5-11-2023

SENSEMAKING IN AI-BASED DIGITAL INNOVATIONS: INSIGHTS FROM A MANUFACTURING CASE STUDY

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Research Paper

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Abstract

Organizations strive to innovate with Artificial Intelligence (AI) to tap new value potentials and outperform their competition. However, despite the enormous expectations associated with AI, incorporating the latter induces novel uncertainties into organizational innovation endeavors. To overcome these AI-induced uncertainties and construct meaningful AI-based innovations, the organizational actors must jointly make sense of AI and derive collective innovation actions. Using an exploratory case study, we investigate organizational sensemaking in two AI-based digital innovation projects at a globally leading automotive manufacturer. We account for the distinct characteristics by which AI differs from traditional information systems and carve out how these AI characteristics trigger AI sensemaking in AI-based digital innovations. We deduce four AI sensemaking mechanisms (i.e., cognition, interaction, regulation, and concretization) to understand better how AI unfolds in digital innovation endeavors in organizations.

Keywords: Artificial Intelligence, Organizational Sensemaking, Digital Innovation, Case Study.

1 Introduction

Digital technologies are undeniable forces that have provoked significant transformation in our economy and society over the last decades (Ciriello et al. 2018; Yoo et al. 2010). Artificial Intelligence (AI) is expected to considerably impact companies across all industries (Goasduff, 2019). Today's AI applications mainly leverage machine learning (ML) techniques (Engel et al. 2022; Lacity and Willcocks, 2021). ML algorithms learn and improve based on past data and enable computer systems to perform complex tasks such as predicting, diagnosing, planning, and recognizing (Jordan and Mitchell, 2015; Kang et al. 2020). Against this backdrop, AI's steep rise can considerably empower organizations' digital transformation, leading to increased productivity at the tactical, operational, and strategic levels (Dwivedi et al., 2021). Organizations put AI high on the agenda, striving to leverage the value potential of AI, for example in the manufacturing context, in quality inspection, process automation, or predictive maintenance applications (Davenport 2018; Ransbotham et al. 2019).

Yet, beyond this AI hype, many companies struggle to turn their AI ambitions into success (Ransbotham et al. 2019). Hence, high initial expectations have resulted in a more pessimistic view of AI (Winkler et al. 2019). However, a company's ability to turn technological opportunities into real business value is not limited to selecting promising technologies. Instead, organizations must make sense of novel technologies within their business environment and integrate value-oriented digital innovations into their socio-technical context – their IT infrastructures and organizational processes (Canhoto and Clear, 2020; Wiesböck and Hess, 2020). Hence, effectively examining the fit between technologies and business or production processes in an organizational context can determine an organization's success or failure (Bednar and Welch, 2020). We know that AI differs from traditional information technology (IT), and managing AI is unlike managing previous information systems (IS) (Berente et al. 2021; van Giffen et al. 2022). Therefore, we problematize that the advent of AI challenges the underlying assumptions of how we understand digital innovation (Alvesson and Sandberg 2011). There is a lack of understanding of how organizations make sense of AI technologies and construct socio-material realities through AI-based innovations. We pose that AI-based digital innovation differs from digital innovation. For example, anecdotal evidence suggests that the unique characteristics of AI induce novel uncertainties in digital innovation projects. Such uncertainties trigger an increasing demand for organizational sensemaking (Griffith 1999). Consequently, organizations need to make sense of AI within their socio-technical, situated context (Robey et al. 2013) and reconsider previous innovation practices to account for the unique AI characteristics. Understanding organizational AI sensemaking helps explain how AI challenges digital innovation endeavours in organizations. Thus, we pose the following research question:

How does organizational sensemaking unfold in AI-based digital innovations?

To answer this question, we draw an exploratory case study with rich empirical data and aim at adding an AI perspective to organizational sensemaking research. Our findings highlight AI sensemaking as a critical organizational capability to realize AI-based digital innovations successfully.

2 Theoretical Foundation

2.1 Artificial Intelligence

The term Artificial Intelligence dates back to the 1950s when researchers like Alan Turing investigated the nature of human intelligence and its transferability to computer systems (Stone et al. 2016). While 'general AI' is an allegory for replicating human intelligence, we are today witnessing the growing use of 'narrow AI' applied to automate cognitive tasks within a narrow scope (Chui 2017; Davenport 2018; Stone et al. 2016). AI broadly supports three business needs, i.e., process automation, cognitive insights, and cognitive engagement (Collins et al. 2021; Davenport and Ronanki, 2018). Today's implemented AI applications mainly leverage ML techniques (Engel et al. 2022; Lacity and Willcocks, 2021). ML algorithms learn and improve based on past data and enable computer systems to perform complex tasks such as predicting, diagnosing, planning, and recognizing (Jordan and Mitchell, 2015; Kang et al. 2020). Research has identified four characteristics that delimitate AI from traditional IT, constituting a paradigm shift (Engel et al. 2021; van Giffen et al. 2022). First, the experimental character of AI refers to the probabilistic outcomes of an AI system that do not follow a traditional 'if-then' logic (Amigoni and Schiaffonati, 2018). Second, the context-sensitivity of AI refers to the fact that the performance of an AI system (i.e., its output) in a specific context depends on the input data of that same context (Lieberman and Selker, 2000). The context-sensitivity of AI is particularly challenging in highly specialized environments, such as manufacturing, which hinders organizations from buying and implementing ready-made plug-and-play AI solutions. Third, AI's black-box character refers to the non-trivial explainability of an AI system's data processing, making it difficult to explain what happens between data input and AI system output (Castelvecchi 2016). Fourth, the AI learning requirement refers to an AI system's dependence on learning from data-based examples. For example, AI systems based on supervised learning techniques require vast amounts of labeled high-quality data to perform appropriately (Kang et al. 2020; Litjens et al. 2017). Labeling is the process of adding meaningful information to data for which ground truth is available and then using it as part of a training dataset, extracting features, and training AI algorithms (Benton 2020).

