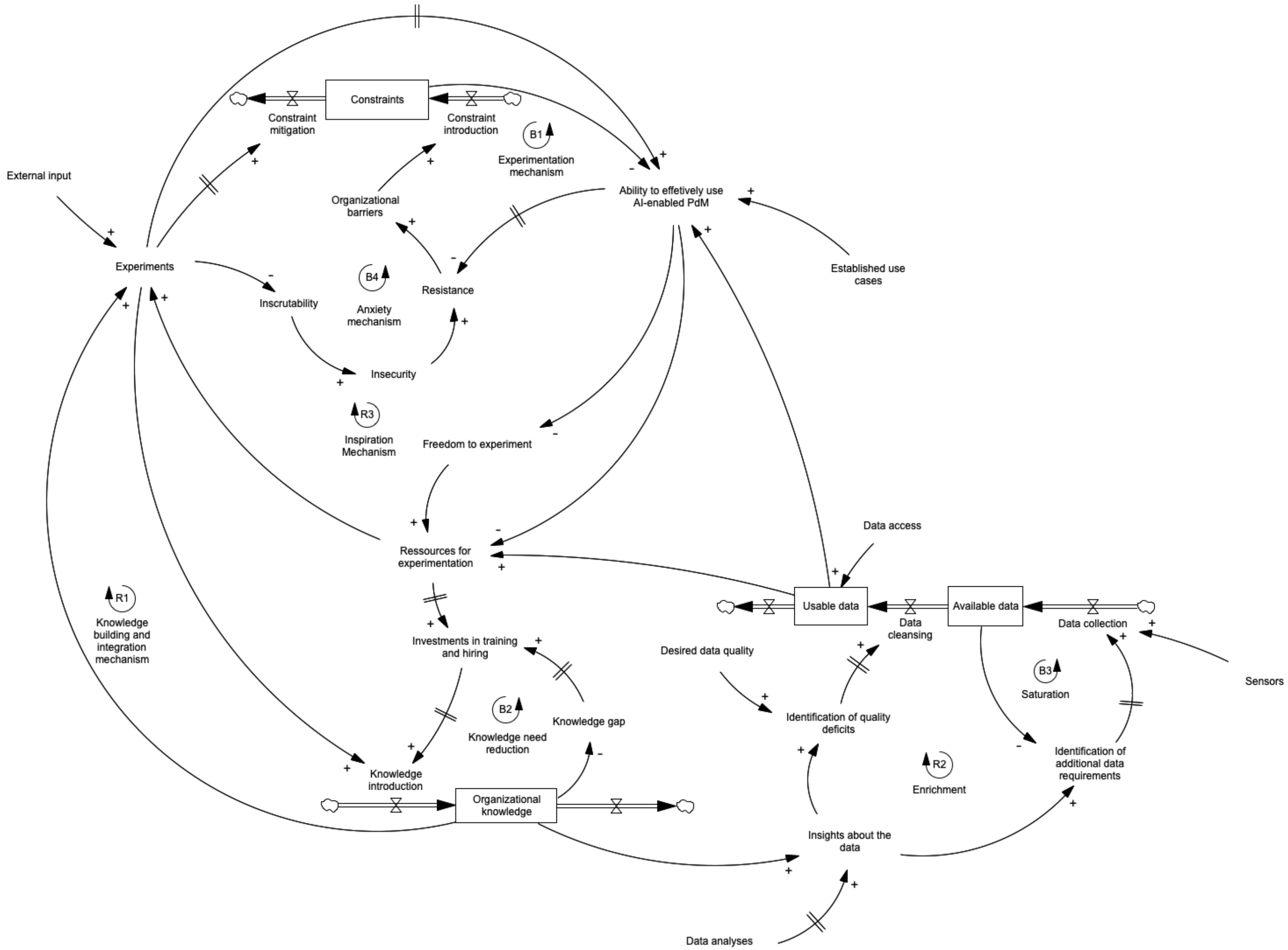

Fig. 5. Socio-technical dynamics of generative mechanisms shaping the implementation of AI-enabled PdM

4.5. The inspiration mechanism

Despite this negative feedback loop, organizations – particularly those involved with ProdAI – managed to progress toward effective usability. This success was at least partly due to mitigating dynamics that resulted from the growth of conceptual understanding gained by conducting the experiments. Better conceptual understanding helped to decrease inscrutability and counteracted the negative feedback loop behind the anxiety mechanism. Interviewee 1 describes the effects the experiments had within their organization, saying these experiments helped them to better understand how the algorithms predict errors:

> *"Our organization must be able to rely on the recommendations of the predictive maintenance system […] In this regard, experimenting with the error sensitivity issue helped us. These experiments showed that there is no single solution, but rather that you need to make specific adjustments depending on the use case. These adjustments helped us better understand and build trust in the solution, which contributed to the internal acceptance of the algorithmic solution." [I1, ProdAI]*

In our cases, we observe that the AI-enabled PdM projects benefited when organizations promoted employee curiosity. That is, employees were given the *freedom to* run PdM *experiments* without the constraints of strict boundaries, nor the requirement to provide a complete business case. This observation was particularly present in the ProdAI case study, where the parameters of the applied research project featured conditions that allowed experimentation. In this open environment, participating employees ran several projects with AI-enabled PdM. As interviewees 2 and 6 emphasize:

> *"We were conducting research on different tracks together with analytics experts. We set up a server and fed it with various data from our machine interface. After a while, we tested an algorithmic solution to analyze the data. At the same time, we discussed and compared our solution with other companies to have a benchmark." [I2, ProdAI]*

> *"It helped that we had the freedom to explore the whole subject area." [I6, ProdAI]*

Based on these looser conditions, the employees were able to develop a deeper understanding of the application of AI-enabled PdM to their specific business context, which stimulated the dynamics of the *experimentation mechanism* (B1). These dynamics helped the organization to progress toward effective usability of AI-enabled PdM. Communicating the experiences gained through experimentation, as well as the benefits of AI-enabled PdM, subsequently enabled employees in the two cases to generate interest in their projects. This inspired others to follow their example, and reduced resistance to AI-enabled PdM. We refer to the process by which positive results from experimentation provide the respective actors with the inspiration to reduce both inscrutability and resistance, and thus to progress toward effective usability as the *inspiration mechanism* (R3). Nevertheless, communicating those benefits was again a cumbersome process, which resulted in delays to the process of reducing resistance. Interviewees 7 and 19 stress how they were required to persevere:

> *"An infinite number of internal meetings and presentations. I perform something like internal customer acquisition, where the customer is my own colleague. This is a very strenuous and time-consuming work." [I7, ProdAI]*

> *"For instance, we had a project where we predicted the time to a possible breakdown of the cutters. I think the success of this project helped us increase the sensitivity for this topic [AI-enabled PdM] because people recognized the benefits. [...] The next step is to get everybody together. You must get these pilot projects over the finish line first. You must show people that it provides benefits, and you must take the fear away from people." [I19, CarAI]*

However, organizations need to exit the experimentation phase at some point. As the organizations – particularly in the CarAI case – progressed toward being able to effectively use AI-enabled PdM, they reduced the freedom to experiment and decided for a more focused approach to effectively use AI-enabled PdM. For instance, interviewee 15 describes this need to exit experimentation at some point:

> *"I think it is good to start with pilot projects. Just get started and try to overcome the first hurdles. To continue, we meticulously document processes and contact persons. [...] The employees are typically doing that in parallel to their regular tasks. At the*

beginning, it is always very time-consuming until you get to the people who can help you and be more efficient. […] At some point, we need to decide to prioritize the topic and choose a more focused approach." [I15, CarAI]

Fig. 5 displays the complete topology of the described generative mechanisms of AI-enabled PdM

5. Discussion and implications

We began our study with the observation that many – especially more traditional - organizations struggle to realize business value from their AI initiatives and projects. We then hypothesized that many of these struggles may be rooted in a high degree of uncertainty regarding the socio-technical dynamics of AI implementation (Keller, Stohr, Fridgen, Lockl, & Rieger, 2019; Roy et al., 2016; Wuest, Weimer, Irgens, & Thoben, 2016). To reduce this uncertainty, we drew on the example of AI-enabled PdM and unpacked five major generative mechanisms that describe how these dynamics play out, and how certain techno-organizational context factors shape the implementation of AI-enabled PdM (Bygstad et al., 2016).

5.1. A model of interrelated generative mechanisms connected to AI-enabled PdM

Our five mechanisms stress that organizations need to be aware of various socio-technical dynamics when they explore and engage with new and emerging technologies such as AI-enabled PdM. These dynamics can support or constrain emerging IT endeavors, particularly in the field of AI (see Table 3). Their underlying cause-effect relationships are closely connected, and they mutually influence and shape outcomes of the individual mechanisms.

Table 3

Generative context mechanisms connected to the implementation of AI-enabled PdM.