2.2 AI-Based Digital Innovation

Digital innovation may be defined as “a product, process or business model that is perceived as new, requires significant changes on the part of adopters, and is embodied in or enabled by IT” (Fichman et al. 2014, p. 333). Digital innovation can be rooted in emerging technological opportunities and domain-driven needs (Wiesböck and Hess, 2020). Digital innovation is understood as a multifaceted phenomenon that includes constant exploration, creation, and a combination of functions enabled by digital technologies (Ciriello et al. 2018; Nambisan et al. 2017). The (potential) innovation outcomes aim at value improvements such as gains in productivity and profitability or improvement in risk mitigation and customer loyalty (Kohli and Melville, 2019). The literature on digital innovation is extensive and highlights various facets such as innovation types (Lyytinen et al. 2016; Nambisan et al. 2017), development (Nambisan et al. 2017; Yoo et al. 2010), enablement (Henfridsson and Bygstad, 2013; Nambisan 2013), and governance (Bharadwaj et al. 2013; Matt et al. 2015). Nevertheless, we still know little about the intricacies emerging AI technologies may bring to digital innovation and respectively in AI-based digital innovation (Benbya et al. 2021; Berente et al. 2019; von Briel et al. 2018; von Krogh 2018; Wiesböck and Hess, 2020).

We understand AI-based digital innovation as the distributed or combinatorial innovation of products, processes, or business models using AI technologies (Ciriello et al. 2018, Skog et al. 2018) and position AI-based digital innovation as a subclass of digital innovation. AI can lead to implications for all innovation actions, resulting in new or altered AI-induced digital innovation actions within a project or the (organizational) environment in which the innovation gets shaped. The four AI characteristics mentioned above (see 2.1) can confront organizations with novel uncertainties in their innovation projects. First, the experimental character of AI, leading to non-deterministic results, increases uncertainty about the achievable performance of an AI-based digital innovation outcome, which is pivotal for investment decisions. Thus, AI portfolio planning and resource allocation may be subject to uncertainty. Second, the context-sensitivity of AI, leading to uncertainty about reliability in operations, increases the need to monitor an AI system and respond to contextual changes. Thus, operating costs may increase, and AI performance in operations may require additional monitoring and control mechanisms. Third, the black-box character of AI, leading to poor understandability for at least non-AI experts, increases the need for AI experts to guide AI-based digital innovation activities. Thus, new processes, project guidelines, and AI training for project members may be required. Fourth, the learning requirement of AI, leading to high upfront data demands, increases the dependency on domain experts and IT infrastructure to provide the initial, possibly labeled datasets.

2.3 Organizational Sensemaking in AI-Based Digital Innovations

Organizational sensemaking is a social process triggered by violated expectations, in which organizational members interpret their environment and derive actions through interaction with others (Tan et al. 2020; Weick 1995; Maitlis 2005). In the IS field, sensemaking has been used as a theoretical lens to focus on the social aspects of various systems’ implementation (Tan et al. 2020). In contrast to decision-making, which is about evaluating and choosing among alternative courses of action, sensemaking is about doing things that have already turned out to be meaningful (Boland 2008). A sensemaking process consists of four process steps, in line with Weick’s sensemaking model (Weick et al. 2005), which was confirmed by Tan et al. (2020) and applied in the context of ERP (enterprise resource planning) implementation: (1) initiation, i.e., contrasting environmental cues with organizational norms to trigger innovations, (2) enactment, i.e., retrospection of innovation triggers and primary decision makers’ mental models to formalize rationales for innovation, (3) selection, i.e., competition between sensemaking accounts to shape system requirements and design, and (4) retention, i.e., merging of sensemaking accounts into joint sensemaking leading to collective action. The sensemaking perspective is very well suited to illuminate situations requiring a shared understanding among several stakeholders to enable collective action (Weick 1993), which we deem vital considering the pervasive economic and organizational AI phenomenon (von Krogh 2018). We adopt a broad definition of sensemaking as a “process promoted by violated expectations that involves attending to and bracketing cues in the environment, creating intersubjective meaning through cycles of interpretation and action, and thereby enacting a more ordered environment from which further cues can be drawn" (Maitlis and Christianson, 2014, p. 67). This definition is helpful for our study, as it directs our attention to 'violated expectations' (induced by AI) as triggers within an organization. Sensemaking describes a constant dialogue of discovery and invention, in which people actively construct realities in partly overlapping processes and then give them meaning in retrospect (Brown et al. 2015).

Sensemaking allows us to examine the socio-technical organizational interplay in the presence of AI-based digital innovations, as it simultaneously references and fabricates social environments. AI-based digital innovations depend not only on their material functionalities but also on the situated socio-technical context, drawing "on the expertise, organizational processes and procedures, controls, boundary-spanning approaches, and other social capacities present in the organization" (Zammuto et al. 2007, p. 752). Digital innovation per se "calls for relentless deframing and reframing of innovation outcomes and processes, influenced by a social process" (Nambisan et al. 2017, p. 229) and thus is shaped by and part of a sensemaking process itself. Consequently, AI-based digital innovation projects may be understood as a social construction process of AI-based artifacts through shared cognition and joint sensemaking amongst innovation agents (i.e., organizational members) engaged in collective action. As such, individuals work in socio-technical contexts where routines, technologies, norms, social structures, and connections exist. When these established patterns are exposed to the novel nature of AI, shared cognition gets violated and must be revised in a socio-technical negotiation process. Re-establishing joint sensemaking then retrieves common behavior and organizational action.

We acknowledge, in line with recent literature, that AI-based digital innovation differs from classic digital innovation and that AI-based digital innovation endeavors likely require novel innovation practices and organizational change. For instance, Benbya et al. (2021) note that "AI technologies offer both novel distinctive opportunities and pose new and significant challenges to organizations in ways that differ from other digital technologies" (p. 281). Thus, the advent of AI violates prior expectations for implementing new technologies and challenges the underlying assumptions of how an organization approaches digital innovation, triggering organizational AI sensemaking. Organizational sensemaking becomes particularly relevant when a coherent and shared understanding among relevant stakeholders becomes vital for collective action (Weick 1993). This socio-technical alignment is key in digital innovations, which are characterized by "the fluid boundaries of the innovation space and the heterogeneous actors that populate it (distributed innovation agency)" (Nambisan et al. 2017, p. 227). Therefore, organizational sensemaking provides a suitable lens (i.e., guiding theory) for our research, helping us to explore how AI sensemaking manifests in digital innovation projects.

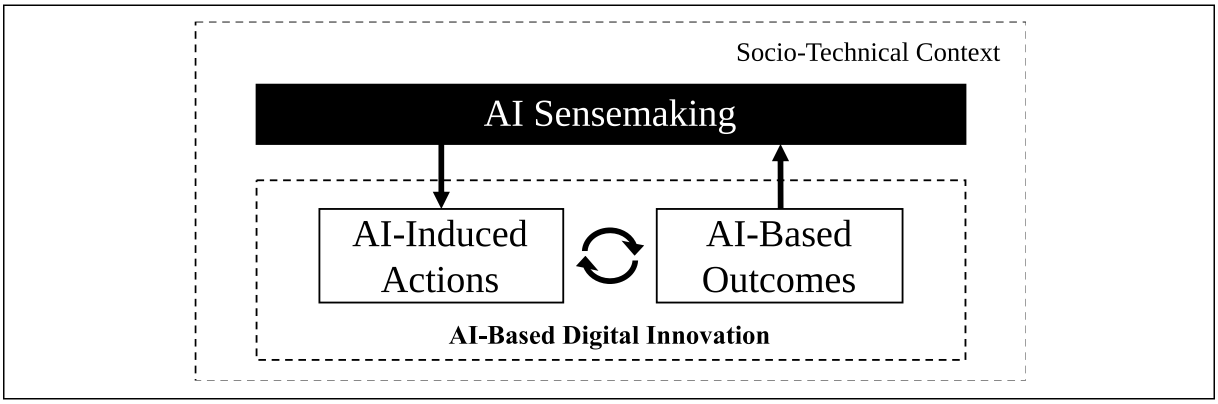


Figure 1. Conceptualization of AI sensemaking in AI-based digital innovations.

Building upon our theoretical foundation, we conceptualize AI-based digital innovation as a recursive shaping between actions and outcomes over time (see Figure 1) (cf. Nambisan 2017; Kohli and Melville, 2019). AI-based outcomes inform the AI sensemaking process, leading to further AI-induced actions. These AI-induced actions can be project-related innovation activities (i.e., use case initiation, development, implementation, or exploitation) or efforts directed to the internal organizational environment (e.g., business strategies, knowledge management, organizational practices). In contrast, AI-based outcomes are either aspired or realized products, processes, or business models with AI at the core. We refer to AI sensemaking as the organizational sensemaking within an organization's socio-technical context, which is directly linked to the peculiarities of AI-based digital innovation.

3 Research Design and Method

We adopted an inductive qualitative research approach due to the topic's novelty and a lack of prior research at the intersection of AI and digital innovation. Exploratory case study research is suitable for investigating a nascent field and deriving insights from a real-world context (Eisenhardt 1989; Myers 1997; Yin 2003). We seized the unique opportunity to collect our data in the context of a leading global automotive OEM (Original Equipment Manufacturer) that makes sense of AI technologies to improve its manufacturing processes. We use organizational sensemaking as our guiding theoretical lens to analyze two focal AI-based digital innovation projects in manufacturing and contrast AI from traditional information systems through its distinctive AI characteristics.

3.1 Case Context: Automotive Manufacturing

The automotive industry is a traditional manufacturing division of significant economic importance with a long-standing tradition and lots of experience in technology management and innovation. Over more than two centuries, technological innovations have altered and transformed the manufacturing industry, particularly in areas where human physical limitations have been reached (Dwivedi et al. 2021). Today, the manufacturing industry faces digital transformation, primarily incorporating data-driven technologies in manufacturing systems, such as Industrial Internet of Things, Big Data, and AI. The AI-empowered digital transformation is predicted to cause significant benefits and productivity gains at all company levels (Duan et al. 2019; Dwivedi et al. 2021). Experts predict AI use cases along the entire car manufacturing value chain (Demlehner et al. 2021). For example, AI-based process automation has great potential for manufacturing organizations and ultimately helps them transform into data-driven productions. Whereas the focus of previous IT was primarily on administrative activities, the new technologies influence operational activities and even take direct control of operational processes (Lasi et al. 2014; Margherita and Braccini, 2020). Application scenarios of AI in manufacturing are, e.g., predictive maintenance, prediction of malfunctions, automated decision-making in production control, material disposition, process-integrated quality control, or quality prediction of screw connections. Today, many lighthouse projects and proof-of-concepts showcase the value proposition of AI technologies. However, manufacturing organizations are still facing AI realization challenges. Many AI-based digital innovation projects fall short of expectations, which indicates the novelty of handling and managing AI-based digital innovations.