Mechanism	Definition
Experimentation	A process by which the pursuit of being able to effectively use AI-enabled PdM leads to investments in resources for experimentation, with the experiments eventually helping the organizations to mitigate constraints and prepare the technology for effective use (B1).
Knowledge building and integration	A process by which resources for experimentation are invested in training and hiring to foster interdisciplinary and interdepartmental collaboration and cooperation (R1). This building and integration of organizational knowledge

	paves the way for experiments with AI-enabled PdM (B1) and further knowledge generation. However, the investments in training and hiring will decrease as the gap in knowledge required for AI-enabled PdM narrows (B2).
Data	A process by which the engagement with previously collected data and quality-control measures generates fresh insights and encourages further data collection (R2). This enrichment loop is mitigated by the effect of saturation (i.e., a reduction of additional data requirements for a growing set of usable data) (B3).
Anxiety	A process by which the inscrutability of AI gradually nurtures feelings of insecurity in users that can lead to resistance to current and future projects (B4).
Inspiration	A process by which the granting of freedom to innovate helps employees to generate positive results from experimentation and encourages others to follow suit when these results are effectively communicated (R3).

The nexus of interdependencies between the five mechanisms emphasizes an important characteristic of generative mechanisms: their transfactuality, which means that their effects are contingent on other mechanisms (Fleetwood, 2009; Henfridsson & Bygstad, 2013). Some mechanisms can counteract each other, such as the *inspiration* and the *anxiety* mechanisms or the *anxiety* and the *experimentation* mechanisms. Others may reinforce each other, such as the *knowledge building and integration* and the *experimentation* mechanisms or the *knowledge building and integration* and the *data* mechanisms. It is thus important to establish a comprehensive view of an organization's techno-organizational context, as well as its propensity to generate counteracting and reinforcing mechanisms. Moreover, time is an important factor when considering the mutual effects of different mechanisms and the initiation of short- or longer-terms vicious and virtuous cycles. For instance, the dynamics of the *anxiety mechanism* will typically set in quickly, but it will take some time before the *knowledge building and integration* and *inspiration* mechanisms can balance insecurity dynamics. Fortunately, system dynamics and generative mechanisms lenses offer powerful tools to unpack both the interdependencies between mechanisms and their temporal contingencies to provide a more comprehensive view on the socio-technical dynamics that shape the implementation of AI-enabled systems (see Fig. 5).

These two lenses may often reveal experimentation as an essential (re-)starting point. As we saw in the ProdAI case, experimental activities can be very important – especially when a new AI-enabled system lacks established use cases, and an organization does not have previous experiences with the technology. Experimentation can help to iteratively resolve technical and organizational challenges that may emerge during the implementation process and to develop organizational AI capabilities (Keller et al., 2019; M. C. Lee et al., 2023; Shollo et al., 2022). However, it is important that organizations approach experimentation from a business perspective and with the goal to effectively use the new AI-enabled system. Otherwise, they may get trapped in a continuous state of experimentation, the “pilot purgatory” (Abbatemarco, Gaur, & Meregalli, 2022). Thus, striking the ”right” balance between exploration and exploitation is also important at such an early stage (Andriopoulos & Lewis, 2009; Tushman & O'Reilly, 1996).

But even if organizations find this balance, they may never proceed beyond experimentation when they are not able to counteract the *anxiety mechanism.* When employee insecurity is high, experimentation may not be enough. This is commonly the case when AI-enabled systems are perceived as inscrutable “black boxes” (Asatiani et al., 2021; Berente et al., 2021). Insecurity can be especially high when these AI-enabled systems are also perceived as being untrustworthy (Thiebes, Lins, & Sunyaev, 2021) or as a challenge to professional roles and identities (Strich et al., 2021). In these situations, much attention is required to communicating and demonstrating the benefits of AI-enabled systems to counteract *the anxiety mechanism.* Empowering “first-mover” employees and encouraging constructive curiosity can be important releasing conditions (Bolino, Thompson, Norris, & Kuo, 2023; Coleman, 2023) as can be pilot projects (Hertzum, Bansler, Havn, & Simonsen, 2012; Kim & Kankanhalli, 2009). However, these projects need to remain focused on creating business value to avoid the pitfalls of “pilot purgatory”. Otherwise, pilot projects – particularly those with a strong focus on short-term effects – may fail to scale (Gebre-Mariam & Bygstad, 2019). When “first-mover” employees and pilot projects are successful at communicating (Barkin & Davenport, 2023) and demonstrating the benefits of AI-enabled systems, they may inspire other employees to follow their example, initiating what we refer to as the *inspiration mechanism*.