3.2 Data Collection

Our data collection spans two use cases in the focal manufacturing organization. Because of the long-standing relationship with one of the authors, we were able to assess the focused organization with a unique source of data (Patton 1990). Both cases have gone through or at least touched upon all innovation stages. We have deliberately chosen two use cases to increase the empirical basis and put our research findings on a broader conceptual footing. We deduce our insights from variance analysis between the following two cases: (Case 1) AI-based computer vision for crack detection. Computer vision allows deriving meaningful information from visual inputs like digital images, allowing to automate visual tasks from a real-world context such as a factory line. Cameras capture real-time images of the environment, the images get analyzed, and the results get used to make business logic decisions. The crack detection system detects cracks on deep-drawn sheet metal parts in the press line using convolutional neural networks. It is designed to assist workers and reduce manual inspection efforts. (Case 2) AI-based condition monitoring for welding spot inspection. The system is based on supervised learning techniques analyzing various sensor data to detect welding quality problems. It helps to optimize the welding parameters of robots ultimately.

We conducted interviews using a semi-structured interview guideline that allowed us to dive into the genuinely novel specificities of the organizational AI sensemaking process. For example, we asked: "How did the peculiar characteristics of AI change your interpretation of the specific use case(s)?" Table 1 summarizes the scope and assignment of our interviews. The authors have conducted all interviews themselves and reflected the insights in author team discussions. In addition, we reviewed several case documents (e.g., internal presentations) and attended project discussions and workshops.

Primary Data					
ID	**Position**	**Case 1**	**Case 2**	**Number of interviews**	**Total duration (hours)**
01	ML Engineer	X	X	2	2:00
02	ML Engineer	X		1	1:00
03	Data Scientist	X	X	1	1:00
04	Product Owner	X		3	2:30
05	Product Owner		X	2	1:30
06	Data Scientist		X	1	1:00
07	Technology Expert	X		1	1:00
08	Data Scientist	X	X	1	1:00
09	Innovation Manager	X	X	1	1:20
10	Technology Expert		X	1	1:00
11	Technology Expert	X		1	0:50
12	AI Portfolio Manager	X	X	3	1:45
13	Innovation Manager	X	X	1	0:30
			Total	**19**	**16:25**
Secondary Data					
Meeting observations (7); Write-ups (5); Case presentations (4); Public communication (2)					

Table 1. Overview of data collection.

3.3 Data Analysis

Our data analysis followed a three-stage coding process according to Corbin and Strauss (1990). In the (1) open coding stage, codes emerged through case descriptions and summaries, which we used to summarize our transcripts and provide an initial overview of all case data (Yin 2003). In the (2) axial coding stage, the research team condensed all data based on recurring themes. In the (3) selective coding stage, we focused on investigating the AI-induced triggers leading to violated expectations that preceded sensemaking. Further, to develop an explanatory theory of our observations (Urquhart et al. 2010), we searched for a theoretical lens that helps explain our empirical findings; this ultimately led us to focus on organizational sensemaking. Drawing on the coding process, we reiterated our data. We then further triangulated all data with multiple secondary data sources (i.e., meeting observations, write-ups, case presentations, and public communication). These reiterations helped us adhere to the interpretive research principles of researcher-subject interaction, distrust, and multiple interpretations (Klein and Myers, 1999). We identified AI-induced sensemaking triggers and mapped them to related AI sensemaking processes. Building upon this, we distilled four AI sensemaking mechanisms. These mechanisms helped explain the recursive shaping between AI-based digital innovation actions and AI-based digital innovation outcomes in the focal innovation endeavors. We used ATLAS.ti as our qualitative data analysis software to systematically analyze and manage the collected data. During the coding process, the research team triangulated findings with results from the analysis of internal (e.g., internal presentations) and external (e.g., public testimony) case documents. Discrepancies were discussed with the interviewees so initial assumptions could be discarded, validated, or manifested.

Furthermore, the unique opportunity to participate in selected company-internal workshops helped us to further review, substantiate, and contextualize our analytical insights.

4 Results

We structure our results according to the four-staged digital innovation process proposed by Kohli and Melville (2019), i.e., initiation, development, implementation, and exploitation. We relate AI-induced sensemaking triggers to AI-induced actions, which we observed in the case, and then infer underlying AI sensemaking processes. We incorporate existing sensemaking literature when presenting our research findings. For logical flow, we already map identified sensemaking mechanisms, which we address in the subsequent discussion section (see 5).

4.1 Initiation

The initiation stage involves identifying valid problem-solution parings and building AI prototypes to showcase the AI value potential for a defined business problem. Our respondents consider forming problem-solution pairings in the presence of AI particularly difficult due to its experimental character. Therefore, they emphasized the need for domain and AI experts to jointly elaborate task-specific use cases, driven by mutual *sensedemanding – the process in which human agents demand more depth and breadth of information to decrease uncertainty and equivocality* (cf. Vlaar et al. 2008). On the one hand, AI experts can help to classify the AI potential correctly and to transfer it into a more concrete technical question. On the other hand, domain experts can roughly assess the economic viability of a potential solution. Adding to this, interviewees highlighted the provision of an initial data set representing the business problem as another critical action area due to AI's learning requirements. We mainly observed activities around cross-functional collaboration to collect initial data, hands-on data labeling, and training and testing the first AI models. In doing so, the resulting AI prototypes helped to narrow down a shortlist of AI use case ideas through *joint sensemaking – the process in which human agents develop a shared understanding through a mutually co-constituted process* (cf. Maitlis and Christianson, 2014). Our respondents unanimously emphasized that AI-ready use cases do not simply emerge but somewhat get shaped through structured use case screening and intensive dialogues between AI and domain experts. Our interviews also revealed generally inflated expectations of 'AI intelligence' due to its black-box characteristics. Therefore, use case initiators must first formalize the actual AI task within a use case idea and, therefore, data-wise express the business problem (i.e., hypothesis generation). In both analyzed use cases, this generated *sensebreaking – the process in which human agents' interpretation or meaning is destroyed or broken down to allow for novel perceptual constructions* (cf. Pratt 2000).

AI-Induced Actions (*Build an AI Prototype*)	**AI-Induced Sensemaking Triggers** (*AI Characteristics*)	**AI Sensemaking Processes** (*AI Sensemaking Mechanism*)
• Ideating promising problem-solution pairings for AI • Building initial datasets to data-wise represent the business problem	• General-purpose AI technologies must be transferred to specific AI use cases (*Black box & experimental character*) • Tasks performed by humans must be formalized to assess potential AI task performance *(Learning requirements)*	• Domain and AI experts consider promising problem-AI pairings, thereby shaping their interpretation of AI. (*Cognition*) • Domain experts describe AI tasks based on example images, thereby jointly developing a contextualized idea of the AI term. (*Concretization*)

Table 2. AI-induced sensemaking triggers and processes in the initiation stage.

In the crack detection use case, a tech-savvy subject matter expert and later project manager learned about AI-based traffic data analysis at an internal technology event on autonomous driving. At this point, the initial problem-solution pairing was created at the individual level and disconnected from the socio-technical corporate environment. However, he could not answer whether using AI was feasible within the contextual conditions in the press shop. Thus, the project leader's sensedemanding triggered approaching internal ML experts from the IT department. They jointly started to collect data, labeled it on their own, and built a crack detection prototype. A video on ‘detecting cracks’ was then created to showcase the idea to other organizational stakeholders. In the condition monitoring use case, a project team analyzed existing process data using classical data analytics methods before using AI was considered. “You just must tell them not to bring the technology upfront. So, the requester must bring the use case, and the specialists must bring the technology. That’s how it must work.” (ID-09) The AI value expectations emerged during discussions about how to utilize existing welding process data. “We discussed with the maintenance team what to do with the welding process data. Then, we agreed on the welding process because it is highly scalable and mostly distributed in car body construction.” (ID-05) The project team, therefore, perceived AI as a tool to make data analysis more ‘intelligent.’

4.2 Development

The development stage encompasses actions aiming to turn AI prototypes into AI products. In efficiency-trimmed manufacturing systems, such as in our case company, achieving positive business cases requires high system performances and avoiding error slips. “If the AI application only works at 80 percent, then it probably has a value contribution of maximum zero for production.” (ID-01) Therefore, respondents emphasized that economic feasibility requirements can quickly limit exploratory freedom. “A major challenge in AI projects is the profitability calculation. Many things seem uneconomical if the first use case must bear all the start-up costs.” (ID-12) However, we observed *guided sensemaking – the process in which a human agent advises another human’s sensemaking process to produce a unitary, shared account of meaning* (cf. Maitlis 2005). Managers provided financial and human resources for early AI projects, creating an environment for exploring AI innovations without the ubiquity of proof of economic viability. In doing so, they signalized their (longer-term) belief in AI-based solutions, hence encountering the experimental character of AI and related AI-induced uncertainties. The AI learning requirements unfolded in a very close interlocking between the business and IT departments, enhancing an intensified *joint sensemaking* (cf. Maitlis and Christianson, 2014). On the one hand, data scientists were required to optimize the AI models and ensure AI performance transferability (i.e., distributed, representative database). Therefore, they guided the professionalized data collection and labeling process. This process was particularly challenging in our case context due to the skewed nature of manufacturing data with few error samples. On the other hand, business experts provided clear success metrics for business case calculations with a strong mathematical focus to derive AI performance requirements. “It’s like a negotiation. Notionally, production experts may state that they can’t live with 50 percent error detection and require 99 percent. […] Vice versa, an AI expert creates an AI model and demands additional data, particularly of edge cases, to tune the model.” (ID-03)

AI-Induced Actions (*Create an AI Product*)	**AI-Induced Sensemaking Triggers** (*AI Characteristics*)	**AI Sensemaking Processes** (*AI Sensemaking Mechanism*)
• Concentrating on prioritized AI projects and providing required resources • Building a broader database and improving the AI performance through ever more inclusion of data	• A prolonged, longer persisting period of uncertainty regarding business case feasibility despite considerable resource expenditure (*Experimental character*) • Instead of general AI intelligence assumptions, an AI-appropriate business problem must be data-wise represented and hypothesized. (*Black box character & learning requirements*)	• Management allocates resources to AI projects, thereby signalizing the belief in AI technologies to organizational members. (*Concretization*) • Data scientists and domain experts weigh AI performance requirements with data collections efforts, thereby breaking inflated AI expectations. (*Interaction*)

Table 3. Observed AI-induced sensemaking triggers in the development stage.