In the mid- to long-term, the *knowledge building and integration mechanism* can help organizations mature from experimenting at a smaller scale to effectively using AI-enabled PdM. It is important because without it, organizations will likely get stuck at running various experiments with the new AI-enabled system. However, the *knowledge building and integration mechanism* requires patience since its positive effects will often be delayed (Mitchell, 2006; Repenning & Sterman, 2002; Tiwana, 2004; Walz, Elam, & Curtis, 1993). It can thrive when domain experts work alongside traditional data analysts, IT and AI experts in interdisciplinary and interdepartmental settings. Organizations interested in AI should thus consider hiring AI specialists, while also motivating and training their existing employees to engage with AI (Lou & Wu, 2021; Vial, Cameron, Giannelia, & Jiang, 2023; Weber et al., 2023). Effective interdisciplinary and interdepartmental teams may sometimes also require "connectors" who support effective collaboration (Redman & Davenport, 2023) or designers who improve user experience (Roy et al., 2016; Shollo et al., 2022). Such teams foster creativity and performance (Krishnan, Miller, & Judge, 1997; Nijstad & Stroebe, 2006; Paulus & Brown, 2007; Roy et al., 2016) and effectively using AI at scale. Moreover, they can help eliminate the insecurities that fuel the *anxiety mechanism* and instead promote the *inspiration mechanism* This mitigation effect is closely related to the benefits of dialectic organizational learning for change management (Robey, Ross, & Boudreau, 2002).

However, these positive effects will not pe possible if an organization's *data* is not ready (Caserta, Harreis, Rowshankish, Srinidhi, & Tavakoli, 2023). AI-enabled PdM is not an exception (Roy et al., 2016; Vom Brocke et al., 2018). Organizations need to carefully engage with their data to fuel the *experimentation mechanism* and then enable the *inspiration* and *knowledge building and integration mechanisms*. At the same time, the *knowledge building and integration mechanism* will often be necessary to sustain this engagement. More specifically, a broader organizational knowledge base – when properly integrated – can help evaluate the organization's data in terms of quantity and quality (Shollo et al., 2022). Without this knowledge base, data can only partly or not at all be translated into business value. Worse still, organizations that collect data without a well-defined purpose and knowledge base risk creating so-called "data swamps" (Brackenbury et al., 2018). These swamps can even break the *data mechanism*. When AI initiatives and projects fail to demonstrate the benefits from their *experiments* due to not having the "right" data (Hoerl & Redman, 2023), they may increase resistance and strand AI-enabled systems at the experimental stage.

In summary, organizations need to understand the transfactuality of the five generative mechanisms with different short- and long-term effects to effectively use AI-enabled systems and avoid getting stuck at an experimental stage – or worse, not even reaching an experimental stage. While organizations may be able to use *experimentation* and *inspiration* in the short-term to balance *anxiety*, they also need to *build and integrate knowledge* and properly develop their *data* pipeline to sustain and scale their AI efforts in the mid- to long-term. These investments in *knowledge building and integration* as well as in the *data* pipeline can then also pay off in the short term for subsequent AI initiatives and projects.

5.2. Theoretical contributions

Our study provides two theoretical contributions. First, we contribute to the research on AI implementation by identifying and unpacking five generative mechanisms that shape the implementation process. While there is a growing body of research on guidelines and success factors for implementing AI-enabled systems (M. C. Lee et al., 2023; Merhi, 2023), the interdependent nature of these guidelines and factors often falls short. Using causal loop diagramming (Sterman, 2000), we thus provide a rich description of their interplay and the cause-effect relationships that decide about the success or failure of AI initiatives and projects. The resulting topology of five generative mechanism offers an in-depth explanation for how the pre-existing technological base – in conjunction with organizational factors like organizational structure and culture – can affect the implementation process of AI-enabled systems (Berente et al., 2021). In this way, our study also addresses calls for more empirical research on AI implementation that provides a context-specific perspective with a balanced consideration of social and technical factors (Grashoff & Recker, 2023; Jöhnk et al., 2021).