In the AI crack detection use case, a lengthy process of building a larger dataset including sufficient defect parts dominated the development stage. “Since AI is context-sensitive, we could not have simply torn aluminum foil to represent the cracks but needed real data from the production environment." (ID-01) We observed that extensive resources were made available for development after showcasing the AI potential. "At some point, the use case was clear to all, and the project was set. Then, everyone believed in it, and it was suddenly much easier to get support. Everyone wanted to be part of the project." (ID-04) The strong customer support in the local press shops was particularly crucial during image acquisition, mainly because it was not all so clearly assignable what is actually a crack in the images. Therefore, AI experts guided a so-called 'consensus labeling' approach, in which domain experts labeled images independently and multiple times. In case of discrepancies, the individual assessments of the domain experts were objectified in joint discussions. Furthermore, the project team developed an internal training guide and tooling process for subject matter experts to accurately segment the images and ensure ground truth in the labeled data through a defined labeling strategy (multi-eye principle). The condition monitoring use case benefited from management support right from the start, leading to strong *guided sensemaking* (cf. Maitlis 2005). "In the project, the future business value was initially calculated assuming that an AI-based solution is feasible – a leap of faith in AI, so to speak. To legitimize this leap of faith and to obtain resources, you need a management that believes in it." (ID-13) The development stage was also very data-centric. "The AI project must be built around the data scientists and AI experts – just like around the car's engine. For the AI to learn, it needs unified data connections and dashboards to display results to the customer." (ID-05) One key artifact during development was a dashboard created to present and discuss the AI-based data evaluations amongst project members as well as with process and AI experts, allowing for *joint sensemaking* (cf. Maitlis and Christianson, 2014) in multiple iterations. "It needs to be clarified how to present the result to the customer. Meanwhile, we cluster the results completely differently. In the beginning, it was just a division into valid and invalid. Today we have a finer classification, and much more context is extracted from the data. Diving that deep into the data shapeshifts domain and problem understanding." (ID-03)

4.3 Implementation

In the implementation stage, the AI product gets finally deployed in a productive business environment. Notably, the digital nature of AI and its (continuous) learning requirements challenge organizations when integrating an AI product into legacy IT infrastructures. In our manufacturing context, this includes connecting to the actual business processes and creating an operating concept that ensures reliable system operation and automated performance monitoring. Therefore, AI induces a strong need for clarification and coordination between IT experts and members of the innovation project team, what we refer to as *sensedemanding* (cf. Vlaar et al. 2008). "Most of the time, the business department also comes up with non-functional requirements right away, such as the connection to other technologies or the embedding in an existing process. However, the focus of the request is on AI because this is where the greatest challenges are expected." (ID-11) Implementing the (first) AI products into the legacy IT infrastructures is likely to lack IT alignment and stakeholder inclusion. Some key aspects that arise during the bilateral sensedemanding (cf. Vlaar et al. 2008) are reflected in the following quote: "What we have now done in the project paves the way for many things to come. We have built an edge environment. We have shown how high-frequency data can be pushed into the cloud, how the algorithm can be trained, and how it can be deployed again." (ID-05) Besides many technical aspects, our discussions revealed that one of the foundational AI success factors is *sensegiving – the process in which the sensemaking of others is altered toward a preferred interpretation and meaning* (cf. Gioia and Chittipeddi, 1991). Unlike rule-based deterministic systems, probabilistic AI systems are explainable only to a limited extent (i.e., black box character) as they are not following (familiar) cause-effect relationships. Moreover, our discussions revealed that isolated sensemaking within an AI project entails *ubiquitous sensemaking – the process by which individuals develop a shared understanding through a mutually co-constituted process and engage in bidirectional sensegiving to reconcile conflicts of non-shared understandings* (cf. Tan et al. 2010). Therefore, the first AI use cases foster organizational learning through case-related AI sensegiving.

AI-Induced Actions (*Deploy an AI Product*)	**AI-Induced Sensemaking Triggers** (*AI Characteristics*)	**AI Sensemaking Processes** (*AI Sensemaking Mechanism*)
• Embedding the novel AI product into an organizational business environment • Transferring case-specific AI knowledge and case-related training to employees	• Operating AI systems requires finding ways to connect with legacy IT infrastructures and managing large-volume production data (*Learning requirement*) • Limited AI explainability needs to be contextualized for prospective users who work with the AI system (*Black box character)*	• AI project team and IT specialists mutually discuss AI implementation requirements, thereby defining regularities for AI operations. (*Regulation*) • AI project teams include user base in innovation activities, thereby providing simplified interpretation of AI to the user base. (*Interaction*)

Table 4. Observed AI-induced sensemaking triggers in the implementation stage.

We witnessed numerous technical implementation issues in the crack detection use case, such as embedding in legacy IT systems, IT architecture definitions, data protection, rights and roles, operating concepts, and support. To clarify all these aspects, the crack detection team had to go through several approvals and release processes distributed to different specialists. Therefore, interviewees strongly pronounced AI-induced *sensedemanding* (cf. Vlaar et al. 2008). “We have once created a standard set of slides for AI and for what we do in the project. We pulled it out again and again and never changed it.” (ID-04) Moreover, the interviewees emphasized that one critical success factor during implementation was the persistence of the AI product team, as it contributed to maintaining a shared cognition regarding the role and definition of AI and the AI project itself. We further observed *sensegiving* (cf. Gioia and Chittipeddi, 1991) as particularly valuable in conversations with people who do nothing with AI. “When I talked to stakeholders who are not directly involved in the project, the idea was often that the AI simply compares images in the background. You can see that people are trying to describe the new from what they know.” (ID-04) Envisioning the implementation of the condition monitoring use case, the project leader outlined the challenges they had to overcome: “Getting AI into a production environment doesn’t just mean setting up an edge device. It doesn’t just mean having a cloud connection – instead, it requires a huge team, a lot of expertise, and an incredible number of services to train, label, deploy and connect to all the infrastructure. If we want to run AI in production today, it’s a huge project that needs to get everyone on the same page.” (ID-10) Another critical aspect we have observed is customer-focused communication in the project (i.e., *sensegiving*). Interviewees stated that there are many AI-related questions, as there is more skepticism towards AI-based systems than traditional IT systems. “Stable AI operation in series production is complex, and few people are familiar with it. However, I think technological change is relatively straightforward. But besides the technology, implementing AI requires a cultural change that we must go through. […] Therefore, we are preparing a document explaining how AI works so that users can get a general idea.” (ID-05)

4.4 Exploitation

Throughout the exploitation stage, organizations strive to scale AI products to leverage AI value realization across the entire organization. Our case analysis yielded that scaling AI differs from scaling traditional IT technologies due to AI’s context sensitivity and its learning requirements. To address AI-induced peculiarities, the focal organization has established a portfolio and rollout plan that helps to identify and define AI scaling candidates and customers. *Joint sensemaking* (cf. Maitlis and Christianson, 2014) among the distributed innovation agencies at an early stage can be considered a key scaling facilitator. Additionally, AI’s context sensitivity and learning requirements induce the need for continuous model updating of AI solutions. AI model management is organized centrally in the IT department in the focal organization. New AI models are trained centrally, initially run in shadow mode, and monitored before being deployed to a live environment. In addition, organizations need to instantiate semi-automatic data and drift monitoring to check how safe the model performs (uncertainty pipeline) and monitor and detect if a new part passes over the press (drift pipeline). Therefore, the IT department regulates, providing *guided sensemaking* (cf. Maitlis 2005).

AI-Induced Actions (*Leverage an AI Product*)	**AI-Induced Sensemaking Triggers** (*AI Characteristics*)	**AI Sensemaking Processes** (*AI Sensemaking Mechanism*)
• Finding ways to scale implemented AI products throughout the organization • Reusing and adapting the pre-trained models and tools for future innovation projects	• The ease of scaling depends on the interlock between an AI project and its enabling organizational conditions (*Context sensitivity & learning requirements*) • Operating AI at scale requires leveraging synergies between single AI use cases and overall AI architectures (*Context sensitivity & learning requirements)*	• AI project teams (bottom-up) and strategic AI initiatives (top-down) align innovation activities, thereby facilitating AI scaling. (*Interaction*) • AI experts coordinate AI-based innovations from a technical perspective, thereby setting AI tools and standard features. (*Regulation*)

Table 5. Observed AI-induced sensemaking triggers in the exploitation stage.

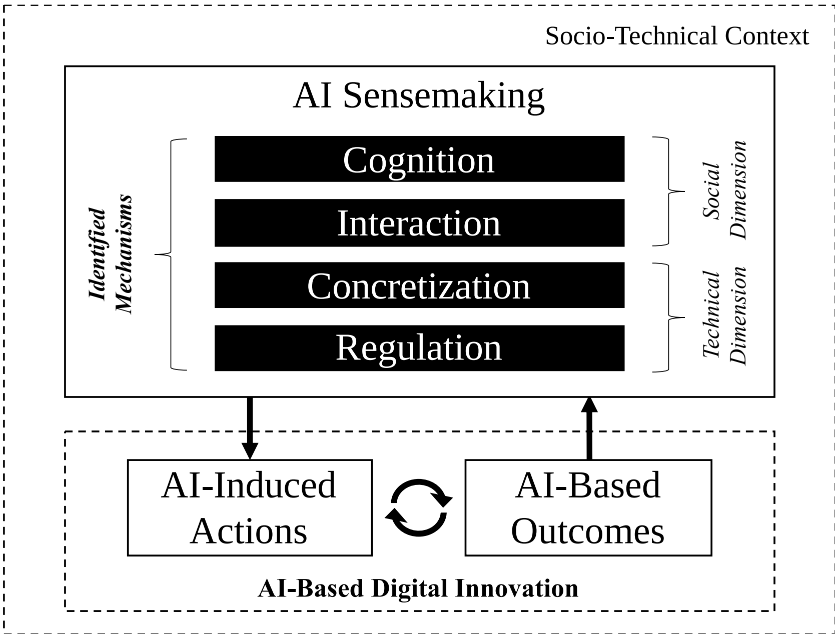
The crack detection use case considered scaling from the outset and benefitted from prevailing *joint sensemaking* (cf. Maitlis and Christianson, 2014). AI engineers avoided a fragmented model landscape and focused on building a universal crack detection model, including data sources from different rollout candidates early on. In doing so, the project team encountered the context-sensitivity of AI at an early stage. “If you now have an AI algorithm at four different locations, one needs technical solutions to monitor the algorithm, import the updates, and establish a continuous integration and development pipeline. There are many related questions, from building a ‘PyTorch model’ to a scalable AI-based software solution.” (ID-01) Both use cases (the condition monitoring use case yet pends scaling) can rely on regularities defined within the organization and refine case-specific requirements for platform-based AI scaling. These contextual conditions reflect pronounced *guided sensemaking* (cf. Maitlis 2005). “Thanks to the platform strategy, the IT architecture is basically set in the AI projects at our company. That is an absolute advantage and saves long discussions.” (ID-12)

5 Discussion and Implications

Our research surfaced four mechanisms by which organizational members make sense in AI-based digital innovation, i.e., *cognition*, *interaction*, *concretization*, and *regulation* (see Table 6). Each mechanism is tied closely to (or induced by) the unique characteristics of AI. These mechanisms were critical for managing AI, anteceded and shaped AI-induced actions, and, therefore, were crucial for managing AI-based digital innovations.