Our critical realist perspective emphasizes especially the transfactual nature of mechanisms (Fleetwood, 2009) and how the actualization of their individual- and organizational-level effects is contingent on other mechanisms (Henfridsson & Bygstad, 2013). That is, we demonstrate that it is not enough to single out specific guidelines and success factors for implementation. Instead, it is necessary to understand the interdependent nature of the mechanisms over time and organizational levels. For instance, organizations may well promote a culture of experimentation and inspiration that emerges from an individual to an organizational level but if their data foundations are not right, they will likely not be able to effectively use AI-enabled systems (Hoerl & Redman, 2023). Moreover, they may not be able to actualize the other four mechanisms without the *data mechanism*. These dependencies across organizational levels and time could explain why some organizations have positive outcomes from the implementation of AI-enabled systems, while others fail to realize business value (M. C. Lee et al., 2023).

Secondly, our study extends the "retroduction" toolkit by demonstrating how causal loop diagraming can help to visualize and analyze the transfactuality of generative mechanisms (Fleetwood, 2009) as well as their self-referential nature (Henfridsson & Bygstad, 2013). Causal loop diagrams require a high level of precision in the modeling of generative mechanisms and their interdependencies (Sterman, 2000). This level of precision will often benefit the clarity and explanatory power of the retroduced mechanisms and encourage more critical reflection throughout the retroduction process (Bygstad et al., 2016).

5.3. Practical implications

This study also offers three important practical implications. First, our topology can help practitioners better understand and navigate the challenges of AI initiatives and projects (Wagner & Hellingrath, 2019). A generative mechanism perspective can help them to pay special attention to their organizations' various (interrelated) physical and social structures and avoid the trap of simply copying the work of pioneering organizations. Moreover, the interdependent and transfactual nature of the identified generative mechanisms may sensitize them to the need to not just focus on a particular physical or social structure. Instead, they need to manage these structures holistically and be mindful of the delayed effects of certain cause-effect relationships. Although generative mechanisms cannot help to predict outcomes or events with certainty, understanding these mechanisms and their interdependencies can nonetheless help organizations improve their management of AI initiatives and projects (Mingers, 2004).

Second, the five generative mechanisms can give practitioners a practical sense of particularly relevant techno-organizational context factors. Equipped with this understanding, they can, for instance, assess whether their teams have an appropriate mix of skills and backgrounds. Organizations interested in AI may also want to invest in an actionable data strategy that ensures that the "right" data is captured (i.e., data of good quality and a proper focus). Furthermore, they may want to establish a culture that promotes innovation and grants their employees the "right" degree of freedom to experiment, while at the same time creating the proper conditions to channel these experiments into longer-term pilot projects and productive systems.

Finally, practitioners should consider investing sufficient time and effort into building and integrating knowledge and competencies regarding AI, as well as communicating achievements with AI-enabled systems. Ideally, they would ensure these competencies are acquired by a substantial share of their workforce, while addressing the anxieties that some employees may experience regarding the potential impact of the technology on their roles and professional identities (Strich et al., 2021).

6. Conclusion

In this paper, we adopt a critical realist perspective to explore the socio-technical dynamics that shape the early stages of engagement with AI-enabled PdM. Based on a study of two AI-enabled PdM cases and using causal loop diagramming, we provide a detailed description theses socio-technical dynamics by way of five interdependent generative mechanisms. Understanding these mechanisms and their interrelated vicious and virtuous effects can help organizations in their endeavors to effectively use AI-enabled PdM and avoid getting stuck in an experimental stage – or worse, not even reaching an experimental stage. Importantly, it does not suffice to only focus on one mechanism, but organization need a balanced approach to both short- and long-term effects of different mechanisms. It is this transfactuality, the interdependence of effects, that makes studying generative mechanisms interesting to better understand the socio-technical dynamics that shape the implementation of AI-enabled PdM. We hope that our work will clear some of the uncertainties and concerns related to engagement with AI-enabled PdM and encourage a broader uptake of generative mechanism research.

As with all research, our study is subject to certain limitations that would be fruitful grounds for further analysis. First, our analysis may not paint a complete picture of all the generative mechanisms at work during the implementation of AI-enabled PdM and their contingent effects. Generative mechanism research is inherently limited by observed events and the outcomes it builds upon, as well as the judgement of researchers in the retroduction of mechanisms from these events and outcomes. While we are confident that the five mechanisms we have identified best explain our empirical evidence (cross-case), we do not claim to provide an exhaustive list of all mechanisms at work. For instance, the ProdAI case suggests that open innovation may also play an important role for certain AI initiatives and projects. Moreover, we have found weak evidence for the presence of what could be characterized as an "over-expectation mechanism" that would have employees idolizing AI and believing that it can be readily applied to their PdM use case. The cumbersome implementation of PdM, however, resulted in disappointment among these advocates and a reduction of their interest in AI. To better understand these (or other) effects, it may be worthwhile to conduct further research on the adoption of AI for different AI technologies and in different contexts.

Second, our research may be limited in its generalizability to follow-up or rather mature implementations of AI-enabled PdM. While we are confident that many of the identified cause-effect relationships will also be relevant for these later implementations, it may be worthwhile to explore how things change during follow-up implementations and effective use of AI-enabled PdM over a longer period and contrast these insights with organizations that got stuck in experimentation. This exploration would offer a comprehensive picture and support far-sighted management of AI implementation for the increasing number of AI initiatives and projects.

Third, our research may be limited in its generalizability to other AI-enabled PdM initiatives and projects, as well as to other AI technologies. While we attempt to mediate the first concern with a multiple-case design, the organizations involved were all established German firms. This raises legitimate questions about the transferability of our findings to more early-stage organizations and organizations in other countries. Moreover, AI-enabled PdM may be an edge case in that it is not fraught with many of the privacy and ethical concerns associated with other AI technologies. Future research could benefit from an exploration spanning different types of organizations and different geographical regions to paint a broader picture of socio-technical dynamics that influence the implementation of AI-enabled PdM.

Appendix A. Case study information

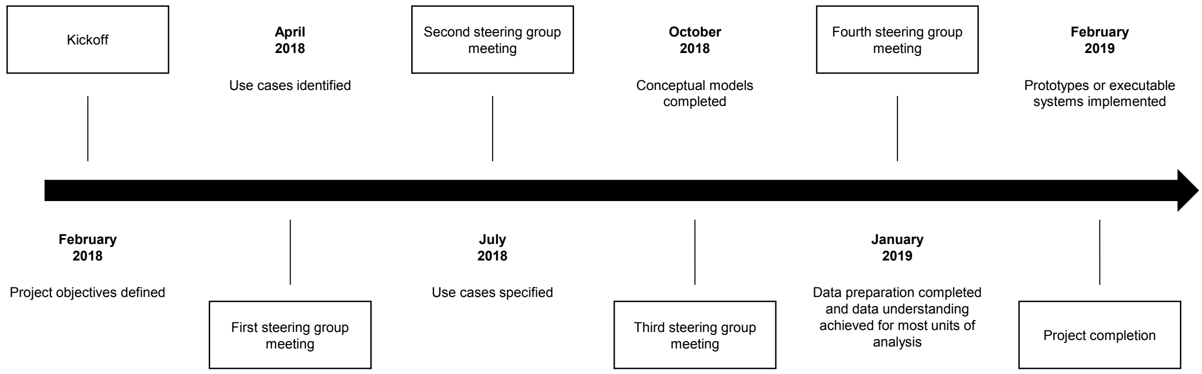

Fig. A. 1. Timeline of ProdAI.

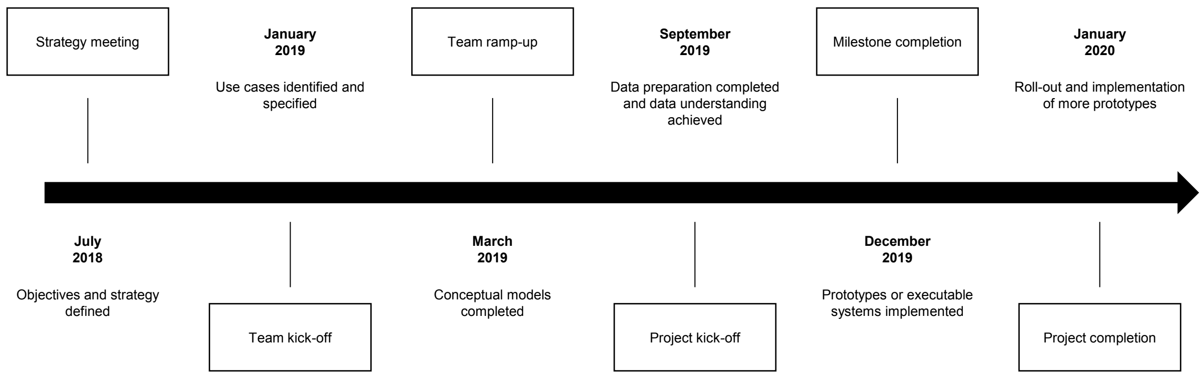

Fig. A. 2. Timeline of CarAI.

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