In the social dimension, *cognition* and *interaction* relate to AI sensemaking of organizational members, who make sense of AI individually or develop new meanings within their social interaction environment. The *cognition mechanism* became apparent, especially in the initiation stage. Triggered by AI’s black box characteristics, AI conceptions were widely inconsistent, and various wishes and ideas get projected onto the AI term. Amongst organizational members, the initially vague AI interpretations pivoted into rather concrete formulations while experimenting with early use case ideas, i.e., with application reference. The *interaction mechanism* was predominantly triggered by AI’s learning requirements and black box characteristics. On the one hand, AI-based innovations demand increased involvement of domain experts with an essential and active role in system development. On the other hand, we witnessed interdisciplinary interweaving and pronounced AI sensemaking amongst organizational members across divisions. AI sensemaking demands have increased coordination efforts in AI-based digital innovations – with both domain experts on domain requirements and with (technical) IT interface experts.

In the technical dimension, *concretization* and *regulation* relate to AI sensemaking concerning technical (AI) challenges and their implications for the organization. The *concretization mechanism* was prevalent due to AI’s learning requirements and experimental character. The experimental character of AI increases the demand for making sense of AI technologies and their translation into specific use cases. Especially if there is insufficient training data or use case scope ambiguity, the prevailing uncertainty is at odds with the usual portfolio planning and resource allocation, which are pivotal to organizational investment decisions. Against this backdrop, AI induced increasing socio-technical interaction and AI sensemaking processes. The *regulation mechanism* occurred due to AI's context sensitivity and learning requirements. The mechanism triggered AI sensemaking, leading to a stronger interaction between IT, domain, and AI experts, for example, to discuss IT landscapes, latency requirements, or AI feature standardization. AI's context sensitivity led to uncertainties regarding the reliability of AI operations, particularly in the case of scaling, requiring constant AI algorithm monitoring during productive operation to react to contextual changes in the event of a drop in AI performance. Therefore, AI-based innovations get integrated into the company's (legacy) IT infrastructure in a regulated manner, preventing a proliferation of AI integration concepts (and thus costs and complexity).



AI Sensemaking Mechanisms	
Cognition	*The mechanism by which organizational members perceive AI and shape their interpretations. This may manifest through projecting inflated expectations or any wishes onto AI-based digital innovations.*
Interaction	*The mechanism by which organizational members mutually exchange their AI interpretations. This may manifest through inferring an intersubjective need for action in AI-based digital innovations.*
Concretization	*The mechanism by which loose AI interpretations get concretized within AI-based digital innovations. This may manifest through altering or restricting innovation-related actions.*
Regulation	*The mechanism by which fixed boundary conditions limit the AI-related design space. This may manifest through determining the degree of freedom in AI-based digital innovations.*

Table 6. AI sensemaking mechanisms in AI-based digital innovations.

In this article, we investigated how organizational sensemaking fosters the scaling of AI-based digital innovation. We carved out AI-induced sensemaking processes based on rich empirical insights and traced them back to AI-induced sensemaking triggers. Generalizing these findings, we propose our distinct set of four mechanisms as a foundation to advance AI-based digital innovation in organizational settings successfully.

Our research contributes to the nascent stream of research on AI that calls for explaining the intricacies that AI technologies bring to digital innovations (Benbya et al. 2021; Berente et al. 2019; von Briel et al. 2018; von Krogh 2018; Wiesböck and Hess, 2020). Previous research has identified challenges where sensemaking is highly relevant. For example, overcoming the AI deployment problem (Benbya et al. 2020) or managing organizational processes (Berente et al. 2021). Our work makes three contributions:

First, we propose four empirically grounded sensemaking mechanisms that describe how the unique characteristics of AI unfold in digital innovation settings. These sensemaking mechanisms underline the "fluid boundaries of the innovation space and the heterogeneous actors that populate it" (Nambisan et al. 2017, p. 227) while acknowledging the role of the materiality of AI as technology in the form of the four distinctive AI characteristics: experimental character, context-sensitivity, black-box character, and learning requirements. Accordingly, our research sheds light on how AI-based digital innovation challenges prior innovation practices. Researchers may investigate these four mechanisms to single out socio-technical views on AI-based digital innovations.

Second, we provide an initial understanding of how organizational members encounter AI-induced uncertainties through sensemaking by linking the identified AI sensemaking mechanisms to AI-induced sensemaking triggers and processes along AI-based digital innovations. Researchers may move beyond our organizational sensemaking view and elaborate sensemaking mechanisms at the individual level of stakeholders, for example, considering their roles and responsibilities in the context of AI-based digital innovations.

Third, the proposed sensemaking lens and the four mechanisms may be fruitful for studying cases in which the characteristics of AI particularly challenge existing innovation practices in organizations, as it suggests a theoretical account that helps to elaborate how organizational actors construct new socio-material realities through AI-based digital innovations. Thus, we contribute to the literature on digital innovation by providing an empirical-based theoretical view on how digital innovation agents in a real-world organizational setting make sense of AI as digital technology. Thereby, we respond to the call of Nambisan et al. (2017). Researchers may further substantiate our findings by drawing on, for example, multiple case studies or cross-case analyses.

For practice, we give timely insights into AI innovation challenges in the manufacturing industry and thus may explain why there are still low AI innovation success rates. Our results illustrate the specific characteristics of how AI characteristics impact AI-based digital innovation projects and how adopting a sensemaking view may help in encountering AI-induced challenges. The identified AI sensemaking mechanisms may help establish action fields that facilitate the successful implementation of AI-based digital innovation projects in a specific enterprise context.

6 Limitations and Conclusion

Our research is not without limitations. First, our findings build on an in-depth single case study of a leading automotive manufacturer. By triangulating our empirical data and selecting two different use cases, we sought to ensure rigor in the best possible way. However, we recognize the limitations to generalizability to AI-based digital innovations in different organizational contexts such as digital ventures. Second, our findings emerged from a qualitative research approach and may be subject to misinterpretation. Therefore, future research can substantiate and extend our results to further specify the unfolding of AI intricacies in AI-based digital innovation projects.

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